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A.Golodnikov*, A.Gritsevskii†, S.Messner‡

1 Introduction

The Environmentally Compatible Energy Strategies (ECS) Project at IIASA is using a dynamic linear programming model, MESSAGE III [1], for the analysis of long-term energy strategies to mitigate climate change. These model analyses utilize information on potential future technology characteristics, energy services demands and resource availability to investigate paths into a sustainable future energy system during the next century.

One major shortcoming of conventional energy optimization models is the requirement to use point estimates for the technology characteristics and other important system parameters. This paper introduces a new approach to overcome this problem by introducing distribution functions for technology parameters into model formulation. The stochastic version of MESSAGE captures the risk of underestimating future technology costs. Computational overhead for applying the approach is very low compared to the original model; for the runs investigated here, no increase in CPU time was detected.

Another problem often encountered with deterministic models, in particular linear programming models, is their sensitivity to input parameters. Linear programming models are, by definition, worst in this respect because they tend to favour single solutions and extreme developments instead of mixing various technologies or strategies. In such cases modelers develop robust scenarios by parameter variations and delimiting the solution space to the area that yields acceptable and robust results. Clearly, this approach is rather labor intensive and requires experience on the modeler's side. The important parameters for variation have to be found, and model runs with combinations of such parameter variations have to be performed. Such investigations can result in a large number of model runs or, more probably, in model outcomes that are not robust with respect to small changes in model parameters. In any case additional constraints introduced to sta-

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bilize model results reflect experts expectations, which are always subjective to a certain degree, representing a certain risk of over- or underestimating the parameters.

The stochastic approach presented here helps to overcome these problems by explicitly introducing the uncertainties concerning expert's opinions of future investment costs of technologies. The data used for the distribution function of investment costs were derived from the greenhouse gas mitigation technology inventory, called CO2DB, developed by ECS over the last five years [2]. Some sample technology descriptions from CO2DB are given in [3], while the data and distribution functions used for the current analysis are documented in [4].

The strategies derived with the stochastic approach possess the required technological diversity without exogenous flexibility constraints. They also have a more robust structure with respect to present uncertainties concerning future parameters. Thirdly, the strategies derived with the stochastic model extension are less costly than strategies obtained on the basis of a purely deterministic model.

2 Model description and data requirements

MESSAGE III, a dynamic linear programming model, has been developed at the International Institute for Applied Systems Analysis (IIASA) for the analysis of energy supply and end-use systems and the associated environmental impacts [1]. MESSAGE analyses future energy strategies in terms of available technologies, resources, energy service demands and pollutant emissions. It is dynamic over time by (a) integrating the optimization for the whole time horizon into one objective function and (b) linking the different time steps (periods) in the model by various types of constraints (e.g., the so-called dynamic or market penetration constraints).

MESSAGE incorporates technical information on the technologies, like efficiency, technical plant life and pollutant emissions. The objective function used in most applications is minimizing the sum of the discounted costs, including investment and operation and maintenance costs of the technologies. The costs or profits from international energy trade, or energy or emission taxes can also be considered in the objective function. Technical, social, political or environmental limitations to the utilization of technologies are represented by several types of constraints. Examples would be the quantity of biomass available in a region or the maximum share of wind power-plants tolerable in an electric grid without stability problems. Other constraints are introduced by the modeler to combat an inherient feature of LP models to always deliver the cheapest option available to the maximum degree possible. A consequence is, that minor changes in cost assumptions can lead to qualitatively different results. This common flip-flop behavior is counteracted by introduction of smoothening constraints, limiting changes over time, limiting new installations of a technologies or linking technologies to each other.

MESSAGE is applicable for a wide range of energy-related issues, like regional or urban energy planning (see [5], [6] and [7] for some examples), and in investigations of the future energy system ([8], [9] and [10] describe such applications). The most recent application has been to the joint IIASA-WEC (World Energy Council) study on long-term energy perspectives [11, 12, 13], where three families of global energy scenarios for the next century have been developed. This analysis relies on assessments of technological characteristics over the coming century, which are, due to the very nature of the problem and the very long time horizon, bound to be uncertain.

One major effort in the preparation of the technology data was the development of CO2DB, the IIASA greenhouse gas mitigation technology inventory [2], which presently covers over 1400 technologies. Out of those, approximately 1000 represent various electricity and co-generation technologies. This extensive data base was used to perform a statistical analysis and develop empirical distribution functions of capital costs and other characteristics of future energy technologics [4]. These distribution functions could be interpreted to encompass energy experts' views, or "conventional wisdom", about future performance characteristics of electricity generation technologies. It should be noted, however, that these estimates of future technology characteristics may not be all independent from each other since such studies are quite often cross-referenced and there can be considerable variation in performance and cost due to locational and many other factors that for obvious reasons cannot be excluded from our statistical analysis.

Performance characteristics of technologies that are mature and widely applied are quite well-known. In contrast, for new technologies, that presently hold low market shares (e.g., power-plants based on the combined-cycle technology) or undergo fundamental changes (e.g., nuclear reactors), the range of parameters is considerably wider. For technologies, that are not economically (PV, fuel cells) or even technically viable (fusion), the funnel of future cost and other characteristics opens wider and wider with growing uncertainties.

Table 1: Investment cost range and arithmetic mean for eight new technologies (costs are in US(90)$/kWel)

technology	ar. mean $/kWel	minimum $/kWel	maximum $/kWel	range $/kWel	range max/min
conv. coal	1350	650	2450	1800	2.77
adv. coal	1695	1195	2905	1710	1.43
conv. gas	570	330	1050	720	2.18
gas cc	815	514	1702	1188	2.31
biomass	1580	500	3020	2520	5.04
nuclear	2145	1070	3600	2530	2.36
solar thermal	3010	1790	4490	2700	1.51
solar PV	6120	1740	12540	10800	6.21

Out of the technologies analyzed in [4], eight classes were chosen for the uncertainty analysis. Table 1 shows the range of investment figures and the arithmetic mean for these technologies. The uncertainty of investment cost estimates is quite considerable for most of them. For coal power plants, the range of estimates varies by US$ 1700 to 1800 per kWel, irrespective if conventional or advanced systems are investigated. For the cheaper conventional systems this translates to a 177% variation, while for the capital-intensive advanced systems, like integrated gasification combined cycles (IGCC) or pressurized fluidized bed combustion (PFBC), the percent variation is only 43%. For solar thermal power generation the range is also 50%, but the absolute difference between minimum and maximum estimate are 2700$/kWel, a value approaching the maximum estimate for advanced coal power plants. Gas-based systems have, compared to the other options, low capital costs, which makes the absolute uncertainty rather low, while the relative range is higher than a factor of 2 and approximately the same as for new nuclear power generation. For solar thermal systems, the range of investment estimates is comparable to nuclear plants (2500 US$/kWel), while solar PV are certainly most uncertain with a large range of more than 10000$/kWel. For all estimates the arithmetic mean of estimates lies below the middle of the range covered.

The model analyis is based on the global energy model used for the joint IIASA-WEC study [11]. The model developed for this study consists of eleven regional models covering the world energy system. Energy flows include all relevant energy carriers and conversion technologies from coal mining and oil drilling via various electricity generation options up to final consumption, e.g., in industrial boilers or in road transport. The time frame of the study is up to the year 2100. For the current analyis a compressed version of this global energy model is applied. It aggregates the eleven world regions into one region, but includes all technological detail concerning electricity generation from the more detailed regional approach. The time frame is up to the year 2050.

Figure 1 shows the sensitivity of electricity generated from gas combined cycle power plants to variations in investment costs of this and some other technologies for the year 2050. The straight line at 100% represents the initial model run using the arithmetic mean as investment costs for the new technologies (here labelled Arithmetic Mean). In addition two types of sensitivity runs were performed: the Low Cost Cases reduce investment costs of one specific technology or all new technologies (labelled ALL) to the minimum estimate from table 1, while the High Cost Cases use the maximum estimates. The results, as displayed for the gas combined cycle, shows that sensitivity is very high to the own cost estimates of the technology: high costs reduce the use to zero, while low costs increase it by another 40% compared to the Arithmetic Mean. If all investments are changed at once (i.e. taking either all low or all high ends of the range), the gas combined cycle is a looser, either because at least one of the others becomes cheaper (Low Cost) or because the combined cycle is too expensive (High Cost). In all cases, where other single technologies are at the low end of cost estimates, the gas combined cycle is reduced between 15% and 30%, while the only case with major gains is when new nuclear reactors become expensive.

This very high sensitivity of the model results to, admittedly, very high cost variations, points to the weakess of the deterministic cost minimization approach: in order to find really resilient strategies, a multitude of model runs would be required, further investigating synergies and competition of the technologies, and also finding more exactly the investment cost points at which the model starts to flip into another stratum of the energy

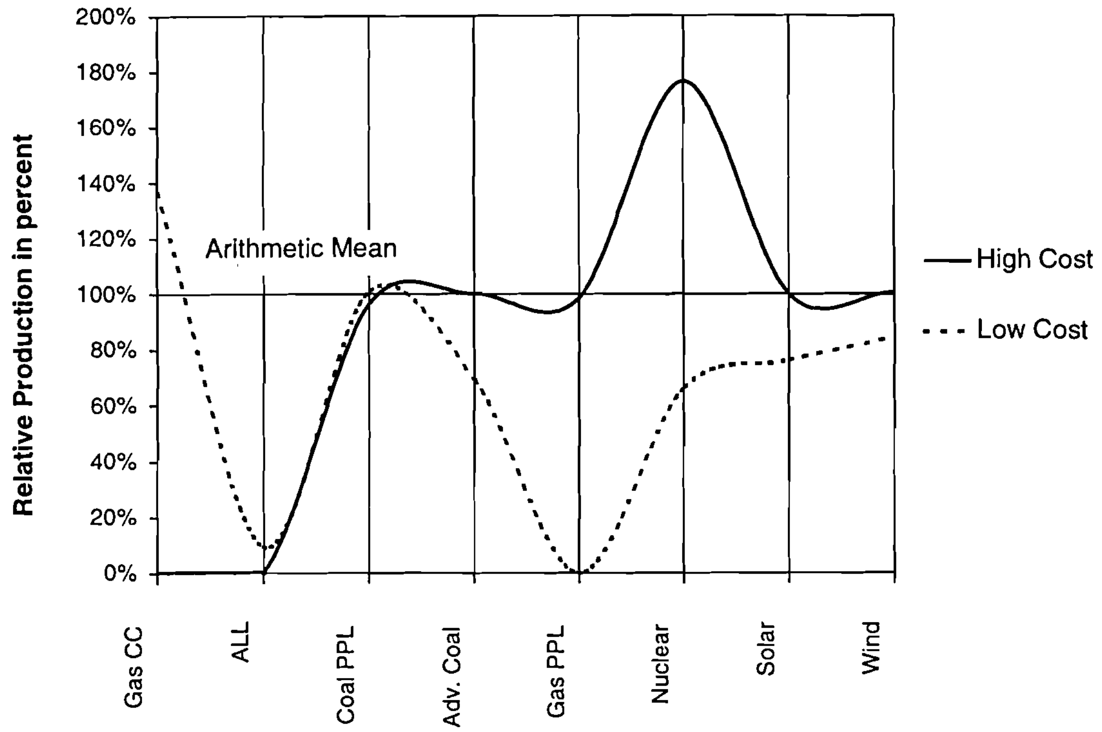

Figure 1: Relative production of gas combined cycle as a function of varying cost assumptions compared to the arithmetic mean, year 2050

system. The approach suggested in the next section enables the modeler to perform such analyses in a closed form, by incorporating the uncertainties and risk concerning future investment costs of the technologies into the mathematical formulation of the model.

3 Dynamic model for stochastic optimization

MESSAGE III has three major types of variables and a variety of equation types such as constrains. The variables are (a) technology activity, (b) annual new installations of technologies and (c) annual resource extraction. The constraints of MESSAGE can be grouped into the following groups: (1) demand constraints assuring that the exogenous demand is satisfied by the appropriate technologies, (2) balancing constraints for the energy carriers (e.g. electricity) that guarantee that not more is consumed than produced, (3) capacity constraints relating production of a technology in a period to the overall capacity existing in the period, (4) dynamic constraints relating the activity in one period to the activity in the previous period, and (5) two types of resource constraints, limiting the overall resource consumption to the quantity available and the annual extraction to a fraction of the quantity still available in a period. All variables and most of the constraints can be attributed to one specific time period. Only the dynamic constraints link two time periods to each other, capacity constraints construct the sum of new installations over the plant life of the technology, and the resource constraints are overall constraints pooling the extraction variables into one overall limit.

The simplified formulation of MESSAGE III can be written as follows:

$$min \sum_{k=0}^{T} < C^k, x^k > \tag{1}$$

$$B_k x^k \geq d^t, t = 0, 1, \ldots, T \tag{2}$$

$$\sum_{k=0}^{T} A_k x^k \leq r \tag{3}$$

$$\sum_{k=0}^{T} P_k x^k \leq e^t, t = 0, 1, \ldots, T \tag{4}$$

$$0 \leq x^t \leq \overline{x}^t, t = 0, 1, \ldots, T \tag{5}$$

where

$c^k = (C_1^k, \ldots, C_n^k)$ is the cost vector at time interval $k = 0, 1, \ldots, T$;

$r = (r_1, \ldots, r_m)$ is the vector of overall resources;

$d^t = (d_1^t, \ldots, d_e)$ is the vector of energy demands at time t or zero for the energy balances;

$e^t = (e_1^t, \ldots, e_l^t)$ is the vector of other exogenous rights hand sides, e.g., attributable to capacities existing in the base year;

A_k is the identity to just sum all consumption of one resource over time;

B_k is a matrix of input/output coefficients of the technologies; and

P_k is a matrix providing relations between periods, e.g., the capacity constraints.

In this stochastic application the vectors c^k are treated as random. Let us define them as $c^k(w)$ where w an element from a probability space indicating the dependence of the real cost vector $c^k(w)$ on a random event that is characterized by a probability measure $dP(w)$. This measure may be derived from real observations or from expert judgments. We assume that the initial distributions at $t = 0$ are given as in [4] and described in the previous chapter.

If the cost vector C^k is stochastic then the real cost $\sum_{k=0}^{T} < C^k(w), x^k >$ of a given strategy $x = (x^0, \ldots, x^T)$ may be derived from the deterministic total cost (1).

The underestimation of the expected cost incurred by using the deterministic model can be calculated as follows. For a given strategy $\{x^t\}, t = 0, 1, \ldots, T$ and an observed "scenario"

w of the cost-path $\{C^t(w)\}, t = 0, 1, \ldots, T$ the positive deviation of the "real" (observed) total cost $\sum_{k=0}^{T} < C^t(w), x^t >$ from the calculated cost $\sum_{k=0}^{T} < c, x^t >$ is defined as

$$\sum_{t=0}^{T} max\{0, < C^t(w) - C^t, x^t >\}$$

where

$$max\{0, < C^t(w) - C^t, x^t >\} = max\{0, \sum_{j=1}^{n} < C_j^t(w) x_j^t > - \sum_{j=1}^{n} < C_j^t x_j^t >$$

Let us denote this deviation as $R(x, w)$ for strategy $x = (x^0, x^1, \ldots, x^T)$. It is an expression of the underestimation of the real costs for the strategy x by using the deterministic cost function. The expected cost of underestimating $R(x) = \mathbf{E}R(x, w)$ can be used as an indicator of the economic risk associated with strategy x. The risk function $R(x)$ could be taken as an additional nonlinear constraint to the original deterministic model, or it may enter the objective function as an additional "penalty" term. An extensive discussion of motivation, formulation and solution procedures for the optimization of functions, expressed in terms of expectations similar to $R(x)$, can be found in [14].

Applying the second alternative, the stochastic model explicitly taking into account the risk of underestimating future investment costs can be formulated as minimizing

$$F(x) = \sum_{t=0}^{T} < C^t, x^t > + \rho R(x) \tag{6}$$

subject to the original constraints (2)-(4). It is also possible to add some or all constraints (5). ρ can be regarded as a risk factor, which in particular may be equal to 1. In the case $\rho = 1$ the first term of $F(x)$ corresponds to the expected cost associated with the energy developments and the second one to the expected underestimation of the real cost. Applying a risk factor $\rho > 1$ emphasizes the risk (risk aversion), while $\rho < 1$ reflects a tendency towards risk neutrality.

It is possible to impose additional constraints on the level of risk $R(x)$

$$R(x) \leq \overline{R} \tag{7}$$

where $\overline{R}$ is an upper bound on the underestimation of the real costs. In a sense the parameters ρ and $\overline{R}$ regulate the robustness of a strategy x with respect to the uncertainties.

The resulting stochastic optimization problem is solved on the basis of successive approximation of $R(x)$ by N sample functions

$$R(x) \sim \frac{1}{N} \sum_{s=1}^{N} R(x, w^s)$$

where $w^1, \ldots, w^s, \ldots, w^N$ are independent simulations ("scenarios") of possible cost paths $\{C^t(w^s)\}$, $t = 0, 1, \ldots, T$ and $s = 1, 2, \ldots, N$. The performance function $F(x)$ is then approximated by including the sequence of random functions

$$F^N(x) = \sum_{t=0}^{T} < C^t, x^t > +\rho \frac{1}{N} \sum_{s=1}^{N} R(x, w^s).$$

The simple sequential optimization procedure is designed to follow the solution path of the optimal strategies $\{x^N\}$ with $N \to \infty$, that are derived from optimization of the functions $\{F^N(x)\}$ for $N \to \infty$.

4 Results of numerical experiments

In order to study the performance of the stochastic version of MESSAGE we analyze three cases:

- the deterministic bounded case, where the solution structure of the deterministic model is regulated (bounded) by additional exogenous constraints on the decision variables. This case corresponds to the Arithmetic Mean Case in section 2;
- the deterministic unbounded case, where the exogenous constraints to guide the deterministic model are not included; and
- the stochastic unbounded case, where the stochastic performance function is added to the deterministic unbounded model.

This choice of cases was induced by the problem analysis in section 2, where one of the shortcomings of a deterministic approach using models like MESSAGE was identified to require additional constraints to make the model more robust. The model of the Arithmetic Mean Case, here labelled deterministic bounded case, is relaxed in terms of the exogenous constraints on the investigated technologies. This model with a larger solution space, the deterministic unbounded case, shows where the modelers have applied their expert judgement in order to constrain the solution towards the direction they think to be more appropriate and to gain results that are more resilient to parameter changes. Based on this case, the stochastic model was used to investigate strategies that minimize the risk of cost overrun due to the uncertainties in investment costs.

Figures 2 and 3 show the development of coal- and gas-based electricity generation for the three cases up to the year 2050. One of the reasons for the limitations in the Arithmetic Mean Case is that effects of present policies and planned installations are incorporated this way. Figures 2 and 3 indicate, that in the deterministic bounded case more coal and less gas is used for electricity generation in the nearer future than in the other cases. This reflects the regulations that were or are still applied in many European countries[1], the

[1] Germany still supports the use of domestic coal in power generation by a subsidy system; In the UK power generation is, despite the privatization of the industry, contractually bound to domestic coal production [15].

strong emphasis that international organizations like the International Energy Agency (IEA) put on coal-based electricity generation and a general reluctance of utilities to use natural gas for electricity generation. In the unbounded cases this constraint is relieved and leads to an immediate substitution of natural gas for coal. In future applications, constraint relaxation will have to be related only to the more distant future, while limits on the nearer future should remain intact.

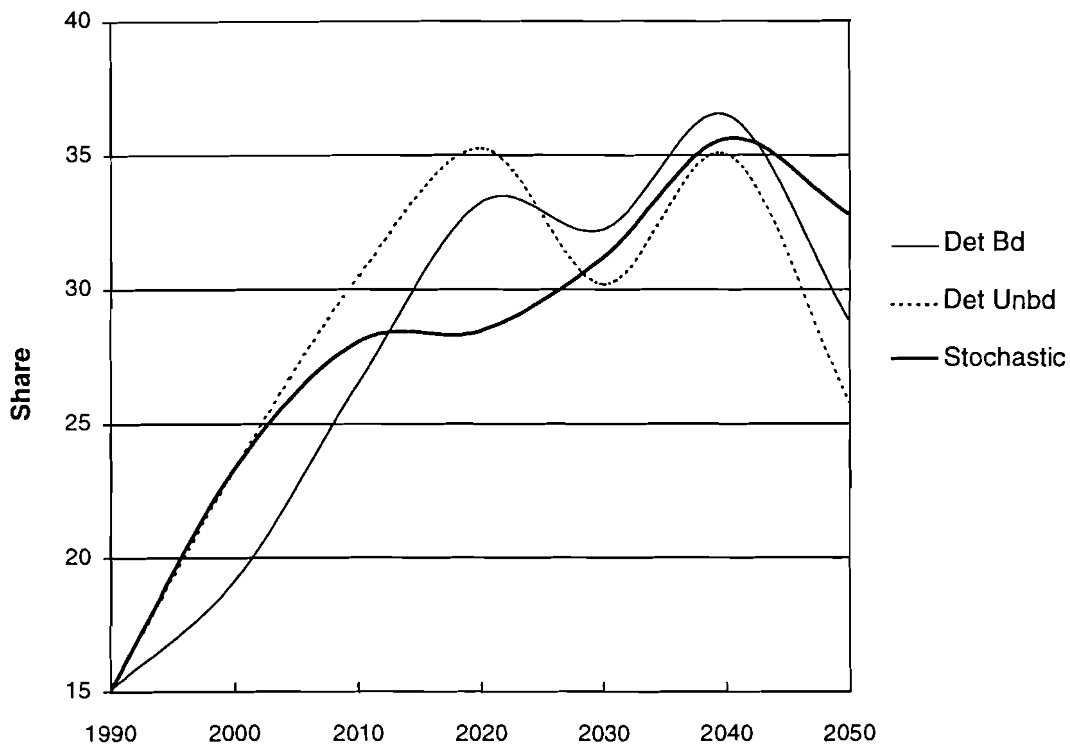

Figure 2: Share of gas in electricity generation for the three cases

The general trend for all model applications is similar, with coal use declining and gas use increasing over time. However, the deterministic unbounded case uses most gas, with a strong swing around 2030, which is reduced in the deterministic bounded case and practically avoided in the stochastic model. This generally leads to reduced gas use towards the end of the horizon, and, in the deterministic unbounded case, to a rebound of coal-based power generation. This rebound can be avoided in the deterministic bounded and the stochastic case.

Figure 4 compares electricity generation by technology for the year 2050. In the deterministic cases, the use of conventional coal power plants and, to a lesser degree, nuclear power plants, is reduced in the bounded case as compared to the unbounded case. On the other hand, gas-fired combined cycle power plants are used to a lesser degree in the unbounded model. Introducing the stochastic model formulation gives the interesting result, that the tendencies enforced in the bounded as compared to the unbounded deterministic case are supported by the model outcomes. Gas combined cycles are applied to an even higher

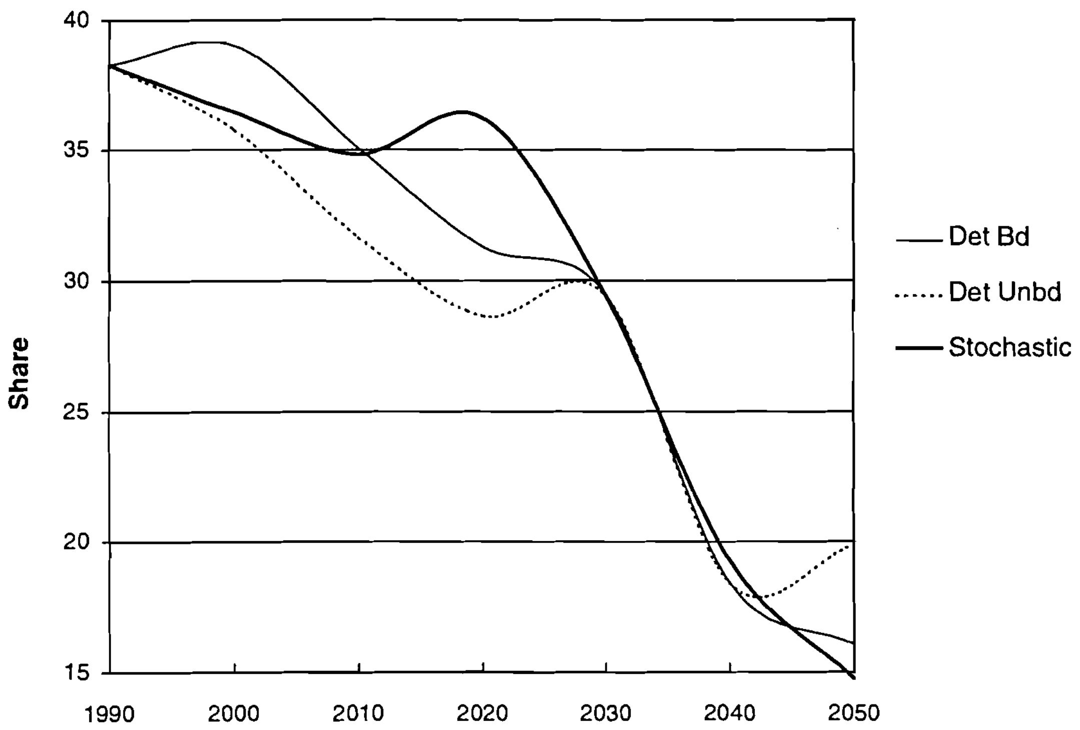

Figure 3: Share of coal in electricity generation for the three cases

degree than in the deterministic unbounded case, while coal-based power generation and nuclear reactors supply even less electricity.

The interpretation of this result is that in the deterministic bounded case the modeler, anticipating the uncertainties concerning future developments of model parameters, chose bounds to minimize the risk of wrong technology selections. In the stochastic unbounded case, these modeler's choices are applied in an even more pronounced manner.

The split among the two different systems for coal-based and gas-based electricity generation deserves special attention: In the case of coal-based systems, i.e. conventional and advanced coal power plants, the cheaper and slightly less efficient conventional systems are prefered. If the uncertainties of investments are incorporated, a diversification takes place and some 20% of the coal-based systems are advanced systems. For gas-based systems, the effect is different: the new systems, combined cycles, are preferred already in the deterministic cases. The stochastic case has two effects: it sharply increases the application of the combined cycle technology and it also reduces the use of conventional steam-based power generation from gas. This shows, that the gas combined cycle has the most attractive cost structure, even including uncertainties of future investment costs. The reason lies in the distribution of investment costs of gas combined cycles: 30% of the estimates are at the lower end of investment figures, around 500 US$/kW. Clearly the majority of experts envisages gas-based combined cycles to be very competetive technologies.

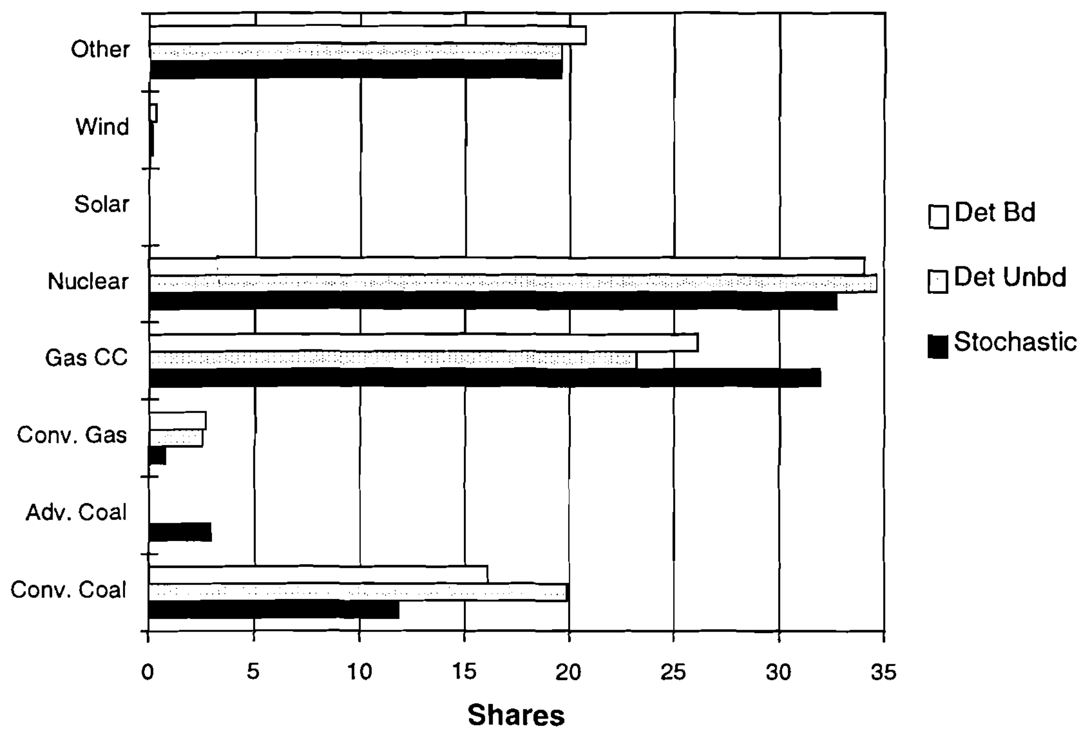

Figure 4: Electricity generation by technology in the three cases in 2050

Finally, one general conclusion is attributable to the approach taken. Since the diversification in the stochastic model is obtained in a "natural" way, without constraining model flexibility, the overall cost of the optimal strategy derived by the stochastic model is considerably lower than in the deterministic model. This result was to be expected, because hard limits could at any time also eliminate desired solutions, while incorporating additional information in the objective function leaves the model the flexibility to choose good solutions.

5 Conclusions and Outlook

The goal of this paper was to introduce the stochastic version of MESSAGE and to analyze and compare structures of energy development strategies derived from the deterministic and stochastic versions. The stochastic version deals with uncertainties concerning future investment costs by incorporating the expectation of incurring higher costs due to these uncertainties in the objective function.

The first, rather striking result of the experiments is that skilled model application of a deterministic model yields results with diversification features comparable to the stochastic version. Experienced modelers will, by iterative model adaptations and analysis of the result, reach results displaying adequate robustness with respect to the model parameters.

However, the results of the numerical experiments also show several advantages of the stochastic model. In stochastic models the diversification of development strategies is reached in a natural way as a result of an anticipation of possible variations rather than as result of additional flexibility constraints. Consequently, the diversification in the stochastic case is less "expensive" than a diversification through flexibility constraints. In other words, the optimal value of the objective function in the stochastic model is lower than the optimal value of the objective function for the bounded deterministic model.

Applying the stochastic approach to energy strategy evaluation leads to a substitution of energy production from technologies with high sensitivity to parameter changes towards technologies with less sensitivity, even if they are more expensive in some cases. A consequence of this and the inherent minimization of risks related to singular development paths is the early diversification into new technologies.

Uncertainties concerning future technology characteristics clearly do not only concern economic indicators like investment costs. Prime candidates for further investigations are the technical performance, primarily expressed by the conversion efficiency and the accompanying pollutant emissions. Distribution functions for efficiency estimates of electricity generation technologies are avaiable in the same fashion as the investment cost functions and could be readily incorporated into an extended stochastic version of MESSAGE. But also other parameters, like the date of introduction of new technologies, and potentially the cost and performance effects of "learning by doing" (the so-called technological learning), are interesting for future investigations.

Leaving aside the representation of technologies in MESSAGE, this model incorporates many more constraints where experts opinions diverge, like resource quantities available world-wide, or required limits on CO_2-emissions to mitigate global warming. The developments of stochastic approaches covering these cases are challenging from a methodological point of view, especially taking into account the large scale applications of MESSAGE.

An important direction of further studies concernes the development of generators for dependent random parameters with a possible reduction of uncertainties. In our study we ignored dependencies between variations of investment costs for a technology and, as an example, total cumulative investment in this technology. On the other hand, economic recession or increase of activity affect all activities and causes correlation between changes in time and between various types of model parameters. The analysis reported in this paper could serve as a basis for possible approaches to investigate such situations in a more realistic manner.

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