Advanced Bottom-up Modelling for National and Regional Energy Planning in Response to Climate Change*

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Abstract

This paper describes an advanced bottom-up approach for modelling the energy-environment sector to study greenhouse gas abatement. Three new features are described which give significant new capabilities to this class of models. These are: endogenization of end-use demands which allows computation of partial equilibria in energy markets; modelling future uncertainties using multi-stage stochastic programming; and, combining several bottom-up models as a multi-region model to explore issues of co-operation and burden sharing. Each of these new features is illustrated by results taken from large scale Extended MARKAL models of Québec and Ontario. The focus of the paper is on the nature of issues which can be addressed by this methodology, rather than on specific conclusions drawn from the discussed examples. We believe that a very promising avenue of research lies in exploring the role of multiple advanced bottom-up models in the integrated assessment of climate change.

Keywords: *Climate Change**,** GHG Abatement, Bottom-up Energy models, Supply-Demand Equilibrium, Stochastic Programming, Multi-region Models.*

1. Introduction

The Global Warming of the terrestrial atmosphere induced by an increase in Greenhouse Gas (GHG) concentration has moved from speculation to fact in the recent years. Hundreds of researchers, not only in atmospheric and earth sciences, ecology, biology, but also in economics, ethics, and other social sciences, are studying the origin, development, and impacts, present and future, of Climate Change on human and environmental systems. A recent, major set of studies by the Intergovernmental Panel on Climate Change (IPCC, 1995 a, b, c) summarizes research in these areas over the last 10 years. While scientists in each of the concerned disciplines continue to generate new knowledge of each subsystem, it has been recognized from the beginning that an understanding of the inter-relationships between the

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three major phenomena is crucial for the purpose of policy making regarding Climate Change. These are: (i) the emission of GHG into the atmosphere, (ii) the modification of global and local climates resulting from increased GHG concentration, and (iii) the impact of climate change on the Earth, and more particularly on flora, fauna, and the human ecosystem. These three phenomena are strongly inter-related, and the relationships work both ways: for instance, whereas the reduction of GHG emissions impacts on climate, and ultimately on economic and social systems, the reverse is also true, since a change in socio-economic habits and structures may have a major influence on the emissions of GHG. What makes the study of these interactions difficult, is the inherent complexity of the physical phenomena at work, as well as the many uncertainties still present in the various links, the great variability of human and ecological impacts across the planet, and the persistence of such impacts over long periods of time.

In a nutshell, the basic problem facing policy makers at the global level is to decide upon the levels and timing of the possible emission abatement, climate adaptation and geo-engineering responses to climate change, while taking into account the diversity of impacts and interests in different countries and regions of the world, as well as the presence of uncertainties. In this paper, we focus on the abatement aspects, which are strongly related to an understanding of the energy system of each country.

Policy makers at the local (i.e. country, state, or province) level have concerns which are very specific, and which include the precise set of measures (techno-economic as well as political) that would achieve some desired emission target at minimum social cost. The setting of national emission targets itself is an important task, and represents the single most crucial link between local and global levels of GHG abatement analysis. Indeed, it is highly desirable that local emission targets be set so as to guarantee that global emissions are controlled efficiently, i.e. at minimum overall societal cost.

In this research, we wish to report on methodological approaches which can potentially improve the quality of analyses of the GHG emission subsystem at the local and regional levels, while taking into account the global nature of the problem. This initial principle may be called: local planning within global thinking. It is clear that no single model can, for the time being, be fully global (i.e. represent all major world regions), and at the same time fully local (i.e. provide sufficiently detailed representation of each and every national system for detailed decision making). The MESSAGE regionalized model (Messner and Strubegger, 1995), MERGE (Manne et al., 1995), GCAM (Edmonds et al., 1993) and ICAM-2 (Dowlatabadi et al., 1994) are examples of models which take the global viewpoint while keeping some degree of detail at the regional level. However, each is a compromise that approaches such an ideal, but at the expense of some loss of detail and realism for individual country representation. Detailed local models thus have a role to play.

Here, we shall describe a way to use local/regional detailed energy-environment models to perform long-term analyses of GHG abatement that is compatible with overall climate change objectives which would be established at the World level. The analyses have the capability to incorporate the inherent uncertainties, as well as inter-regional linkages. Such modelling makes it possible to generate and explore very specific and robust options for controlling the energy sector carbon emission. Moreover, as the model is for a nation or a province, the results are immediately relevant for the policy makers, thus insuring the interest and support of the various stakeholders at the local level (governments, industries, and non governmental organizations).

We describe the methodologies in the next section. In section 3, we illustrate the approach via analysis of several results from the recently modified MARKAL model for two Canadian provinces. Section 4 concludes the article.

2. GHG abatement analysis with advanced bottom-up energy models

2.1 Detailed Energy sector modelling

Energy sector models have been around for more than two decades, and have undergone major changes over that period. The first models deserving the name (i.e. integrating all sub-sectors, including end-use of energy) are the EFOM (Van der Voort et al., 1985), MESSAGE, and MARKAL (Fishbone et al., 1981, 1983) families of models, all developed in the late 1970's and early 1980's. The methodology (some would say philosophy) used in all these models is Optimization, which allows the convenient computation of a partial equilibrium (P.E.) on energy markets. All such models are multi-period, and accept limits and/or taxes on the emissions of GHG (and other gases) by the energy system. Of course, the extent of the partial equilibrium depends heavily of the quality of the database defining the particular instance of each generic family. The exogenous inputs into these models, beside emission targets or taxes, are essentially an *economic scenario* which specifies a set of demands at the sub-sector level, as well as a *price scenario* for imported energy forms (all internal energy forms are endogenously determined). Typically, a model instance describes in much detail the individual technologies (present and future) that constitute the energy system, and includes explicit variables representing the investment and operations decisions on each technology over the many periods of the model. This feature has earned them the name "bottom-up" in the economic literature (Hourcade, 1993; Grubb, 1993; Loulou et al., 1997), because the system is described at the "grass-roots" level, as opposed to the more aggregated representations in the so-called "top-down" models. Alternate names are: process models, activity analysis models, and techno-economic models. We shall use these names more or less interchangeably.

With the present enhanced performance of modern computers, the tendency has been to include a large amount of detail in a national (or state, provincial, etc.) process model. We view this as a good thing, as it increases confidence in the model by energy system engineers and analysts who are used to thinking at a detailed technological level. The counterpart of this is of course increased data collection and maintenance efforts.

2.2 Prices, marginal costs, and marginal system values

A useful, albeit incomplete way to think of a process model is as an "engine" that, given a set of inputs (demands, emission caps, etc.) produces (a) the minimum total system's discounted cost for satisfying the inputs, and, more importantly (b) a set of *marginal costs* for satisfying the demands and the emission caps. Such marginal costs are easily obtained via the dual solution of the Linear Program. For example, the model computes the marginal cost of each demand category (e.g. marginal cost of one ton of aluminium, or of one kilometre of auto travel). This acts as the *implicit price* (or *shadow price*) of the commodity that this demand represents. In the case of intermediate commodities (such as the energy carriers), there is no

direct explicit demand for them in an integrated process model; rather, there is a *derived demand* for each energy form. For such commodities, the model computes a *marginal system value*, rather than a marginal cost, and that value also plays the role of implicit price of the commodity, within the model (Berger et al., 1994). Not only are such prices useful in their own right, they also play an important role in the validation of the model's instance (it is part of the modelling folklore that the dual solution's values are much more sensitive to data errors, and thus much more useful to validate a model's database than the primal solution).

We may now give more substance to the type of partial equilibrium (P.E.) that is computed by a process model: its exogenous demands are specified by scenario, its intermediate demands are derived endogenously, and all prices are computed endogenously as the marginal system's values, i.e. the shadow prices attached to the commodities.

Before discussing the advanced features which deal with uncertainty and multiple regions, we wish to make three important remarks about the general bottom-up approach:

1. When the model builder elects to eliminate all taxes and subsidies from the model, the partial equilibrium qualifies as a *competitive* one. Conversely, if taxes and/or subsidies, as well as some regulatory constraints are modelled, the equilibrium becomes a *regulated* one. There is considerable flexibility in the type and amount of regulation that can be modelled in this way. The modeller's choices are then reflected in the shadow prices computed, which then become regulated marginal costs (or values), rather than purely competitive ones.

2. The above discussion seems to suggest that demands for goods and services are always exogenous in process models. Although this was the case for a long time, it is no longer so, at least not necessarily so. Some recent model developments have introduced own price elasticities in the models (Loulou and Lavigne, 1996), so that the initially specified demand scenario will be adjusted endogenously by the model, in response to the implicit demand prices. This feature confers added scope to the partial equilibrium that is computed[†].

3. Another important extension of process models goes further, by including macro-economic variables and equations, thus transforming the model into a General Equilibrium (G.E.) one, where the objective is no longer the minimization of energy cost, but rather the maximization of a national utility function, of which energy cost is only a portion. MARKAL-MACRO (Manne and Wene, 1992) is the premier representative of such an extension. In section 3.1, we present a more focused discussion of the relative merits of a P.E. model such as MARKAL, and its G.E. counterpart, MARKAL-MACRO, by means of examining their respective results.

2.3 Modelling of uncertainties

The long term analysis of an energy system is fraught with uncertainties, be it the specification of demands and prices, or the availability and characteristics of future technologies, or the

[†] With endogenous economic demands, our partial equilibrium approaches a general equilibrium, the only remaining difference being that macro economic variables such as income, labor or total investments are not endogenously affected by energy system decisions. The gap between a P.E. with elastic demands and a G.E., is much narrower than was the case before the introduction of elastic demands, as discussed in Loulou and Lavigne (1996).

emission targets that should be adopted. Traditional process models have a deterministic approach, and optimize the system accordingly. This is also the case of traditional G.E. models. In the absence of explicit modelling of uncertainties, model users resort to scenarization, i.e. the capture of possible futures via contrasted scenarios of demands, prices, and emission levels. Although the multiple scenario approach is very useful, it remains somewhat incomplete, or even embarrassing, for the following reason: suppose that two scenarios are modelled and run by a process model, and suppose further that one main (uncertain) event is going to occur say 15 years from now. To fix ideas, we consider an example where the event is the discovery of a key energy technology. It is quite likely that the two alternate scenarios run on the model (i.e. *with* vs. *without* the technology) will produce very different recommendations on investments. If we focus our attention on investments in the initial 15 years (i.e. prior to the event resolution date), we may face two widely different investment recommendations from the model, and we have no easy way of resolving the dilemma.

An alternate approach to multiple scenarios consists in building a single scenario, but one where the future bifurcation is embedded. The resulting *stochastic model* will be quite different in nature from the initial process model. The *Stochastic Programming* paradigm succeeds in representing multiple scenarios, each with a chance of occurring, within a single coherent optimizing model. The key to success is simply to define, for each particular decision, as many variables as there are possible scenario realizations at that time period. For instance, in the example evoked above, there should be a single copy of investment and other variables for the 15 years prior to uncertainty resolution, precisely because a single strategy *must* be followed during that period of time. On the contrary, for all later periods, the outcome of the event is known, and therefore, there should be *two* sets of variables, each representing a particular decision *contingent on the outcome of the uncertain event*. Stochastic programming is easily generalized to any number of uncertain events, each with possibly many possible outcomes. The resulting stochastic scenario is usually represented by an event tree, such as the one discussed in section 3.2.

In the context of energy-environment systems, stochastic modelling has been extensively used to study the energy resource extraction process (MacDonald, 1994; Clarke and Reed, 1990; Behrens, 1990; Yeung and Hartwick, 1988) and optimizing the electricity generation process (Bunn and Paschentis, 1986; Terry et al., 1986; Kunsch and Teghem, 1987; Grosfeld-Nir and Tishler, 1993; Gorenstin et al., 1993). Studies of socio-economic impacts of the uncertain outcomes of global warming have also used stochastic models (Fankhauser, 1994; Kolstad, 1994, Manne and Richels, 1995). A model for stochastic power generation planning problem was presented with a simple application in Louveaux and Smeers (1980).

A two-step model for robustness analysis in energy planning was suggested in Wene (1982). A comprehensive description of the method and its application can be found in Larsson and Wene (1993) and Larsson (1993). The method provided for assessing the efficiency and robustness of exogenously determined alternative strategies. Similar work using the MESSAGE model was reported by Gerking and Voss (1986). Larsson and Wene's work, which used the MARKAL model, can be considered as the precursor to our research presented in this paper.

Birge and Rosa (1996) have included uncertainty in the return on investments in new technologies in the Global 2100 model. Stochastic programming has been used for energy-

environment policy modelling recently, but mostly by the very aggregated global models like DICE (Nordhaus, 1993), MERGE (Manne et al., 1995), and CETA-R (Peck and Teisberg, 1995), which have a distinct 'economics' flavor. While the global models have received wide exposure, they have also been criticized for their inability to faithfully represent the details of national economies. As a consequence, the aggregated economic models experience a 'credibility gap' among national policy makers (this was expressed in the 1995 and 1996 meetings of the IPCC and COP). In this respect, detailed bottom-up models such as ours are perfectly suited to complement the global models.

Reports on formal inclusion of future uncertainties in bottom-up energy-environment modelling are scant. Fragnière and Haurie (1996) have taken an approach similar to ours on this problem, but it has a vastly different implementation. Another recent work has addressed a similar problem using the two-stage recourse problem formulation (Kanudia, 1996).

Stochastic Programming belongs to the class of methods for decision making under uncertain outcomes. One important issue raised by uncertain or risky outcomes is the choice of the objective to pursue. The common *expected cost* criterion compute a weighted average cost, where each outcome's weight is its likelihood of occurrence. While expected cost is the most often discussed and used criterion, it presupposes first of all that probabilities of event outcomes are indeed available, and second of all that the decision maker is risk neutral. Both of these assumptions are debatable in long term strategic policy analysis, where certain events are truly uncertain (i.e. there is no consensus on the likelihoods of their outcomes, e.g. the cost of impacts resulting from a 3^{o} C rise in global temperature), and where certain outcomes would carry such a huge cost, that it would not be acceptable to accept them however low their probability. The second concern may be addressed by replacing the expected cost criterion by an expected utility criterion, where the utility is defined so as to reflect the policy maker's biases with respect to certain cost outcomes (e.g. various degrees of risk aversion). The first concern may also be addressed by defining an objective which does not make use of probabilities. In this respect, the Savage criterion consists in choosing the strategy that minimizes the largest regret that could be experienced by the policy maker (the regret is defined as the difference between the most favorable outcome and the one incurred with the minimax regret strategy). In section 3.2, we describe the implementation and results of Stochastic Programming in the MARKAL model, with various criteria. Kanudia and Loulou (1996) reports the Stochastic MARKAL methodology in greater detail, in the context of technological assessment.

One limitation of the stochastic programming approach is the model size, which may reach gigantic proportions when complex event trees are modelled. This drawback is much less acute now than in the past, thanks to the rapid progress of computing power and of algorithms. Care must nevertheless be exercised to model only the major uncertainties, so as to keep the event tree reasonably succinct.

2.4 Multi-region process models

There is no fundamental reason why a single process model could not represent several countries (or states, provinces), and this has been done in several instances. In a multi country model, care must be exercised to model not only each country's energy system, but also the interchanges of energy and emissions between them, which now become endogenous variables. Such regional models have the capability to analyze the joint response to emission targets, in the presence of emission and of energy trading. We shall illustrate this capability in section 3.4. The multi-country capability is technically only limited by the speed and memory size of the computer platform. However, in practice, such a tight integration of several local models is limited by the enormous demands it imposes on data collection, maintenance, and acceptance by stakeholders. Our own view of such *hard-linked* multi-region models is that they should be confined to a set of geopolitical entities (for example, provinces of a country) for which it makes practical sense to centralize decision making, and hence model building and maintenance. For the composition of many detailed individual country models, more flexible (soft) links may be used.

3. GHG Analyses for two Canadian Provinces with the Extended MARKAL Modelling System

MARKAL is a flexible dynamic linear programming model that can be used to represent the energy system of a community, a region, or a country, over a medium to long time horizon, usually nine periods of five years each. This model is supported by a user-friendly interface, MUSS (**M**ARKAL **U**sers **S**upport **S**ystem, Goldstein, 1994), which manages the input data and the model output. There exists a standard version of MARKAL, and other versions resulting from modifications and additions by individual countries. The Canadian MARKAL model (Berger et al. 1992), also named Extended MARKAL, is significantly different from the standard as well as from other versions of MARKAL. It was developed in several stages since 1984, each stage being motivated by specific applications that could not easily be implemented with the previous model versions. Although some of the features of Extended MARKAL may have been independently developed by other modellers as well, no single other model contains as many new capabilities.

As compared to the standard version of MARKAL, following are the additional features and capabilities of Extended MARKAL:

- the introduction of material flows, alongside energy flows
- the regionalization of electricity and district heating grids
- a better description of seasonal and diurnal demand of electricity by end-use technologies (particularly useful for the modelling of dual energy heating systems with electricity as one of the inputs)
- the additional capabilities for detailed modelling of flexible oil refineries
- the annual and seasonal management of reservoirs for hydroelectric power plants
- the availability of generalized ADRATIO tables (allowing the user to define more general relations, not standard in the model, when they are needed. This capability is particularly useful for the modelling of the various life extension and retrofitting options of a given technology)
- the introduction of sunk and released flows of materials and energy. Material flows are considered to be sunk in a technology when it is installed. For instance, huge quantities of steel and aluminium are present in an industrial facility or in all the cars of a given region. These materials are not available for use during the lifetime of the technology but are released at the end of its lifetime. They are then available for recycling or re-use. The same may be true for some energy flows, as for instance the uranium core of a nuclear reactor.

Besides these features, there are three major extensions that go a long way in refining a bottom-up analysis of the energy-environment system. All three new features are available simultaneously or separately in a single model shell, which we call Extended MARKAL. The extensions are described in the following four sub-sections.

3.1 Endogenizing the demands[‡]

In the Extended MARKAL model, the energy end-use demands are no longer entirely fixed by scenario. They are elastic to their own prices (the prices themselves are endogenously computed by the model as part of the equilibrium), and will self adjust if some scenario conditions affect the prices significantly. The user specifies demand functions of arbitrary form, but usually chosen to be constant elasticity functions in our implementation. A Base Case scenario is used to calibrate the demand functions. The elasticities may be different for different demand categories and for different time periods. Furthermore, a demand category may have asymmetric elasticities for positive and negative variations around the base case demand.

The computational approach is based on the equivalence of the equilibrium and of a certain mathematical program (Samuelson, 1952; Takayama and Judge, 1971), which may be stated as follows*: A supply/demand equilibrium is reached when the sum of producers and consumers surpluses is maximized*. This is graphically illustrated in **Figure 1**, where the maximand is the area between the two curves, and its maximization leads to the intersection of the curves, i.e. the sought equilibrium. As a consequence the model's objective function now comprises two terms: the energy/technology costs, and the loss of welfare due to demand reduction. Mathematical details of the formulation are given in Appendix I. The non-linear inverse demand functions have been approximated by staircase functions in order to linearize the objective function. The user may choose the precision of the staircase approximation as well as the allowed range of demand variation. Tosato (1980) had first proposed such an approach, with minor variations.

This formulation has been implemented in Extended MARKAL by defining additional variables in the code, and thus making the elastic demands an integral, user friendly part of the model. However, it is also possible for a user of other MARKAL versions to implement this model by using *dummy technologies* (Loulou and Lavigne, 1996).

One application to the Québec energy system allows a maximum demand reduction of 20% (5 steps of 4% each), and a maximum demand increase of 15% (3 steps of 5% each). The elasticities usually start with a low value of 0 to 0.1 in the first period, and may reach -0.15 or -0.30 at later periods. These values were derived from earlier estimations performed by Bernard and Genest-Laplante (1995), and adjusted to our situation with the help of expert judgement.

We provide below some highlights of results obtained from three scenarios: base case, severe carbon tax profile without elastic demands, and the same tax with elastic demands. The tax trajectory (Edmonds et al. 1994) starts at $8 per tonne CO_2 in 1995 and reaches $61 per tonne

[‡] Authors acknowledge the contribution of Denis Lavigne from GERAD, in modelling elastic demands.

CO_2 in 2035. The dual solution of the base scenario was used to calibrate the demand functions.

Table 1 shows the percentage reduction in end-use demands as a result of the carbon tax. The carbon dioxide emission trajectories are shown in Figure 2. Assuming that energy systems effect is about the same under the two tax scenarios, the demand loss contributes 18% to the emission reduction.

At this point, it is instructive to recall the results obtained for the Netherlands (Scheper and Kram, 1994). The results from MARKAL and MARKAL-MACRO were compared to see how a 50% reduction target is achieved by the two models. MARKAL-Netherlands has to achieve 100% of the emission reductions through substitutions in the energy sector as it does not have the elastic demand feature. MARKAL-MACRO (Manne and Wene, 1992), on the other hand, is a General equilibrium model were not only demands may vary but other national aggregate variables such as Consumption and Savings. MARKAL_MACRO allocated the emission reductions as follows: 84% via energy system measures, 13% via end-use demand reduction, and 3% via GDP reduction. In view of these facts, it seems clear that the main effect outside the energy system is captured by the demand elasticities, whereas GDP adjustments play a very minor role. We may therefore legitimately expect that a partial equilibrium model such as Extended MARKAL is well adapted to energy analyses, and that not much precision is lost by ignoring the other macroeconomic effects of energy policy.

Table 1 End-use Demand Losses with Elastic Demands (Percent per Year)

Demand Category	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**2025**	**2030**	**2035**
Other Commercial & Institutional	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
Other Commercial & Institutional ELC	4.0	8.0	8.0	8.0	12.0	16.0	16.0	16.0	8.0
Air Transport	0.0	4.0	8.0	8.0	8.0	12.0	16.0	12.0	8.0
New Commercial Heat	0.2	4.0	4.0	8.0	8.0	8.0	12.0	12.0	8.0
New Institutional Heat	0.0	0.0	4.0	8.0	8.0	8.0	8.0	8.0	8.0
Other Industries	0.0	4.0	4.0	8.0	8.0	8.0	5.7	8.0	4.0
Rail Transport	0.0	4.0	0.0	0.0	0.0	12.0	16.0	4.0	0.0
Cement	0.0	0.0	0.9	4.0	4.0	4.0	4.0	4.0	4.0
Residential Water Heat	0.0	0.0	0.0	2.3	4.0	4.4	5.6	4.0	4.2
New Apartments 10+	0.0	0.0	4.0	0.0	0.0	4.0	4.0	4.0	4.0
New Apartments 2-9	0.0	0.0	0.0	0.0	4.0	4.0	4.0	4.0	4.0
Old Commercial Heat	0.1	4.0	8.0	0.0	4.0	4.0	0.0	0.0	0.0
Residential Lighting	0.0	0.0	5.1	4.0	4.0	4.0	0.0	0.0	0.0
Agriculture and Other Residential	0.0	0.0	0.0	0.0	4.0	4.0	4.0	4.0	0.0
Commercial & Institutional Space Cool	0.0	0.0	4.0	4.0	4.0	4.0	0.0	0.0	0.0
Old Institutional Heat	0.1	4.0	4.0	0.0	4.0	4.0	0.0	0.0	0.0
Titanium Slag	0.0	0.0	0.0	4.0	4.0	4.0	4.0	0.0	0.0
Zinc	0.0	0.0	0.0	0.0	4.0	4.0	4.0	4.0	0.0
Commercial Light Incandescent	0.0	0.0	4.0	0.0	4.0	4.0	0.0	0.0	0.0
Existing Apartments 10+	0.0	0.0	0.2	4.0	4.0	4.0	0.0	0.0	0.0
Existing Apartments 2-9	0.0	0.0	0.0	4.0	4.0	4.0	0.0	0.0	0.0
Existing Houses	0.0	0.0	4.0	3.7	4.0	0.0	0.0	0.0	0.0
Miscellaneous Products	0.0	0.0	0.0	0.0	0.0	4.0	4.0	4.0	0.0
New Houses	0.0	0.0	4.0	0.0	4.0	4.0	0.0	0.0	0.0
Stainless Steel	0.0	0.0	0.0	0.0	0.0	4.0	4.0	4.0	0.0
Other Diesel Engines	0.0	0.0	0.0	0.0	0.0	4.0	4.0	0.0	0.0
Aluminum	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0
Commercial Light Fluorescent	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0
Incandescent Light	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0
Magnesium	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0
Steel Bar & Shapes	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0
Steel Sheet	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0
Steel Wire Rod	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0

3.2 Dealing with uncertainty: Stochastic Extended MARKAL (Minimizing Expected Cost)

Extended MARKAL may optionally incorporate multiple scenarios, each with a specified probability of occurrence (Kanudia and Loulou, 1997). It is based on the multi-stage Stochastic Programming paradigm (Dantzig, 1955; Wets, 1989). A mathematical formulation is given in Appendix II, and its main characteristics are summarized below:

1. At each period, there are as many replications of the MARKAL variables as there are different scenario realizations at that period. At those periods when there are multiple realizations (as

in periods 4 to 9 in the example shown in **Figure 3**), each variable set should be considered as a set of *conditional* variables, i.e. variables representing *contingent actions* which will be taken only if the corresponding realization occurs.

2. Each set of variables corresponding to a possible scenario must satisfy all constraints of MARKAL. Therefore, whatever scenario eventually realizes, the corresponding set of variables (decisions) is fully feasible. The multi-period constraints, such as capacity transfer, cumulative emission and cumulative resource usage, are thus defined along each path of the event graph. The single period constraints are repeated as many times as there are different realizations at that period, and that number differs with the period.

3. The objective function (expected cost) is equal to the weighted sum of the scenarios objective functions (costs), each weighted by the scenario's probability of occurring.

3.2.1 Implementation of Multistage Stochastic Programming in Extended MARKAL

The formulation described in the last section has been implemented on the Extended MARKAL model. The existing user interface (MUSS) has been extended to capture the event tree probabilities and the different levels of end-use demands and GHG emission limits. Extensive modifications have been made in the MARKAL code (written in OMNI) to generate the required stochastic program. A new report writer collects the appropriate variables and compiles the results for each scenario.

In the example shown in **Figure 3**, four alternate scenarios have been defined, resulting from the combinations of high vs. Low mitigation and high vs. Low demand. The four scenarios combine to form a probabilistic composite scenario.

Figure 3 shows the four scenarios, with the dates at which each type of uncertainty is resolved, and the event probabilities. The Mitigation uncertainty is assumed to last for three periods and to be resolved at the beginning of period 4 (year 2008). The demand uncertainty is resolved at the beginning of the fifth period (year 2013) represents a possible macroeconomic impact of carbon mitigation. Thus, decisions for the first three periods are taken under mitigation uncertainty and those for the first four under demand uncertainty. In the High Mitigation event, cumulative GHG emissions over 45 years must not exceed 1.87 Billion ton of CO2-equivalent, whereas in the Low Mitigation event, they must not exceed 2.78 Billion ton. In comparison, if emissions remained constant from 1993 to 2037, they would amount to approximately 3.1 Billion tons. Therefore, the Low mitigation cap represents a reduction of 10.5% and the High mitigation cap, a reduction of nearly 40% relative to constant emissions. The fact that the caps are not set for each period, but rather on the cumulative emissions, allows the energy system to "make up" in later periods, if "mistakes" are made in the early ones. The probabilities of these two events are set at 0.5 each. As for the different levels of demands, the High demands exceed the Low ones by an average of 5 to 10%. Note also that the probability of high demand is lower (0.4) under High mitigation than under Low mitigation (0.5), translating the additional economic burden of large abatement efforts into a slowed down economic growth. The combination of these two uncertain events leads to the four branches of the stochastic MARKAL scenario.

Remark: A Stochastic Scenario leads to a *single run* of the (stochastic) model, and therefore to a *single strategy*. However, that strategy contains contingent actions, which will differ at periods later than the resolution dates. We will call it the Hedging Strategy. In contrast, the classical

approach of using several alternate scenarios (each deterministic) leads to as many strategies as there are scenarios (4 in our study). These strategies will differ between themselves *even prior to the resolution dates.* As noted earlier, this is unrealistic, and constitutes a major reason for using Stochastic Programming. We shall call these four strategies, the 'Perfect Foresight" strategies. The phrase "Perfect Foresight Strategy" indicates that the policy maker "believes" that a particular deterministic scenario will realize, but in actual fact, any one of the four possible futures may yet happen; therefore, when a particular scenario does realize, the policy maker must adjust his actions to respond correctly to the revealed state of nature, by re-solving an optimization problem from the date of realization onward.

The complete Stochastic model comprised 28,940 constraints and 41,703 variables. It was solved using the CPLEX optimizer on a PC with a 133 MHz Pentium processor. The computational time was about 2 hours, starting without previous basis.

The legend for strategies and scenarios is given in **Table 2** below.

Table 2 Strategies and scenarios

STRATEGY	LEGEND	DESCRIPTION
PERFECT	PF-HM.HD	**P**erfect **F**oresight Strategy under **H**igh **M**itigation and **H**igh **D**emand Scenario
FORESIGHT	PF-HM.LD	Perfect Foresight Strategy under High Mitigation and Low Demand Scenario
	PF-LM.HD	Perfect Foresight Strategy under Low Mitigation and High Demand Scenario
	PF-LM.LD	Perfect Foresight Strategy under Low Mitigation and Low Demand Scenario
HEDGING	HS-HM.HD	**H**edging **S**trategy if **H**igh **M**itigation and **H**igh **D**emand Scenario occurs
	HS-HM.LD	Hedging Strategy if High Mitigation and Low Demand Scenario occurs
	HS-LM.HD	Hedging Strategy if Low Mitigation and High Demand Scenario occurs
	HS-LM.LD	Hedging Strategy if Low Mitigation and Low Demand Scenario occurs

3.2.2 Results and Analysis

Figure 4 shows the annual GHG emission trajectories under all strategy/scenario combinations. Note carefully that, in Figure 4, a perfect foresight trajectory is the one that would prevail if the actual realization concurs with the state of nature assumed by the decision maker for that strategy. In all other cases, the trajectory would have to be corrected after the realization date, as discussed in the remark of subsection 3.2.1. Evidently, the hedging strategy takes an intermediate path till the uncertainty is resolved. Subsequently, the annual GHG emission falls sharply in case severe mitigation realizes.

Note that the annual emissions with the hedging strategy are lower than those with perfect foresight strategy under high mitigation in later periods. This offsets the higher emissions in the pre-resolution period in order to meet the constraint on cumulative GHG emission.

The technology and fuel level response underlying this overall *middle of the road* position is very interesting. Different energy forms and technologies show a considerable variation in their penetration trajectories. For instance, prior to resolution, the electricity supply capacity follows an intermediate path, whereas natural gas and renewable energy tend to follow the low mitigation trajectory, and oil supply approaches the high mitigation trajectory. Further, a set of *specialized hedging technologies* has been identified, which appear to be more competitive in the hedging strategy than in any of the perfect foresight ones. For example, as shown in Figure 5, electricity consumption in the transport sector is initially higher in the hedging strategy than in either perfect foresight ones. It is therefore evident that a stochastic programming treatment of major uncertainties can yield insights that are beyond the scope of an analysis based on multiple deterministic scenarios.

Discounted System Costs

First of all, the analysis indicates significant expected cost savings when using a hedging strategy, over any of the perfect foresight ones. This can be measured by evaluating the cost that would be incurred if a particular perfect foresight strategy were adopted. Each choice of a perfect foresight strategy at the beginning of the planning horizon is associated with four possible scenarios, only one of which conforms with the decision maker's initial belief. Hence, for the three other outcomes, the actual cost incurred is higher than anticipated by the Perfect Foresight strategy adopted. In this way, we can define an *expected loss* for each of the perfect foresight strategies, over that of the hedging strategy. **Table 3** exhibits the losses for each of the four PF strategies (of course, following the hedging strategy is precisely the way to avoid these costs, which may be seen as the penalties for following a PF strategy, without regard for the probabilistic nature of future events).

Remark: The expected losses have been determined through the following two-step process, for any PF strategy:

Step 1 The model was run with the parameters corresponding to the *assumed* perfect foresight scenario. Then, appropriate bounds were added to the model in order to freeze all the decisions taken prior to the resolution of uncertainty.

Step 2 The model was run again three more times, with the parameters set to those of each of the other three possible realizations, and with the initial decisions frozen as said in step 1. The difference between the system cost derived from each second run and that derived from the hedging strategy is the loss of the PF strategy under a particular realization. The expected loss of the PF strategy is computed as the expectation of the four losses just computed (one such loss is zero).

Table 3 Expected Value of Loss under Perfect Foresight Strategies (CDN$ Billion)

STRATEGY	PF-HM.HD	PF-HM.LD	PF-LM.HD	PF-LM.LD
EV of LOSS	3.27	0.58	10.42	12.50

As can be seen from **Table 3**, the losses are rather high, especially if one of the low mitigation PF strategies is adopted. The least expensive of the PF strategies is High Mitigation combined with low demand, with an expected discounted loss of 580 million dollars.

Another useful concept when planning under risk, is the Expected Value of Perfect Information (EVPI, see Raiffa, 1968), i.e. the cost savings that would accrue if all uncertainties were resolved right now rather than at some future date. EVPI is easily computed by forming the difference between the expected cost of the hedging strategy and the expected value of the four PF strategies. It is equal to $4.86 billion in our case, a fairly hefty amount. This is how much it would be worth to us to know the truth about the future right now (and of course then act accordingly by choosing the adequate perfect foresight strategy).

3.3 Implementation of Minimax Regret strategy in Stochastic Extended MARKAL[§]

One difficulty with classical Stochastic Programming is the correct assessment of scenario probabilities. The Savage or Minimax Regret criterion (see e.g. Raiffa, 1968) dispenses with probabilities, requiring only the identification of the states of nature. Under this criterion, the decisions prior to resolution would be taken such that the maximum subsequent regret is minimized, the regret being defined as the difference between the system cost of the hedging strategy and the cost of the corresponding perfect foresight strategy. Appendix III describes the formulation of this problem as a Linear Program. To implement this formulation in Extended MARKAL, the objective function is re-arranged after an MPS file has been created for the classical Stochastic Program. This is done using a FoxPro program.

In Table 4, we show the regrets resulting from 7 strategies: the six PF strategies, the Minimax Regret strategy, and a Stochastic Programming strategy that assumes that each of the five scenarios has probability 1/5 of realizing (the so-called Laplace criterion, see Raiffa, 1968). We note of course that the Minimax regret strategy yields the smallest worst case regret (1659 M$), the next best being the Laplace equal likelihoods strategy with 1978 M$, a 19% increase. Following any PF strategy, even a middle-of-the-road PF strategy such as the 20% target, has a much higher regret of 2391 M$ (a 44% increase over the Minimax Regret).

The Minimax Regret approach may well be an excellent ground for striking a compromise when policy makers who are indeed able to reach consensus on the list of possible outcomes, but not on their probabilities of occurrence. Furthermore, it has been experimentally verified that the Minimax regret strategy depends essentially on the extremal reduction targets (i.e. the least and the highest targets) but not on the intermediate targets.

Table 4: The "Regrets" (Million $)

	SCENARIO					
STRATEGY	*Constant Emission*	*10% RED.*	*20% RED.*	*30% RED.*	*40% RED.*	**MAX. REGRET**
Constant Emission	0	185	835	2115	11976	11976
10% RED.	199	0	241	1004	6912	6912
20% RED.	1092	297	0	295	3315	3315
30% RED.	2391	1245	313	0	935	2391
40% RED.	5991	4422	2604	1212	0	5991
Laplace	1513	625	106	101	1978	1978
MiniMax Regret	**1659**	**804**	**279**	**58**	**1521**	**1659**

§ The authors wish to thank Douglas Hill for the initial discussion that lead to the Minimax Regret formulation.

3.4 Multi-Regional analyses with Extended MARKAL

A capability to combine individual MARKAL models into a multi-region model has been developed (Kanudia and Loulou, 1997). The main characteristic are summarized below:

- Several countries may be represented within the same overall model
- Each country model may use stochastic scenarios
- Each country model may use elastic demands
- Joint emission targets can be specified
- Energy trading between countries are explicitly represented and endogenously optimized, if the user specifies which fuels are tradable between each pair of regions
- The model is supported by a self-contained report writer that can handle multiple countries. The report writer can optionally export results to MUSS as standard tables. The report writer produces a complete and flexible set of reports and graphs, ready to be included in a Word document, in an automated fashion.
- The results of a run may be displayed country-by-country, and also in an aggregated way for the whole set of countries.

The model is generated by a FoxPro program that takes the MPS files from individual MARKAL models as input. The objective function and joint emission constraints are adjusted automatically to represent a single problem. The program also adds variables and constraints for inter-regional energy trade, based on a list of tradable commodities given by the user.

This model has been tested on a two-province example (Québec and Ontario), reaching about 23,000 rows and 40,000 columns, using CPLEX, and without use of decomposition. Adding several more regions and scenarios will require decomposition, which is being worked upon at present. We now highlight some results from this case study.

3.4.1 The Dividends of Inter-Provincial Co-operation

What is the impact of a joint emission target and electricity trading on the cost of carbon abatement in Québec and Ontario?

The model described above was used to perform four sets of runs, each comprising 6 runs, i.e. one free emission run, and five with cumulative GHG emission reductions of 0%, 10%, 20%, 30%, and 40%, respectively, with respect to the 1990 emission levels. The four sets were: no co-operation (NC), joint emission target (JE), electricity exchanges (EE), and joint emission target with electricity exchange (JEEE). These results were used to construct the trade-off curves shown in **Figure 6**. Clearly, there is a significant cost saving when electricity exchanges are allowed. However, joint emission targets have only a marginal impact on the abatement costs. Electricity trading is shown to result in total discounted savings ranging from $7 billion in the constant emission case to $10 billion in the 40% reduction case, whereas under the free carbon scenario, the savings amount to only $0.48 billion.

A more subtle analysis of emission and electricity trading is made possible by examining the behaviour of electricity exchanges on one hand, and of emission trading on the other hand, across all reduction scenarios. **Figure 7** shows the marginal cost of CO_2 abatement (which is the dual value of the cumulative emission constraint), under different policy scenarios, and **Table 5** shows the emission trading that occurs for the two policy scenarios that involve

emission trading, viz. JE and JEEE. Figure 8 shows the electricity trading that occurs under the JEEE scenario and for each reduction target. Note from **Figure 7** and **Table 5** that although there is a significant difference in the marginal abatement costs in the two provinces through the entire range of reductions, equilibrium is attained with a relatively small trading of emissions, and that the direction of emission trading is reversed when electricity exchanges are allowed.

We first analyze the JEEE case, where the sale of GHG permits by Ontario to Québec, as well as electricity sales peak for the 20% target. The reason is as follows: for moderate reductions, Québec is able to let its consumption sector use some more natural gas, thus freeing some of its hydroelectricity, which is most useful in Ontario (where the main GHG free alternative to Québec's hydro is nuclear power, an expensive source with long lead time). The penetration of natural gas in Québec's residential sector explains the higher GHG emissions in the province and hence the purchasing of permits from Ontario. However, when the reduction target is more stringent (30% or 40%), Québec and Ontario *both need GHG free electricity*, and it becomes more advantageous to use that source close to its production site so as to avoid transmission losses and investments in transmission lines.

Table 5 Emission Trading from Ontario to Québec

Scenario	**40% Red**	**30% Red**	**20% Red**	**10% Red**	**Const Em**
JEEE	32.80	82.95	170.00	121.50	4.05
JE	-68.80	-107.70	-98.30	-138.55	-277.10

Cumulative Million Tons

In the JE case, Ontario buys emission permits from Québec so that it can shift some of the nuclear power generation to gas based plants. Québec implements higher reductions by substituting oil with alcohol in the transport sector. This explains the negative signs on the second row of **Table 5**.

3.4.2 The Impact Of Co-operation On The Nuclear Option

It is therefore clear inter-provincial co-operation, besides reducing the joint cost of meeting reduction targets, has the additional advantage of reducing the need for additional nuclear power in Ontario. Given the currency of the debate on this issue, we conducted additional runs to answer the following question: *how much more does it cost to implement emission reductions without investing in nuclear power, and what is the role of electricity trading in such a scenario?*

Ten more runs were performed, which are plotted in **Figure 9**. These are the five different reduction targets with a 'No New Investment in Nuclear' constraint under the No Co-operation policy (No Nuc NC); and the same set under Joint Emission and Electricity Exchange policy (No Nuc JEEE). The scenarios NC and JEEE have been included for comparison.

The main observation is that a nuclear freeze under NC policy more than doubles the cost of meeting the 40% reduction target (a $170 billion increase over NC, in net discounted cost terms). Whereas, under JEEE, the freeze costs just about $20 billion more. Even for the more moderate reduction targets, the advantage of co-operation is very large, as shown by the distance between the No Nuc NC and the No Nuc JEEE curves in **Figure 9**. This is a major finding, as it provides an attractive alternative to nuclear in the event of the adoption of a GHG emission target.

4. Conclusion

In this research, we have attempted to give an updated description of advanced bottom-up modelling in the energy-environmental sector, with emphasis on greenhouse gas abatement. Besides many technical and implementation improvements, three main new features were discussed, which give significant new capabilities to this class of models. The endogenization of demands allows these model to compute partial equilibria on energy markets, and brings them closer to General Equilibrium approaches, while retaining the technological detail which is the hallmark of process models, and which makes the latter more relevant for detailed policy analysis. The correct treatment of uncertainties is an extremely welcome feature, especially when modelling major climatic constraints that may affect the long run in a dramatic way. Finally, the composition of several bottom-up models helps in regional analyses that address co-operation issues and the sharing of burdens.

Each of these new features has been illustrated by results taken from large scale Extended MARKAL models of Ontario and Québec, so as to demonstrate the beneficial effects of the new features on the quality of analyses. We have focused our analyses on the insights gained, rather than on specific quantitative conclusions on the particular examples treated. It is noteworthy that Extended MARKAL incorporate all these features in a single shell that is very user friendly and flexible. In the future, the applicability of this class of models will be enhanced by the ever increasing power of personal computers which allow model size to increase significantly. In addition, research on robust decomposition algorithms is expected to result in the more routine use of this technique when model size makes its handling impossible by direct optimization methods.

As they are, advanced bottom-up models have partly closed the gap between bottom-up and top-down approaches. Equipped with stochastic programming and multi-region capability, these are powerful tools for operational planning in the energy sector, especially in the context of GHG abatement. A very promising avenue of research lies in exploring the role of multiple bottom-up models in the integrated assessment of global issues as the Climate Change. A forum such as the ETSAP (Energy Technology Systems Analysis Project) has already contributed joint analyses of multi-country responses to abatement targets (Kram, 1992), and is in the process of implementing a new study among its members. If successful, such an approach would represent a very useful complement to global top-down models, which are excellent for gaining insight on the main global phenomena, but not to provide a convincing case to local and national policy makers. We see such a research path as a potentially major contribution to the analysis of the Climate Change issue over the next several years.

Appendix I: Elastic MARKAL Formulation

The regular MARKAL model can be written as the following LP:

$$\text{Minimize } cX \qquad (1)$$

subject to:

$$\sum_k CAP_{k,i}(t) = DM_i(t) \qquad (2)$$

$$\forall i = 1,..,I; t = 1,..,T$$

$$BX \le b \qquad (3)$$

where, X is the vector of all MARKAL variables. (1) represents the total discounted system cost, (2) is the set of demand constraints, and (3) all other MARKAL constraints. There is one demand constraint for each demand category in each time period.

Now we define a demand curve for each demand category, assumed to be constant elasticity relationship given by (4)

$$DM_i(p_i) = K_i \times (p_i)^{e_i} \qquad (4)$$

where, DM_i is the ith demand, p_i is its price, taken to be the marginal cost of satisfying the ith demand constraint, and e_i is the own price elasticity of that demand. Note that the period index, t, has been omitted (only for clarity) in equations 4 and 5. The constant K_i can be obtained if one point (p_i^0, DM_i^0) is known on the demand curve. Thus, we can rewrite equation 4 as follows:

$$p_i(DM_i) = p_i^0 \times \left(\frac{DM_i}{DM_i^0}\right)^{\frac{1}{e_i}} \qquad (5)$$

Invoking the Equivalence Theorem (See Figure 1), the original LP can be written as:

$$\text{Maximize } \sum_i \sum_t \int_a^{DM_i(t)} p_i^0(t) \times \left(\frac{q}{DM_i^0(t)}\right)^{\frac{1}{e_i}} dq - cX$$

subject to:

$$\sum_k CAP_{k,i}(t) - DM_i(t) = 0 \qquad (6)$$

$$\forall i = 1,..,I; t = 1,..,T$$

$$BX \le b \qquad (7)$$

where, (6) expresses the net social surplus, and (7) is simply (2) rewritten to highlight that DM is now a vector of variables rather than fixed demands.

Appendix II: Stochastic Programming (Minimum Expected Value Formulation)

The formulation described here is based on Dantzig (1955) and Wets (1989). The notation has been devised to closely represent the problem context.

A general multi-period multi-stage stochastic program is given in (1) to (3).

Minimize

$$Z = \sum_{t \in T} \sum_{s \in S(t)} C(t,s) X(t,s) p(t,s) \tag{1}$$

Subject to:

$$A(t,s)X(t,s) \geq b(t,s) \quad \forall t \in T, \forall s \in S(t) \tag{2}$$

$$D(s)X(t,s) \geq e(s) \quad \forall s \in S(T) \tag{3}$$

where,

t	=	time period
T	=	set of time periods
s	=	scenario index
S(t)	=	set of scenario indices for time period t For Figure 1, S(1) = 1; S(2) = 1; S(3) = 1; S(4) = 1,2; S(5) = 1,2,3,4; S(6) = 1,2,3,4; S(7) = 1,2,3,4; S(8) = 1,2,3,4; S(9) = 1,2,3,4;
X(t,s)	=	the (row) vector of decision variables in period t, under scenario s
C(t,s)	=	cost (row) vector
p(t,s)	=	event probabilities
A(t,s)	=	the coefficient matrix (single period constraints) in time period t, under scenario s
b(t,s)	=	right hand side (column) vector (single period constraints) in time period t, under scenario s
D(s)	=	the coefficient matrix (multi-period constraints) under scenario s
e(s)	=	right hand side (column) vector (multi-period constraints) under scenario

Appendix III: Stochastic Programming (MINIMAX Regret Formulation)

Consider a flexible strategy *x*, which comprises a set of decisions x_1 till the uncertainty is resolved, and a set x_2^i thereafter. The second set of decisions will depend upon the scenario that realizes. *The strategy x is to be chosen such that the maximum regret is minimized*.

The cost of the strategy under scenario s^i is given by:

$$c_1 x_1 + c_2 x_2^i$$

A strategy *x* is feasible when it satisfies the constraints imposed by the RES, the emission caps, and non-negativity:

$$Bx = d$$
$$Ax \leq e^i \qquad \forall i$$
$$x \geq 0$$

Let m^i represent the cost of a perfect foresight strategy, i.e. the minimum possible cost, under a scenario s^i. Then, the regret under scenario s^i can be written as:

$$R(x, s^i) = c_1 x_1 + c_2 x_2^i - m^i$$

The complete Minimax problem is to minimize over *x*, the maximum of $R(x, s^i)$. This can be defined as:

$$\underset{x}{Min}\left[\underset{i}{Max}\left\{ c_1 x_1 + c_2 x_2^i - m^i \right\} \right]$$
$$st$$
$$Bx = d$$
$$Ax \leq e^i \qquad \forall i$$
$$x \geq 0$$

Finally, linearizing the objective function:

$$\underset{x}{Min}[\theta]$$
$$st$$
$$\theta \geq c_1 x_1 + c_2 x_2^i - m^i \qquad \forall i$$
$$Bx = d$$
$$Ax \leq e^i \qquad \forall i$$
$$x \geq 0$$

References

Altdorfer, F., (1981), "Introduction of price elasticities on energy demand in MARKAL", Memorandum No 345, KFA, Julich, Germany.

Behrens, A. (1990), "Optimal Resource Extraction Under Stochastic Terms of Trade," *Resources and Energy 11/4*, 321-327.

Berger, C., R. Dubois, A. Haurie, E. Lessard, R. Loulou, and J.-Ph. Waaub, (1992), "Canadian MARKAL: an Advanced Linear Programming System for Energy and Environment Modelling", INFOR, Vol. 20, 114-125.

Berger, C., Lavigne, D., Loulou, R., Loulou, S., Savard, G., and Waaub, J.-P. (1994), Technological Evaluation of Renewable Energy via MARKAL, Cahier du GERAD G-94-19, GERAD, Montreal, Canada.

Bernard, J.-T., and Genest-Laplante, É. (1995), Les élasticités-prix et revenu des demandes sectorielles d'électricité au Québec: revue et analyse, GREEN, Department of Economics, University of Laval, Québec, Canada.

Birge, J. R., and Rosa, C. H. (1996), "Incorporating Investment Uncertainty into Greenhouse Policy Models," *The Energy Journal*, 17/1, 79-90.

Bunn, D. W., and Paschentis, S. N. (1986), "Development of a Stochastic Model for the Economic Despatch of Electric Power," *European Journal of Operations Research 27/2*, 179-191.

Clarke, H. R., and Reed, W. J. (1990), "Oil-well Valuation and Abandonment with Price and Extraction Rate Uncertain," *Resources and Energy 12/4*, 361-382.

Dowlatabadi, H., M. Ball, et al. (1994), "An Overview of the Integrated Climate Assessment Model version 2 (ICAM-2)," Vancouver, Canada, Western Economic Association.

Edmonds, J. , Pitcher, H., Rosenberg, N. and Wigley, T. (1994), "Design for the Global Change Assessment Model", Proceedings of the International Workshop on Integrative Assessment of Mitigation, Impacts, and Adaptation to Climate Change, IIASA, Luxembourg, Austria, 13-15.

Edmonds, J. A., Wise, M. A., and MacCraken, C. N. (1993), "Advanced Energy Technologies and Climate Change: An Analysis using the Global Change Assessment Model (GCAM)," Pacific Northwest Laboratory, Richland, Washington, USA.

Fankhauser, S. (1994), "The social cost of GHG emissions: an expected value approach", *Energy Journal 15/2*, 157-184.

Fishbone, L.G., and H. Abilock, (1981), "MARKAL, A Linear Programming Model for Energy Systems Analysis: Technical Description of the BNL Version", International Journal of Energy Research, Vol. 5, 353-375.

Fishbone L G, Giesen G, Hymmen H A, Stocks M, Vos H, Wilde, D, Zoelcher R, Balzer C, and Abilock H. (1983), "Users Guide for MARKAL: A Multi-period, Linear Programming Model for Energy Systems Analysis", BNL Upton, NY, and KFA, Julich, Germany, BNL 51701.

Fragnière, E. and Haurie, A. (1996), "MARKAL-Geneva: A Model to Assess Energy-Environment Choices for a Swiss Canton", in C. Carraro and A. Haurie (eds.), *Operations Research and Environmental Management*, Kluwer Academic Books.

Gerking. H., and Voss, A. (1986), "An Approach on How to Handle Incomplete Foresight in Linear Programming Models," International Conference on Models and Uncertainty in the Energy Sector, Risö National Laboratory, Denmark, 11-12 February, 1986, p. 145.

Goldstein, G. A. (1994), "PC-MARKAL and the MARKAL Users Support System (MUSS)", Biomedical and Environmental Assessment Group, Brookhaven National Laboratory, New York.

Gorenstin, B. G. et al. (1993), "Power System Expansion Planning Under Uncertainty," IEEE Transactions on Power Systems, 8, 1, pp 129-136.

Grubb, M., (1993), "Policy Modelling for Climate Change: The Missing Models," Energy Policy, 21, 3, pp 203-208.

Hogan, W.W., (1975), "Energy Policy Models for Project Independence", Computers and Operations Research, 2, 251-271.

Hourcade, J. C. (1993), "Modelling Long run Scenarios," Energy Policy, 23/1, 309-326.

IPCC (1995a), Climate Change 1995 - The Science of Climate Change, Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

IPCC (1995b), Climate Change 1995 - Impacts, Adaptations and Mitigation of Climate Change: Scientific-Technical Analyses, Contribution of Working Group II to the Second Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

IPCC (1995c), Climate Change 1995 - Economic and Social Dimensions of Climate Change, Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Kanudia, A. and Loulou, R. (1997), Extended MARKAL: A brief User Manual for the Stochastic Programming and Multi-Region Features, Cahier du GERAD G-97-11, GERAD, Montréal, Canada.

Kanudia A. and Loulou R. (1996) "Robust Energy Technologies via Stochastic MARKAL: The case of Quebec," accepted for publication in European Journal of Operational Research. Also available as GERAD discussion paper G-96-13, 1996.

Kanudia, A. (1996), "Energy-Environment Policy and Technology Selection: Modelling and Analysis for India," *doctoral dissertation*, Indian Institute of Management, Ahmedabad, India.

Kolstad, C. D. (1994), "George Bush Versus Al Gore," *Energy Policy 22/9*, 771-778.

Kunsch, P. L. and Teghem, J., Jr. (1987), "Nuclear Fuel Cycle Optimization Using Multi-Objective Stochastic Linear Programming," *European Journal of Operations Research 31/2*, 240-249.

Kram, T., (1993), "National Energy Options for reducing CO2 Emissions, Vol. 1: the International Connection", ECN-C-93-101 Report, ECN, Petten, The Netherlands.

Larsson, T. and Wene, C.-O. (1993), "Developing Strategies for Robust Energy Systems. I: Methodology," *International Journal of Energy Research 17*, 503-513.

Larsson, T. (1993), "Developing Strategies for Robust Energy Systems. II: Application to CO_2 Risk Management," *International Journal of Energy Research 17*, 505-535.

Louveaux, F. And Smeers, Y. "A Stochastic Model for Electricity Generation," Proceedings of the IIASA/IFAC Symposium on Modelling of Large-Scale Energy Systems, February 25-29, 1980, 313-320.

Loulou, R., and Lavigne, D. (1996), "MARKAL Model with Elastic Demands: Application to GHG Emission Control", in Operations Research and Environmental Engineering, C. Carraro and A. Haurie eds., Kluwer Academic Publishers, Dordrecht, Boston, London, pp. 201-220.

Loulou R., Shukla P. R. and Kanudia A. (1997), Energy and Environment Policies for a Sustainable Future: Issues, Models and Analysis for India, Allied Publishers, New Delhi, India.

Macdonald, D. G.; Power, M.; and Fuller, J. D. (1994), "A New Discovery Process Approach to Forecast Hydrocarbon Discoveries," *Resources and Energy Economics 16/2*, 147-166.

Manne, A., Mendelsohn, R. and Richels, R. (1995), "MERGE: a Model for Evaluating Regional and Global Effects of GHG Reduction Policies", Energy Policy 23/1, 17-34.

Manne, A. S. and Wene, C-O, (1992), "MARKAL-MACRO: A Linked Model for Energy-Economy Analysis," BNL-47161 report, Brookhaven National Laboratory, Upton, New York, USA.

Messner, S. and Strubegger, M. (1995), User's Guide for MESSAGE III, WP-95-69, IIASA, Luxembourg, Austria.

Nordhaus, W. (1993), "Rolling the DICE: an optimal transition path for controlling GHG's", *Resources and Energy Economics 15/1*, 27-50.

Peck, S. C., and Teisberg,T. J. (1992), "CETA: a model for carbon emissions trajectory assessment", *Energy Journal 13/1*, 55-77.

Peck, S. C., and Teisberg,T. J. (1995), "Optimal CO 2 Control Policy with Stochastic Losses from Temperature Rise," *Climatic change*, 31/1, 19-34.

Terry, L. A., Pareira, M. V. F., Araripe Neto, T. A., Silva, L. F. C. A., Sales, P. R. H. (1986), "Coordinating the Energy Generation of the Brazilian National Hydrothermal Generation System," *Interfaces 16/1*, 16-38.
Raiffa, H., (1968), Decision Analysis, Addison-Wesley, Reading, Mass.

Samuelson, P.A., (1952), "Spatial Price Equilibrium and Linear Programming", American Economic Review, 42, 283-303.

Scheper, E., and T. Kram, (1994) "Comparing MARKAL and MARKAL-MACRO for The Netherlands", ECN Policy Studies, Draft, presented at the May 1994 meeting of ETSAP.

Takayama, T., and Judge G.G., (1971), Spatial and Temporal Price and Allocation Models, North Holland, Amsterdam.

Tosato, G.C., (1980), "Extreme Scenarios in MARKAL LP Model: use of Demand Elasticity", presented at the 5th Italian-Polish Symposium on Applications of Systems Theory to Economics and Technology, Torun, June 11-16 1980.

Van der Voort, E. et al. (1985), Energy Supply Modelling Package - EFOM 12C MARK I. Vol. II (user guide) EUR 8896 EN, Vol. III EUR 8896 EN, (CEC).

Yeung, D. and Hartwick, J. M. (1988), "Interest Rate and Output Price Uncertainty and Industry Equilibrium for Non-Renewable Resource Extracting Firms", Resources and Energy 10/1, 1-14.

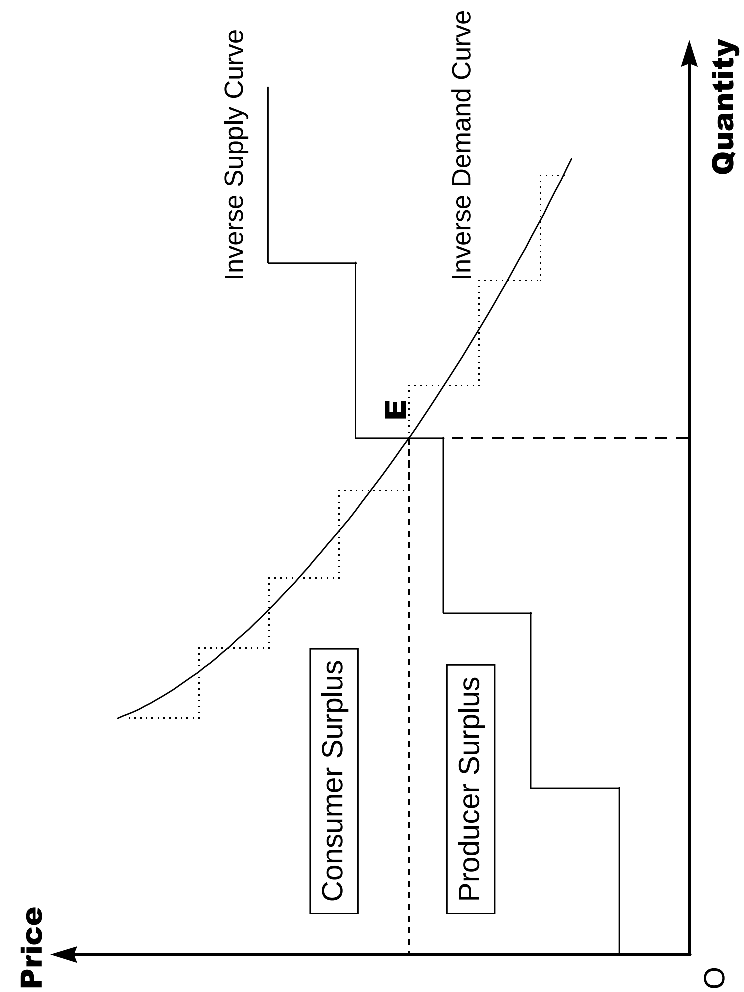

Figure 1 Illustration of supply-demand equilibrium

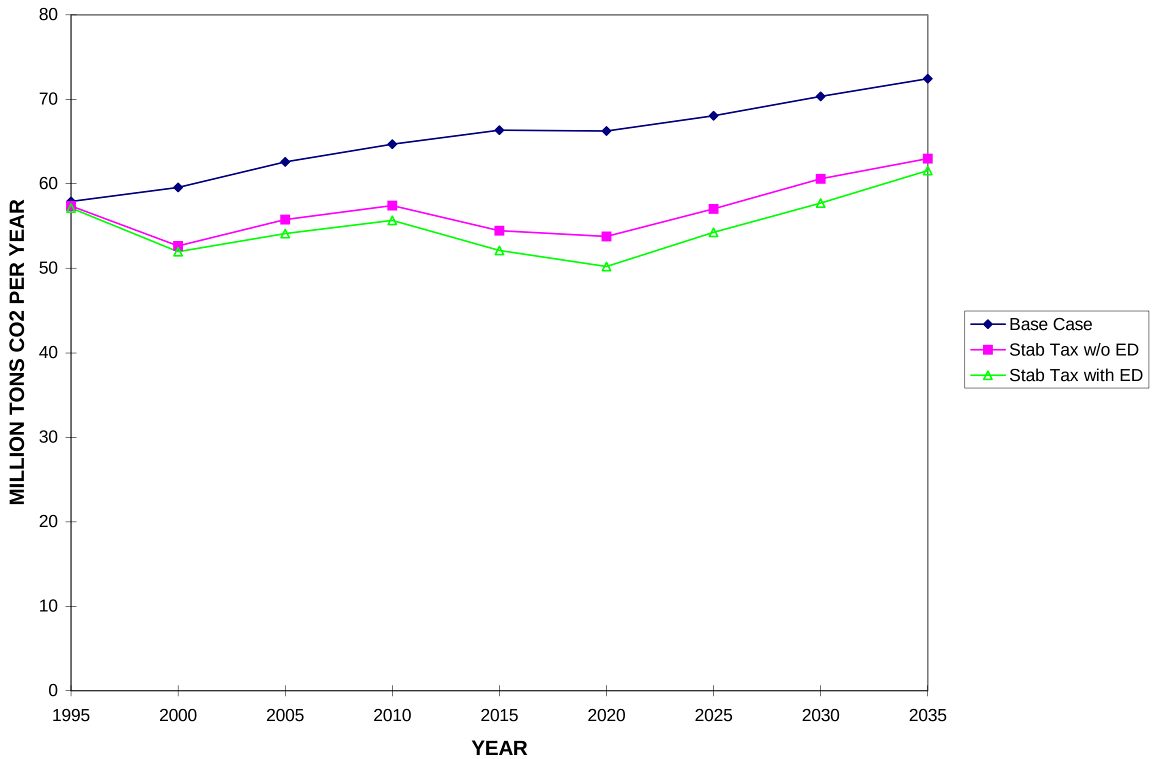

Figure 2 Aggregate Annual CO2 Emission

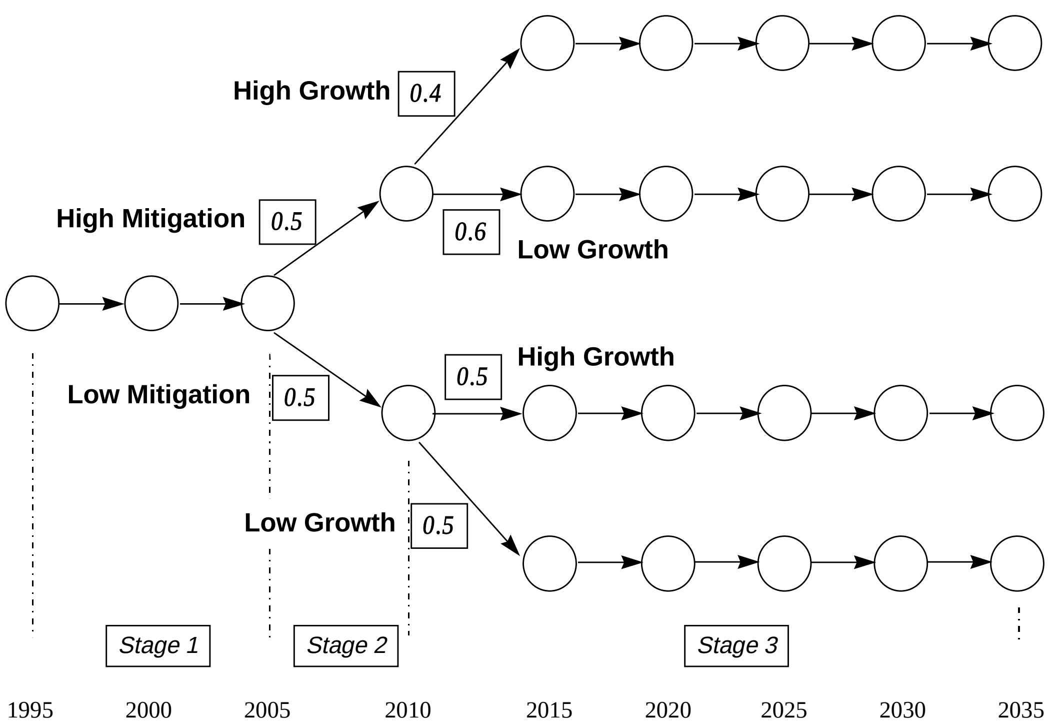

Figure 3 Event Tree for Stochastic MARKAL Example

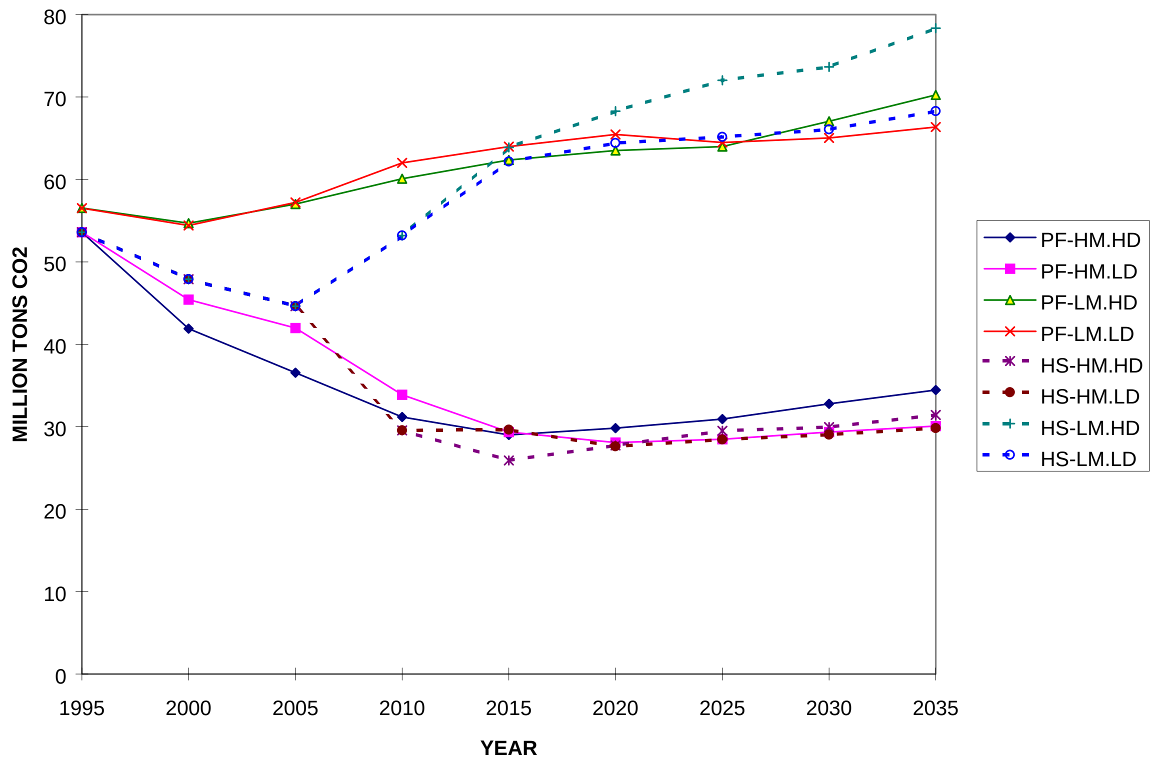

Figure 4 Annual Carbon Dioxide Emission

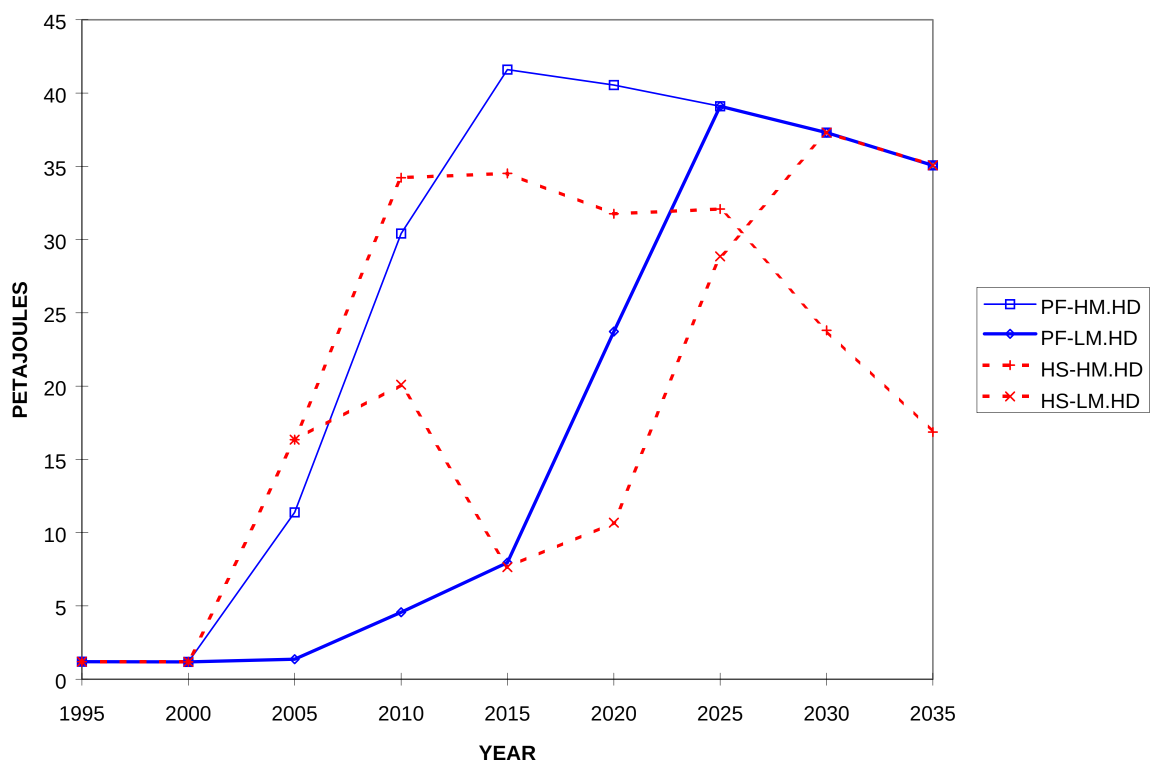

Figure 5 Electricity Consumption in the Transport Sector

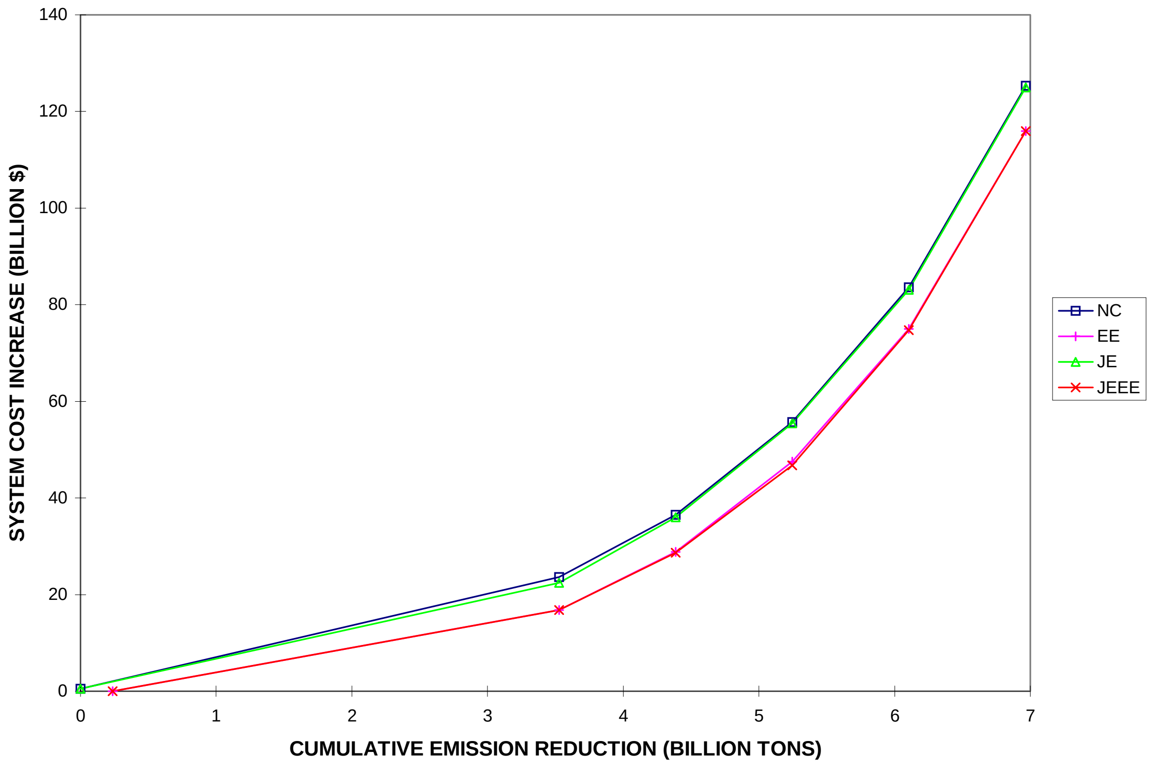

Figure 6 Cost-Emission Reduction Trade-off Curves

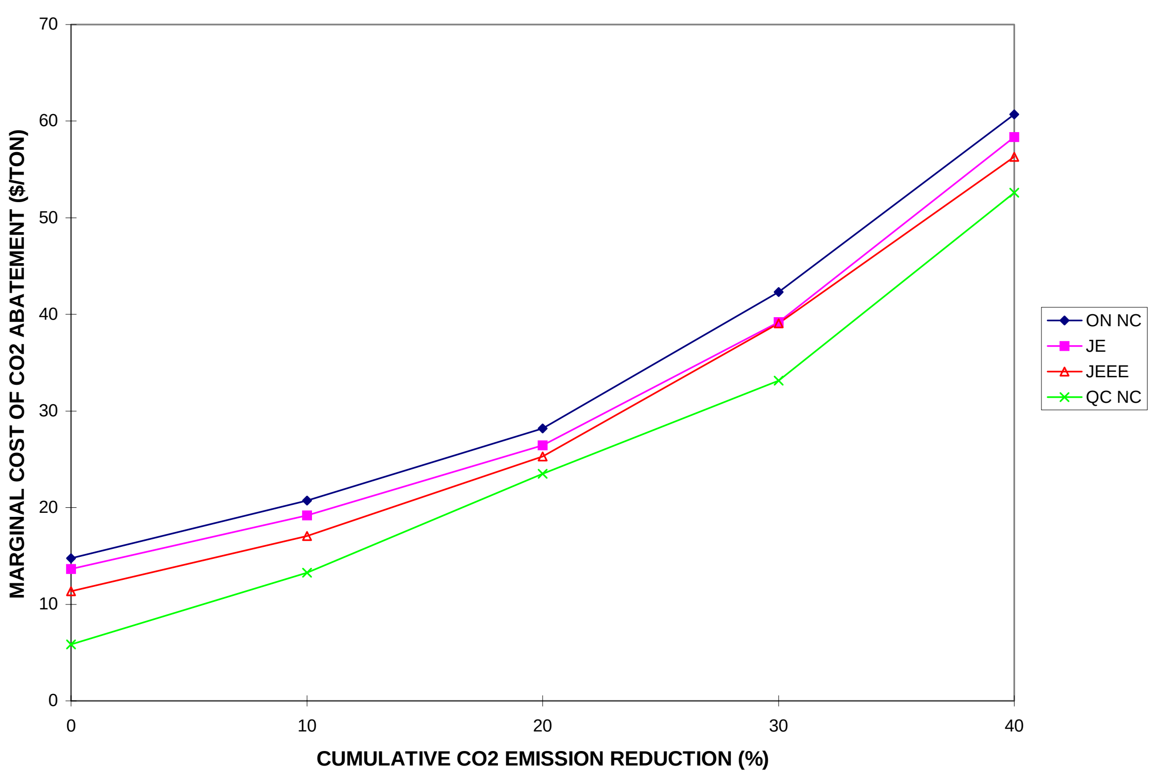

Figure 7 Marginal Cost of CO2 Abatement

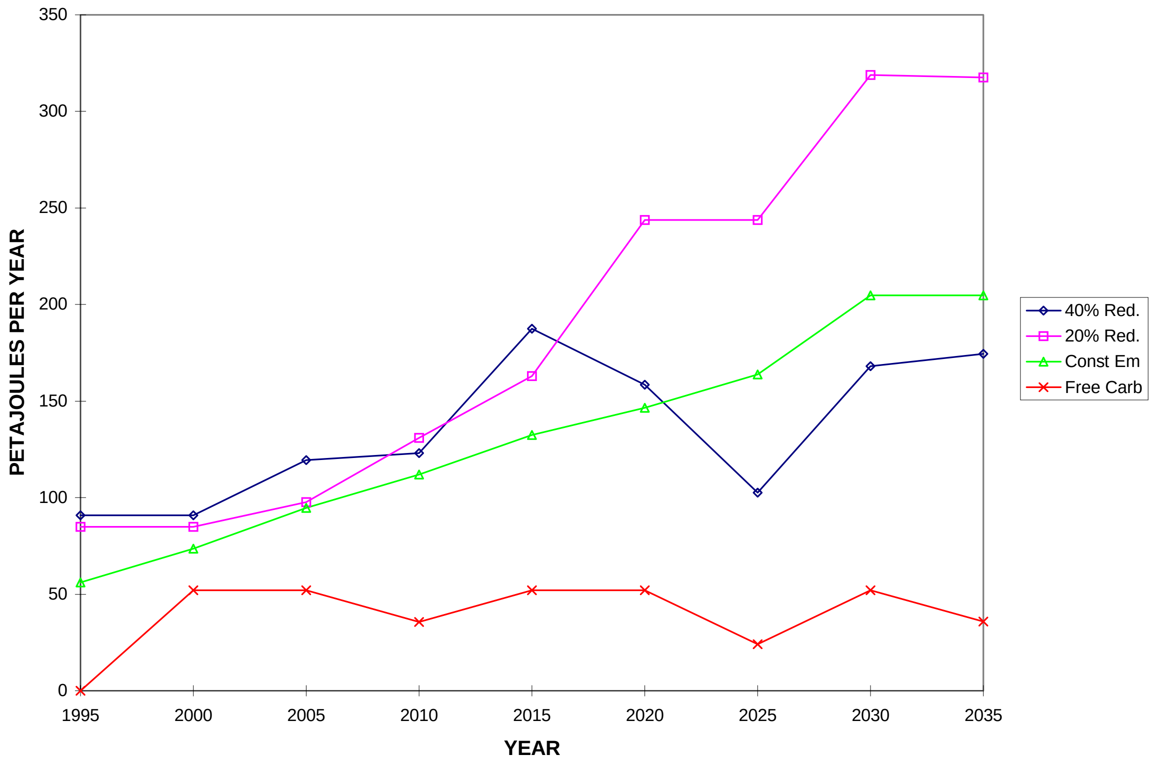

Figure 8 Electricity Exports from Québec to Ontario

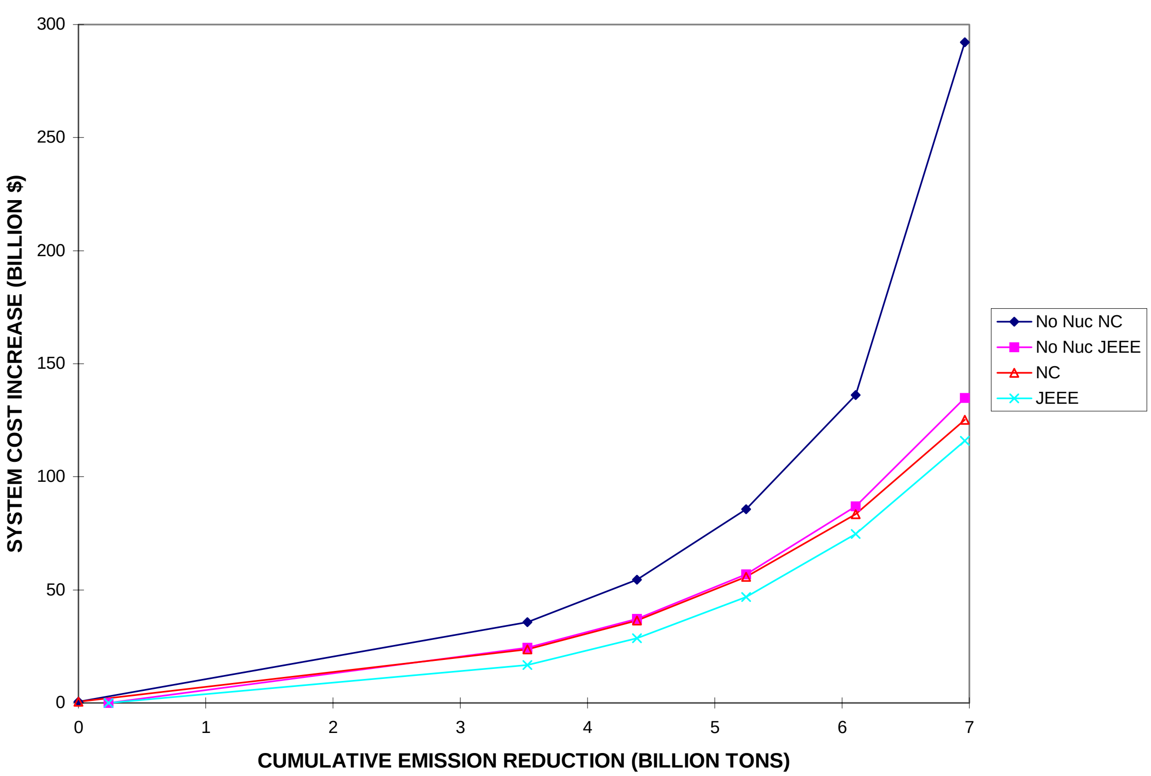

Figure 9 Cost-Emission Reduction Trade-off Curves (Nuclear-Free Case)