Advancing Oil (and Gas) Scenarios:
The ACEGES Computational Laboratory

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Abstract:

This paper describes the computational model: Agent-based Computational Economics of the Global Energy System (ACEGES). This is agent-based in that it determines aspects of the global energy system by modelling interactions between individual agents (decision-making entities) that act within this system. The model contains a number of different classes of agents, and the behaviour of each agent within a given class follows user-defined rules. Multiple model runs allow statistical envelopes of behaviour ranges to be generated. Since considerable complexity can arise in a wide range of systems when even simple individual rules are being followed, it is suggested that the agent-based approach presents a realistic way to capture such overall system behaviour.

This paper illustrates the use of this agent-based approach for forecasting global oil and gas supply, and presents details both of the model and of indicative results. It is recognised that the model needs further expansion (for example, by incorporation of additional information on the difference between the supply of conventional and non-conventional hydrocarbons) if it is to provide a full picture of reality. This expansion is underway and will be reported in subsequent papers.

1. Introduction

In times of uncertainties, scenarios offer a particularly useful approach. Scenarios are intended to challenge a manager's personal microcosms, and to reflect both the present and the past, before structuring the uncertainties of the future. In this sense, scenarios can act as an 'early warning system', by focusing on the driving forces that make differences to a system as perceived by decision-makers.

Scenarios, as critical planning and decision-support tools, work well when the business world is best characterised by 'morphogenesis' rather than 'stasis' – this is when the business environment is populated by 'resting points' rather than 'fixed point attractors' that can be forecast. The acceptance of the world of morphogenesis requires acceptance and inclusion of uncertainty in the decision-making process, and a focus on how the constituent components of the world work and interact.

Conventionally, scenarios are built upon a dynamic sequence of events or changes. However in times of unprecedented uncertainties and increasingly complex interconnections scenarios should be built upon a dynamic network of *interacting* events or changes. To that end, we put forward the framework called Agent-based Computational Economics of the Global Energy System (ACEGES), which is based on the agent-based modelling paradigm.

The premise is that ACEGES-based scenarios are more robust and useful for planning by supporting policy makers and business executives to 1) think about where their organization may be out of alignment with the emerging business megatrends - incipient societal, political, technological and economic shifts; 2) understand how the business environment as a coherent whole evolves, growing organically from bottom-up; 3) become more adept about the ways to foster their organization and its decision-making. The key idea is that the future should not be regarded as 'complicated' but as 'complex', in that there are uncertainties about the driving forces that generate unanticipated futures, which are difficult to explore analytically.

As the forces of change become more inter-connected, scenarios cannot neatly decompose them into separate and isolated sub-processes of change, which can be analysed independently. Aggregation of individually analysed sub-processes by means of summation to provide narratives of a coherent whole fails when the correct process of aggregation is not a sum. This is because of the existence of interacting and heterogeneous forces and agents such as, in this case, individual oil/gas producing organisations and countries.

Unlike conventional approaches that use computation, for example, for the empirical analysis of observational data and the calculation of the equilibria of systems of equations, agent-based models take us in a new direction that focuses on computer laboratories of complex dynamic systems, such as is the case with real-world energy systems. Agent-based computational laboratories add a new approach to the existing toolbox for understanding oil and gas markets. This new tool is fundamentally different because it accepts under a single umbrella:

- A higher degree of inter-connectedness between the building blocks of the business world: from hierarchical to network structures.
- A higher degree of heterogeneity: removal of "N-replication" of decisions made by representative agents/pool of agents such as oil producing countries/OPEC.
- Explicit representation of multi-layered space: physical, regulator, business and socio-economic.
- Development of data-free representations: important for business megatrends

– incipient societal, political, technological and economic shifts.
- Handling of a far wider range of nonlinear dynamics than conventional approaches: the computer keeps track of the many interactions in order to see what happens over time.

Agent-based models need not be complex or complicated because simple micro-foundations (without the assumption that the business world will move towards a predetermined state) can generate complex macro-regularities.

2. Why and When to Use Agent-based Modelling?

Agent-based models (ABM) – a bottom–up simulation-based modelling approach – is a methodology that has the potential to overcome the shortcomings of traditional analytical methods to model complex markets (Tesfatsion (2006) and references therein). In a nutshell, ABM models are computational models of micro-agents (e.g., oil producing companies) operating in an environment (e.g., oil reserves, pipelines, tankers), in which they interact repeatedly with other agents over a period of time, thereby permitting the computational study of phenomena as complex adaptive systems (CASs). For Tesfatsion (2006), CAS is a complex system that includes planner units, i.e., units that are goal-directed and that attempt to exert some degree of control over their environment to facilitate achievements of these goals. Voudouris (2011) argues that the development of realistically rendered ABM models offers a better way for the representation and scientific investigation of complex, dynamic phenomena such as energy markets

Historically, modellers have addressed questions about how decisions (of oil and gas production or demand) are made with aggregated models by generally assuming perfect information and rational behaviour. The key distinction between ABM models and other types of economic modelling is that of agent autonomy and the interactions between them (see Fig. 1). Agents in ABM models are decision-making entities capable of reactivity, social communication, goal-directed learning, and, most important of all, self-determinism on the basis of private internal processes such as profit maximisation. Thus, the agent is modelled as an independent entity that makes decisions and takes actions using the limited share of influence and/or uncertain information (bounded rationality) available to it, similar to how organizations and individuals operate in the real world. A main feature of ABM models is the repetitive and competitive interactions between the agents – an agent makes publicly available to other interacting agents only a subset of their private information and actions (see Fig. 1).

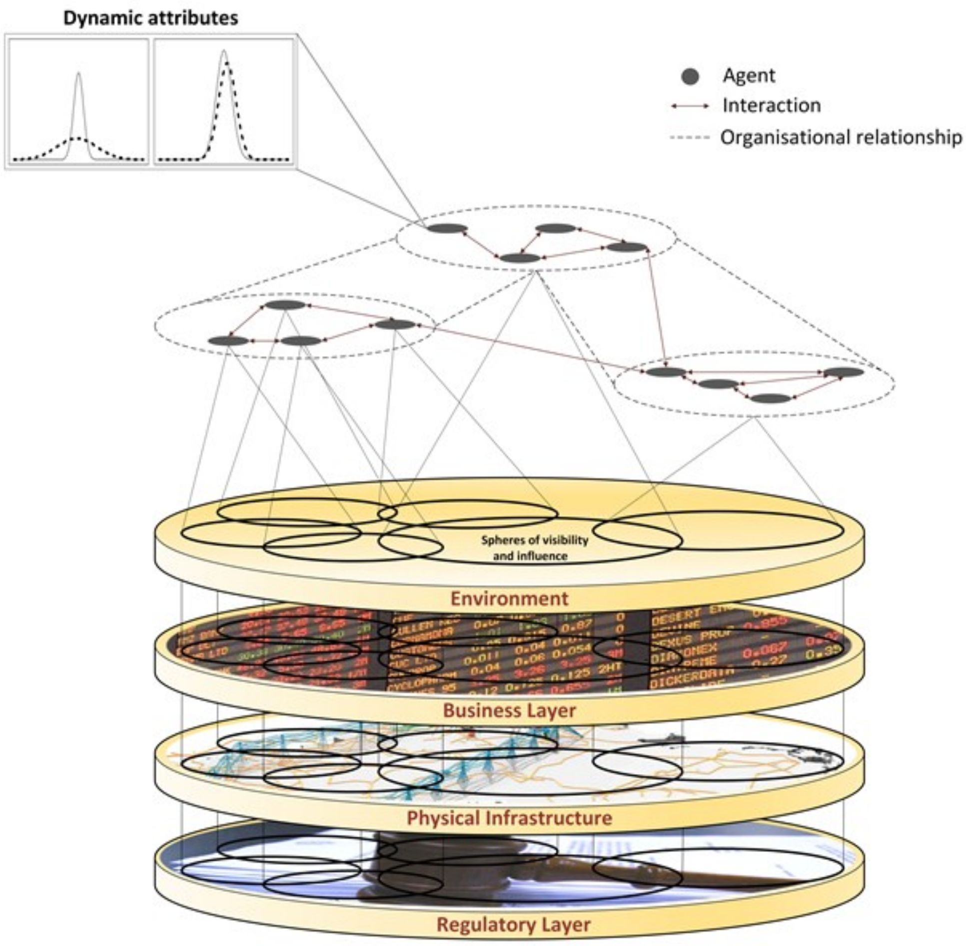

Figure 1: The architecture of an ABM model (adopted from Voudouris, 2011).

The other important building block in the ABM paradigm is the representation of the physical and social environment (i.e., ‘space’) within which agents operate. Each agent may observe only a subset of the multilayer environment (representing bounded rationality). ABM models define the initial state of the market by specifying the attributes and methods of each agent and the characteristics of the environment using observational micro-data. The initial attributes of any particular agent might include type characteristics, structural characteristics, and initial information about other agents. The initial methods might include market protocols, learning modes (e.g., reinforcement learning), trading rules (e.g., profit maximisation), and rules for changing rules (e.g., strategy updating of forecasting models based on past performance). The market then evolves over time without further intervention. All events that subsequently occur arise from the historical evolution of agents’ interactions (Jennings, 2000; Tesfatsion, 2006).

ABM models offer three main benefits over other modelling techniques for the representation of wholesale power markets. They:

- Capture emergent phenomena, which result from the interaction of the individual entities.

- Provide a natural description of a complex adaptive system. If the system is composed of behavioural entities, agent-based models better capture the reality of these systems.
- Are flexible. The flexibility comes in different dimensions. More agents for instance can be added, and the complexity of their behaviour – in the form of their degree of rationality, ability to learn and evolve – can be fine-tuned. This is important when different market designs need to be integrated in the model.

ABM models are useful when:

- The interaction between the agents is complex (see Fig. 2).
- The agents exhibit complex behaviour, including learning.
- The representation of physical space is crucial. In the case of oil production, it might be important to represent the physical infrastructure that might limit the export capacity or crude oil storage.
- The aim is to reveal and explain the complex and aggregate market behaviours that emerge from the interactions of the heterogeneous agents (Koritarov, 2004).

However, ABM models are not appropriate when:

- The dynamics of the systems are linear.
- The representation of physical space is of limited importance.
- The interactions between the constituent components of the system is limited.
- Micro-data is not available. For example, if you want to develop a detailed agent-based model of global crude oil demand, limitation of survey data on consumer behaviour (of transport) limits the usefulness of a detailed agent-based model for demand dynamics.

3. The ACEGES model

Here, we detail the latest version of the ACEGES model [first proposed by Voudouris (2011) and demonstrated by Voudouris *et al*. (2011)] to estimate plausible trajectories of future country-specific crude oil (and natural gas) production and export capacities.

Since agent's interactions take place at the knowledge level (Newell, 1982), decisions need to be made about which goals to follow, at what time, and by whom. This means that agents choose to interact with other agents directly, or with organisations or institutions (see Figure 1). They may also choose to be part of an organisation in searching to fulfil their designed goals. According to Jennings (2000, page 280), "*agents are flexible problem solvers, operating in an environment over which they have only partial control and observability*". This control and observability depend on their own state and behaviour, and on those of their organisations. The organisations (e.g. subsystems) may also interact directly.

In particular, the ACEGES model facilitates the exploration of plausible futures (long-term scenarios) by means of computational experiments that require setting up the key driving forces of the model, such as crude oil production capacity growth rates, crude oil demand growth rates, the peak/decline point (e.g., the proportion of EUR cumulatively produced after which the production decline phase starts) and estimated volumes of oil originally present before any extraction (oil EUR). The important point here is that the key uncertainties are not necessarily restricted to a limited set of values, but are defined by highly flexible country-specific probability distributions.

Using the simulation engine of the ACEGES model, these distributions are used to explore the full uncertainty space of the long-terms scenarios of crude oil production and demand. Therefore, the scenarios are published in the form of conditional probability distributions rather than as point forecasts to avoid suppressing the very wide degree of uncertainty surrounding the projections.

The ACEGES model is a hybrid economic and resource-constrained model by modelling both the demand and the supply side of the global oil market. Because of the high flexibility of the ACEGES model, long-term scenarios can be developed based upon the 'predict (demand) and provide (supply)' philosophy, or based upon dynamic adjustments of demand and supply.

3.1 Agent's demand function

Currently, the demand side of the ACEGES model is a probabilistic function defined by Equations 1.1 and 1.2. The specification of g^t_a (the country-specific demand growth rate) is used to capture a range of factors (e.g., prices, energy efficiency measures, technological innovation) that can affect the growth rate of the country-specific demand for crude oil. Therefore, g^t_a can be a (parametric or non-parametric) regression function with explanatory variables (including time).

Equation 1.1

$$demand_{a_t} = demand_{a_{t-1}} * \exp(g^t_a)$$

Equation 1.2

$$\begin{aligned} g^t_a|\mu_t,\sigma_t,\nu_t,\tau_t &\sim SST(\mu_t,\sigma_t,\nu_t,\tau_t) \\ log(\mu_t) &= s(gdp_t/population_t) + s(price_t) + efficiency_t \\ \log(\sigma_t) &= s(time) \\ \log(\nu_t) &= s(time) \\ \log(\tau_t) &= s(time) \end{aligned}$$

Equations 1.1 and 1.2 define the demand function of the ACEGES agents. For an explanation of the terms of these equations, see text.

Because of its simplicity, Equation 1.1 is used during the exploration stage of the scenario development process when the focus is on exploring the dynamics of the supply side. Specifically, g^t_a is exogenously specified based upon assessment of empirical data and extensive literature review, or on specific studies such as the *World Energy Outlook* (*WEO*) by the International Energy Agency (IEA). In the latter case, by fixing the demand based upon existing studies of the *WEO*, we can explore the supply dynamics of the crude oil market and compare the results of the ACEGES model with the results of *WEO*, and also to other studies that are based upon *WEO* estimates.

Alternatively, Equation 1.2 can be used, which explicitly models g^t_a as a stochastic process with explanatory variables (e.g., GDP per capita, price). This postulates that the demand growth rate following the Skew student t distribution while we assume a multiplicative model for μ (resulting from the log link for μ, which represent the location (mainly expectation) of the distribution) because of a change in one of the explanatory variables is likely to result in a change in g^t_a as a fixed percentage rather than a fixed amount.

Specifically, the expected growth rate is a smoothed function of country-specific variables such as GDP per capita, the oil price, and energy efficiency. The other distribution parameters (affecting the scale and shape of the predictive distribution of g^t_a) change over time (no explanatory variables is assumed). Clearly, the above generic model for g^t_a can be extended to include additional variables (or distributions) if the scenario team wants to try alternative model specifications. Note the function s(.) is the P-splines of Eilers and Marx (1996).

An alternative approach is to model the demand as the sum of a number of end-use energy demand projections (see Figure 2 and Figure 3). For example, the demand for crude oil can be the sum of crude oil demand from transport, industry, residential and commercial end-use energy demand sectors.

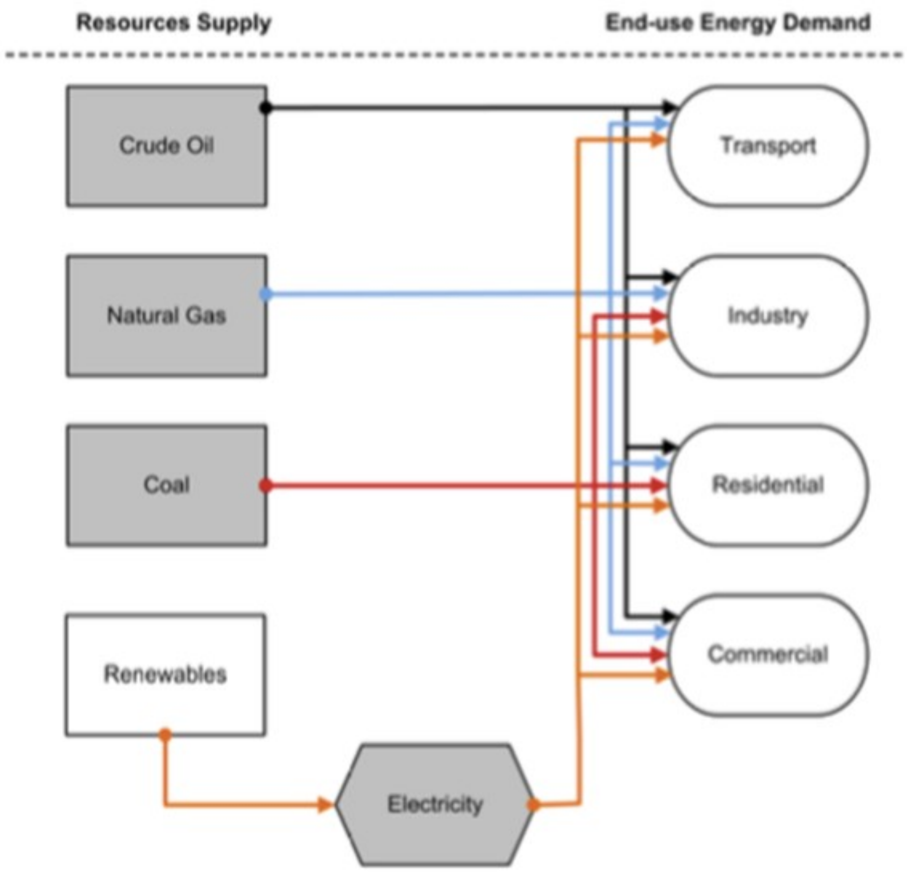

Figure 2: Model architecture of the extended ACEGES model.

Taking as an example the transport end-use energy demand sector, the demand for crude oil can be estimated by the Box 3.a of Figure 3 below. Effectively, the demand for crude oil is a function of the growth rate of the demand for total energy for transport and the growth rate of the share of crude oil. The growth rate of the total demand for energy transport and the growth rate of the share of crude oil are estimated using economic and social indicators (e.g., growth rate of income per capita, growth rate of total freight turnover, growth rate of total passengers turnover, urban population growth rate and growth rate of energy demand in preceding year).

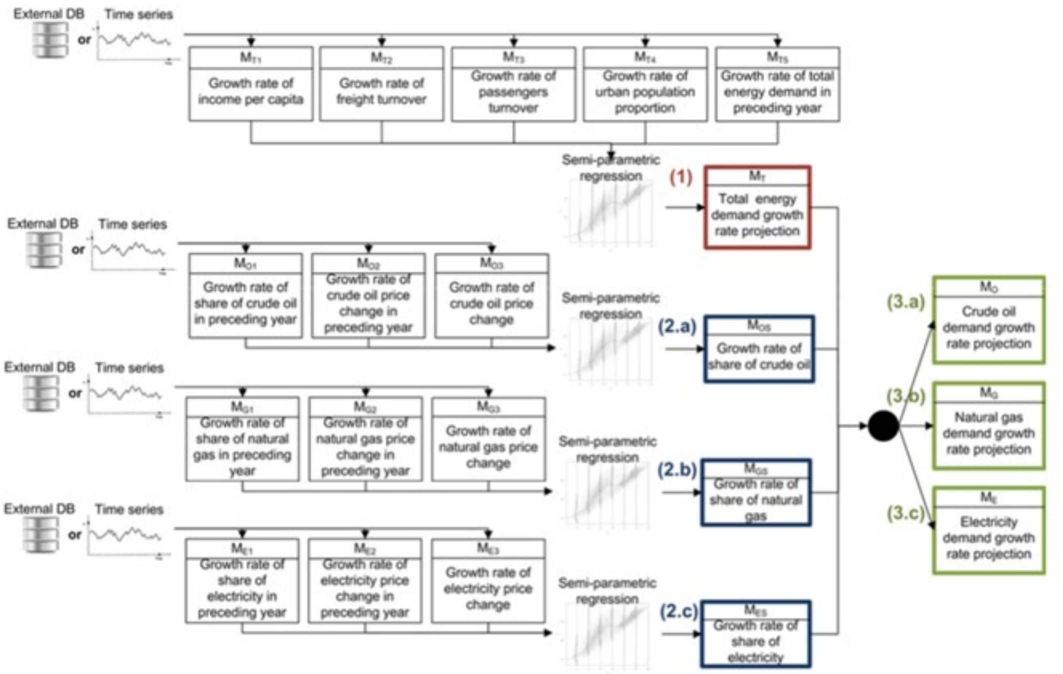

Figure 3: Structure of the model for demand of crude oil in transport

To better demonstrate the flexibility of the demand functions, figure 4 below shows, by way of an example, the two dimensional surface of gasoline demand based upon the age of consumers and the price of gasoline. This surface has been fitted using a survey data in Canada [see Yatchew and No (2011) for a description of the data].

The important point here is that the elasticity of price depends on the age of the consumer. For example, when a consumer is over 65, his elasticity is much higher (a small price increase causes a sharp decline in demand). This is not the case when a consumer is under 35 where a price increase has almost no effect on demand for gasoline. These different effects are important to be captured by respecting the heterogeneity of the demand agents within an agent-based model. This is why the demand agent's within the ACEGES model use the flexibility of the equations 1.1 and 1.2 above.

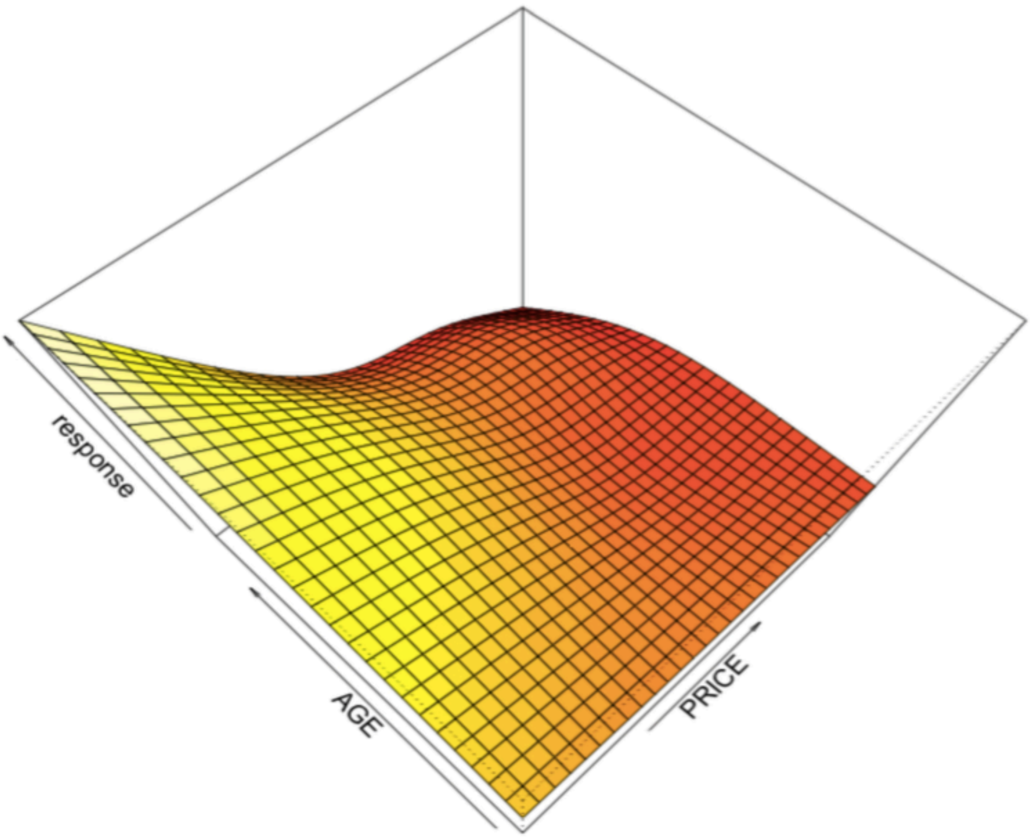

Figure 4: Example of a two dimensional surface of gasoline demand (response)

3.2 Agent's supply function

Now we turn to the agent's supply function. This is given by Equation 2, which is made up of 4 sub-equations, and defines the supply of oil (and gas) for the heterogeneous agents (two or more agents might be unlike in their characteristics or decision rule). Equation 2.1 represents the production decision of the swing-producer countries. This decision is based on the assumption that (a) the swing-producer countries will continue to produce oil to fulfil the net unfulfilled global demand for oil and (b) the swing-producer countries will not produce oil at their maximum capacity, unless it is necessary. This is, effectively, an approximation of the 'consumers logic', an approach first developed by Royal Dutch Shell (Jefferson and Voudouris 2011).

Equation 2.2 is adjusted (as needed) based on the maximum allowable (country-specific) production growth from time t to t + 1. This model specification is important, for example, in cases where a country (e.g., a pre-peak producer) has enough reserves but cannot meet its domestic demand for oil because of below- and/or above-ground constraints, or because it is uneconomical to further stimulate capacity growth (as it can be less expensive to import oil, until the 'organic' growth in the production capacity from t to t + 1 meets the domestic demand). Equation 2.3 shows the production decision of post-peak producers.

The above supply function of Equation 2 can become probabilistic by developing regression-type functions similar to Equation 1.2. For example, the production could be a non-linear function of remaining reserves, short-term price elasticity (to account for the possibility of immediate supply response to sudden increased/decreases of oil prices) and long-term price elasticity (to account for increase of production capacity because of long-term investments).

Equation 2.1

$$production_{a_t}A = production_{a_{t-1}} + (\exp(g_a^t) - 1) * demand_{a_{t-1}} + wd_{a_t},$$

Equation 2.2

$$production_{a_t}B = production_{a_{t-1}} + (\exp(g_a^t) - 1) * demand_{a_{t-1}},$$

Equation 2.3

$$production_{a_t}C = production_{a_{t-1}} * (1 - production_{a_{t-1}} / remainingOil_{a_{t-1}}),$$

Equations 2.1 to 2.4 define the Supply Function of the ACEGES agents.

How many variations of the production function are needed depends on the scenarios that are being developed. The basic idea is to start with the simple production functions and then enhance the supply side of the ACEGES model as required.

3.3 Agent's trade/interaction

Finally in this section, we turn to an agent's ability to trade in oil (or gas). This is because an agent's decision rule should not only determine the production or demand decision of that agent. It should also define the interactions (trading) of the agents. Although there are many interactions that can be modelled within ACEGES model, Voudouris (2013) suggests the use of the stochastic portfolio theory of Equation 3 (proposed by Fernholz (2002) for the construction of equity portfolios).

Equation 3

$$\gamma_\pi = \sum_{i=1}^{n} \pi_i \gamma_i + \frac{1}{2}[\sum_{i=1}^{n} \pi_i \sigma_i^2 - \sum_{i,j=1}^{n} \pi_i \pi_j \sigma_{ij}],$$

under the constraints

$$\sum_{i=1}^{n} \pi_i = 1,$$

and

$$\pi_1, \ldots, \pi_n \geq 0.$$

Equation 3: Agent's trade using the stochastic portfolio theory.

By way of an example, the portfolio growth rate γ_π of an oil import portfolio is equal to the weighted average oil export capacity growth rate + the excess growth rate. The excess growth rate is half the weighted average of oil export capacity variance (denoted by σ_i^2) - the portfolio variance that is based on the covariance (denoted by σ_{ij}) of oil export capacities. While a country j constructs its portfolio, if trade between a country i is not desirable for political or any other above ground or below ground factors, then π_i can be set to 0 or restricted to a very small number [see Voudouris (2013) for details].

4. An Example of ACEGES-based Scenarios for Crude Oil Production

Now we turn to the application of the ACEGES model, and use it here by way of example to examine possible scenarios of future global oil production.

Perhaps the most common way to forecast the future of oil production is to make a single line forecast, where the forecast itself can be generated via a variety of methods, such as using historical data and a curve-fitting approach. An alternative approach is to reject the 'surprise-free' approach and introduce more than one line pathways by incorporating specified uncertainties, for example, three estimates for the size of oil reserves. This approach is used, for example, by the US Department of Energy, Energy Information Administration and others. It results in a finite number of lines, and in a discrete scenario approach to the handling of uncertainties. The general idea of presenting more than one line pathway is sound as a way of communicating the inherent uncertainty around the outlook of, say, conventional oil production.

An alternative approach is to use density-based pathways, as shown in Figure 5, to quantify the risks facing an executive in order to emphasize the inevitable uncertainties. Figure 5 depicts the scenario planner's judgment of the probability of various outcomes for oil production in the future conditional on a set of key uncertainties. The colour bands represent-probabilistic statements of oil production levels. The most likely outcome is represented by the dark red (scenario 1) or dark grey (scenario 2) colours. Because of the finite nature of oil, the uncertainty decreases as we move into the future. The shape of the 'probability bands' represents:

- Central projection of oil production, which determines the profile of the central darkest band;
- Degree of uncertainty, which determines the width of bands; and
- Skewness and/or kurtosis, which determines the probability of extreme outcomes.

The assumption behind the two scenarios shown in the Figure 5 are detailed in Voudouris *et al*. (2011). For example, scenario 2 is the high–high heterogeneity scenario (H–H scenario). For scenario 2, the ACEGES Monte Carlo engine is used for all the four key uncertainties:

(i) Estimated Ultimate Recovery (EUR). The EUR is defined as an agent-specific distribution. If the purpose of the scenario is to explore the dynamics of convention crude oil, the EUR needs to be specified for convention crude oil.

(ii) Demand growth for oil – what is the expected demand for crude oil (see section 3.1).

(iii) Maximum allowable production growth rate (this is the maximum allowable increase of production capacity).

(iv) Peak/decline point (i.e., the percentage of a producer country's EUR at which production decline is assumed to occur).

Given the uncertainty of these four key drivers of the scenario (using data as of 2010), the H–H scenario shows that the global peak of oil production is likely to happen in the vicinity of 2020. However, the upper centile (99th centile) suggests that peak might happen in the vicinity of 2030.

Voudouris *et al.* (2011), Matsumoto *et al.* (2012), Voudouris (2013), Voudouris *et al*. (2014), and Matsumoto and Voudouris (2015) have published a range of different oil (and gas) ACEGES-based scenarios corresponding to a range of model assumptions, input data values, and classes of modelling functions selected.

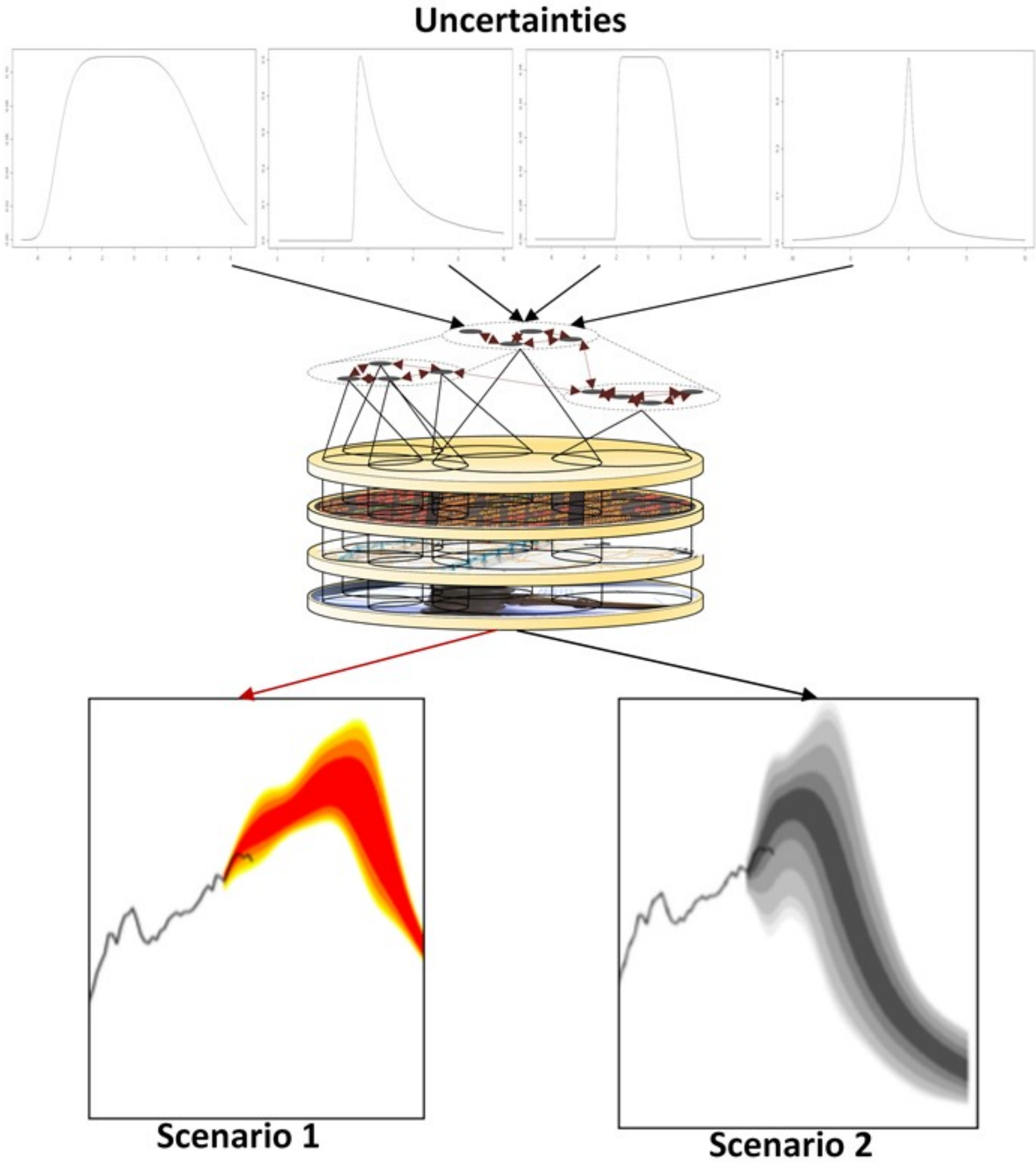

Figure 5: ACEGES-based oil scenarios (adopted from Voudouris et al., 2011 & Voudouris et al., 2014)

Below is an example of the data used to initialise the ACEGES model (depending on the requirements of the scenario):

- The domestic demand of oil in 2001 (total petroleum liquids—an 'averaged proportion' of the demand for liquefied petroleum gas) from the United States

Department of Energy (USDOE), Energy Information Administration (EIA). The 'averaged proportion' represents the part of the liquefied petroleum gas (LPG) consumption covered by the natural gas plant liquids (NGPL) production rather than crude oil production.

- The volume of oil originally present before any extraction (EUR) from:
    - Campbell and Heapes (2008): Data available for 62 countries with global EUR of 1.9 trillion barrels;
    - US Geological Survey (USGS) World Petroleum Assessment 2002 (WPA02) EUR 5%-likely: Data for 52 countries with global EUR of 3 trillion barrels (excluding reserves growth);
    - Central Intelligence Agency (CIA) World Factbook 2010 (WFB10): Data available for 93 countries with global EUR of 2.4 trillion barrels. Note that CIA provides estimates of the proved reserves of oil. Therefore, the CIA EUR is the sum of the cumulative production for all the using the data sources discussed below and proved reserves. Note that the CIA EUR does not include 'oil-yet-to discover'. The main advantage of the CIA EUR is the construction of EUR for 93 countries. This is to say that by modelling more of the nations of the world, and having both production and demand for them, the model has a more accurate picture of the net demand for imports, which is what is being appor- tioned among the pre-peak net producers. Having said that the CIA EUR should not be used alone as this is potentially a large underestimate of actual EUR for selected countries.
- The annual oil production (crude oil including lease condensate) from the EIA International Energy Data, Analyses, and Forecasts. Because of the use of crude oil, we are really testing whether the EUR estimates, in the form of crude oil, generate results consistent with the empirical data. The difference between crude oil production and conventional oil production is significant for some countries such as Brazil, Angola, Canada and Venezuela. If the aim were to explore the outlook of conventional oil as defined by Campbell and Heapes (2008), we would need to adjust starting oil production, cumulative oil production, oil demand, and all production to remove oil unconventional by their standards.
- The cumulative production is based on:
    - API - Petroleum Facts and Figures (1971) from 1964 to 1994;
    - DeGolyer and MacNaughton inc. (1994) from 1964 to 1994;
    - EIA's International Energy Data, Analyses, and Forecasts.

5. Conclusions

It is generally recognised that agent-based models have the potential to improve the theory and the practice of modelling complex real-world phenomena. Yet, to-date, there has been little systematic analysis at the conceptual and practical levels of how to develop data-driven agent-based models for the representation and reasoning of energy systems.

We recognize that it is nearly impossible to predict the exact future evolution of country-specific oil production and export capacities and to construct long-term energy portfolios for oil trade. However, the ACEGES model is a computational laboratory that enables us to explore plausible futures of export and production of oil and gas. The key advantage of the ACEGES model is the high degree of heterogeneity that can be incorporated in the scenarios in order to quantify the uncertainties within each scenario.

Our longer run goal for the ACEGES model is a complete computational laboratory that rings true to industry participants and policymakers, and which can be used as a tool for long-term planning and investment processes as well as for the construction of active oil and gas portfolios for physical trade.

As the research programme of energy modelling progresses, the aim of building an integrated theory of agent-based models for energy systems will be within sight. The work presented here suggests a way forward through the development of the ACEGES model.

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