Assessing current modelling practices
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Abstract

Existing energy- and climate-economic modelling approaches are increasingly seen with skepticism regarding their ability to forecast the long term evolution of economies and energy systems. The economic, climate and energy sphere are highly complex non-linear systems and so far most often only poorly dealt with when assessing the transition pathways leading to a desirable future. This Working Paper reports a structured meta-analysis of state-of-the-art national and international energy-economic modelling approaches, focusing on their ability and limitations to develop and assess pathways for a low carbon society and economy. In particular, we set out to identify those existing models and/or model components/modules which could be of interest in developing a research plan for the creation of an open source model for analysing a national transition to a low carbon society by 2050, here more specifically applied for Austria. We find that existing methodological approaches have some fundamental deficiencies that limit their potential to understand the subtleties of long-term transformation processes. Therefore, we suggest that a methodological framework for analysing long-run energy and greenhouse gas emission system transitions has to move beyond current state of the art techniques and simultaneously fulfill the following requirements: (1) dynamic analysis, describing and investigating explicitly the path between different states of system variables, (2) specification of details in the energy cascade, in particular the central role of functionalities that are provided by the interaction of energy flows and corresponding stock variables, (3) a clear distinction between structures of the energy systems and (economic) mechanisms and (4) ability to find optimal pathways. Furthermore, a crucial task in modelling is to specify whether each model element is determined endogenously or exogenously, ideally governed by the demands of the underlying question to be answered.

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1 Introduction

This working paper serves as a background paper on current energy-economic modelling practices for the research project ClimTrans2050. The guiding question for the ClimTrans2050 project is: **What kind of modelling framework is most suitable for assessing the long-term transformation processes needed to drastically reduce Austria's GHG emissions**? The aim of Work Package 1 of this project is to provide a structured meta-analysis of state-of-the-art national and international energy-economic modelling approaches with respect to their ability and limitations to develop pathways for a low carbon society and economy, both in total and for the main sectors contributing to greenhouse gas emissions. The underlying question of this working paper is therefore which models and/or model components/modules are most suitable to be integrated in an open source modelling framework for the analysis of a low carbon energy transition.

In recent years, the number of energy-economic models has grown tremendously, to a large extent due to expanding computing possibilities. At the same time existing energy- and climate-economic modelling approaches are being confronted with increasing skepticism with respect to their ability to forecast the long term evolution of economies, which are highly complex non-linear systems, and to assess the transition pathways leading to that future state (Pindyck, 2013; Pindyck and Wang, 2013; Rosen and Guenther, 2015). Moreover, the question arises whether it is feasible at all to predict an economy's future evolution in the presence of deep or fundamental uncertainties (variations around expected system behaviour that cannot be quantified) and catastrophic risks (Rosen and Guenther, 2015; Scrieciu et al., 2013).

The existing models to assess energy- and climate-economic research questions vary considerably and the question arises which model is most convenient for a certain purpose or situation, in our specific context the long term transition to a low carbon energy future. A classification scheme can provide insight in the differences and similarities between energy-economic models and thus facilitates the selection of the proper models or specific modules to assess the problem at hand (van Beeck, 1999).

In a first step we suggest a set of characteristics or dimensions derived from the existing literature and from discussions within the ClimTrans2050 project team for a **categorisation of the different modelling approaches** focusing on characteristics that are relevant for a model to be suitable for long term transition analyses. In a second step we **identify specific "prototypical" models** of different model classes that have been used in the analyses of energy policies in the context of Austria and Europe, which could be of interest in developing a research plan for the creation of an open source model for analysing Austria's transition to a low carbon society by 2050. In a third step, we **evaluate these different energy-economic modelling approaches in terms of their strengths and weaknesses to carry out low carbon transition analyses** and discuss their advantages and disadvantages to that end.

2 Characteristics for the classification of energy-economic modelling approaches

A general characteristic all models share is that a model always is a purposeful and simplified representation of aspects of reality (Starfield). Purposeful in that sense, that a model is always developed in order to answer a specific research question. For example, there is no generic forest model applicable in all circumstances, as the concrete model design always depends on the specific research question (e.g. optimal harvesting, forest soil, species, forest fire risk, etc.). Simplification in that sense, that first, the just identified concrete purpose of a model already paves the way for a simplified representation of this specific aspect of reality, and that second, real world constraints, such as limited time and financial resources, require further simplifications.

Besides this general characteristic there are many individual characteristics or criteria which differ substantially between modelling approaches. Hence, it seems reasonable to set out to classify existing energy-economic modelling approaches and specific models to allow for an identification of the most appropriate approach for the problem setting at hand – out of the multitude of existing models out there. While there have been some attempts in the literature to classify existing energy models (Grubb et al., 1993; Herbst et al., 2012; Hourcade et al., 1996; van Beeck, 1999), no systematic classification of energy-economic models serving the purpose of analysing energy transition pathways has been carried out so far. Hence, by relying on the existing literature on energy model classification and by building upon the discussions of the ClimTrans2050 project team, we identify the 8 most important characteristics and dimensions to classify energy-economic models and present a systematic classification of the existing relevant modelling practice. The present categorisation exercise differs from the existing literature in that we are focusing on the models' suitability for long term transition analyses. Hence we put special emphasis on certain (sub)characteristics, mainly linked to the model structure and modelled mechanisms, which are crucial for our purpose. The 8 dimensions/characteristics include (cf. van Beeck, 1999):

- The general purpose and intended use
- The analytical approach and conceptual framework (Top-Down, Bottom-Up, Integrated Assessment/hybrid energy-economy model)
- The model structure and external assumptions: modelled mechanisms and assumptions (implicit/endogenous and explicit/exogenous mechanisms/assumptions; technological details). How an energy-economic model treats the following features/mechanisms is crucial for its ability to carry out long term transition analyses.
    - (disruptive/non-linear) technological change
    - technological detail
    - international (trade) relations
    - detailed representation of the energy cascade
    - price & market mechanisms

  - economic feedbacks and rebound effects
  - non-market mechanisms (such as non-market damages and climate feedbacks)
  - structures vs. mechanisms – how do mechanisms influence structures
  - stocks vs. flows
  - financing/investment (of e.g. energy efficiency measures)
  - institutions
  - behavioural mechanisms
  - out of equilibrium situations
  - risk and uncertainty
- The time horizon
- The underlying methodology (Optimization, Simulation, Econometric, Equilibrium etc.; estimation vs. calibration)
- The treatment of path dynamics (Comparative Static VS Dynamic ("path explicit"))
- Development of a baseline/reference scenario
- Geographical and sectoral coverage
- Data requirements

The listing of these characteristics already follows an ordinal/hierarchical logic modelers should follow when setting out to identify the most appropriate approach for their very specific research questions. Modelers first have to be clear about the general and more specific purpose of the model. Next the analytical approach has to be chosen, i.e. whether the eventual model should rather take a top-down or bottom-up or hybrid perspective. Closely related is the choice of the modelling structure which boils down to choosing internal and external assumptions, or more precisely, what mechanisms should endogenously be determined within the model and what mechanisms should be based on exogenous assumptions. Before choosing the specific underlying methodology of the model, a modeler should also reflect on the time horizon her model should be able to operate in. After deciding on all that characteristics and choosing a specific method, the most appropriate mathematical approach has to be identified. Finally, the geographical and sectoral coverage of the eventual model has to be decided upon and the data requirements assessed.

2.1 The purpose and intended use of energy-economic models

Modelling is a general kind of activity that follows certain principles independent on what is modelled and what technique is used. As mentioned above, a model is always a purposeful and simplified representation of an aspect of reality. Hence, models are usually developed to address specific research questions and are only applicable for the purpose they have been designed for. An application of a specific modelling technique for an inappropriate purpose may lead to significant misinterpretations of the problem at hand and eventually to poor policy recommendations negatively affecting real world socioeconomic systems. In the following we distinguish between general and more specific purposes of an energy-economic model.

General purpose

Hourcade et al. (1996) define as the general purpose of the model the different ways how the future is addressed in a modelling framework and distinguish between three general purposes which are also applicable in the case of energy-economic models:

- **Prediction or forecasting models**

  Many models are developed to try to "predict" the future and to estimate impacts of likely future events. This purpose imposes very strict methodological constraints on modelers as forecasting models require the establishment of a business as usual scenario against which future policy induced deviations from this best-guess future development can be assessed. This requires an endogenous representation of economic behaviour and general growth patterns. Such models are based on the extrapolation of trends found in historical data and try to minimize the usage of exogenous parameters. Models built for a predictive purpose are most suitable for short term analyses, since a number of critical underlying parameters (such as elasticities) cannot reasonably be assumed to remain constant for longer time frames. Hence, this approach is mainly found in short term, econometrically driven economic analyses.

- **Explorative scenario analyses models**

  Due to the inherent difficulties associated with the extrapolation of past trends in the long run, modelers might set out to "explore" rather than "predict" the future. An explorative purpose can be served by employing a scenario analysis approach. This requires the definition of different coherent visions of the future, determined by different values for key assumptions about economic behaviour, economic growth, population growth, (natural) resource endowments, productivity growth, technological progress etc. A reference or nonintervention scenario is developed and then contrasted to different policy or intervention scenarios. It is important to note that these alternative scenarios only make sense in relation to the reference scenario and should therefore not be analysed in isolation from it or in absolute terms. Furthermore, sensitivity analyses are crucial to provide information on the effects of changes in underlying assumptions.

- **Backcasting models**

  The basic concept of backcasting models is to look back from *desired futures*, which are developed e.g. in expert stakeholder processes, to the present, and to develop *pathways* for actions that have to be taken in order to reach these desired futures. The backcasting methodology allows for the identification of major (technological) changes and discontinuities that might be required to achieve a certain desirable state of the future.

Specific purpose

More specific purposes are linked to the aspects of the economy, energy system, or the environment a model focuses on. With respect to energy-economic models one could distinguish between models that serve the purpose of modelling energy demand, energy supply, economic or environmental impacts from energy supply or conducting project appraisals (van Beeck, 1999). Historically there has been a strong focus on single-purpose models, contemporary models often pursue an integrated approach. Demand-supply matching models and impact-appraisal models are two examples of multi-purpose energy-economic model approaches.

Also for the development of an integrated modelling framework for the analysis of a transition to a low carbon society, a multi-purpose approach constitutes a promising approach. A model constructed as a modular package would (1) allow for the selection of the most promising building blocks from different existing modelling frameworks to serve the more general purpose and (2) enable the user to select only those (sub)modules that are relevant for answering specific questions.

2.2 The analytical approach and the conceptual framework

Models for the analysis of an energy transition can also be classified according to their degree of detail. On the one end of the spectrum there are "bottom-up" techno-micro-economic models, which are built to describe economic sectors or sub-sectors (e.g. the electricity sector). These models are rich in (technological) detail and are well suited to simulate market penetration and related cost changes of new (energy) technologies, to present detailed pictures of plausible energy futures and to evaluate sector- or technology-specific policies. However, this technological detail comes at the cost of a limited representation of macroeconomic implications. Bottom-up models typically do not capture feedback effects with other parts of the socioeconomic system (e.g. other economic sectors, households, the public sector, macroeconomic relationships, the environment etc.).

On the other end of the spectrum there are "top-down" economic models with only limited explicit representation of alternative technologies using elasticities to implicitly reflect technological variability. They may even be more abstract and aggregated "integrated assessment models" (IAM) or "hybrid energy-economic models", which strive to close the loop between a specific economic activity and the surrounding environment. Within the class of IAM one can further distinguish between "hard-linked" models which are built as one set of consistent (differential) equations, working within one closed model system, and "soft-linked" models which couple separate models and solve them sequentially using input/output exchange routines. In general, IAM allow capturing feedback effects between aspects of the system under consideration (economy, climate system, society, other environment). However, both types of IAM have shortcomings: Hard-linked models usually work on a very coarse level of detail by using (e.g. damage-) functions relating e.g. economic indices like a region's GDP and global mean temperature changes. Such simplifications are problematic as effects within the economic system cannot be revealed and they can hardly be used to account for singular events and catastrophic risks. Damage functions have often been calibrated based on limited expert judgment, which has implications for their validity (see the recent debate on Integrated Assessment Modelling and Social Costs of Carbon: e.g. Pindyck and Wang, 2013; Pindyck, 2013). Soft- linked models on the other hand allow for more detail; however problems may arise in convergence and consistency among the models used.

In general, the distinction between top-down and bottom-up models is of substantial importance, as both approaches tend to deliver different – sometimes even opposite – outcomes. The difference in model outcomes of top-down and bottom-up modelling approaches arises from the distinct ways how these models treat technological change, the adoption of new technologies, the decision making of agents and how markets and institutions operate (Hourcade et al., 1993). Grubb et al. (1993) associates the top-down approach with a "pessimistic" economic paradigm and the bottom-up approach with a more "optimistic" engineering paradigm.

Purely economic top-down models and much more so IAM have no explicit representation of technologies. In economic models technologies are regarded as a set of techniques by which a combination of inputs can be used to produce useful output, typically represented by production functions. Elasticities of substitution between different inputs in an aggregate technology production function are employed to implicitly reflect technological variety and in combination with an exogenous assumption of so-called "autonomous energy efficiency improvements" (i.e. efficiency improvements which happen w/o any explicitly modelled technological change) account for technological change in top-down economic models.

Engineering studies, on the other hand, start with a description of technologies, including their performances and direct costs, to identify options for technological improvements. From an engineering standpoint, the most energy efficient technologies have not been adopted so far and therefore an "efficiency gap" prevails, which could be closed by employing the most energy efficient technologies. The differences in outcomes eventually arise from the fact that the "optimistic" engineering bottom-up models tend to ignore existing constraints which hinder the actual adoption of most efficient technologies, such as hidden costs, transaction costs, implementation costs, market imperfections and macroeconomic relationships (Grubb et al., 1993).

A further distinction between bottom-up and top-down models can be drawn along the lines of data used in the different model analyses. While top-down economic models use aggregated data to examine interactions of different economic sectors as well as macroeconomic performance metrics, bottom-up models usually focus on one specific sector exclusively (e.g. the energy sector) and therefore use highly disaggregated data to describe energy technologies and end-use behaviour in greater detail. Hourcade et al. (1996) summarises (in the context of mitigation cost studies) that existing bottom-up and top-down modelling approaches are primarily meaningful at the margin of a given development pathway. Therefore their application is valid under the following conditions: (1) Top-down models are valid “as long as historical development patterns and relationships among key underlying variables hold constant for the projection period” (Hourcade et al., 1996, 281) while (2) bottom-up models are valid “if there are no important feedbacks between the structural evolution of a particular sector in a mitigation strategy and the overall development pattern” (Hourcade et al., 1996, 281).

While historically the distinction between bottom-up and top-down energy-economic models has provided the framework for the contemporary modelling debate, there have been first attempts to develop “hybrid” models, merging the benefits of both analytical approaches (Hourcade et al., 2006; Jochem et al., 2007; Schade et al., 2009; Catenazzi, 2009). For example a more detailed representation of different electricity generation technologies has been integrated in top-down economic models (Böhringer and Rutherford, 2008; Steininger and Voraberger, 2003).

2.3 The model structure: modelled mechanisms and external assumptions

Different research questions are addressed by different models, capturing only those mechanisms of the real world that are relevant to answer the stated question (i.e. to serve their purpose). Therefore another basis for the distinction of different modelling approaches is the nature of the model itself or, more precisely, the assumptions and mechanisms embedded in the mathematical structure of the model. Hourcarde et al. (1996) distinguish between four major dimensions to characterise structural differences of existing energy-economic models.

The first structural characteristic relates to the degree of endogenization, the extent to which behavioural assumptions and mechanisms are endogenized in the model equations so as to minimize the number of exogenous parameters. The more behavioural assumptions and mechanisms a model internalizes, the better it is suited to predict actual outcomes. Those models that are externalizing most mechanisms are, on the other hand, more suited to simulate the effects of changes in historical patterns (Hourcade et al., 1996).

The second structural characteristic describes the extent to which non energy sector components of the economy or the environment are considered. The more detailed a model describes these mechanisms, the better it is suited for the analysis of wider economic effects of energy policy measures. A huge variety of models designed to serve different purposes can be found, which endogenize very different assumptions or mechanisms, such as economic, behavioural, engineering, geophysics or earth science mechanisms. There are also models capturing not only one of these mechanisms but a portfolio of them. The question of modelled mechanisms closely relates to the choice of the analytical framework, as for example IAMs aim to include as many mechanisms as possible, and – at least in their current state – are, however, subject to severe drawbacks as well (e.g. highly uncertain damage functions; see e.g. Pindyck and Wang, 2013; Pindyck, 2013).

Many state of the art economic models only capture a limited amount of economic and other mechanisms explicitly. In CGE models for example the sole mechanism that leads to the new equilibrium after an exogenous shock is the relative price mechanism. Many other mechanisms capturing behavioural, political, social, technological elements are neglected. Hence, the potential real world implications derived from results of such modelling exercises have to be critically reflected and complemented by other modelling techniques to eventually derive a more comprehensive and holistic picture. With respect to the analysis of long run low carbon transition pathways, there is increasing concern regarding the applicability of traditional economic models rooted in neoclassical economic theory, as some main modelling characteristics and implicit mechanisms are questioned: the relevance of prices, the implicit behavioural assumptions, the dynamics of technologies, the emphasis on flows over stocks.

The third and fourth structural characteristics refer to the extent of description of energy end uses and energy supply technologies, respectively. Models that describe end uses in more detail are more suitable for the analysis of energy efficiency measures, while models that focus on internalization of energy supply technologies are more suitable for the analysis of technological potentials (Hourcade et al., 1996).

Moreover, the various model specifications have to be checked whether they are able to separate the description of the structure – e.g. the elements of an energy system – from the mechanisms that are generating these structures. This is a major problem with neoclassical specifications since they intimately link structures and mechanisms. Similar problems might occur with system dynamic (SD) and agent based modelling (ABM) type specifications.

Every type of model is relying on exogenously given parameter values and assumptions regarding interdependencies within the scope of parameters and variables which are in turn triggering endogenous responses within the model. A crucial task in modelling is to decide whether a model element is determined endogenously or exogenously, depending on the underlying question to be answered. In CGE models, for example, modelers have to choose between certain variants of economic model "closures" (savings-investment, government budget, external balance). Furthermore, while some economic models such as CGE or IO models assume certain behavioural characteristics of agents (e.g. utility and profit maximization, representative agents) other approaches (ABM or SD) set out to endogenously derive behavioural details related to the emergence of complex phenomena.

2.4 The time horizon

Modelers have to be clear about the time horizon underlying their analyses, as different economic, social and environmental processes may behave differently or become relevant at different time scales. Hence the time horizon eventually affects the choice of the specific modelling methodology (see the following section), as long run analyses may assume economic equilibrium in which all markets clear and all resources are fully allocated, while short-run models need to incorporate transition dynamics and situations of disequilibrium (at least in some markets, e.g. unemployment). With respect to the definition of different time horizons, no standard procedure exists. However, short term is often assumed to reflect periods of five years or less, the medium term to range between 3 and 15 years and the long term to start at 10 years and beyond.

2.5 The underlying methodology

For energy and emissions related analyses the following methodological approaches have been employed, and are thus discussed in detail in section 3 below:

- Econometric Models
- Macroeconomic (Post-Keynesian) Input-Output Models
- Neoclassical Economic Equilibrium Models
- System Dynamics and Simulation Models
- Backcasting Models
- Optimization Models
- Partial Equilibrium Models
- Multi agent or Agent Based Models (ABM)

Optimization versus simulation

One aspect relevant across the above methodological approaches is the issue of optimization versus simulation. Building a model aims to serve a general purpose (prediction, exploration, backcasting) and to answer a more specific question of interest, all within a specific time horizon. The character of this stated question then determines the methodology eventually employed in the modelling exercise. Basically there are two different kinds of questions which are commonly stated by economic modelers: The first one is about the right choice in certain situations of interest; this demands optimization models. The second question scientists often ask is "what if…?"; this demands simulation models.

For example, CGE analysis is a mix of both: Mathematically, a CGE model solves an optimization problem; however, by changing input parameters the optimization routine gives different outcomes which can also be interpreted as simulations. Other types of models, such as ABMs and SD models do not optimize target functions with respect to certain constraints but simulate in a dynamic way the actions and interactions of either multiple autonomous agents or more aggregated system elements in an attempt to re-create and/or predict the appearance of complex phenomena.

For our field of analysis, i.e. in the context of transitions and a very-long run perspective, however, optimization per se is highly questionable for many reasons, among them ethical and uncertainty about technological developments.

2.6 The treatment of path dynamics (comparative static VS dynamic ("path explicit"))

Analysing the long-term transformation process to a low carbon society can be based on different modelling frameworks that differ with respect to their treatment of time and their explicit representation of transition paths. **Comparative static** models compare different states of system variables without taking into account the development between these states (for example GDP before and after policy interventions). Many economic models, such as static Input-Output and static Computable General Equilibrium (CGE) models are characterised like this. When developments over time are analysed with this kind of models, modelers often interpolate between different points in time to generate a hypothetical development path, however whether the development really follows this interpolated trajectory is not at the core of interest of such modelling approaches.

The counterpart to comparative static analysis is **dynamic** analysis, describing and investigating explicitly the path between different states of system variables. In the context of models that are rooted in neoclassical theory, development over time can be analysed either by **discretely** taking over values of system variables from one point in time to the next (e.g. "recursive dynamic" models, optimizing only within each period, but thereby implicitly also determining the intertemporal development), or by **continuously (fully dynamic)** optimizing intertemporal functions; for example maximizing discounted utility over the full time horizon at any point in time. Both versions of dynamic economic models have their drawbacks. On the one hand discrete dynamic models are nothing more than static models solved iteratively and their results dependent on exogenous assumptions (e.g. the interest rate), on the other hand fully dynamic CGE models assume perfect foresight and perfectly informed decision makers – assumptions that are not readily comparable with real world behaviour of economic agents.

To account for and simulate the real world, dynamic actions and interactions of different autonomous agents and their emergent effects on the system as a whole in the context of a transition to a low carbon society, the employment of agent based models (ABM) might be suitable.

While ABM focus on individual behaviour, actions and interactions, system dynamic (SD) models try to give an understanding of the behaviour of complex systems over time at a more aggregate level (i.e. by not explicitly distinguishing between autonomous individuals). The merit and main difference of SD models from other models studying the dynamic behaviour of complex systems over time is its use of internal feedback loops, the stocks and flows concept, and time delays that affect the behaviour of the entire system.

Furthermore, ABM and SD models – as well as any other non-stochastic model specification – allow for the introduction of randomness, uncertainty and emergent characteristics by e.g. using Monte Carlo Methods.

2.7 Regional and sectoral coverage, data requirements

The regional/geographical and the sectoral coverage reflect the level of detail at which the analysis takes place. The level of detail is an important factor linked to the structure of the model, as it determines which economic mechanisms and elements are endogenized in the model and which are treated as exogenous assumptions. Models at a global scale set out to explicitly model the global economy characterised by explicit market relationships. Regional models, most often referring to international regions such as the European Union or Southeast Asia, and local models focusing on subnational regions (such as Styria in an Austrian context), treat world market conditions as external assumptions.

Likewise to the geographical scope of a modelling framework, energy-economic models differ with respect to the explicit representation of individual economic sectors. Encompassing a high number of sectors within a country – or focusing on the most relevant, major economic sectors – allows for a comprehensive analysis of the most important cross-sectoral feedback effects and interrelations.

3 Methodological Approaches

3.1 Econometric methods in energy modelling

Energy systems are undergoing fundamental changes, driven by disruptions in technologies, markets and policy designs. Econometric methods have a long tradition in accompanying modelling and analyses of energy systems. We evaluate econometric practices with respect to their adequacy in dealing with long-term transformations of energy systems.

The method

A simple econometric specification for the demand of energy

Mainstream approaches to determining the demand for an energy flow *e* typically postulate the relationship

$$(1) \qquad e = e(q, p, x, z)$$

with the causal variables *q* for an economic activity, *p* for a (real) energy price, *x* for other variables (e.g. a weather variable) and *z* for an autonomous technical change.

Assuming a sample of time series, a general econometric specification of this relationship might be the following linear relationship

$$(2) \qquad a(L)e_t = b(L)q_t + c(L)p_t + d(L)x_t + z.t + u_t$$

which exhibits lag distributions, a linear trend component and a stochastic error term u_t. Typically the variables are transformed into logarithms, thus obtaining elasticities for the estimated parameters.

This modelling approach faces a number of limits. The number of parameters to be estimated, in particular those for the lag distributions, require a long sample range which in turn may violate the underlying model specification of an invariant structure. Furthermore this model specification is not able to deal with interfuel substitution, i.e. switching the energy mix.

These limits lead to extended model specifications which include on the one hand additional data by using also cross-section information (panel data) and on the other hand additional restrictions on the parameters of the general specification (2).

Dealing with interfuel substitution

Demand for energy obviously needs to be considered in the context of an energy mix which in turn stimulates research for explaining the causalities for the composition of the bundle of energy consumed by households or needed in the production of goods. For modelling this interfuel substitution basically two approaches have emerged.

The Almost Ideal Demand Systems (AIDS) results from a consumer demand model that partition total expenditures (i.e. for energy) for a bundle of goods (i.e. different fuels) according to the prices of the individual goods (i.e. fuel prices).

A production-based approach explains energy as the output of several factors (i.e. fuels). A further extension includes non-energy inputs, as the capital, labour and materials in a KLEM model. In a so-called translog specification the main drivers for these models are relative energy and relative factor prices.

The econometric implementation of these modelling approaches suffer most often from rather unreliable time series on factor prices and energy prices, a deficiency that is echoed in the rather weak significance of estimated direct and cross price elasticities.

Modelling integration, co-integration and Granger causality

A very different modelling paradigm has emerged over the last three decades in the context of non-stationary stochastic processes. Accordingly economic variables as GDP and energy are investigated with respect to their individual long-term behaviour (typically exponential trends before the economic crisis that started in 2008) and thus classified by what is called the degree of integration. In a next step joint relationships of variables are investigate under the heading of co-integration. Finally statements are made, if one variable improves the prediction of another variable and this is termed Granger causality.

It seems to be fair to say that these modelling approaches just reflect the application of econometric methodology that has become available to energy data without reflecting if this methodology is adequate to the issued to be dealt with. The exponential trends of the past seem to be gone, a fixed long-term relationship, even of a stochastic type, is rather not desirably if we postulate this for an energy flow and an economic activity. Finally predictability should not be prematurely mixed with causality in the sense of cause and impact.

Representative econometric models for the energy system of an economy

A typical representative model with a global coverage is E3ME, a macro-econometric E3 (Energy-Environment-Economy) model. Models like E3ME claim as a distinctive feature their treatment of resource use, including energy, and the related greenhouse gas emissions embedded into sectoral economic framework.

Despite the merits of such an integration many deficiencies as to the treatment of energy remain that are crucial for obtaining a better understanding of long-run transition processes. These shortcomings concern the rather simplistic treatment of technological progress, the overstated role of prices as drivers for structural changes, and the limited treatment of the cascade structure of the energy system.

Some conclusions for long-term transition analyses

In view of the usability of econometric models for obtaining a better understanding of the long-term transition options in an energy system, the conclusions are rather sobering.

Almost all econometric specifications include market driven behavioural assumptions, visible in the role of energy prices in the model specifications. The specifications are therefore hardly able to deal with non-price determined mechanisms that are representative in particular in the context of innovation policies. The estimated elasticities for prices and activities have very limited credibility because of the inherent conflict between the required long time series from a statistical point of view and the accompanying structural changes that violate the statistical model assumption of structural invariance. Most econometric analyses of the energy system just ignore this issue by not reporting the sensitivity of their estimates with respect to variations in the sample size and in the specifications.

Other deficiencies are even more fundamental, as the almost complete absence of details in the energy cascade, in particular the central role of functionalities that are provided by the interaction of energy flows and corresponding stock variables. This extended view of an energy system emerges, however, as a prerequisite for understanding the subtleties of long-term transformation processes.

3.2 Dynamic New Keynesian Input-Output Models

The method

One of the model classes that aim at introducing innovative modelling techniques are New Keynesian models. They are developed in the tradition of general equilibrium models in the sense that their long run equilibrium results from market clearing prices. As CGE models and many macroeconometric models, New Keynesian Models build on an input output structure displaying the interlinkages between sectors.

In the short run, institutional rigidities and constraints, such as wage bargaining or liquidity constraints, imply a deviation from the long run equilibrium path.

New Keynesian Models are inter alia applied to address the critical role of environmental and resource constraints for economic development (Jackson et al., 2014). The model structure and the underlying assumptions are suited to illustrate the impacts of the demand for goods and services on energy and resource use or on emissions.

Typical building blocks of a New Keynesian Model

The typical building blocks of a New Keynesian Model comprise the household sector, the production sector, labour market and the government sector. In the short run the demand driven model shows deviations from the long run equilibrium stemming from liquidity constraints or other rigidities. The adjustment paths to the long run equilibrium solutions can be modelled in different level of detail for the different building blocks of the model. In the long run, adjustments in the wage rate determine the full employment equilibrium in the labour market, which in turn determines household income and respectively consumption.

Models that integrate environmental aspects typically treat energy demand as a separate category of non-durable commodities, differentiating between different fuel types. In the long run, demand for different fuel types is determined by (equilibrium) income, autonomous technical change and fuel prices.

Energy demand in the WIFO DYNK model

The DYNK model by WIFO (Kratena and Sommer, 2014) treats energy use in a detailed way. In the household sector, an innovative approach for modelling energy demand is used: Starting point is energy service demand which is the result of the energy efficiency of the capital stock and final energy demand by fuel type. This approach explicitly illustrates the role of stock-flow interactions in the provision and demand of energy services. Household energy service demand is determined by the energy service price, as a function of the energy price and the energy efficiency parameter. In the short run, liquidity constraints and a fixed capital stock – reflected in a given efficiency parameter – imply that energy service demand is determined by changes in the energy price. In the long run, changes in energy prices induce adjustments of the capital stock that can result in changes in the energy efficiency parameter and thereby affect the energy service price.

In the production sector, the input factors capital (K), labour (L), energy (E), imported non-energy materials (M^m) and domestic non-energy materials (M^d) are differentiated. The shares of the different input factors in production are determined using a translog specification based on factor prices. In a second step, the shares of the different fuel types are estimated, also based on a translog function. Technological change is modelled via autonomous technological change, for the different input factors as well as in form of total factor productivity.

Some aspects for long run transition

With respect to gaining insights into long term transformation processes a number of fundamental uncertainties with respect to the development of economic activities and prices and the convergence to an equilibrium solution remain. The model solutions depend strongly on the development of (relative) prices that drives changes in the economy.

As in most economic model classes, in New Keynesian Models long run development is implemented as an extrapolation of trends observed in the past. Technological change is modelled as incremental technical change; radical technological change cannot be captured in such models. When used for policy evaluation it is the underlying set of uncertain assumptions in the reference case that mainly determines the effects of policy shocks. The decisive role of prices for model solutions typically constrains the simulation of policy alternatives to price instruments like taxes.

The merit of the WIFO DYNK model is that it illustrates the interaction of stocks and flows for energy services. What drives the demand for energy services, however, is exclusively driven by prices.

3.3 Optimization Models

The method

An optimization approach aims for the minimization (e.g. costs, CO_2-emissions) or maximization (e.g. profits) of an objective function. The results of such models are solutions found by the "solver"-algorithm which are considered as optimal (or close to the optimum) with respect to the objective (or target) function. Therefore optimization models are prescriptive rather than descriptive. This means that this approach can rather be used for "*how to*" instead of "*what if*" research questions (Ravindranath et al., 2007).

Optimization models usually constitute from at least two parts: The first part is the modelling environment used for the model formulation and model building. Most optimization models are written in high-level, functional programming language in a declarative way. The computation is then done by evaluating the mathematical expressions. Commonly used optimization program languages are GAMS, MPL, AMPL, AIMMS or MOSL. In a subsequent step, the modelling environment translates the source code into equation system. The "solver"-software forms the second part of the model, which derives the solution by solving the equation system and thus evaluation the optimality of solutions simultaneously. For several widely applied (bottom-up) optimization models (e.g. MARKAL, TIMES, MESSAGE, OSeMOSYS) a third component, the model-builder-toolbox using a graphical user interface (GUI) exists (e.g. Excel-file in case of the OSeMOSYS). This has the advantage that model-building can be done more easily as the developer doesn't need to write source-code. However it is also limited to the model capabilities as defined by the GUI.

Although most optimization models follow this pathway, this is not necessity. Also a procedural model definition can be applied. An example for a procedural model approach is the

REMod (Renewable Energy Model) developed by the Fraunhofer ISE institute. The model itself is written in a Pascal-derivate, some sort of solver is applied which then identifies a (close-to-)optimal solution by consecutively evaluation the optimality of different solutions.

Optimization approaches are used for Top-down models (e.g. CGE (e.g**. GEM-E3 model)** or partial equilibrium models (e.g. (MARKAL-)MACRO) as well as Bottom-up (technology explicit) models (e.g. MARKAL, MESSAGE or TIMES model).

The mathematical approach for solving

Van Beeck's (2009) fifth dimension, the **mathematical approach,** defines how optimization models solve the problem. Most energy related bottom-up optimization models use common mathematical methods such as Mixed Integer Linear Programming (MILP), partly Multi-Objective Linear Programming (MOLP). If the model optimizes the path from an existing system towards the optimal system state, also Dynamic Programming (DP) methods are to derive their solutions. Top-Down optimization models and some (bottom-up) energy models use more advanced methods such as Non-Linear Programming (NLP), Mixed Integer Non-Linear Programming (MINLP), and (Multi-Objective) Fuzzy (Linear) Programming ((MO)F(L)P). The Fuzzy Logic approach (or Fuzzy Programming, FP) constitutes an improvement with respect to penny switching behaviour. Similar (in a non-mathematical definition) to the logit model and other probability approaches commonly used in discrete choice analysis, Fuzzy Logic allows that a variable is "partly true" and defines "*how much*" a variable is a member of a set. Thus, Fuzzy Logic approaches are more suitable to find realistic solutions for decentralised optimization problems with a medium or high degree of uncertainty than conventional approaches (Zimmermann, 1978; Jana and Chattopadhyay, 2004).

Strengths

The main advantage of optimization models is that they inherently consider the optimality of a solution (as measured by the objective function). Therefore this kind of models automatically rules out less preferable solutions.

Weaknesses

The solver-software, responsible for finding the (close-to-)optimal solutions needs to evaluate a large number of systems states with respect to status concerning the objective function and the model constrains. Therefore such models are limited to a restricted complexity and/or simplifications, in order to find a (close-to-)optimal solution within a reasonable time. With respect to complexity and simplifications, linear models (linear programming) define one end of the spectrum. Modern computers are easily able to solve such systems with millions of equations, however the restriction to linear systems makes this kind of model formulation basically unusable for real-life research questions. A less restricted formulation are Mixed-Integer-Linear-Programs (MILP) that allow variables not just to be an element of rational numbers but also of a restricted set of integers. Again such models can be solved for very large number of equations and variables within a reasonable time (days?) if the model is defined carefully. Yet, integrating part load behaviour into such a structure already requires substantial modelling in order to keep the model (easily) solvable. Most bottom-up energy-system models apply the MILP approach. On the other end of the spectrum range Non-Linear Programming (NLP), Mixed Integer Non-Linear Programming (MINLP) which are much harder to solve. This is especially the case for models with positive feedback loops (concave models). NLP or MINLP therefore require that the defined model has a low degree of complexity.

Another disadvantage of (commonly solved) optimization models is their behaviour with respect to inferior technologies. Usually the degree to which a given technology is part of the solution depends only on superior technologies and their restrictions as well as their own restrictions, while it is independent from inferior technologies (penny switching behaviour). This is probably the main reason for the commonly held position that conventional optimization techniques, are not particularly suited to analyse systems where many individual decision-makers decide on many rather small subjects. This "penny switching behaviour" is not necessarily given and could be avoided in principal – at the cost of increased computational time. Yet most applied energy systems optimization models accept such a behaviour in order to keep the model reasonable solvable.

Representative optimization models for the energy system of an economy

The MARKAL (MARKet ALlocation) model, its successor the TIMES (*The Integrated MARKAL-EFOM System*) model, the MESSAGE model (*Model for Energy Supply Systems And their General Environmental impact*), and the OSeMOSYS (*Open Source Energy Modelling System*) are well-known and widely applied energy system optimization models (Pfenninger et al., 2014).

Some conclusions for long-term transition analyses

Optimization models are well suited and widely applied to describe solutions for a "technological-optimal" hypothetical target system in a distant future as well as the "technologically optimal" pathway towards such a system. They are however less suited to evaluate realistic forecasts for systems stages which are far from the optimal solution as defined by the objective function, which is usually the case for real-life systems. They are furthermore not particularly suited to evaluate the real-life effects of policy measures or other framework conditions for complex energy systems.

3.4 Neoclassical Computable General Equilibrium (CGE) models (top-down optimization)

The method

Typically, a computable general equilibrium (CGE) model depicts the economy as a closed system of monetary flows across production sectors and demand agents on a yearly basis. These flows are based on real-world national input output tables as well as additional accounting data and are combined with the general equilibrium structure developed by Arrow and Debreu. Accordingly, CGE models solve numerically to find a combination of supply and demand quantities as well as (relative) prices in order to clear all of the specified commodity and factor markets simultaneously (Walras' law).

The basic underlying mechanisms are that producers minimize their production costs (or maximize profits) subject to technological constraints (production functions), whereas consumers maximize their consumption (or "welfare") subject to given resource and budget constraints (factor endowments and consumption functions).

Once the model is calibrated to a "benchmark" equilibrium of a certain base year it is shocked exogenously, triggering adjustments in supplied and demanded quantities and thus relative prices until all markets are in equilibrium again. The emerging new equilibrium depicts the state of the economy after the shock (i.e. shows how the economy would look like, if a certain policy had been introduced) and is compared to the benchmark equilibrium to analyse changes in endogenous variables such as activity levels of sectors and consumption, relative prices or welfare.

Mathematically CGE models are optimization problems since producers and consumers maximize/minimize their objective functions; however the use of CGE models is more of simulation character, as typically different counterfactuals are used in economic impact analysis, leading to different solutions of the models' optimizations routine, which then are interpreted as different results of simulation scenarios.

Strengths

The main advantage of CGE models is their ability to capture interlinkages across all economic sectors and agents. This means that "indirect" or "knock-on" effects of e.g. the introduction of an energy tax can be quantified, giving a broader picture than an isolated sectoral analysis.

Since the effects to the whole economy are captured by CGE models, the effects on typical macro indicators, such as GDP, national consumption or welfare and tax income, can be analysed. These changes in macro indicators then may be decomposed into different parts, e.g. the different contributions of sectors of interest to the change of GDP, which makes this approach very attractive.

Weaknesses

Next to the strengths of the CGE approach there are also limitations and weaknesses. In general the underlying neoclassical theory of general equilibrium is subject to heavy critique. However, the aim of the underlying paper is to analyse the ability of different methodological approaches in the specific context of energy-transition, hence we do not further address this very general discussion of general equilibrium theory.

A fundamental weakness in the CGE method is that only annual monetary flows are modelled explicitly. Capital stocks, such as buildings or power plants, are not captured, despite their importance in energy-transition modelling.

Another drawback of CGE models is that they are often too aggregate and coarse with respect to technological detail. Many CGE models use sector aggregates such as the energy sector, which includes generation and distribution of all kinds of energy. The supply side of these aggregates is typically modelled as constant elasticity of substitution (CES) production functions, which combines different production inputs such as primary factors (capital, labour, resources) and intermediate inputs (material and services) to generate output. Since the different inputs are partly allowed to substitute each other, elasticities of substitution are necessary. These elasticities usually stem from regression analysis based on historical time series, leading to the problem that there is no guarantee that they will not change in the future (Grubb et al., 2002).

When analysing energy transition pathways it is crucial to model different technologies separately, since their production structures may differ fundamentally. Even if different technologies are modelled separately in CGE models (such as in top-down bottom-up hybrid models as in Fortes et al., 2014) the problem remains that no radical changes are possible endogenously within the model framework since the production functions do not change over time. Regarding technological change usually factor productivity improvements are applied, however using this method radical changes or the emergence of fundamentally new technologies are not possible. Next to supply side issues, there are also weaknesses regarding the demand side. More precisely, substitution possibilities in final and intermediate demand are of crucial importance, requiring again elasticities of substitution.

Representative CGE models for the energy system of an economy

Typical CGE models which focus on energy-economy-environment interaction are the GEM-E3 model (General Equilibrium Model for Energy-Economy-Environment interactions) for the European Union (Capros et al, 2013a) and PACE (Policy Analysis based on Computable Equilibrium; Löschel, 2015).

GEM-E3 focuses on the European Union and is of recursive dynamic type, solving in 5-year steps until 2050. It is mainly used to assess climate and environmental policy, hence including primary energy sources and energy technologies. PACE is a similar model, however static comparative.

Some conclusions for long-term transition analyses

A first conclusion to be drawn for long-term transition analysis using CGE models is that the underlying fundamental mechanism of optimization of producers and consumers – assuming perfect information and rational behaviour solely based on prices – is unrealistic, leading to unrealistic results. Many other factors than just prices determine the actual behaviour of agents, hence in that regard CGE models are too short sighted.

The basic emission reduction mechanisms in CGE models are the following (cf. Capros et al., 2014): (i) substitution processes between fossil fuel inputs and non-fossil inputs, (ii) emission reductions due to a decline in economic (sectoral) activity and (iii) purchasing abatement equipment. However, CGE models do not allow for radical endogenously changes in the energy system (bifurcation points) which are necessary for deep decarbonization, since production and consumption functions are determined ex ante and do not change over time. Technological change thus only happens at the margin via price induced factor substitution (endogenously), productivity growth and autonomous energy efficiency improvements (both exogenously) (cf. Böhringer and Löschel, 2004).

Despite these drawbacks CGE modelling may offer also opportunities to capture the indirect effects of certain policy interventions or technological change can be provided to shock the model exogenously (on the premises of having enough data on possible future developments regarding energy technologies and energy demand available). These indirect effects are of crucial importance, as sectoral models which do not take into account a macro-economic embedding may under- or overestimate effects.

3.5 Partial Equilibrium Models (bottom-up optimization)

The method

The basic concept of equilibrium models is to determine the state where demand and supply of different commodities are equal (equilibrium price) and thus market clearance is achieved. Partial equilibrium models only consider a specific market or sector where the economic equilibrium is determined independently from prices, supply and demand from other markets. Therefore other markets and sectors are considered to be fixed, not considering possible interrelations. Thus all parameters not incorporated directly within the model have to be provided exogenously.

The advantage of partial equilibrium modes is that they are capable of describing specific markets more detailed and disaggregated. This is also beneficial for analysing the effects of different policies.

Representative Models

Since partial equilibrium models are only capable of a single (or limited amount) market or sector they consider specific problems. Prominent examples for partial equilibrium models are PRIMES and CAPRI. PRIMES is an energy model to calculate developments on the energy market (for details see also chapter 4.2). CAPRI is a model for the agricultural sector used for the assessment of agricultural and trade policies with a focus on the EU (CAPRI 2015). Both models are extensively used be the European Commission.

Some conclusions for long-term transition analyses

Some models like PRIMES have been extensively used to describe long term transitions (Capros et al., 2013b). A possible drawback is that those models rely on exogenous parameters (e.g. world market prices for fossil fuels, CO_2 permit prices) and neither provide direct feedback nor consider interrelationship to the sectors and markets exogenously provided. This may have considerable drawbacks on the long run, e.g. significant changes in energy market may have a considerable impact to the whole economy.

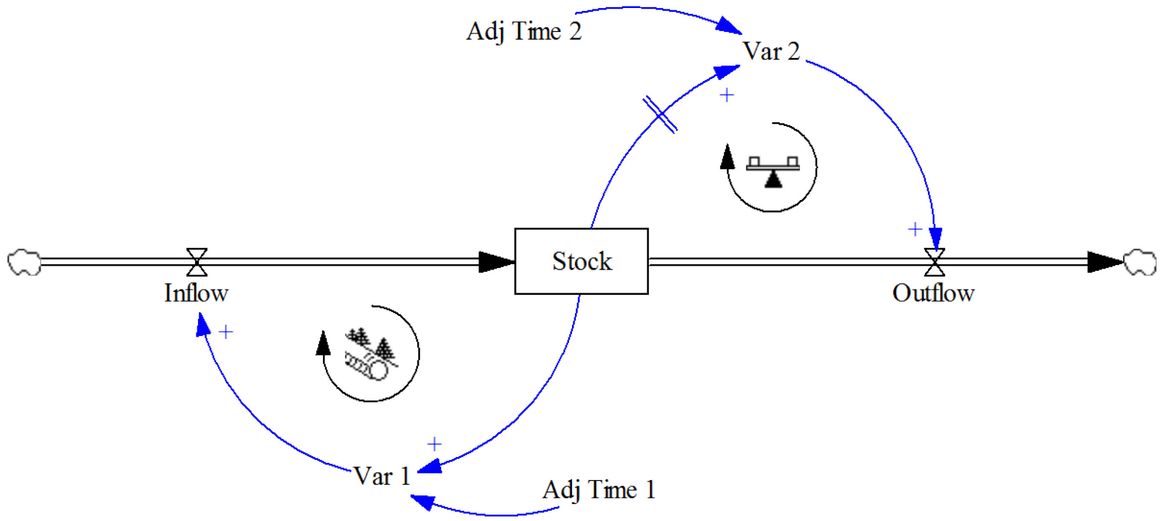
3.6 System Dynamics and Simulation Models

The method

The concepts of system dynamics was developed by Jay W. Forrester in the late fifties with the aim to asses and improve industrial processes. System dynamics models allow in a very intuitive way to model, simulate and analyse complex dynamic problems. The basis of a system dynamics model is a system of differential equations which are numerically solved in a sequence of time steps. Characteristic to system dynamics is the incorporation of complex feedback structures within the different system variables. Thus they are simulation but not optimization models.

The two central concepts of system dynamics are stock and flows in combination with the generated feedback and interrelations. A general stock and flow diagram is shown in Figure 1. The 'stock', which is visualised by the rectangle, contains the current level of an entity (e.g. price, demand). This level is increased and decreased by 'flows' connected to the stock. These flows are illustrated in Figure 1 by the thick arrows with the 'valve' symbol. These flows are influenced by different parameters, variables and stocks generating complex feedback loops.

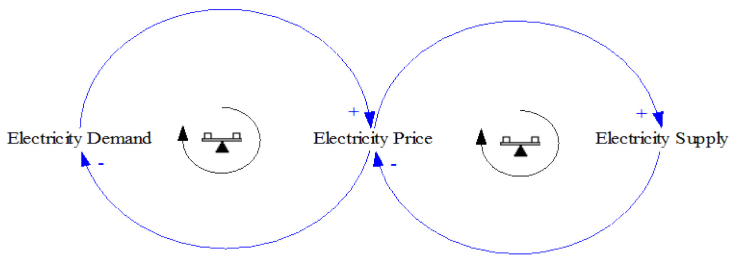
Figure 1 General example of stock and flows within the system dynamics approach.



The level of the stock, which is indicated by the rectangle, is altered by the flows ('Inflow', 'Outflow'). The blue arrows indicate the influence of parameters, variables and the stock on the different flows. The feedback loop 'Inflow', 'Stock' and 'Var 1' generate a reinforcement (indicated by the sledge) whereas the feedback loop 'Stock', 'Var 2' and 'Outflow' result in a balancing situation (indicated by the scales). The double stroke on the arrow from 'Stock' to 'Var 2' indicates a time delay until the feedback from the stock shows effects von 'Var 2' (Dykes 2010).

Besides the possibility to simulate the effects of the different interrelationships within the model it also provides a convenient way to analyse the driving forces within the system. In Figure 2 a simple example of feedback loops are illustrated. Feedback loops result either in reinforcement or in balancing (in Figure two balancing feedback loops are shown).

Figure 2 Simple example of feedback loops in an energy system.



On the left an increase of the electricity demand results in a higher price which results in a decrease of the demand (balancing; indicated by the scales). On the right an increase of the electricity price results in an increased supply of electricity which induces a decrease of the price (balancing)(Dykes 2010).

Besides the capability to describe dynamic and complex problems appropriate system dynamics model are increasingly combined with other methods like generic algorithms, iterative algorithms and game theoretical approaches. Also stochastic approaches, like Monte Carlo simulation, may be implemented (Teufel et al., 2013).

Representative models

Regarding the energy market a number of system dynamics models have been developed and successfully applied (Teufel et al., 2013). An example would be the model Kraftsim (Vogstad 2004) used for investigating the Nordic electricity market and simulating the effects on greenhouse gases caused by different policies. A more comprehensive overview can be found in Teufel et al. (2013).

Some conclusions for long-term transition analyses

Available system dynamics models have shown to be capable of describing energy and power systems adequately, including transformation processes until 2050. The incorporated consideration of interrelations may be an advantage for describing long run transformation processes.

However as this approach is a simulation and not an optimization method it may be appropriate to simulate complex problems but it lacks the possibility to find optimal pathways (e.g. least costs) for the transition. Regarding this aspect the combination with other methods may be a possible approach.

3.7 Backcasting Models

The backcasting[1] approach was developed in the 1970s by Amory Lovins for the analysis of energy systems. Backcasting is seen as an alternative to conventional energy forecasting approaches that estimate a continuous and substantial increase in energy demand. Since the 1970s the approach has been frequently applied in energy studies as well as in studies dealing with sustainable development in general.

In contrast to forecasting models that are usually based on past trends, backcasting approaches start from a normative vision for a desirable future, such as a low carbon society with a reduction of GHG emissions by 80-90% by mid century compared to 1990. From that vision of the future, a development path is traced back to the current situation. Backcasting is hence well suited for modelling complex issues such as a transformation towards sustainable consumption and production patterns. Furthermore, the approach allows for modelling structural breaks that cannot be captured with traditional forecasting approaches. This is a valuable feature for modelling the very long-run, as a mere continuation of past trends over the next decades is very unlikely.

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[1] The term 'backcasting' was introduced by Robins (1982), while Lovins initially used the term 'backwards-looking analysis' (Quist, 2007).

Backcasting is frequently used for (more or less) qualitative descriptions of the future (see e.g. Wächter et al. 2012 for Austria). In their energy perspectives for Austria, Köppl and Schleicher (2014a, b) use the quantitative backcasting model sGAIN for analysing low carbon energy structures in Austria for 2030 and 2050.

The WIFO sGAIN modelling framework

sGAIN by WIFO represents a detailed bottom up model of the energy system. In Köppl and Schleicher (2014a,b) the model is used for backcasting, using the EU 2050 Roadmap as normative vision for 2050. The modelling framework puts energy services into the center of the analysis of energy structures that are compatible with long term low carbon targets. Data for energy services are typically not available. Information from useful energy balances are used to demonstrate quantity and quality of energy used for the provision of energy services. The model structure details useful energy categories by sector and energy source and puts a strong emphasis on innovation and energy productivity at all levels of the energy chain including the supply side. Various combinations of changes in the demand for energy services and energy productivity that achieve the same output in terms of energy flows and emissions are displayed.

Some aspects for long run transition

Relevant for long run transitions is the ability to capture structural breaks that are necessary for a fundamental transformation of existing energy systems. This applies also to a clearer depiction of specific technologies and thus comes closer to include more radical technological change. Backcasting requires the definition of explicit target values that need to be thoroughly chosen and argued. The same holds true for modelling of the paths between the future vision and the current situation.

3.8 Multi Agent or Agent Based Models (ABM)

The method

The approach of ABM is a very general one as it can be used to model nearly any system in dependency of the purpose of the model. The variety of application ranges from physical over biological to social systems, while the approach is often seen in contrast to Equation Based Modelling (EBM) or System Dynamics, which have a similar general applicability. In a strict technical perspective, there is no difference between ABM and EBM as any ABM can be also expressed by an explicit set of mathematical formulas used by EBM (Epstein, 2006, p.xiv, p.27). However, in practice this set of formulas would be of hardly manageable size and complexity. The specifics of ABM, constituting a manageable modelling framework and distinguishing them from other modelling approaches, refer to 3 crucial points.

1. The subjects of modelling are the system's individual components and their behaviour. The behaviour of the modelled agents depends on the local interaction with other

system elements and individual optimization based on each agent's particular characteristic (as e.g. endowment, location or size).

2. The possibility of (geographical) special representation of system elements. Agents do usually not interact with all possible system elements but only with those in their neighborhood. This specification can capture particularities for interaction including topological circumstance, transfer of information and network structures.
3. The stochastic process of simulation. Other than deterministic approaches, in which the outcome of a model is fully determined by the parameter setting and the initial conditions, stochastic approaches as ABM bear an inherent randomness. Therefore one individual model simulation with a specific parameter setting and initial conditions can show only one possible outcome out of a well-defined function space, but not a general solution (Epstein, 2006, p.29).

As an implication of the first specific, a system behaviour may arise, which cannot be predicted from the behaviour of the individual agents, as it emerges from the adaptive interaction between the agents and their environment. In that way ABM are a Bottom-Up approach in which the autonomous behaviour of the agents determines the state of the system instead of a Top-Down approach (like System Dynamics, CGE,…) in which the state of the system is described only by variables. Further, an analysis of an ABM can be made not only on the aggregate system output but also on the agent level. However, an empirical ABM approach usually needs not only other/unconventional sources of data but also relies more heavily on more comprehensive data, specifying the multiple agents' particular characteristics.

Concerning the second specific, a large range of modelling possibilities becomes relative easily accessible. Models of social or economic systems in an agent based framework are only seldom restricted to *homo economicus* decision rules and can relax certain stringent conditions from neoclassical models, like perfect information, location or size of agents, while still yielding a fruitful analysis (cf. Epstein, 2006, p.xvif).

The third specific of a stochastic simulation is closer to processes in the natural world because of its inherent randomness. However, this has the price of stark increasing complexity of the model, demanding a comprehensive way of simulating and analysing the model. On the other hand, stochastics determine discrete decisions of agents and simulation in discrete time steps.

Strengths

- With ABM questions of emergence can be treated as the systems behaviour results of the interaction of its components. ABM can merge the micro with the macro perspective in that sense that well studied individual behaviour (as e.g. of plants, animals, people,…) can be modelled in one framework with changing system conditions – the state of system changes because of the individual behaviour and at the same time the individuals adapt their behaviour to the changes of the system.

- Within the approach of ABM uncertainties can be addressed because of the stochastic modelling character.
- ABM can handle also "nonequilibrium dynamics" – if equilibrium exists but is not attainable (e.g. on acceptable time scale) (cf. Epstein, p.xiii)

Weaknesses

- Additionally to mathematical and statistical modelling abilities, as necessary in other approaches (e.g. econometrics), also further modelling as well as programming and simulation skills are needed. This contains on the one hand the inclusion of different concepts as adaptive behaviour, interaction and emergence. And on the other hand, stochastics affords an iterative way for testing and analysing models.
- As already mentioned, data mining for empirical modelling with ABMs in social sciences is a big issue, as mostly micro data on an individual base for a large number of agents would be often required.

4 Identification and evaluation of existing "prototypical" models (selection)

For each of the model classes which we define by their underlying methodology, we select a "prototypical" model for further investigation. As a "prototypical" model we define a model which is prominently used in the analyses of energy-economic research questions either by the research community or by policy makers (such as the EU). These "prototypical" models have been classified by making use of the spreadsheet classification scheme developed in this WP on the basis of the previously described characteristics that are relevant for the suitability of energy-economic models for long term transition analyses.

4.1 Evaluation of specific "prototypical" models

PRIMES (Partial Equilibrium)

The *Price-Induced Market Equilibrium System* (PRIMES) is an energy system model to calculate projections of energy markets for the analysis of energy and climate policies in Europe. The model simulates the development of energy demand, energy supply and technology on the basis of market equilibrium (PRIMES 2014). Hence, PRIMES is a partial equilibrium model for the European energy system. Furthermore the model aims to represent agent behaviour within the multiple markets. This is achieved by a modular approach where each module represents a specific agent, either a demander or supplier of energy. The behaviour of the agents is modelled through a microeconomic foundation which maximises the benefit (profit, utility, etc.) of each representative agent. To combine the sub-models equilibrium prices in different markets and equilibrium volumes considering balancing and constraints are determined.

PRIMES provides detailed energy balances in line with Eurostat statistics including sectoral demand by fuel as well as the structure of the power system and other fuel supplies.

Moreover, energy prices and costs can be obtained such as costs per sector, investment costs, overall costs and consumer prices.

Since the economic development is modelled outside PRIMES there is no feedback generated by developments in the energy market. For the power system, daily and seasonal variations are modelled at an hourly resolution taking into account typical intra-day power load, wind velocity and solar irradiance. Despite this and detailed coverage of interconnecting capacities of electricity and gas flows, the model lacks information and representation at below-country levels such as retail infrastructure. This may be a particular concern if more volatile and decentralised production of electricity exceeds local grid capacities at short. Nevertheless, PRIMES should be well capable of simulating long term energy system transformation and restructuring up to 2050, both in the demand and the supply sides.

POLES (Simulation / System dynamics)

The POLES (Prospective Outlook on Long-term Energy Systems) model is a global energy supply, energy demand and energy prices forecasting model, developed within the VENSIM system-dynamics software package[2]. It has been developed by Enerdata and the CNRS National Center for Scientific Research.

It simulates the energy supply and demand (energy balances) of 15 economic sectors and of more than 57 countries and world regions within a partial equilibrium framework and explicitly considers about 50 energy supply technologies. The demand is modelled taking "into account the combination of price and revenue effects, techno-economic constraints and technological trends."[3] The simulation is done on a yearly basis.

POLES is a proprietary model, analyses with this model are rather provided as service by Enerdata; it is not (off-the-shelf) foreseen to hand-out the model to customers. Furthermore the included technologies are fixed and cannot be altered (by customers).

GEM-E3 (CGE)

The GEM-E3 model (General Equilibrium Model for Energy-Economy-Environment interactions) for the European Union has been applied for various climate and energy policy simulations to support decision makers within the European Commission. The main features are as follows (c.f. Capros et al, 2013a): (i) the model is of multi-country type with specific representation of all EU-15 member states, which are linked through endogenous bilateral trade, (ii) in every country multiple sectors and agents exist, allowing to analyse distributional effects and (iii) GEM-E3 is of recursive dynamic type, solving for general equilibrium in a specific year and then passing data on to the next year, for which a new equilibrium is solved. Furthermore the model includes taxes, subsidies and public spending (including deficit financing).

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[2] http://www.enerdata.net/enerdatauk/solutions/energy-models/poles-model.php.

[3] http://www.enerdata.net/enerdatauk/solutions/energy-models/poles-model.php.

GEM-E3 is mainly used to assess climate and environmental policy (e.g. by Mayeres et al., 2008; Pan, 2005; Saveyn et al. 2011 or Jansen and Klaassen, 2000) and therefore special focus lies on the competition between the main power generation technologies (coal, oil, gas, nuclear, wind, biomass, solar, hydro, CCS coal and CCS gas) with the respective greenhouse gas emissions (see Capros et al., 2014 for more details). Recently, the model was also deployed to analyse macroeconomic climate change impacts (e.g. by Ciscar et al., 2012).

Regarding low carbon transition and pathway analysis GEM-E3 was linked to various bottom-up optimization model such as TIMES (e.g. by Fortes et al., 2013, 2014) to overcome the caveat of poor technological detail of the CGE model, but being able to quantify the macroeconomic implications of low carbon (policy) scenarios. Similar modelling practice was carried out by Koopmans and te Velde (2001), Kumbaroglu and Madlener (2003), Messner and Schrattenholzer (2000), Scaramucci et al. (2006) and Wing (2006). Such studies (integrating bottom-up and top-down models) may serve as a good starting point for a holistic integrated assessment of energy-economic low carbon transition analysis for Austria.

MARKAL / TIMES (Optimization)

MARKAL and TIMES are dynamic (path dependent) bottom-up optimization modelling toolboxes developed by the International Energy Agency (IEA) within the Energy Technology Systems Analysis Programme (ETSAP). MARKAL was developed in the mid 90s, TIMES in the early to mid 2000s. According to the MARKAL[4] homepage is now applied by more than 70 institutions in more than 35 countries.

MARKAL focuses on the energy sector only, the main purpose of MARKAL models is to identify and evaluate "target-oriented integrated energy analysis and planning" using a least cost approach. The MARKAL toolbox has been superseded by the TIMES (*The Integrated MARKAL-EFOM System) toolbox*. The main advantage of TIMES compared to MARKAL is its flexibility. It allows several interacting regions and to sub-divide the year into several user-defined time periods. Both toolboxes contain a partially equilibrium models for the energy sector (considering supply curves of and demand curves for energy carriers and the subsequently derived energy prices).

One of the main advantages of MARKAL and TIMES is that they are widely used in the energy system planning community and easy-to-use model building (less steep learning curve). A disadvantage is the still rather rigid structure. Furthermore, they do not optimize the electricity supply for medium- to long-term energy system planning, energy policy analysis, and scenario development with a large share of intermittent energy sources (e.g. wind and PV).

GAINS (Scenario analysis or optimization)

The *Greenhouse gas Air pollution Interaction and Synergies* (GAINS) model is an integrated assessment model which is based on a technology specific bottom-up approach. It derives

[4] http://www.iea-etsap.org/web/Markal.asp.

on the basis of emission factors and abatement effects the anthropogenic emissions, the resulting atmospheric pollution and impacts on human health and environment (Amann, 2012).

The GAINS model can be operated in a 'scenario analysis' and an 'optimisation' mode. In the 'scenario analysis' mode it analyses the pathway from the emitting source to the impact and allows therefore to assess the costs and benefits of different emission abatement strategies. In the 'optimisation' mode it derives the optimal combination of different abatement and mitigation options which achieve the best overall benefit at minimum costs.

To be able to calculate the emissions of different pollutants on the basis of activity data the GAINS model incorporates around 1000 types of emission sources which are specific regarding economic sector and country (Capros et al., 2013b).

In order to describe the different mitigation options and pathways GAINS considers around 1,500 end-of-pipe measures to assess the abatement of a wide range of different air pollutants including greenhouse gases. The different mitigation effects are derived on country and sector specific implementation costs. This allows a detailed assessment of the environmental impact of different policies and measures (Amann, 2012).

Since the different activity levels are exogenous the different costs of the abatement measures generate no feedback regarding the underlying economic models.

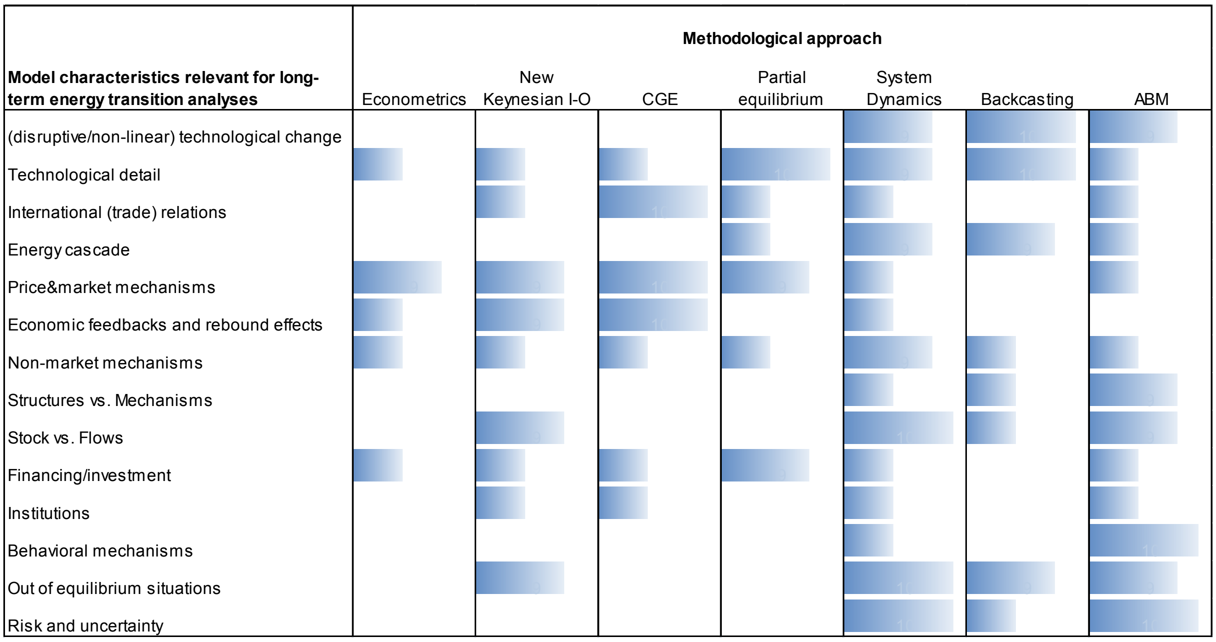
5 Conclusions

Existing energy- and climate-economic modelling approaches are increasingly seen with skepticism regarding their ability to forecast the long term evolution of economies and energy systems. The economic, climate and energy sphere are highly complex non-linear systems, so far most often only poorly dealt with when assessing the transition pathways leading to a desirable future. This Working Paper reports a structured meta-analysis of state-of-the-art national and international energy-economic modelling approaches, focusing on their ability and limitations to develop and assess pathways for a low carbon society and economy, both in total and for the main sectors contributing to greenhouse gas emissions. In particular, we set out to identify those existing models and/or model components/modules which could be of interest in developing a research plan for the creation of an open source model for analysing a national transition to a low carbon society by 2050, here more specifically applied to Austria.

We find that existing methodological approaches have some fundamental deficiencies that limit their potential to understand the subtleties of long-term energy transformation processes. Table 5 depicts a qualitative scoreboard for different methodological approaches' capability of dealing with characteristics relevant for long-term energy transition analysis. It is important to note here that this scoreboard is only a first qualitative mapping based on the authors' expert judgement and feedback by the CLIMTRANS consortium. Most modelling approaches that were analysed (specifically econometric, computable general equilibrium, and New

Keynesian approaches) are characterised by an almost complete absence of details of the energy cascade, in particular they lack to model the central role of functionalities that are provided by the interaction of energy flows and corresponding stock variables. Further they are not well equipped for analysing radical technological changes. Model results often depend on only a single mechanism depicted by the modelling approach, e.g. for computable general equilibrium models, partial equilibrium models or New Keynesian models (relative) price changes are the key drivers. Reversely, top-down integrated assessment models aim to include as many mechanisms as possible and are hence capable of capturing feedback effects between aspects of the system under consideration (economy, climate system, society, other environment), but this comes at the cost of either (a) working on a very coarse level of detail, with e.g. only limited explicit representation of alternative technologies and using highly uncertain (e.g. damage-) functions between relating e.g. economic indices like a region's GDP and global mean temperature changes (hard-link IAMs) or (b) experiencing problems in convergence and consistency among the models used (soft-link IAMs). Bottom-up, partial equilibrium optimization models investigating energy systems are capable of depicting a rich technological detail and of identifying technologically optimal solutions (as defined by an objective function) and hence rule out inferior solutions. However, due to high computing requirements these models are limited to restricted complexity (e.g. convexity and missing macroeconomic feedbacks) and are therefore less well suited to evaluate realistic forecasts of energy system states which are far from the optimal solution as defined by the objective function, which is usually the case for real-life systems. Comparatively novel methodological approaches such as System Dynamics (SD) or Agent Based Models (ABM) do allow for representing stock-flow relationships and dynamic, disruptive transformation processes but lack the possibility to find optimal pathways (e.g. least cost, minimizing energy demand, minimizing emissions) for the transition and tend to be highly resource intensive regarding empirical data input, which is, however, critical for deriving real world relevant results. Moreover for SDs and ABMS, just as for more traditional approaches such as computable general equilibrium approaches, problems might occur regarding the separation of the structure – e.g. the elements of an energy system – from the mechanisms that are generating these structures. What is true for all modelling techniques mentioned so far is that the respective results are heavily driven by exogenous input (parameter) assumptions (e.g. price elasticities, perfect information, rational behaviour of agents, model closures) which are in turn triggering endogenous responses within the model.

Table 1 Qualitative scoreboard for different methodological approaches' capability of dealing with characteristics relevant for long-term energy transition analysis



Based on this meta-analysis we suggest that a methodological framework for analysing long-run energy and greenhouse gas emissions system transitions has to move beyond current state of the art techniques and simultaneously fulfill the following requirements: (1) inherent dynamic analysis, describing and investigating explicitly the path between different states of system variables, (2) specification of details in the energy cascade, in particular of the central role of functionalities that are provided by the interaction of energy flows and corresponding stock variables, (3) a clear distinction between structures of the energy systems and (economic) mechanisms and (4) ability to find optimal pathways (e.g. least cost, minimizing emissions, minimizing energy demand). Furthermore, a crucial task in modelling is to specify explicitly whether a model element is determined endogenously or exogenously, ideally governed by the demands of the underlying question to be answered.

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