Robust Responses to Climate Change via Stochastic MARKAL: The Case of Québec*

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Abstract

Future patterns of climate change and economic growth are critical parameters in long-term energy planning. This paper describes a multi-stage stochastic programming approach to formulate a flexible energy plan. The plan incorporates multiple future scenarios and provides for mid-course corrections depending upon the actual realizations of future uncertainties. Results are derived from the stochastic version of Extended MARKAL (MARKet ALlocation) model for Québec, developed for this purpose.

The analysis indicates significant savings of overall system cost in using a hedging strategy over any of the perfect foresight ones. With a fifty percent probability of implementing stringent carbon mitigation measures after fifteen years, the emission trajectory takes the middle path till this uncertainty is resolved. Prior to resolution, electricity supply follows the middle path, natural gas and renewable energy tend to follow the low mitigation trajectory, and oil supply approaches the high mitigation trajectory. A set of *specialized hedging technologies* has been identified, which emerges more competitive in the hedging strategy than in any of the perfect foresight ones.

The paper concludes that such treatment of future uncertainties can give insights that are beyond the scope of an analysis based on deterministic scenarios.

1. Introduction

The control of Greenhouse Gas (GHG) emissions is one of the very difficult and important questions facing public policy makers in the 1990's, at national as well as global levels. The problem is important because of the possibly dire consequences of the global warming effect created by the increase of atmospheric GHG concentration. It is difficult because it involves large, complex energy systems, as emitters of GHG, and because it is a long term issue, with consequences far into the future (Houghton et al., 1990; UNFCCC, 1992; Wigley, 1992). Most authors consider for their analyses of the Global Warming problem, horizons between a few decades and a few centuries (Manne and Richels 1992, 1995, Peck and Teisberg 1992, Cline 1992; Edmonds et al., 1994). The global issue is conveniently broken down into the following two sub-problems: (i) the analysis of the impacts of climate change on the world populations

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and environment, and (ii) the analysis of techno-economic measures to implement for the abatement of GHG emissions. To simplify, the first problem concerns the costs of emitting GHG's, while the second concerns the costs of not emitting GHG's. Over such long periods, large degrees of uncertainty prevail in both problems, especially concerning the first one, i.e. the future impacts of climate change. The second question (GHG abatement) is better known, but still fraught with uncertainties, the most obvious of them being the amount of abatement that will be necessary to keep the global impacts at a sustainable level. Indeed, the two problems are inter-related inasmuch as the degree of desirable GHG abatement can only be fixed by analyzing both problems at various levels of GHG control, and then selecting the level that strikes a socially optimal balance between the two types of cost.

As the problem is fairly young, most of the current policy research is aimed at evaluating the efficiency and effectiveness of the possible alternatives. In this vein, our research explores the use of stochastic programming in detailed (bottom-up) modeling of the energy-environment system. In particular, we analyze the set of desirable measures for the Province of Québec in response to the threat of global climate change, while recognizing that the optimal level of GHG abatement is not yet determined, and could vary considerably depending on the scientific knowledge that will accrue over the next decade or so. While it is tempting to adopt a "wait and see" attitude consisting of doing nothing on the abatement side until consensus is reached on the desirable level of GHG reduction, such an attitude is not necessarily adequate. To illustrate, if no abatement takes place in the initial period, and if it is later established that drastic GHG reductions are necessary, the initial inaction may prove to be very costly. Conversely, if severe reductions are effected immediately, and if the overall impacts later prove to be rather mild, then the huge initial abatement cost will have been largely wasted. In some sense, the approach taken here is an attempt at reconciling the two extreme viewpoints, by incorporating the two possible futures in a single analysis.

Future uncertainties have usually been examined individually through deterministic (alternate) scenarios. However, such scenario analyses have a grave drawback: whenever two contrasted scenarios tell us to do widely different things in the immediate future (i.e. prior to the resolution of uncertainty), they leave us in a quandary, since in real life, only one set of actions may actually be selected. As an example, it is quite possible that the analysis under a *high GHG mitigation* scenario will recommend an early investment in large hydro electric projects, whereas analysis under a *low mitigation* scenario will recommend little or no new electric generation. If that is the case, what are we to recommend when nobody knows with certainty which scenario will prevail? This is precisely what the **Stochastic Programming** paradigm attempts to clarify, by merging two or more alternate scenarios in a single model, and by recommending actions which are optimal in the presence of uncertainty. In addition, Stochastic Programming will always select a single course of action at all periods prior to the resolution of the uncertainty. It is therefore more realistic than traditional scenario analysis. Finally, as will be shown on the Québec example, the method achieves the scenario objectives at less cost than that obtained from any strategy based on a single "perfect foresight" scenario. In section 2, we give a brief description of the Québec situation followed by additional details on Stochastic Programming, and by analysis of model results in section 3. Section 4 concludes this article.

2. A Stochastic version of the MARKAL energy/environment model

2.1. The MARKAL-Québec Model

MARKAL (Fishbone and Abilock, 1982) is a large scale, technology oriented, activity analysis model, integrating the supply and end-use sectors of an economy, with emphasis on the description of energy related sub-sectors. The model has nine time periods of five years each (thus covering the 45 year span from 1993 to 2037), and utilizes three variables for each technology represented, i.e. the investment, the capacity, and the level of activity of the technology, at each time period. The time periods are indexed with the central years, for example, period 1 centered in 1995 refers to the years 1993-1997. At period 1, the actual installed capacities of all technologies are imposed, thus constraining MARKAL to exactly represent the real system being modeled. MARKAL computes a dynamic, partial equilibrium on energy markets by minimizing a single objective function which is the system's discounted total cost (the equilibrium is partial rather than general, since MARKAL does not include links with other macro-economic variables, such as aggregate savings, consumption etc.). The model uses a discount rate of 5%, which is intended to be representative of the market rate of return on capital. The system's cost includes investment and operations and maintenance costs for all technologies, plus procurement costs for all imported fuels, minus the revenue from exported fuels, minus the salvage value of all residual technologies at the end of the horizon. The model satisfies all important constraints of an energy system, such as conservation of energy flows, satisfaction of demands, conservation of investments, peak-electricity constraints, capacity limits, and many others. In addition, MARKAL allows the optional accounting and/or constraining of emissions of pollutants from all technologies present in the model, by means of emission coefficients and of special constraints, called “emission caps”, which may be defined period by period, or in a cumulative fashion. Alternatively, one may impose emission taxes rather than constraints. In order to simultaneously respect these constraints and minimize system cost, MARKAL uses optimization (Linear Programming). A recent modification of MARKAL allows the specification of own price elasticities for all energy services, and therefore will adjust demands in response to particular scenarios (Loulou and Lavigne, 1995).

The database for MARKAL Québec includes more than 500 technologies, approximately 70 energy forms (fuels plus heat plus electricity), and 69 categories of energy services, with particular detail in the energy intensive sectors. For instance, electricity generation has more than 30 distinct technologies, oil refining includes some two dozen processes and 13 final products. On the demand side, there are 13 residential demand categories, serviced by about 100 technologies; there are 14 commercial and institutional demand segments, serviced by around 100 technologies; 30 industrial demand segments, with more than 100 technologies; and in transport, there are 12 segments, and about 70 technologies (vehicles). In most demand segments, special technologies represent specific energy conservation measures such as efficient devices, insulation, etc. Full details on the model and database are available from the authors. Several previous applications of the MARKAL model in Québec and Ontario appear in previous publications (Berger et al., 1990, 1991, 1992, 1993, 1994) which stress specific model features and results. The MARKAL model is particularly well adapted to compute the responses of energy systems to constraints on emissions (or to taxes levied on them). This is so because of the linear programming nature of the model, where any number of additional constraints may be added, including emissions caps. This is a real advantage of this class of models, which is

not emulated by simulation or by econometric models. Furthermore, the cost minimization feature of MARKAL ensures that the system response to emission caps or taxes, is optimally allocated to the globally efficient abatement measures.

The MARKAL Québec model has been developed over the past fifteen years thanks to direct contracts with the Canadian Departments of Energy and of the Environment, and their counterparts at the Provincial level. In addition, the model has been transferred to Hydro-Québec, a major publicly owned power generation and distribution company based in the Province of Québec. However, he conclusions reached in this paper reflect the authors' views, and should not be construed as policy positions of any government or other organization.

2.2. Stochastic MARKAL

In the context of energy-environment systems, stochastic modeling 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). 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). This method provided for assessing the efficiency and robustness of exogenously determined alternative strategies.

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 modeling 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 modeling 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 MARKAL is a very recent model built upon the MARKAL model. It explicitly incorporates multiple scenarios, each with a specified probability of occurrence. It is based on the multi-stage Stochastic Programming paradigm (Dantzig, 1955; Wets, 1989). The formulation is described in Appendix I and the 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 those periods when there are more than one realization (as in periods 4 to 9 in the example shown in **Figure 1**), 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 prevails.

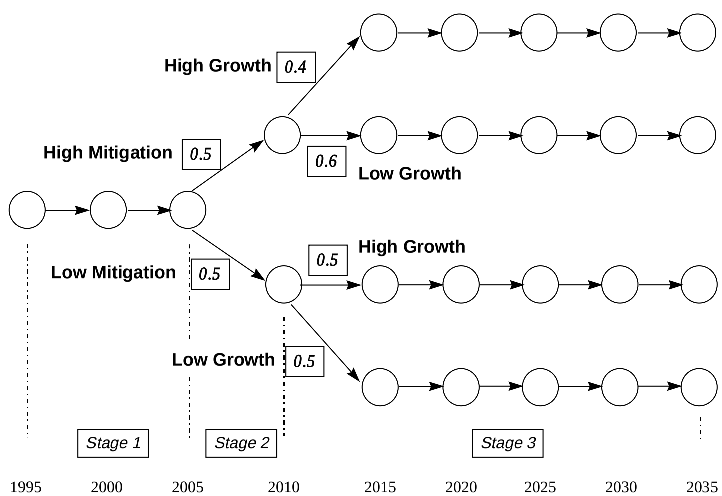

Figure 1 Event Tree for Stochastic MARKAL Example

(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 tree. Each such path represents one scenario, as shown by the solid lines in **Figure 2**. The single period constraints are repeated as many times as there are different realizations at that period, and that number differs with the period, as also shown in **Figure 2**.

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

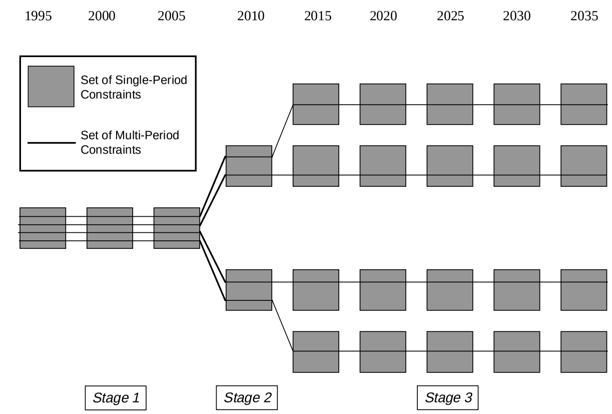

Figure 2 Sketch of Linear Programming Constraints for Stochastic MARKAL

2.3 Implementation of Stochastic MARKAL

The formulation described in the last section has been implemented on the Extended MARKAL-ED model for Québec (Kanudia and Loulou, 1997). The model has a user interface, MUSS (**M**ARKAL **U**sers **S**upport **S**ystem, Goldstein, 1994), which manages the input data and generates the linear program for the model. The Extended MARKAL uses OMNI for matrix generation. The existing 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 OMNI code to generate the required stochastic program. A new report writer collects the appropriate variables and compiles the results for each scenario. These developments constitute a user-friendly software, which can be used to quickly take runs with different assumptions and easily analyze the results.

In the example shown in **Figure 1**, four alternate scenarios have been defined, resulting from the combinations of High Vs. Low demand and High Vs. Low mitigation. The four scenarios combine to form a probabilistic composite scenario.

Figure 1 shows the four scenarios, with the dates at which each type of uncertainty is resolved, and the event probabilities. Namely, the Mitigation uncertainty is assumed to last for three periods and to be resolved at the beginning of period 4 (year 2008). We have assumed that high mitigation will result in a higher probability of lower economic growth, i.e., 0.6 instead of 0.5 probability of low growth. Furthermore, this effect lags by 5 years[†]. Thus, decisions for the first three periods are taken under mitigation uncertainty and those for the first four under demand

[†] There should clearly be a lag between the policy decision of severe mitigation and a possible economic slow down. The model has 5 year time periods. Since 10 years appeared too long for an economic repercussion, we chose a lag of one period.

uncertainty. In the High Mitigation event, cumulative GHG emissions over 45 years must not exceed 1.87 Billion tonnes of CO2-equivalent, whereas in the Low Mitigation event, they must not exceed 2.78 Billion tonnes. In comparison, if emissions remained constant from 1993 to 2037, they would amount to approximately 3.1 Billion tonnes. 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) given High mitigation has realized than if Low mitigation has realized (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: The 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 in turn 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 (PF)" 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/her actions to respond correctly to the revealed state of nature, by re-solving an optimization problem from the date of realization onward.

The legend for strategies and scenarios is given in **Error! Reference source not found.** below.

Table 1 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

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 from a null basis.

3 Results and Analysis

3.1 GHG Emissions

Figure 3 shows the annual GHG emission trajectories under all strategy/scenario combinations. Evidently, the hedging strategy takes a middle path till the uncertainty is resolved. Subsequently, the annual GHG emission falls sharply in case severe mitigation realizes.

Note that the annual emissions with 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 severe constraint on cumulative GHG emission. The marginal costs of GHG abatement are given in **Error! Reference source not found.**. An interesting fact is that with hedging strategy, the shadow prices are null/negligible in the event of low mitigation. This means that actions taken prior to the resolution are such that the system will *naturally* emit less GHG over the entire horizon.

For the purpose of clarity, only the effect of mitigation uncertainty is discussed in all subsequent discussion in this paper. So, two perfect foresight strategies have been compared with two components of the hedging strategy, keeping the demand scenario fixed at the high level.

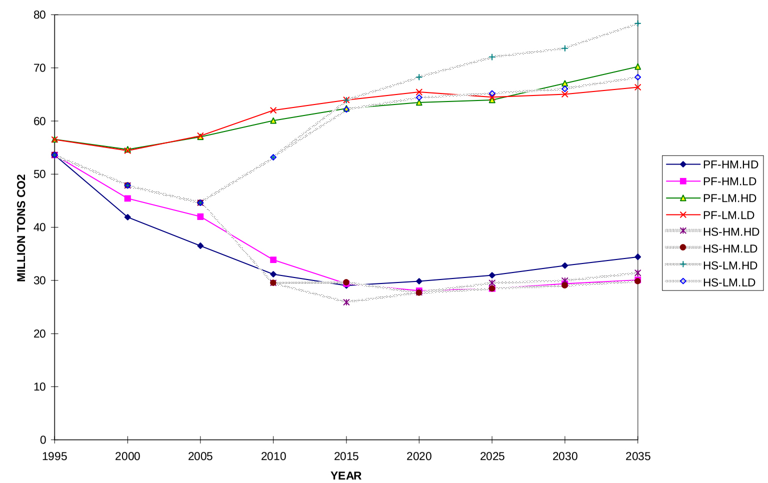

Figure 3 Annual Carbon Dioxide Emission

Table 2 Shadow Prices of Cumulative GHG Emission Constraint (CDN$/ton CO2)

SCENARIO	STRATEGY	
	PERFECT FORESIGHT	HEDGING
HM.HD	374.86	1046.80
HM.LD	337.65	366.10
LM.HD	32.17	3.56
LM.LD	8.55	0.00

3.1 Aggregate Energy Supply

Figure 4, Figure 5, Figure 6, and Figure 7 show the aggregate supply of electricity, natural gas, oil and renewable energy respectively. It is evident that electricity (hydro based) and renewable energy substitute oil in response to a severe carbon mitigation. Note that prior to resolution, electricity (**Figure 4**) adopts a "middle-of-the-road" position compared to the low and high mitigation levels, whereas, natural gas (**Figure 5**) and renewable energy (**Figure 7**) are closer to their levels under a low mitigation strategy. On the other hand, oil (**Figure 6**) is closer to the high mitigation trajectory. This is clear evidence that a hedging strategy cannot be derived from the perfect foresight strategies via a simple "averaging" procedure.

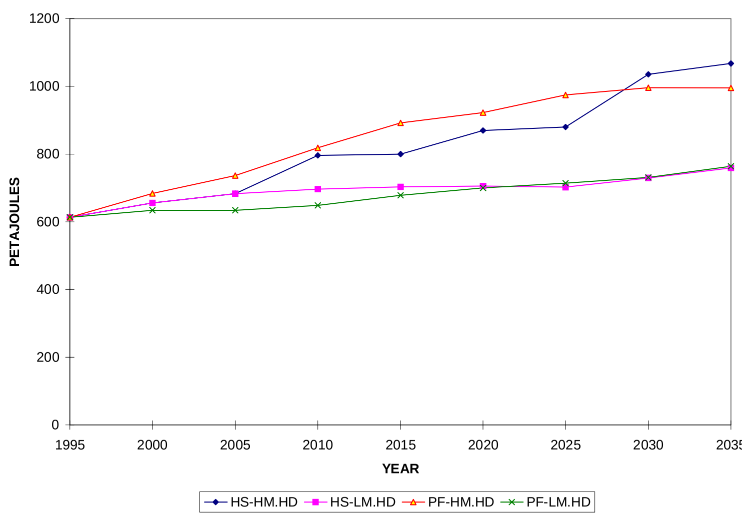

Figure 4 Aggregate Supply of Electricity

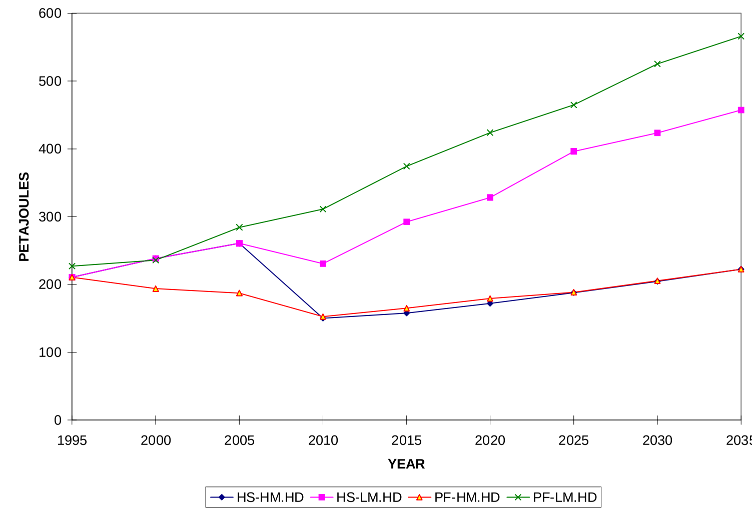

Figure 5 Aggregate Supply of Natural Gas

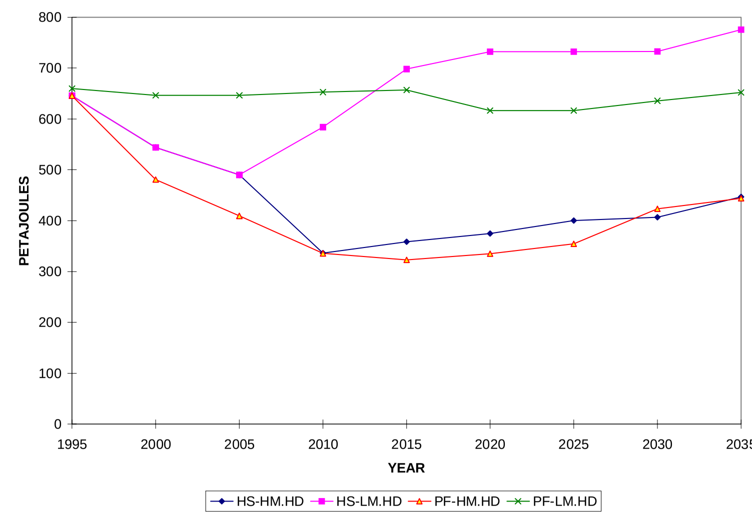

Figure 6 Aggregate Supply of Oil

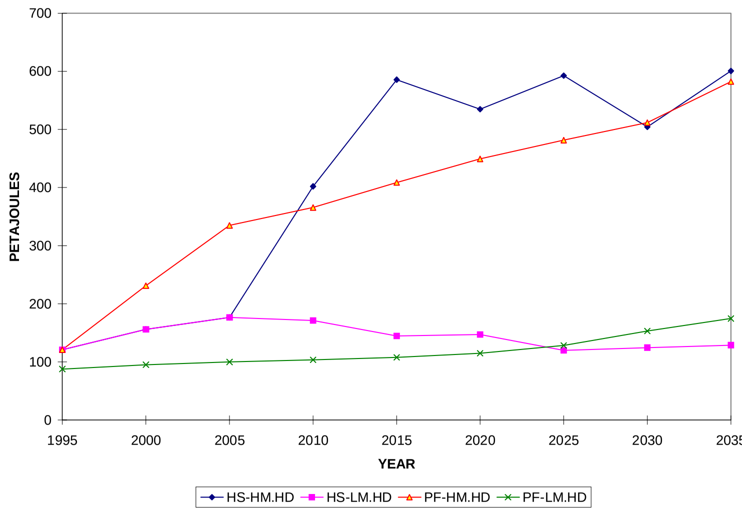

Figure 7 Aggregate Supply of Renewable Energy

3.3 Technology Mix

Technology selections prior to the resolution of mitigation uncertainty indicate the role of various technologies in carbon mitigation. In what follows, we propose a classification of technologies according to the role they play in the hedging strategy versus the individual deterministic scenarios, prior to the resolution of mitigation uncertainty. Indeed, the pre-resolution periods are the crucial ones insofar as they require judicious decisions while still facing major uncertainties. The decisions recommended by stochastic programming usually differ from those recommended by individual deterministic scenarios. We propose the following categories:

1. *Robust*: Technologies that have identical profiles across all deterministic and probabilistic mitigation scenarios.

2. *High Mitigation options*: Technologies that assume a trajectory similar to that of the severe mitigation scenario even before the GHG mitigation uncertainty is resolved.

3. *Low Mitigation options*: Selections that follow the low mitigation path till the resolution of uncertainty.

4. *Compromise*: Technologies that have trajectories lying in between those obtained under the two perfect foresight strategies, prior to the resolution date.

5. *Super Mitigation options*: Prior to resolution of mitigation uncertainty, the selection is higher than that in either of the perfect foresight strategies.

6. *Sub Mitigation options*: Prior to resolution of mitigation uncertainty, the selection is lower than that in either of the perfect foresight strategies.

Categories 5 and 6 are especially interesting and somewhat counter intuitive. They form a set that may be called *transitional*. The *transitional* technologies conclusively show that scenario aggregation through stochastic programming may lead to a solution which cannot easily be derived from a combination of the solutions of deterministic individual scenarios. A brief description of technology choices made in different energy supply and end-use sectors is given below.

Electricity Generation Sector: Increasing the aggregate electricity supply turns out to be a compromise option, according to the above definition. Aggregate electricity generation capacity follows an intermediate trajectory till resolution of mitigation uncertainty (year 2010), as shown in **Figure 8**. In case of severe mitigation realization, additional capacity is created immediately to make the overall capacity more than that in the corresponding perfect foresight scenario. Under the hedging strategy, the investment in hydro based electricity generation capacity is delayed and that in wind based electricity is advanced (**Figure 9**), compared to the high mitigation perfect foresight strategy. Wind based technologies penetrate only in the event of severe mitigation.

In initial periods, the marginal value of electricity is 2.5 cents per kWh in the low mitigation deterministic scenario. At later periods, it is more than 6 cents under severe mitigation scenario. Under the hedging strategy, the marginal value increases to 3.5 cents per kWh in the second period and then follows the trend of the respective perfect foresight strategies.

Transport Sector: The oil based technologies are in the *compromise* category, as shown in **Figure 10**. However, electricity based transport vehicles (i.e. electric cars) fall in the *super mitigation* category, as shown by the large penetration of electricity in 2005 (**Figure 11**).

Commercial Sector: Both electricity and gas based technologies are high mitigation options in 2000, and compromise options in 2005, as shown in **Figure 12** and **Figure 13**. Note that high mitigation increases electricity consumption, but decreases gas consumption in this sector.

Residential Sector: Both electricity and gas based technologies are in the *compromise* category.

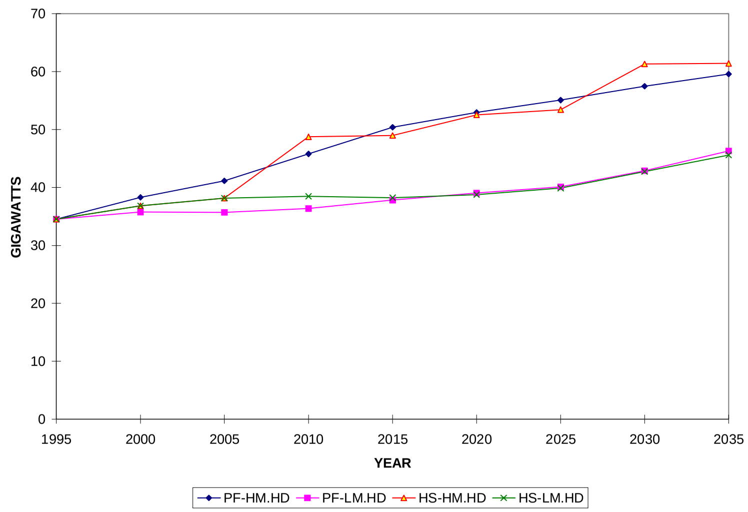

Figure 8 Aggregate Electricity Generation Capacity

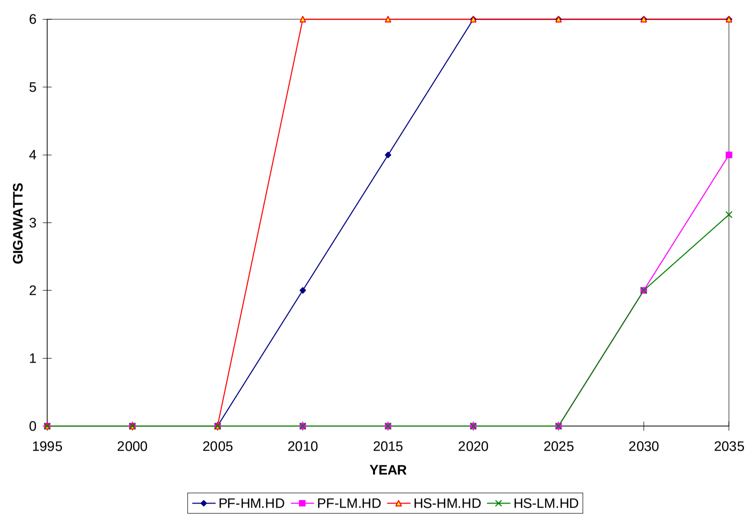

Figure 9 Wind Based Electricity Generation Capacity

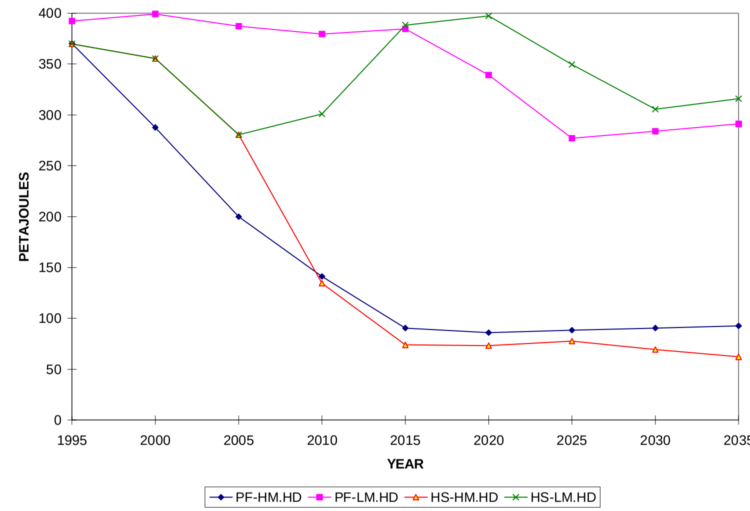

Figure 10 Oil in Transport Sector

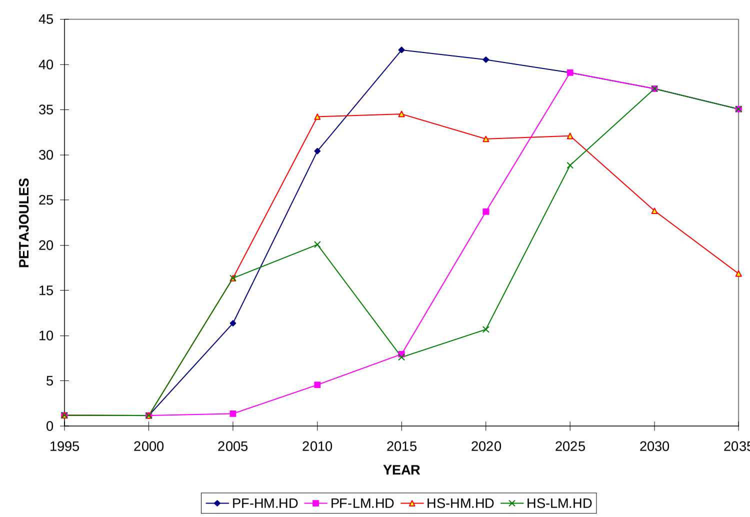

Figure 11 Electricity in Transport Sector

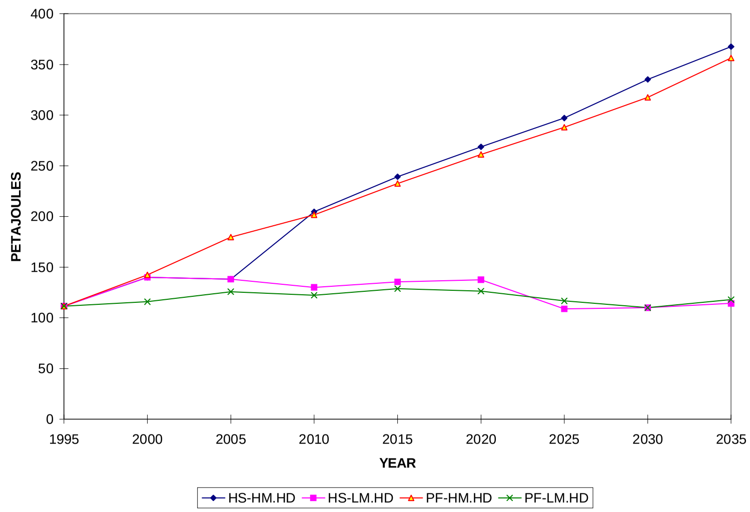

Figure 12 Electricity in Commercial Sector

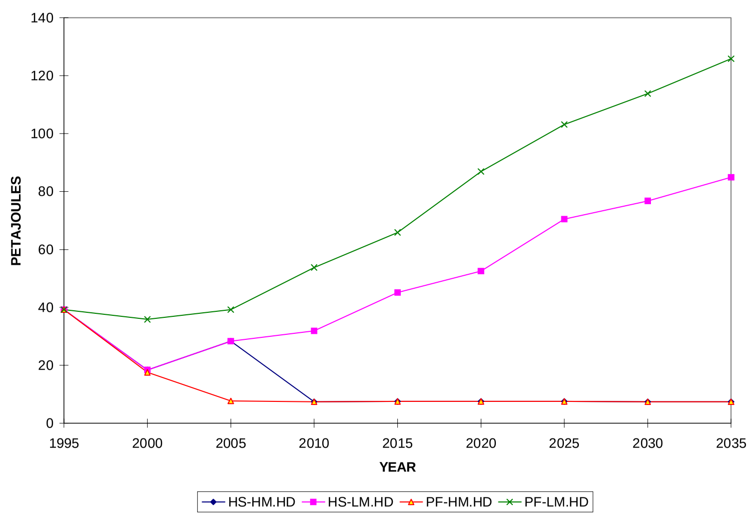

Figure 13 Natural Gas in Commercial Sector

3.4 Discounted system costs

Under the hedging strategy, the expected discounted system cost is higher than the weighted average of the four system costs obtained for the deterministic scenarios. This is so because the latter quantity is equal to the expected system cost under perfect information (i.e. if all uncertainties were resolved in 1995). The difference between the two quantities represents precisely the *Expected Value of Perfect Information* or *EVPI*, equal to $4.86 billion in our case. 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).

Another interesting cost we might want to know is that which would be incurred if a particular perfect foresight strategy were adopted, even though the future events were not known. 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 cases, the actual cost incurred is higher than anticipated by the Perfect Foresight strategy adopted. In this way, we can define an *expected value of loss* for each of the perfect foresight strategies, over that of the hedging strategy. **Table 3** exhibits the values for each of the four PF strategies (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 costs of wrong initial assumptions have been determined through the following two-step process:
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 with the parameters of the realized scenario and the initial decisions frozen according to the assumed scenario. The difference between the system cost derived from the second run and that derived from the hedging strategy is the required cost.

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

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

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.

4. Conclusion

In this research, we have presented a stochastic programming version of MARKAL and applied it to the analysis of GHG abatement in Québec over the next 40 years, under contrasted uncertain GHG emission caps. The analysis of results has pointed at certain technologies which should play a key role in the initial three periods (until 2013), inasmuch as they represent robust hedging choices under the probabilistic scenario. In most sectors, the recommended hedging decisions are markedly different from those under any deterministic scenario, thus justifying the use of the stochastic programming approach. In a few cases (notably electric vehicles), the hedging decision does not even lie at an intermediate level between those of the extreme deterministic scenarios, which makes the methodology even more pertinent.

We have also been able to compute the expected value of perfect information (EVPI), i.e., the value of resolving today the main uncertainties considered in the model. The EVPI is in excess of $4 billion, showing that it is economically important to speed up the acquisition of knowledge on the global warming issue.

Finally, the analysis has also permitted to evaluate the cost incurred by following a perfect foresight strategy, i.e., of ignoring the uncertainties while devising a strategy. The rather large values of such losses pleads in favor of the stochastic programming approach.

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Appendix I: Stochastic Programming

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

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

Subject to:

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

$$D(s)\,X(t,s) \geq e(s) \qquad \forall s \in S \qquad \textbf{(3)}$$

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)	=	(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)	=	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)	=	coefficient matrix (multi-period constraints) under scenario s
e(s)	=	right hand side (column) vector (multi-period constraints) under scenario s
S	=	set of scenario indices in the last period