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Study of the evolution of the northwestern European natural gas markets using S-GaMMES

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Keywords: Energy markets modeling, Game theory, Generalized Nash-Cournot equilibria, Quasi-Variational Inequality, Equilibrium problems, Stochastic programing.

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Study of the evolution of the the northwestern European natural gas markets using S-GaMMES.

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December 16, 2011

Abstract

This article presents an application of S-GaMMES in order to study the evolution of the natural gas trade in northwestern Europe. S-GaMMES is a stochastic dynamic Generalized Nash-Cournot model that describes the evolution of the natural gas markets. The major gas chain players are depicted including: producers, consumers, storage, and pipeline operators, as well as intermediate local traders. The gas demand is made random because of the oil price fluctuations. The model has been applied to represent the northwestern European natural gas market and to forecast, until 2035, after a calibration process, consumption, prices, production, and long-term contracts prices and volumes in the different scenarios. Finally, we defined and calculated the value of stochastic solution adapted to our model.

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1 Introduction

S-GaMMES, Stochastic Gas Market Modeling with Energy Substitution is a Stochastic Generalized-Nash Cournot model that describes the natural gas market trade. The key features of the model are the following: energy substitution between coal, oil and natural gas is taken into account, long-term contracts (LTC) are endogenously described and the oil price's fluctuation is captured by modeling the oil price as a random variable. Therefore, S-GaMMES is particularly well suited to describe the European gas trade, which is still mainly dominated by long-term contracts in the upstream and where the LTCs are oil price indexed. This paper is an application of our model to the northwestern European natural gas trade. The perimeter of the study and the calibration process are presented in the first section. Then the results are discussed and analyzed. These results contain scenario forecasts of the consumption, prices, production, and gas dependence in Europe. LTC prices and volumes are also provided and analyzed. In the following section, we define and calculate the value, the loss, and the gain of the stochastic solution in order to quantify the usefulness of taking into account stochasticity in the model. The last section concludes the paper.

We refer to the theoretical presentation of S-GaMMES for a description of the economic structure and the scenario tree, as well as for the notation used.

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2 The European natural gas markets model

This section puts the model at work and presents our numerical results.

2.1 The representation

This section presents an application of the model to the northwestern European natural gas market. The representation is very similar to the one presented in the deterministic version of GaMMES [1]. The following array summuerizes the main actors, production and storage sites and the seasons studied:

Producers	**Fields**	**Consuming markets**	**Independent traders**	**Storage sites**
Russia	Russia$_f$	France	France$_{tr}$	France$_{st}$
Algeria	Algeria$_f$	Germany	Germany$_{tr}$	Germany$_{st}$
Norway	Norway$_f$	The Netherlands	The Netherlands$_{tr}$	The Netherlands$_{st}$
The Nethherlands$_f$	NL$_f$	UK	UK$_{tr}$	UK$_{st}$
UK	UK$_f$	Belgium	Belgium$_{tr}$	Belgium$_{st}$

Seasons	**Time**	**Time step**	**# Scenario nodes**	**# Branches at each time step**
off-peak	2000 – 2035	5 *years*	31	2 or 1
peak				

We aggregate all the production fields of each producer into one production node. We assume that each consuming market is associated with one independent local trader (indexed by tr). As an example, France$_{tr}$ would be GDF-SUEZ and Germany$_{tr}$ would be E-On Ruhrgas. All the storage sites are also aggregated so that there is one storage node per consuming country. As for the transport, the different gas routes given in Figure 1 were considered.

The local production in the different consuming countries and the imports from non-represented producers, which are small, are exogenously taken into consideration.

We remind that the scenario tree representation we have used concerns the fluctuations of the oil price. Figure 2 shows that scenario tree. [1]

The model has been solved, in its extensive form, using the solver PATH [20] from GAMS. In order to have an algorithm convergence in a reasonable time, we used a five-year time-step resolution. We chose five years because it is the typical length of time needed to construct investments in production, infrastructure or storage. Also, the inverse demand function has been linearized.

2.2 The calibration

The calibration process has been carried out in order to best meet:

- the global natural gas consumption,
- the industrial sector gas price and
- the volumes produced by each gas producer,

[1] We refer to the theoretical description of S-GaMMES for the values chosen for λ_1, λ_2 and μ.

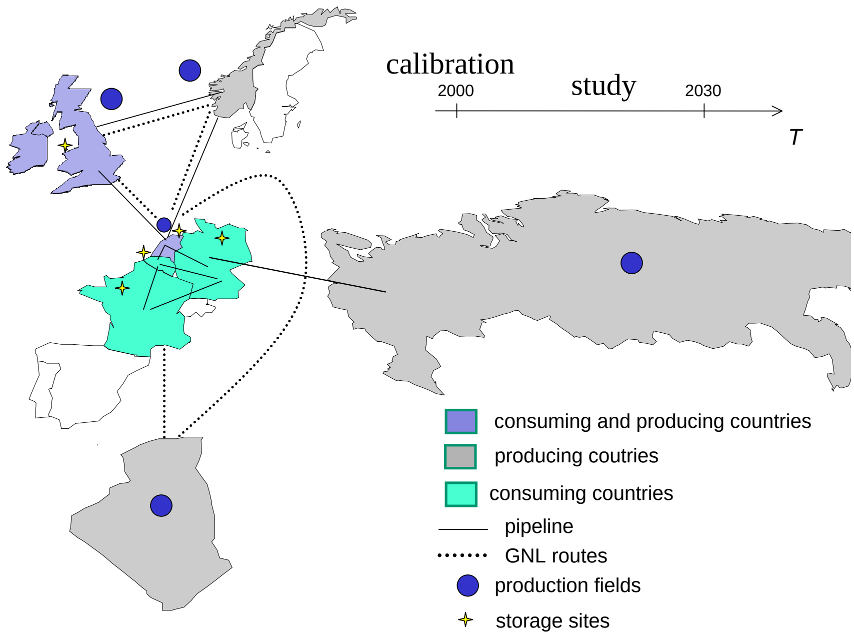

Figure 1:
The northwestern European natural gas routes, production, and storage sites.

at scenario node 0. We recall that this node corresponds to the time period between 2000 and 2004 (the first time period). Therefore, there is no randomness associated with this node.

The data for the market prices, consumed volumes, and imports is the publicly available set from IEA [36]. We define a new variable $exch^t_{mpd}$ that represents the exported volume from producer p to market d. More precisely :

$$\forall t,\ m,\ p,\ d,\ exch^t_{mpd} = \sum_i B_{id}\ zp^t_{mpi} + x^t_{mpd}$$

The matrix B is such that $B_{id} = 1$ if the independent trader i is located in market d (e.g., GDF-SUEZ in France, E-On Ruhrgas in Germany) and $B_{id} = 0$ otherwise. Hence, one can notice that the exchanged volumes include both the spot and long-term contract trades.

The calibration elements we used are the inverse demand function parameters α^t_{md}, γ^t_{md}, pc^t_{md} and β^t_{md}. The idea is that the system dynamics model is run in order to calculate all the inverse demand function parameters, for all the markets and at each year and season of our study. The calibration technique slightly adjusts these values to make the model correctly describe the historical data (between 2000 and 2004). More details about the calibration of the demand function and its parameters' values are given in [3]

In order to calibrate the produced volumes properly, we introduced security of supply parameters that link each pair of producer/consuming countries (p, d). A security of supply measure forces each country not to import from any producer more than a fixed percentage (denoted by SSP) of the overall imports.This property can be rewritten as follows:

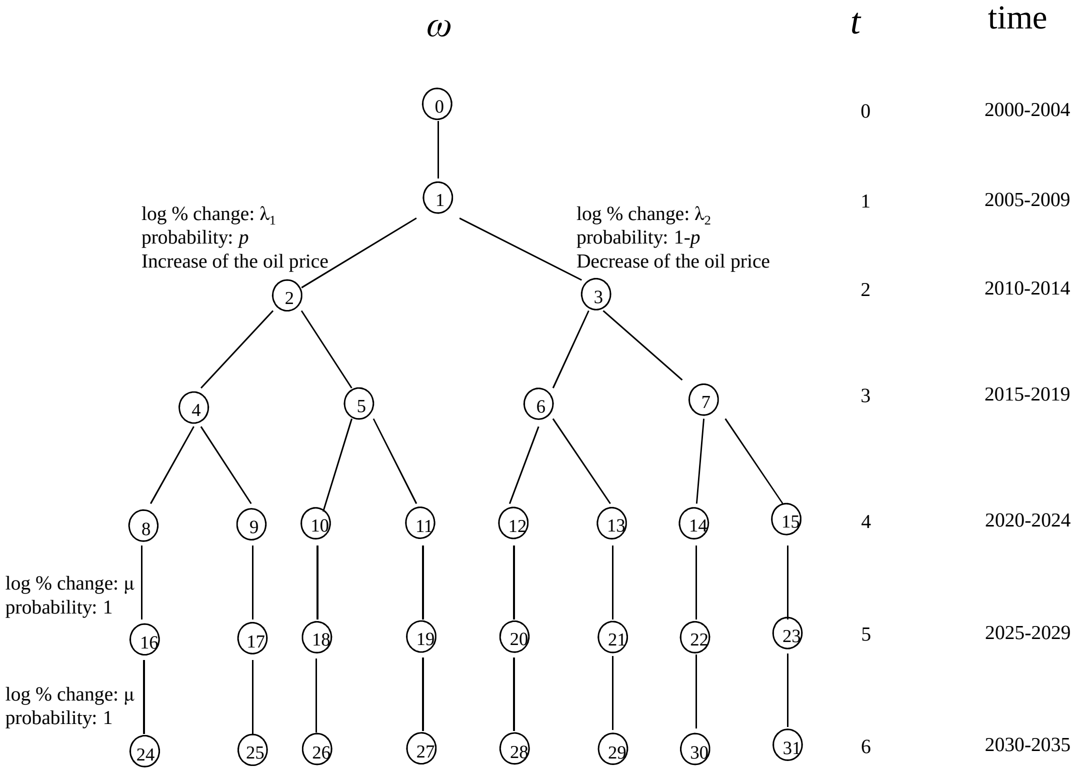

Figure 2:
The scenario tree.

$$\forall t,\ m,\ p,\ d,\ exch^{t}_{mpd} \leq SSP_{pd} \sum_{p} exch^{t}_{mpd}$$

The security of supply parameters are also an output of the calibration process.
The calibration tolerates a maximum error of 5% for the prices and consumed quantities and 10% for the imported/exported volumes. The tolerated error is higher for the exchanged volumes because they depend on the exports decided by the producers for all the targeted consumers, even those that are not in the scope of the model. As an example, the exported volumes from Russia to CIS (CEI) countries are exogenous to our model.

2.3 Results

We refer to [1] for a more detailed analysis of the results. This section focuses mainly on the theoretical results, in order to highlight the role of randomness in the model.

In order to estimate the demand function parameters, our model requests exogenous inputs: the markets' global energy demand and coal price evolution (scenario provided by the European Commision [18]). We assume that the coal price remains constant and that the oil price follows a Markov chain regime. The annual gross consumption growth per year is given in the following chart (starting from 2000).

Annual growth	Total gross consumption (in % per year)
France	0.46
Germany	0.06
United Kingdom	0.02
Belgium	0.06
The Netherlands	0.11

Figure 3 gives the evolution of the consumption and prices in the demand markets between 2000 and 2035, for the different scenarios given in Figure 2. We consider the different leaves of the tree, indexed by their scenario node number (between 24 and 31) and draw the evolution of the consumption, with time, following the path in the tree that leads to the corresponding leaf. It is important to remember that all the possible scenarios are solved simultaneously while respecting the non-anticipativity conditions. To analyze the actors' and markets' behavior, we also run S-GaMMES with two deterministic evolutions of the demand:

- A "High" demand case, where the oil price follows the path that leads to node 24. This corresponds to a deterministic increase of the oil price between 2000 and 2035 (a logarithmic change of $\lambda_1 \geq 0$).
- A "Low" demand case, where the oil price follows the path that leads to node 31. This corresponds to a deterministic decrease of the oil price between 2000 and 2035 (a logarithmic change of $\lambda_2 \leq 0$).

In the "High" and "Low" cases, it is assumed that the players know exactly, *a priori*, whether the oil prices are going to follow path 24 (constant and continuous increase of the oil price) or path 31 (constant and continuous decrease of the oil price).

One can notice that the evolution of the consumption and prices in all the scenarios is bounded by the deterministic "High" and "Low" scenarios. This result is intuitive because in both cases,

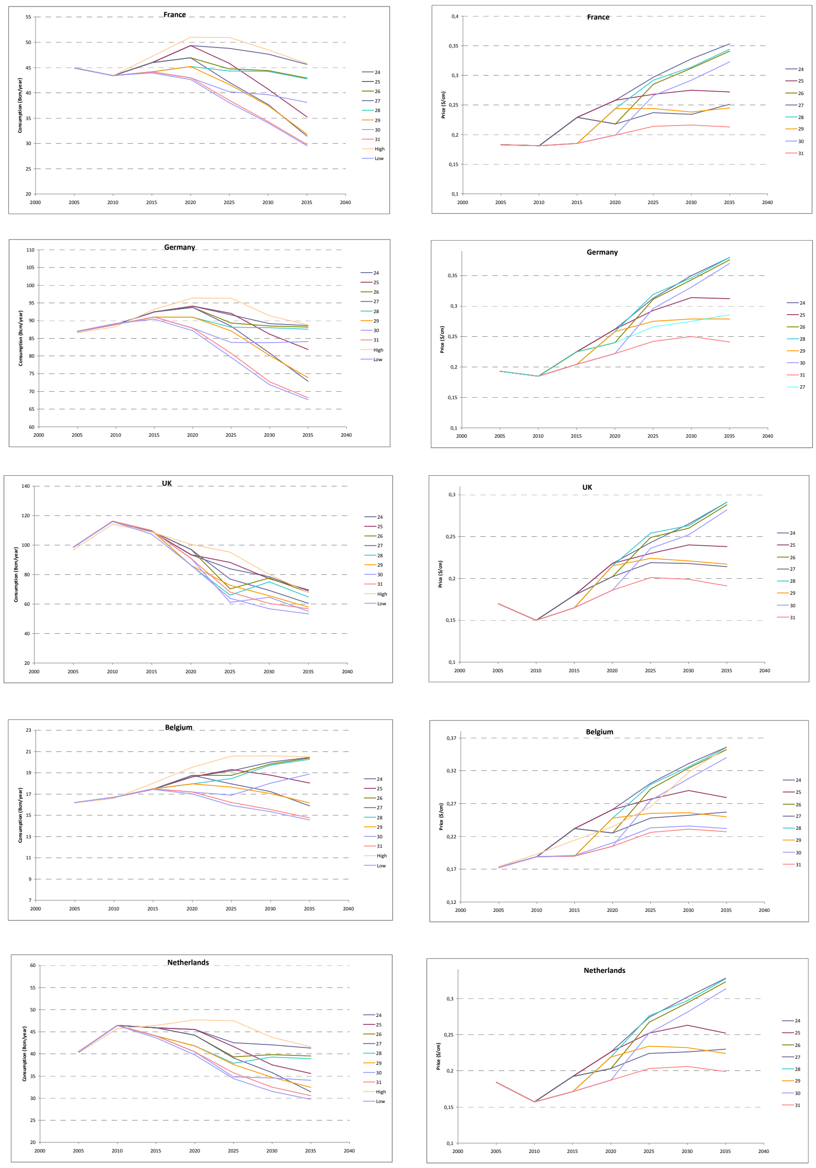

Figure 3:
Consumption and prices in the different scenarios.

it is assumed that the players have perfect foresight of the demand evolution. Besides, scenarios 24 and 31's results bind the other scenarios' consumption and prices evolution, because they correspond to a continuous a constant increase (scenario 24) or decrease (scenario 31) of the oil price.

The following table gives the consumption annual percentage growth (APG) mean value, between 2005 and 2035, in the European countries studied. The ratio betwen the standard deviation and the mean value of the consumption in 2035 (last period) is also given. The latter quantifies the impact of randomness on the spread of consumption with time. More particularly, we will define the spread by the following:

$$spread = \frac{\text{Standard deviation in 2035}}{\text{Mean value in 2035}} \tag{1}$$

The spread, a measure of the standard error, can be defined for all the parameters or market outcome that depend on the scenarios (consumption, prices, production, etc.). Intuitively, if the spread is high, this means that randomness may play an important role in the decisions made by the actors that influence the market outcome. This situation indicates that a stochastic model is more accurate to represent the market behavior as compared to a deterministic one. This notion will be detailed later while introducing and calculating the value of the stochastic solution.

Consumption	France	Germany	UK	Belgium	The Netherlands
(APG) mean value (%/year)	-1.15	-0.62	-1.76	-0.09	-0.81
Spread (in %)	11.1	8.5	4.9	10.4	6.5

One can notice that the spread has the highest value in France, which suggests that the fluctuations of the oil price influence the French gas consumption a great deal. On the contrary, the spread is relatively low in the United Kingdom. This country also has the highest decrease of consumption (in all scenarios). Indeed, the decrease of consumption is mainly due to the fact that the United Kingdom has low gas reserves (around 900 Bcm in 2000, [10].) and will have to rely on foreign (especially Russian and Algerian) supplies in the coming decades. Therefore, the evolution of the consumption in the UK is greatly dependent on the supply and less on the oil price fluctuations.
One can notice that the natural gas consumption is expected to decrease between 2000 and 2035, in most of the scenarios, even if the demand increases. This is mainly due to the fact that the initial natural gas reserves in Europe are relatively low compared to the demand. Since we do not represent explorations activities (for Shale gas for instance), the foreign dependence, especially toward Russia and Algeria, will grow with time, which will force the prices up mainly because of two reasons: first, the growing market power exerted by Russia and Algeria and second, the high transportation costs.

The following table gives the price annual percentage growth (APG) mean value and the spread, between 2005 and 2035, in the European countries studied.

Price	France	Germany	UK	Belgium	The Netherlands
(APG) mean value (%/year)	0.89	1.14	0.73	1.25	0.65
Spread (in %)	17.2	17.1	15.5	16.3	18.4

The spread is higher for the prices than for the consumption. This is intuitive because the gas prices are more correlated to the oil price as compared to the consumption. Like for the consumption, France has the highest price spread in 2035.

Figure 4 shows the evolution of the production (dedicated to the consuming countries we studied) over time, in the different scenarios.

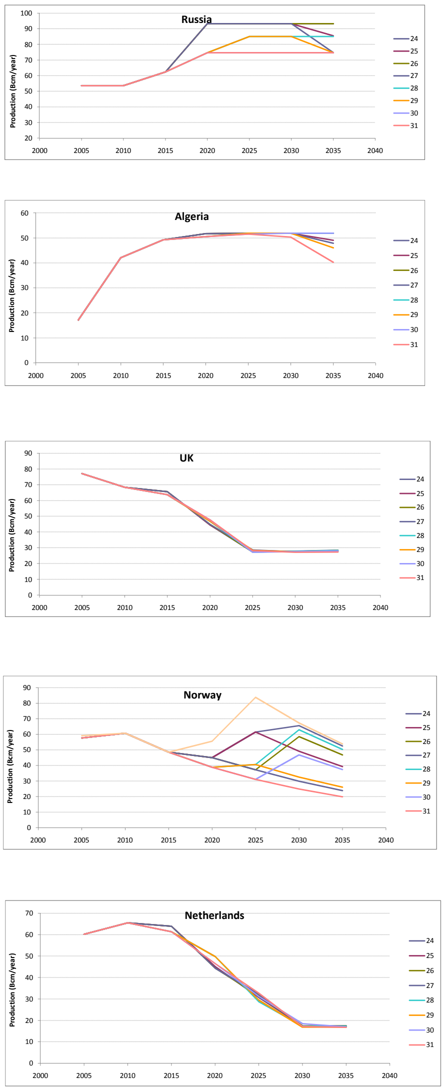

Figure 4:
Production in the different scenarios.

The Russian and Algerian shares in the European consumption is expected to grow, in all the possible scenarios. The Deutch and The UK production is expected to decrease with time, with a very small spread. This is mainly due to the limited reserves of gas initially present in these countries that reduces the correlation between the supply of these countries and the demand which is linked to the oil price that is random. The Norwegian production varies a lot with the scenario and has a relatively high spread.

Now it may be interesting to analyze the impact of randomness on the long-term contracts. The following table gives the different long-term contracts' (LTC) volumes and prices between the producers and the independent traders (stochastic). In order to compare with the deterministic version, we also report the LTC results in the High and Low cases. [2]

Stochastic

Volume(Bcm/year)	France	Germany	UK	Belgium	The Netherlands	Total
Russia	0.84	32.26	0.00	0.00	0.00	33.10
Algeria	4.03	0.00	0.00	8.80	0.00	12.84
The Netherlands	0.00	0.00	0.00	9.42	5.91	15.33
Norway	0.00	0.00	0.00	12.16	0.00	12.16
UK	0.00	0.00	24.55	0.00	0.00	24.55
Total	4.87	32.26	24.55	30.38	5.91	97.98

High

Volume(Bcm/year)	France	Germany	UK	Belgium	The Netherlands	Total
Russia	0.31	33.61	0.00	0.00	0.00	33.92
Algeria	4.04	0.00	0.00	8.79	0.00	12.83
The Netherlands	0.00	0.00	0.00	9.23	5.84	15.06
Norway	1.11	0.00	2.88	12.44	0.00	16.43
UK	0.00	0.00	23.64	0.00	0.00	23.64
Total	5.47	33.61	26.53	30.45	5.84	101.89

Low

Volume(Bcm/year)	France	Germany	UK	Belgium	The Netherlands	Total
Russia	0.86	30.95	0.00	0.00	0.00	31.80
Algeria	3.93	0.00	0.00	8.88	0.00	12.81
The Netherlands	0.00	0.00	0.00	9.58	5.58	15.16
Norway	0.00	0.00	0.00	12.02	0.00	12.02
UK	0.00	0.00	24.89	0.00	0.00	24.89
Total	4.78	30.95	24.89	30.48	5.58	96.69

Stochastic

Price($/cm)	France	Germany	UK	Belgium	The Netherlands
Russia	0.12	0.12	nc	nc	nc
Algeria	0.12	nc	nc	0.13	nc
The Netherlands	nc	nc	nc	0.13	0.14
Norway	nc	nc	nc	0.13	nc
UK	nc	nc	0.15	nc	nc

[2] nc denotes a no-contract situation.

High					
Price($/cm)	France	Germany	UK	Belgium	The Netherlands
Russia	0.13	0.13	nc	nc	nc
Algeria	0.13	nc	nc	0.14	nc
The Netherlands	nc	nc	nc	0.14	0.16
Norway	0.13	0.16	0.14	nc	nc
UK	nc	nc	0.16	nc	nc

Low					
Price($/cm)	France	Germany	UK	Belgium	The Netherlands
Russia	0.12	0.12	nc	nc	nc
Algeria	0.12	nc	nc	0.12	nc
The Netherlands	nc	nc	nc	0.12	0.14
Norway	nc	nc	nc	0.12	nc
UK	nc	nc	0.15	nc	nc

One can notice that if a pair of producer-independent trader contract on the long-term, the corresponding LTC price is nonnegative. Besided, the spot prices in the consuming countries, reported in Figure 3 are in general higher than the LTC prices. One can also notice that the Belgian trader is the one that diversifies the most his gas supplies (three sources). This is due to its geographical location, which is close to three producing countries: Norway, The Netherlands and Algeria (we remind that the Algerian production node is directly linked to Belgium via a GNL route). A consuming country, which produces natural gas, such as the UK or The Netherlands, sees the corresponding independent trader contract on the long-term exclusively with the local producer. This is quite intuitive because of the geographical proximity. Besides, for a particular trader, the LTC price is the same with respect to all the possible supply sources. This suggests that the LTC prices are correlated to the spot prices. An independent trader may tolerate high supply marginal costs if his marginal revenue or the spot price in his spot market, which is the market where he has to support the least transportation costs, is high enough.

A comparison between the Stochastic, High and Low cases shows that the LTC volumes contracted are, on average, 1.5% higher in the Stochastic case than in the Low case. On the contrary, LTC volumes are, on average, 4% lower in the Stochastic case than in the High case. There are even some contracts in the High case that do not exist in the Stochastic case: Norway-UK (2.9 Bcm/year) and Norway-France (1.1 Bcm/year). Regarding the prices, the results are similar: the Stochastic LTC prices are, on average 2.5% higher than in the Low case and the Stochastic LTC prices are, on average 9% lower than in the High case.

These results are quite intuitive: in the stochastic model, the strategic players need to hedge their decisions on the long-term, against the oil price fluctuations. In a High scenario perfect foresight, the demand increases constantly with time and the independent traders need to contract more important volumes in order to ensure a sufficient supply. In that situation, the spot price is expected to be relatively high (see Figure 3) and therefore the independent traders can support higher supply costs, which benefits to the producers. This explanation holds for the Stochastic-Low cases LTC comparison.

2.4 The value of the stochastic solution

Now we define a measure that allows us to quantify the utility to introduce stochasticity in the S-GaMMES model. Following [54], we adapt the concept of the value of the stochastic solution, introduced by [7] to analyze the performance of stochastic programing, to the context of imperfect competition and Equilibrium problems.

For that purpose, we will compare the Stochastic Model (SM) and the Mean Value Model (MVM) results, which will be defined later. In our representation, at each time period, the oil price is modeled as a random variable whose mean value will be denoted by:

$$p_t = \langle p_t^{\omega} \rangle_{\omega} \tag{2}$$

The mean value is calculated by considering all the scenarios ω that correspond to time-step t.

The Mean Value Model is a deterministic model where, at each time step, we approximate the oil price by its mean value p_t. Figure 5 is a schematic description of both models.

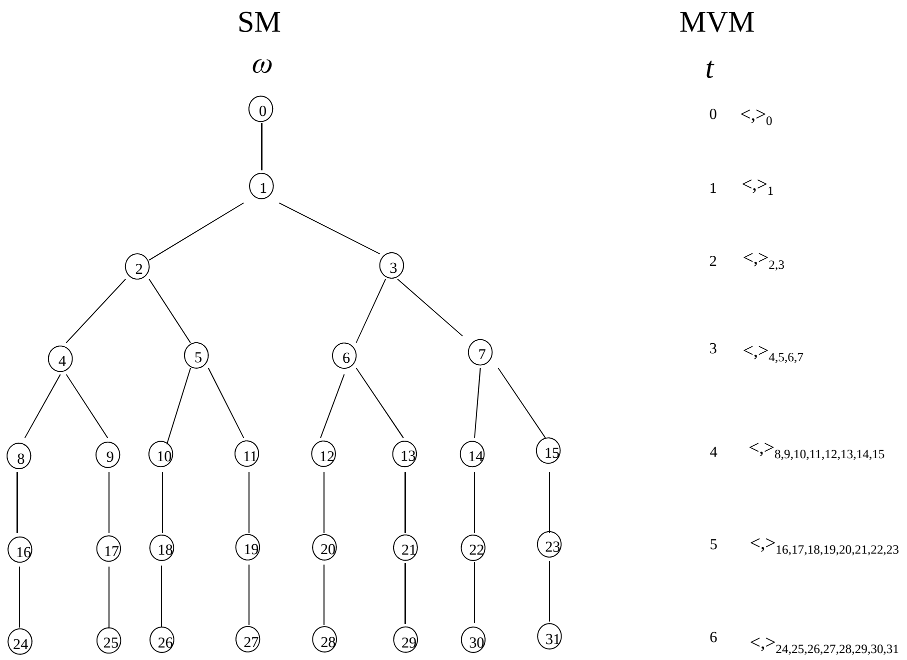

Figure 5:
The stochastic Model (SM) and Mean Value Model (MVM).

We will compare the different players' utilities in the Stochastic and Mean Value cases. We will also compare the Stochastic, the High demand and Low demand cases utilities. For a particular player, we will define:

- The SM utility Π_{SM} by the expected value of its global utility over the possible scenarios, in the SM output.
- The MVM utility Π_{MVM} by the value of its global utility over time, in the MVM output.
- The HM utility Π_{HM} by the value of its global utility over time, in the High case output.
- The LM utility Π_{LM} by the value of its global utility over time, in the Low case output.

- The value of the stochastic solution defined by:

$$VSS = \Pi_{SM} - \Pi_{MVM} \tag{3}$$

- The loss of the stochastic solution defined by:

$$LSS = \Pi_{SM} - \Pi_{HM} \tag{4}$$

- The gain of the stochastic solution defined by:

$$GSS = \Pi_{SM} - \Pi_{LM} \tag{5}$$

Note that the Mean Value Model, the High demand and Low demand cases are deterministic situations, where the players have a perfect foresight of the future. The VSS is a means to quantify the importance of using stochasticity in the model. The GSS measures the gain obtained by the players when taking into consideration stochasticity, as compared to a deterministic low demand regime. To the contrary, the LSS measures the loss supported by the players when taking into consideration stochasticity, as compared to a deterministic high demand regime. In linear and non-linear stochastic programing, Birge and Louveaux [7] demonstrated that the VSS is nonnegative. However, this result may not hold for MCPs or Equilibrium Stochastic Problems. Indeed, since we do not deal with a unique objective function to optimize, but rather with multiple correlated ones, it is not straightforward that each player would benefit from taking care of stochasticity. The same conclusions hold for the GSS and LSS. Indeed, in stochastic programing, it is intuitive that the GSS is nonnegative whereas the LSS is negative. However this may not be true when dealing with MCP formulations.

The following table gives the VSS, GSS and LSS for the producers.[3] A producer's utility is his profit.

	VSS (*10^9 \$)	VSS (%)	GSS (%)	LSS (%)
Russia	9.23	9.23	19.45	-19.85
Algeria	0.91	1.43	7.23	-17.32
The Netherlands	-0.87	-0.58	0.75	-4.69
Norway	-0.29	-0.29	2.4	-14.66
UK	-1.18	-0.72	0.8	-5.42
Total	7.80	1.35	4.80	-10.79

The average VSS for the producers is 1.35%, which is nonnegative. This means that on average, the producers benefit from the use of randomness in their optimization programs. There are some cases where the VSS is negative (The Netherlands, Norway and The UK). However, the corresponding values are relatively small. Russia is the producer that benefits the most from the use of stochasticity, with a VSS of 9%. Regarding the GSS and LSS, their average values are 4.8% and -10.8% respectively. All the producers have a nonnegative GSS and negative LSS.

The following table gives the VSS for the independent traders. An independent trader's utility is his profit.

[3] The VSS in % is defined by $\frac{\Pi_{SM} - \Pi_{MVM}}{\Pi_{SM}}$. The definition is similar for the GSS and LSS in %.

	VSS ($*10^9$ \$)	VSS (%)	GSS (%)	LSS (%)
France	-0.03	-0.54	3.89	-27.08
Germany	0.15	0.37	4.09	-13.40
UK	0.17	1.28	1.01	-18.17
Belgium	-0.15	-0.51	1.24	-6.81
The Netherlands	0.55	14.29	12.08	2.55
Total	0.69	0.73	3.05	-12.17

The average VSS for the traders is 0.73%, which is nonnegative. This means that on average, the independent traders benefit from the use of randomness in their optimization programs. Nevertheless, there are some cases where the VSS is negative. The Dutch trader is the one that benefits the most from the use of stochasticity, with a VSS of 14%. The average GSS is 3.05% and the average LSS is -12.17%. The Dutch trader has a positive LSS. However, the value is relatively small compared to the GSS or the VSS.

The previous results concerned the strategic players, who directly take into consideration randomness in their profits. Now it may be interesting to measure the VSS for the non-strategic players.

The following table gives the VSS for the consumers. The consumers' utility is their surplus: if the inverse demand function is $p(q)$ and the consumed quantity is Q, then the utility is defined by $\int_0^Q (p(q) - p(Q))\, q \, dq$.

	VSS ($*10^9$ \$)	VSS (%)	GSS (%)	LSS (%)
France	0.76	0.28	2.43	-16.52
Germany	1.86	0.46	2.49	-9.28
UK	3.23	2.54	2.71	-2.93
Belgium	0.33	0.42	2.39	-11.1
The Netherlands	1.37	1.26	2.9	-12.5
Total	7.55	0.76	2.54	-10.88

The average VSS for the consuming countries is 0.76%, which is nonnegative. This means that in general, the consumers benefit from the use of randomness. Note that this result is not intuitive because the consumers' surplus is not taken into account in the producers or the traders payoff. However, this can be explained by the fact that in S-GaMMES, the strategic players have a better representation of the demand fluctuations that directly influences the consumers' surplus. The United Kingdom is the country that benefits the most from the use of stochasticity, with a VSS of 2.5%. The average GSS and LSS values are respectively 2.5% and -10.88%

The following table gives the VVS for the pipeline (TSO) and storage operators (SSO). The utility is the opposite of the cost they minimize. The VSS and GSS are also nonnegative, whereas the LSS is negative.

	VSS ($*10^9$ \$)	VSS (%)	GSS(%)	LSS(%)
TSO	5.69	8.33	0.67	-38.67
SSO	0	0	0	0

In conclusion, the use of the Value of the Stochastic Solution allows us to quantify the gain earned by the players (strategic and non-strategic) when considering stochasticity in their decisions. When calculated in S-GaMMES, the results suggest that, on average, all the strategic and non-strategic players benefit from the use of randomness. However, since we are dealing with an Equilibrium Stochastic Problem, there are some players who may suffer from that situation, which may lead to their utility becoming smaller.

3 Conclusion

This paper applies S-GaMMES to the northwestern European gas trade. The model was solved using the solver PATH on GAMS. After the calibration process, it was applied to understand the European natural gas trade forecast between 2000 and 2035 in terms of consumption, prices, production, and LTC prices and volumes, in the different possible scenarios allowed by the scenario tree. In particular, we have defined and calculated the spread of consumption and prices in the different countries in order to quantify the importance of taking into account stochasticity in the model. We have also compared LTC prices in the stochastic versus the deterministic situations, in order to understand how the producers hedge their investment-related risk when dealing with an uncertain demand.

More generally, we have defined the value of the stochastic solution, as well as the gain and loss of the stochastic solution. This can be carried out by comparing the stochastic model results and its deterministic equivalent. This also allows one to quantify the importance and usefulness of taking into consideration the demand randomness. The value of the stochastic solution can be calculated for all the players in order to identify those who benefit from the use of stochasticity from those who do not. On average, taking into account stochasticity benefits to all the players. However, since we are dealing with imperfect competition, some players may reduce their utility when dealing with stochastic programming. Such players have been identified in this paper.

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References

[1] I. Abada, V. Briat, S. A. Gabriel & O. Massol, 2011, *A Generalized Nash-Cournot Model for the European Natural Gas markets with a Fuel Substitution Demand Function: The GaMMES Model.*, Economix Working Paper, http://economix.u-paris10.fr/.

[2] I. Abada & O. Massol, 2011, *Security of supply and retail competition in the European gas market. Some model-based insights.*, Energy Policy 39 (2011), 4077-4088.

[3] I. Abada, V. Briat & O. Massol, 2011, *Construction of a fuel demand function portraying interfuel substitution, a system dynamics approach.*, Economix Working Paper, available at http://economix.fr/fr/dt/2011.php.

[4] F. R. Aune, K. E. Rosendahl, E. L. Sagen, 2009, *Globalisation of natural gas markets - effects on prices and trade patterns*, Special Issue of The Energy Journal 30, 39-54.

[5] J. F. Benders, 1962, *Partitioning procedures for solving mixed-variables programming problems*, Numerische Mathematik 4, 238-252.

[6] J. F. Benders, 1962, *Partitioning procedures for solving mixed-variables programming problems*, Computational Management Science 2, 3-19.

[7] J. R. Birge & F. Louveaux, 1997, *Introduction to Stochastic Programming.*, Springer-Verlag, New York, Inc.

[8] J. R. Birge, 1982, *The value of the stochastic solution in stochastic linear programs with fixed recourse.*, Mathematical Programming 24, 314-325.

[9] M. G. Boots & F. A. M. Rijkers & B. F. Hobbs, 2004, *Trading in the Downstream European Gas Market: A Successive Oligopoly Approach*, The Energy Journal, 25(3), 73-102.

[10] BP Statistical Review of World Energy, 2009, www.bp.com.

[11] W. A. Brock, W. D. Dechert, B. Lebaron & J. Scheinkman , *A Test for Independence Based on the Correlation Dimension.*, Econ Working Papers http://econpapers.repec.org

[12] J. Dupacová, N. Gröwe-Kuska, W. Römisch, 2003, *Scenario reduction in stochastic programming.*, Mathematical Programming 95, 493-511.

[13] R. Egging, S. A. Gabriel, 2006, *Examining market power in the European natural gas market*, Energy Policy 34 (17), 2762-2778.

[14] R. Egging, S. A. Gabriel, F. Holtz, J. Zhuang, 2008a, *A complementarity model for the European natural gas market*, Energy Policy 36 (7), 2385-2414.

[15] R. Egging, F. Holz, S. A. Gabriel 2010, *The World Gas Model: A Multi-Period Mixed Complementarity Model for the Global Natural Gas Market*, Energy. 35 (10), pp. 4016-4029.

[16] R. Egging, 2010, *Multi-Period Natural Gas Market Modeling - Applications, Stochastic Extensions and Solution Approaches*, Ph.D. Dissertation, University of Maryland.

[17] European Commission, 2007, DG Competition Report on Energy Sector Inquiry 2007, Luxembourg: Office for Official Publ. of the Europ. Communities. *available at http://ec.europa.eu/dgs/energy.*

[18] European Commission, 2008, European energy and transport: trends to 2030, update 2007, Luxembourg: Office for Official Publ. of the Europ. Communities. *available at http://ec.europa.eu/dgs/energy_transport/figures/trends_2030_update_2007/.*

[19] F. Facchinei & J. -S. Pang, 2003, *Finite-Dimensional Variational Inequalities and Complementarity Problems*, Springer, New York.

[20] M. C. Ferris & T. S. Munson, 1987 *The PATH solver*, Elsevier Science Publishers B.V. (North-Holland).

[21] S. A. Gabriel, S. Kiet, J. Zhuang, 2005a, *A Mixed Complementarity-Based Equilibrium Model of Natural Gas Markets*, Operations Research, 53(5), 799-818.

[22] S. A. Gabriel, J. Zhuang, S. Kiet, 2005b, *A Large-scale Complementarity Model of the North American Gas Market*, Energy Economics, 27, 639-665.

[23] S. A. Gabriel, K. E. Rosendahl, R. Egging, H. Avetisyan, S. Siddiqui, 2009 *Cartelization in Gas Markets: Studying the Potential for a 'Gas OPEC'*, in review.

[24] S. A. Gabriel, J. Zhuang & R. Egging, 2009, *Solving Stochastic Complementarity Problems in Energy Market Modelling Using Scenario Reduction.*, European Journal of Operational Research, 197(3), 1028-1040.

[25] S. A. Gabriel & J. D. Fuller, 2010, *A Benders Decomposition Method for Solving Stochastic Complementarity Problems with an Application in Energy.*, Computational economics, Volume 35, Number 4, 301-329.

[26] GDE-SUEZ Reference Document, 2009, *http://www.gdfsuez.com/.*

[27] R. Golombek, E. Gjelsvik, K. E. Rosendahl, 1995, *Effects of liberalizing the natural gas markets in Western Europe*, Energy Journal 16, 85-111.

[28] R. Golombek, E. Gjelsvik, K. E. Rosendahl, 1998, *Increased competition on the supply side of the Western European natural gas market*, Energy Journal 19 (3), 1-18.

[29] P. T. Harker, 1991 *Generalized Nash games and quasi-variational inequalities*, European Journal of Operational Research, Vol.54 81-94.

[30] P. T. Harker & J. Pang, 1998, *Finite-dimensional variational inequality and nonlinear complementarity problems: A survey of theory, algorithms and applications*, Mathematical Programming 48 (1990) 161-220 (North-Holland).

[31] A. Haurie, G. Zaccour, J. Legrand & Y. Smeers, 1987, *A stochastic dynamic Nash Cournot model for the European gas market*, Technical Report, HEC Montreal.

[32] F. Holz, C. von Hirschhausen, C. Kemfert, 2008, *A Strategic Model of European Gas Supply (GASMOD)*, Energy Economics 30, 766-788.

[33] F. Holz, 2009, *Modeling the European Natural Gas Market - Static and Dynamic Perspectives of an Oligopolistic Market*, Ph.D. Dissertation, Technische Universitat-Berlin.

[34] R. G. Hubbard & R. J. Weiner, 1986, *Regulation and Long-Term Contracting in U.S. Natural Gas Markets*, Journal of Industrial Economics, Vol. 35, No. 1, pp. 71-79

[35] IEA, 2004, *Natural Gas Information* .

[36] IEA, 2009, *Natural Gas Information* .

[37] International Energy Agency, 2007, *World Energy Outlook 2007*, OECD/IEA.

[38] International Energy Agency, 2008, *World Energy Outlook 2008*, OECD/IEA.

[39] International Energy Agency, 2009, *World Energy Outlook 2009*, OECD/IEA.

[40] International Gas Union, Gastech Conference Amsterdam March 2011, 2009, *New Trends in Gas Price Formation.*

[41] W. Lise & B. F. Hobbs, 2008, *Future evolution of the liberalised European gas market. Simulation results with the dynamic GASTALE model*, Energy Policy 36 (6), 1890-1906.

[42] W. Lise & B. F. Hobbs, 2009, *A Dynamic Simulation of Market Power in the Liberalised European Natural Gas Market*, The Energy Journal 30, 119-136.

[43] H. W. Lilliefors, 1967, *On The Kolmogorov-Smirnov Test For Normality With Mean And Variance Unknown.*, Journal of the American Statistical Association, Vol. 62, No. 318. (Jun., 1967), p. 399-402.

[44] L. Mathiesen, K. Roland, K. Thonstad, 1987, *The European Natural Gas Mar- ket: Degrees of Market Power on the Selling Side*, in R. Golombek, M. Hoel, and J. Vislie (eds.): Natural Gas Markets and Contracts, North-Holland.

[45] E. Moxnes, 1985, *Price of Oil, Gas, Coal and Electricity in four European Countries 1960-1983*, Christian Michelsen Institue, No. 852260-1, Bergen, Norway.

[46] E. Moxnes & E. Nesset, 1985, *Substitution between Oil, Gas and Coal in UK Industrial Steam Raising*, Christian Michelsen Institue, No. 842240-4, Bergen, Norway.

[47] E. Moxnes, *The dynamics of Interfuel Substitution in the OECD-Europe Industrial Sector*, Elsevier Science Publishers B.V. (North-Holland), 1987.

[48] Perner & Seeliger, 2004, *Prospects of gas supplies to the European market until 2030. Results from the simulation model EUGAS*, Utilities Policy 12 (4), 291-302.

[49] World Trade Gas Model, Rice, 2004, *www.rice.edu/energy/publications/docs/GSP_ WorldGasTradeModel_ Part1*

[50] Rice, 2005, *http://www.rice.edu/energy/publications/docs/GAS_ BIWGTM_ March2005.pdf.*

[51] Y. Smeers, 2008, *Gas Models and Three Difficult Objectives*, ECORE discussion paper available at http://www.ecore.be/.

[52] P. Stevens: The 'Shale Gas Revolution': Hype and Reality. A Chatham House Report.

[53] H. Xu & Z. Zhang, 2010, *A Trend Deduction Model of Fluctuating Oil Prices.*, IDEAS Working Paper, http://ideas.repec.org/.

[54] J. Zhuang & S. A. Gabriel, 2008, *A Complementarity Model for Solving Stochastic Natural Gas Market Equilibria.*, Energy Economics 30(1), 113-147.

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