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A Review of Policy Analysis Purpose and Capabilities of Electricity System Models

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Abstract

The aim of this study is to investigate the ability of electricity system models to provide scenario based insights for policy purposes. A framework is built from a review of existing studies of model characteristics and their linkages to model scenario types, which are linked to the purpose of policy problem analyses. The framework can be used as a tool to structure the examination of electricity system models, and guide electricity system model selection and enhancement in light of policy problem driven analyses. An illustration of the framework is presented by a review of German electricity model scenario studies. The review shows that current models are used for the policy purpose of indicator assessment and instrument comparison by quantification of indicators such as monetary or pollution impacts. However, they are not suitable to provide the means for option reduction, problem exploration, and political or societal paradigm change exploration, as the endogenous model structure for these is missing. A particular lack of endogenous treatment was found for renewable technology capacity change and policies, learning and productivity growth based technological change, socio-political-technical interactions, and limited demonstrated use of uncertainty treatment techniques.

1. INTRODUCTION

Energy policy in the early 21st century seeks to guide the transition to an energy system underpinned by three characteristics: a secure supply chain from extraction to delivery, affordable supply in relation to economic output, and low environmental impacts especially greenhouse gas emissions (Bocca and Hanna 2013). The alignment of these goals is difficult because trade-offs between energy sources and technologies exist in economic, social, and environmental dimensions (Pappas et al. 2014; Pfenninger and Keirstead 2015). Knowledge of such trade-offs within this complex system is essential to policy makers, who are tasked with the selection, implementation, and adjustment of policy instruments, so as to steer investments and alter the institutional fabric of energy markets. Computer models are increasingly used as knowledge support tools in this policy process because they can calculate mentally complex to grasp interactions, such as between policy instruments and investment decisions (Wild 1996; Strachan et al. 2009).

Traditionally models have been used as a toolbox to aid scientific theory formulation, in order to falsify or add to the credibility of particular theories, by iteratively improving model representations of the real world (Rappaport 1995). More recently, model use was introduced to inform policy decisions for the purpose of analysing the impacts of proposed policy solutions, referred to here as model scenario to policy insight. The transfer of model use from science to policy is not straightforward, however, due to a disparity between model complexity and information wants of policy makers. Computer models cannot provide a clear course of action as a "policy panacea" especially when simulating the future (Strachan 2011) yet policy makers prefer simple effective solutions; their impact ideally expressed in single numbers despite oversimplification and decreased validity (Manski 2013). The disparity can be expressed by several model-to-policy information gaps which deserve attention for computer models to be useful in providing real insights instead of just numbers (Worrell et al. 2004; Pfenninger et al. 2014). Three model-to-policy information gaps can be perceived. First, a stakeholder gap between model scenario exercises and policy maker involvement in building and creating "ownership" of scenarios. Scenarios are seldom developed in a participatory manner with electricity sector stakeholders (Schmid and Knopf 2012). A structured approach which integrates policy relevant stakeholder exercises with energy system modelling is considered essential, such as low carbon pathway studies (Foxon 2013). In this approach scenario events, policies, and assumptions are built into the model inclusive of the mental model of policy makers. Second, an information gap between model results and their use and interpretation by policy makers in the process of policy formulation and implementation. New learning approaches were found necessary to improve efficiency and reliability of research recommendations for use in policy decisions. At a communication level researchers could benefit from taking into account what information is used and how so as to improve policy decision usability. At an institutional level policy makers could be better incentivized to be aware of and use research recommendations in their political judgement. And, at a social level learning effectiveness can be aided by improving trust between researchers and policy makers (Head 2010). Third, a technical gap between outputs models can provide and insights from which policy makers would benefit. Both the purpose of model use for policies and capabilities within that purpose to gain insights are relevant. Model purpose at a macro level can be classified into the presently dominant use of *solution analysis* of proposed policies and impacts, *solution discovery* of new or optimal combinations of policies, and *problem analysis* to gain insights in unexpected or uncertain challenges that cascade from the present situation into the future. Modellers and policy makers need to collaboratively establish what model purposes and features policy makers deem useful

and thus which technical improvements are necessary to enable these. An example of a policy usefulness study looked at MARKAL-MACRO optimization scenarios for UK energy and climate policy (Strachan et al. 2009). Model value by policy makers was found in providing system-wide insights, knowledge improvement by discussing uncertainty using a structured model based approach, and the quantification of GDP and demand using linked energy-economic models.

The aim of this study is to address the third technical model-to-policy gap by investigating the ability of available electricity system models to provide system-wide insights for policy purposes. The first objective is to provide a framework that improves thinking in building and using models as scenario for policy insight tools (Hughes and Strachan 2010), in particular to examine what model capabilities are necessary to exercise particular policy relevant scenarios. To this end the framework describes potential purposes of models in providing policy insights, their relation to categories of scenario exercises, and electricity model characteristics necessary to execute described scenario exercises. The second objective is to provide insights in what type of policy problem analyses can and cannot be carried out using existing electricity system models. And the third objective is to analyse the existing characteristics of electricity system models, so as to ascertain what model improvements need to be made to expand the scenario to policy insight toolbox.

Section 2 gives a methodological overview of different purposes to which models can be employed to gain policy insights (2.1), a review and classification of electricity system model characteristics (2.2), and a description of scenario exercises recast in relation to computer based execution and purpose for policy analysis (2.3). In section 3 results are presented including the framework linking policy analysis purpose to model characteristics based on related scenario exercises (3.1), a review of German electricity mix model studies using the framework (3.2), and the ability of underlying models to reproduce historic German electricity system trends given built model characteristics (3.3). In section 4 the framework is discussed and in section 5 conclusions and policy implications are drawn focusing on potential improvements to increase model abilities to gain policy insights.

2. Methodology

The model policy purpose to model characteristics framework is developed by reviewing three strands of literature; electricity system modelling, political science analyses of political decision structure, and scenario exercises classifications. Their relation is discussed below and shown in figure 1.

In the political science review frameworks were studied which investigate mental models of policy decisions and the policy environment. The focus lies on inferring strategies to analyse political problems that form the purpose of using computer models through scenario exercises. In the scenario exercise review a predictive, explorative, and normative scenario typology (Börjeson et al. 2006) developed outside of computer model use, is recast to align with model based execution of scenario exercises. Thus a link is made between the policy analysis purpose of scenario exercises and the ability of models to carry out scenario exercises given their characteristics.

The electricity system model review focuses on describing model characteristics and application methodologies illustrated with electricity systems model examples. Selected model characteristics were chosen from a policy insight perspective, in contrast to operational decision making, because of their relation to future developments, policy to electricity system interactions, and the representation of decisions by system actors. Characteristics include scope, modelling paradigms, uncertainty treatment, decision structure, technological change, and socio-political-technical interactions.

Excluded are characteristics related to operational technical detail and short term market decisions which were covered in Ventosa et al. (2005) and Weidlich and Veit (2008). The review contributes to the existing energy system literature by its focus on model characteristics related to policy insights, electricity system examples, and creating the link to scenario execution ability and their purpose for policy analysis. Existing reviews were carried out focusing on model to model comparisons (Bhattacharya and Timilsina 2010; Foley et al. 2010), methodologies for particular sub-system purposes such as demand forecasting (Suganthi and Samuel 2012; Torriti 2014), the integration of renewable energy in models (Connolly et al. 2010), models utilising simulation via difference-differential equations (ahmad et al. 2015), sensitivity to energy technology costs across models (Bosetti et al. 2015), or overall model characteristics and capabilities (Ventosa et al. 2005; Pfenninger et al. 2014). An overview of review studies to date can be found in (Pfenninger et al. 2014), who discuss energy system modelling and treatment of spatial and temporal scales, uncertainty, model transparency, and human interactions. The study by Ventosa et al. (2005) specifically focuses on short-term electricity market structure, dispatch and purchasing decision algorithms, and grid representation.



Figure 1 – section overview of components of presented framework and purpose and executions links

The amalgamated model policy purpose to model characteristics framework framework is presented in the results (section 3.1). The analytical use of the framework is presented through a review of studies on German power generation evolution. Germany was selected because of the proliferation in studies following the 80%+ 2050 renewable electricity goal plus 2011 nuclear phase-out decision. The goal is to highlight present abilities to execute certain type scenarios, to gain policy insights, and signal areas of improvement. The literature search was conducted using ScienceDirect, Web of Science, and Google Scholar, using combinations of keywords: "Germany", "electricity", "evolution", "nuclear", "renewables", "coal", "natural gas", "modelling", and "scenario". In total eleven electricity system modelling studies were located. The review is divided into a general review of model characteristics, type of scenario exercises, and policy analyses carried out (section 3.2), and an analysis on the ability of scenario exercises to reproduce historic electricity evolution trends given inbuilt model characteristics (section 3.3). The presented focus on model abilities are complementary to Schmid et al. (2013) who focus on model outcomes of six German electricity system studies.

2.1 POLICY ANALYSIS PURPOSE

Political solutions can be defined by three aspects: the policy instrument, its quantitative setting, and the paradigm determining the instrument's political feasibility (Hall 1993), such as belief in *laissez faire capitalism* limiting choice to non-market interventionist policies. The political structure from which solutions emerge has been described in theoretical frameworks of decision making amidst conflicting values and interests, information flows, institutional arrangements, and socioeconomic variation (Sabatier 2007). The multiple streams framework developed by Kingdon (2010) is employed here because it recognizes scenario uncertainty in political decisions and focuses on problem analysis. Governments are perceived as 'organized anarchies' who address numerous policy issues in parallel streams in an abrupt and disorderly fashion. A stream has a "life of its own" following concerns of individuals plus manipulation by interest groups. The theory describes two aspects shaping the purpose of political problem analysis that can be linked to model use (Zaharadias 2007):

- **Indicator assessment**: problem solutions are assessed by effect and magnitude using simplified quantitative indicators. Modelling can assist to express quantities from known relationships such as electricity grid expansion costs to accommodate variable renewables.
- **Problem exploration**: new dimensions to problems are uncovered by events that cause politicians to shift focus, such as industrial accidents and bottom-up societal concerns. Such events and responses can ex-post or ex-ante be modelled to assess their relevance.

Another key pillar of multiple streams is that few ideas receive serious consideration as time constraints and perceived political feasibility limit options that are scrutinized. The notion is in tune with the poly-heuristic theory of two-stage decision making: policy makers carry out a screening to remove politically infeasible options and subsequently assess gains and losses to find the best solution (Mintz 2005). These theories relate to four model based analyses:

- **Option reduction**: reduce the number of policy instruments deemed not feasible. Models can be used to test feasibility on technical and economic grounds. Political feasibility could be operationalized indirectly through constraints to improve the policy relevance of model results. For instance, reducing wind energy operational efficiency as an indirect assumption of suboptimal placement due to citizens landscape preferences
- **Instrument comparison**: provide an assessment of differences and synergies of policy instruments. Models can explore instrument size (e.g. height of feed-in tariff) and variation (e.g. government subsidy versus feed-in) effects on outcomes by altering parameter values and structure between model runs.
- **Political paradigm exploration**: the instrument prioritization process is biased by the ruling paradigm of how society should be organized following a political ideology. Modelling can function as a 'neutral' testing ground of instruments beyond the current paradigm to explore effects of paradigm change (e.g. particular instruments become available at a selected timestep associated with a policy paradigm change), or quantify outcome differences between instruments related to particular political paradigms (e.g. market driven vs non-market driven instruments).
- **Societal paradigm exploration:** the instrument prioritization process is biased because politicians anticipate societal resistance to proposed changes, or because external support influences their choices. Politicians potentially thus eschew particular instruments to avoid political loss or promote these to reap personal benefits (e.g. windfall taxes on electricity

Accepted Manuscript in Renewable and Sustainable Energy Reviews. http://dx.doi.org/10.1016/j.rser.2016.01.090, © <2016>. This manuscript version is made available companies). Models can explore this using fixed a-priory instrument setting, decision probabilities of instrument implementation, or interactions between societal resistance and policy maker behaviour.

The policy problem approaches described above can be grouped into three phase of the policy making process, problem analysis, solution discovery, and solution analysis (figure 2).



Figure 2 – analytical approaches in policy decisions

2.2 MODEL CHARACTERISTICS REVIEW

In this section an overview is presented of the characteristics of electricity system models. Possible variations in seven structural model characteristics are described (overview figure 3): model scope (2.2.1), modelling paradigms (2.2.2), uncertainty treatment (2.2.3), decision structure (2.2.4), technological change (2.2.5), and socio-political-technical interactions (2.2.6).



Figure 3 – Electricity system model characteristics included and excluded in this study.

2.2.1 SYSTEM SCOPE

The structure of electricity system models varies substantially across the more than 90 electricity system models constructed to date (Pina 2012). A key division is the scope to cover the three sub-systems of the electricity system:

- Short time-step models of electricity supply and demand with market participant exchange. A common structure is a day-ahead spot market model but also forward, bilateral off the counter, and reserve or capacity market models are available (Just and Weber 2008).
- Long time-step models of generation capacity expansion at individual firm or sector investment levels.
- Grid flow models to explore the spatial match between electricity supply and demand. Their use is growing due to increasing renewable energy shares in the electricity mix (Swider and Weber 2007).

Historically, sub-systems were separately treated with as an early exception the MARKAL model despite being limited to annual time-steps (Fishbone and Abilock 1981). This computational constraint is increasingly irrelevant since software and hardware improvements have enabled model operation up to continuous hourly to sub-hourly blocks. An accurate implementation of high resolution grid flows and renewable stochastics which previously limited coupling of the three electricity sub-systems is now feasible (Pfenninger et al. 2014), of which the importance is estimated in Poncelet et al. (2016). Hard-linked models have emerged with an expansive and exceedingly granular temporal scope such as E2M2 (Spiecker and Weber 2014). Also efforts are made to soft-link existing models such as MARKAL for electricity markets plus capacity expansion with PLEXOS for grid flow modelling (Deane et al. 2012).

2.2.2 MODELLING PARADIGMS

The second discussed characteristic is model classification into optimization, equilibrium, and simulation paradigms (Ventosa et al. 2005). Initial models from the 1970s aimed to find energy technology combinations with the lowest supply costs from a "central planner" perspective (Bhattacharyya and Timilsina 2010). This optimization architecture uses objective equations to let the computer find an optimal value such as total sector profit or least costs across all model time-steps. A set of linked constraint equations ensures that a solution takes designated system characteristics into account (Sarker and Newton 2007), such as generation capacity and investment availability. Optimization models also differ by selected algorithmic solver because of numerical problem complexity. A key decision is limiting variables to integer values versus allowing non-integer values in the possibility space resulting in either linear or mixed integer linear programming models (Chong and Żak 2013).

The shift to electricity market liberalization in the 1990s led to a new class of optimization models focusing on electricity supply-demand trading and capacity investment markets (Borenstein et al. 1995; Bushnell and Ishii 2007). These equilibrium models compartmentalise optimization using an objective equation postulated at firm level and solve per time-step (Ramos et al. 1999). Firm behaviour is effectuated through supply bids and price plus capacity allocation and solved by a market clearing equilibrium procedure. Demand is either formulated using price-elastic demand curves or by market participant demand bids (Philpott and Pettersen 2006). Supply bids are placed assuming full or partial knowledge of market demand in response to behaviour of competing firms. Three bidding strategies have been established. In Cournot models firms optimize production quantity variation, in Bertrand models price variation, and supply function equilibrium models let each firm produce a supply curve with price and quantity variation (Rudkevich 1999).

The simulation model class describes changes in an entity or variable state by behavioural algorithms or differential equations (Pfenninger et al. 2014). A division into two approaches is observable. First, differential equation models, originating in the 1970s for electricity systems, where difference equations capture state changes, and continuous differential equations are numerically solved to calculate state changes which provide input into the difference equation (Ford 1997). In engineering these systems are referred to as state-space models and in system dynamics literature as stock-flow models (Cellier and Kofman 2006). The approach enables flexible incorporation of systems behaviour such as feedback by modular mathematical implementation without balancing constraints. Second, agent-based models, introduced in the 2000s for electricity systems based on entities such as firms or households represented by behavioural algorithms (Weidlich and Veit 2008). An agent state change is caused by interactions of agents plus higher system components per time-step. Algorithms are typically described with conditional logic triggered at a continuous or event-response basis (North and Macal 2007). The architecture is especially useful for tracking 'agent' information including learning from past behaviour, agent spatial data, and incorporating network behaviour. Models differ by agent learning algorithms including reinforcement learning, genetic algorithms, and learning classifiers (Sensfuß et al. 2007; Weidlich and Veit 2008; Salehizadeh and Soltaniyan 2016).

The sharp optimization-simulation distinction is blurred when exploiting the modular structure of simulation to incorporate optimization, either via soft-linking simulation with optimization models, or by using meta-heuristic optimisation algorithms (Fu 2002; Barton and Meckesheimer 2006). For example, an agent-based simulation for power supply and demand resolution was soft-linked with a power dispatch optimization model (Sarica et al. 2012).

2.2.3 UNCERTAINTY TREATMENT

A third model characteristic is uncertainty treatment. First, types of uncertainty are described and subsequently techniques to include uncertainty are discussed. A common distinction is the epistemic or aleatory **nature** of uncertainty. Epistemic uncertainty stems from a reducible gap in knowledge and aleatory occurs when uncertainty is irreducible due to inherent system variability (Helton et al. 2006). A characteristic attributed to aleatory uncertainty is the applicability of probability distributions since by definition knowledge is sufficiently complete (Kiureghian and Ditlevsen 2009). The assertion is contentious for complex forward-looking systems as the future is never fully known and "hidden" outcomes may exist. The **location** of uncertainty describes where in a model uncertainty occurs distinguishing between parameter values (parametric) or equations (structural) (Walker et al. 2003). Also of influence and often conflated with uncertainty can be coding, numerical simulation, or data transformation errors. The sum of uncertainty and errors has been named the prediction error between "true" and predicted values (Strong and Oakley 2014). The **nature** and **location** of uncertainty can be related to three **levels** (Walker et al. 2003):

- *Statistical uncertainty*, called risk in economics, indicates a situation where all outcomes plus causes are known. Continuous or discrete probability distributions can be applied when significant empirical data is available. Statistical uncertainty is aleatory in nature and parametric in location.
- *Scenario uncertainty*, called ambiguity in economics, describes a situation where all outcomes are known but causal knowledge is incomplete. The selection of a probability distribution is subjective although feasible (Dequech 2000) and mathematical treatment relying on degrees of belief via possibility theory or fuzzy sets may be better suited (Oberkampf et al. 2002). Scenario uncertainty is usually epistemic in nature and structural in location but can be of aleatory origin given the problem context, such as for nuclear power plant failures.
- *Fundamental uncertainty*, called deep uncertainty in climate science, relates to unknown radical or structural changes (Hallegatte et al. 2012). Most outcomes and causes are speculative and not all outcomes are known such that neither probabilistic nor possibilistic approaches make sense. Adaptive heuristics where a strategy is matched to a changing environment may be a suitable approach (Mousavi and Gigerenzer 2014). Fundamental uncertainty is epistemic in nature and structural in location.

An additional discussion on the **level** of uncertainty can be found in the study by Mirakyan and Guio (2015), who split fundamental uncertainty into uncertain environments where probabilities cannot be associated with outcomes, and ignorant environments where outcomes are speculative. The relationship between the uncertainty classifications at different levels, nature, and location is shown in figure 4, including techniques utilized applied at structural and parameteric levels discussed in the next section.



Figure 4 – uncertainty classification and utilized techniques in the electricity system literature

The description of the **nature** and **level** of uncertainty helps to inform the choice of an appropriate treatment strategy. Uncertainty treatment techniques themselves are applied at either parametric or structural **locations** as respectively discussed in this section. To exemplify uncertainty treatment from a decision influence perspective a system actor's categorisation can be utilised, where system elements are defined as pre-determined, actor contingent elements changeable or initiated by decision makers, and non-actor contingent elements outside decision influence (Hughes et al. 2013). Actor contingent elements can be sub-classified in exercisable actions by governments, consequential actions by firms and citizens, and vice versa (N. Hughes, personal communication, April 29, 2014).

The standard parametric uncertainty treatment is *uncertainty propagation* used in both optimisation and simulation paradigms. Model parameter values fixed within a model run are varied between runs to explore model outcome variation using brute-force Monte Carlo methods or sampling techniques (Helton et al. 2006). Statistical techniques can be employed for sensitivity analyses to explore input parameter contribution to outcomes (McKay et al. 1999). Non-actor elements examples include fuel prices and technology cost development, and actor contingent elements R&D budgets and electricity market floor prices. A key example of structured use of this technique was published for the ESME UK energy system model (Pye et al. 2015).

Simulation models employ *stochastic generators* to introduce parameter value fluctuation representing uncertainty. Either as differential equations with stochastic processes such as (geometric) brownian motion (Botterud 2003; Safarzynska and van der Bergh 2011) or discrete probabilities such as a binomial random variable function (Olsina et al. 2006). Variation introduced by the technique is especially helpful to gain insights in extreme value effects on outcomes. Example cases are weather as a non-actor element and partially randomized investment decisions or price bids as actor contingent.

Multi-stage stochastic programming is a probability based decision tree approach used in optimisation. The model timeline is split in sequential stages between events with multiple a-priori defined outcomes (Hunter et al. 2013). An event outcome is implemented as a parameter with

associated probability. The ex-ante resolution is contingent upon full knowledge of the range within event set(s) and probabilities as a hedging strategy. At event time the parameter value is resolved drawing from a distribution and becomes a "known" value in remaining periods. The technique has been used in "central planner" optimisation models such as TIMES and in equilibrium models of generation capacity expansion with risk averse firms (Ehrenmann and Smeers 2011; Loulou et al. 2004). The approach can introduce structural breaks in parameter values or one-off variable adjustments as discontinuous events. The main use is to test the robustness of policy decisions prior to event onset under uncertainty for any outcome (Loulou et al. 2005). For instance, non-actor infrastructure breakdowns or emissions allowance policy and minimum technology share targets as actor events.

The downside of multi-stage stochastic programming is the assumption of complete knowledge of all futures. Also the technique cannot incorporate continuously changing random values such as wind-speed fluctuation. To overcome this *recursive stochastic optimization* was developed for optimization where selected parameters assume a random value through stochastic processes in each period. The objective function is solved taking into account the world state and a decision vector such as dispatch or capital investment. A recursive algorithm incorporates both present and extrapolated future states to affect decisions (Powell et al. 2012). The technique is analogous to stochastic generators in simulation but can locate optimal outcomes despite algorithmic complexity using approximate dynamic programming. A recursive stochastic optimization in an equilibrium model of electricity market investment was built using markovian processes (Bushnell and Ishii 2007).

Techniques for parametric uncertainty described above rely on probabilistic approaches at a statistical uncertainty level. Few models have incorporated degrees of beliefs assuming scenario uncertainty (Zeng et al. 2011). Production of distributed power plants was simulated using *uncertainty propagation* with trapezoidal possibilistic distributions for solar and wind power operation parameters using evidence theory (Li and Zio 2012). A hybrid *stochastic and possibilistic optimization* model for firm power generation planning was built using triangular fuzzy numbers (Lotfi and Ghaderi 2012).

Structural uncertainty has received substantially less attention. The majority of studies are model comparisons between model structure and results (DeCarolis et al. 2012). For instance, a cournot versus supply function comparison in equilibrium models using a German electricity case study (Willems et al. 2009). A minimum cost versus alternating current optimum network flow comparison within a soft-linked agent-based simulation of electricity markets (Sarica et al. 2012). A comparison between using a single cost and a multi-objective objective including carbon emissions for exploring renewable energy contributions to emissions and costs (Pereira et al. 2016). And a comparison between two electricity system optimisation models MARKAL and TEMOA finding discrepancies due to constant versus variable assumptions of electricity demand at annual timescales (Hunter et al. 2013). The Methods to Generate Alternatives (MGA) technique from operations research was proposed to consistently treat structural uncertainty in optimisation models (DeCarolis 2011). An objective function is modified with a slack parameter to explore near-optimal solutions in the inferior model space. The rationale is inclusion of "hidden" aspects in the model objective such as nuclear power regulatory costs implying deviation from the optimum. The *uncertainty discrepancy* parameter approach can be used when the "true" output value is known to estimate distance to model prediction. The discrepancy is decomposed and a causal evaluation is conducted using discrepancy parameters in model equations (Strong and Oakley 2014).

2.2.4 DECISION STRUCTURE

A fourth characteristic of model classification relates to decision structure. Decisions can implicitly follow from model equations or explicitly be represented in a model as actor responses to exogenous changes or interactions following endogenous linkages. The implementation can be structured by the number of decision makers (allogeneity), decision response (form), and knowledge availability (opsis), as summarized in figure 5 below. The form of decision making can be categorized as:

- **Uniform** in top-down implicit approaches or an explicit decision maker such as a "central planner".
- **Pluriform** for multiple decision makers like large firms in an oligopoly.
- **Omniform** in case of a complete "bottom-up" representation.

The decision response is defined as homogeneous if all actors can perform only one reaction as a change in the same variable(s) in the same direction and quantity, and heterogeneous for multiple possible reactions. For example, a change in increase or decrease in investments of modelled firms and the size thereof. Finally, knowledge used in a decision is structured by opsis (e.g availability of knowledge) either from a model perspective in the implicit case or a modelled decision maker in the explicit case. Knowledge can relate to model parameters, variables, and strategies of other decision makers. Five knowledge availability variants are distinguished:

- **Amblyopia** or "reduced vision" as partial past and present knowledge and no future knowledge.
- **Myopia** or "short sightedness" as complete past plus present knowledge but no or very limited future knowledge.
- **Hyperopia** or "farsightedness" as complete past plus present knowledge and using an expectation of the future to shape decisions.
- **Diplopia,** or "double sightedness" as partial past, present, and future knowledge. The model or actor is able to know a selection of future pathways a-priori.
- **Omniopia** or "all sightedness" as complete past, present, and future knowledge. A common mode in inter-temporal optimization models where the complete solution space is explored.

The choice of optimization or simulation affects incorporation of allogeneity, opsis, and form. Optimization models are suited for uniformity because they are formulated around objective equation(s). Pluriformity can be introduced using multi-objective programming with a particular set of objectives for each decision group solved using weighting to represent trade-offs (Antunes et al. 2004). Response heterogeneity can be expanded by using probabilistic or possibilistic techniques. The practical feasibility of expansive heterogeneity in optimization is recent, however, because of parallel computing and algorithm advancement (Hunter et al. 2013). Optimization models are normally omniopic but time-stepped variants allow myopic or hyperopic settings. An example is the National Energy Modelling System (NEMS) used for the US EIA Annual Energy Outlook which solves market equilibria in each time-period and can incorporate expected price or consumption through extrapolation (Holtberg 2013).

11

Simulation models can describe any form and allogeneic setting as demonstrated for contagious disease diffusion models (Rahmandad and Sterman 2008). However, the architecture of differential equation simulation suits aggregate approaches because bounded entities can easily be lumped under one equation. Pluriformity is achieved by compartmentalization of equation sets, and decision heterogeneity either by sub-compartmentalization per response or stochasticity (Koopman et al. 2001). Whilst theoretically possible to produce an omniform representation using differential equations tractability limits compartmentalization (Rahmandad and Sterman 2008). In cases with large numbers of decision makers, endogenous interactions, and spatial complexity, agent based simulation is better suited. The agent-based explication of conditional decisions is ideal for omniform and heterogeneous response cases (Parunak et al. 1998). In general in simulation it is difficult to include diplopic and omniopic settings as future knowledge is unknown at solution time given model structure. Indirectly future knowledge can be introduced by looping model run outputs into inputs. Hyperopic formulations are possible using forward-looking extrapolation such as in the ENGAGE agent-based model (Gerst et al. 2013).



Figure 5 - decision characteristics for implicit and explicit actor model decisions

2.2.5 TECHNOLOGICAL CHANGE

A fifth characteristic of electricity system models is technological change. It is operationalized as a set of functions which determine technology cost changes and when relevant R&D labour allocation or investment. Other aspects of technological change considered outside of the scope of this paper include demand-side and energy efficiency technology diffusion (see Barreto and Kemp 2008).

The simplest representation is by pre-determined *exogenous cost* scenarios. The model or modelled decision maker selects the cheapest technology based on a pre-determined cost evolution (Ma and Nakamori 2009), such as in the battery integration electricity cost assessment study by Mileva et al. (2016). More insightful are endogenous aggregate "off-the-shelf" cost changes of a technology using *learning curves*. The standard form approximates learning by doing as an effortless passive process using the relationship between cumulative installed capacity and investment cost. The function is based on a power law with a learning rate exponent established by an empirical fit (Söderholm and Sundqvist 2007). An expansion is the two-factor learning rate exponent. Specification of knowledge stock as dependent variables with a searching rate exponent. Specification of knowledge stock allows for knowledge depreciation as "forgetting by not doing" (Barreto and Kypreos 2004). In stochastic variants learning and searching parameter are selected from a distribution (Grübler and Gritsevskii 1997). A novel formulation presents technology adoption with limited foresight under uncertain learning using step-wise optimisation (Chen and Ma 2014).

A third approach used hitherto only in optimization models of electricity systems to the author's knowledge introduces *productivity growth based R&D* to explicate directed technical change. The R&D process improves a technologies output quantity, reduces labour, energy, and capital factor inputs, or both. The factor explication enables linkage to macro-economic growth models (Aghion and Howitt 2005). The formulation in the WITCH model takes a production function with energy efficiency where knowledge stock and energy inputs are required to deliver energy services. Thereby accumulating knowledge stock or "energy related human capital" by R&D lowers energy input requirements to deliver energy services (Bosetti et al. 2007). A second formulation in the REMIND model originates from endogenous schumpeterian growth models of quality innovations. Innovations are generated by a probabilistic R&D investment or labour allocation function with decreasing returns. If successful the innovation causes factor productivity to improve up to a maximum success parameter (Acemoglu 2009; Hübler et al. 2012). A potential advantage of the second formulation is patent explication and thus productivity evolution variation between firms (Aghion and Howitt 2005). Several other variants include technology or firm cost reduction spillover, regional technology diffusion, and regionalized cost curves (Rout et al. 2009; Thompson 2010)

The driver of R&D in optimization paradigms is introduced by adding an R&D investment term to the cost minimization objective. An exogenous R&D budget constraint caps a maximum cost change (Kypreos 2007; Hübler et al. 2012). The driver in simulation paradigms includes an R&D based learning curve, such as in the agent-based ENGAGE model with an exogenous R&D budget as a fraction of GDP (Gerst et al. 2013), and the E3MG differential equation model with induced technological change where decreasing technology costs are a consequence of investment decisions with limited information (Mercure 2012).

2.2.6 Socio-political-technical interactions

A sixth characteristic are interactions between modelled social and technological change and policies. Available models have only a limited capacity to deal with behavioural and technological responses within policy scenarios (Laitner et al. 2003). A historic example can be found in an analysis of 1978-2002 UK energy scenario studies, which ignored the incoming large expansion of natural gas starting mid-1990s, due to a prior consensus of government coal technology prioritization (Trutnevyte et al. 2016). Technological and behavioural systems and policy instruments are simplified into binary exogenous variables (Hughes and Strachan 2010). However, social and technological change are highly intertwined, and policy making is an iterative process where unforeseen issues are addressed in an evolutionary manner (Verbong and Geels 2010; Hoppmann et al. 2014). The challenge remains to endogenously operationalize this evolutionary complexity through interactions between government, firms, and civil society, whom initiate events and policies leading to profound system change (Hughes and Strachan 2010). In the absence of a working operationalization our classification is limited to inor exclusion of socio-political-technical model interactions.

Successful implementation of socio-political-technical interactions can lead to a shift from modelling policy decisions impact, to modelling mechanisms by which a policy instrument affects outcomes, and ultimately into endogenous pathways of policy action as model results (Neij and Åstrand 2006). Initial knowledge can be gained through pathway exercises including socio-technical interactions (Foxon 2013; Bolton and Foxon 2015), stakeholder derived model scenarios with explicated socio-political-technical interactions (Schmid and Knopf 2012), classification of built and conceptual model elements alongside socio-political-technical lines (Wu 2015), and social science theory such as the morphogenesis of decision making structures and civil society action (Archer 1996).

2.3 MODEL SCENARIO EXERCISES

The policy problem analyses as discussed in section 2.1 can be implemented using models via scenario exercises. Six scenario exercises as discussed by Börjeson et al. (2006) are here recast to align them with computer model based approaches for carrying out particular policy problem analyses. Three main scenario types are outlined, **predictive** which looks into how a system will evolve under a-priori assumed trends, **explorative** which focuses on system evolution through interactions as a sequence of events and responses, and **normative** which investigates how a system target can efficiently be met.

The purpose of a **predictive forecast** is to improve insights into what will happen within a single scenario given a set of trends. The scenario includes a-priori chosen policy instruments plus system parameters and has a high perceived probability. The approach is helpful to carry out an *indicator assessment* either of proposed policies, or to track performance of a goal under present policies. The second exercise, **predictive what-if**, is used to gain insights in what will happen by exploring at minimum two scenarios given varying sets of trends. Variations can include a-priori defined what-if type events, model structure alterations, and parametric settings between models runs. The exercise can be used for *instrument comparison* and *option reduction* to test whether a policy instrument leads to minimum desirable impacts.

The third exercise, **explorative external**, functions to assess what can happen following sub-sequent natural or societal events assuming present policies as fixed. The aim is to model systems evolution at firm and societal level to assess resilience to events. Resilience can be operationalised by tracking economic, technical, and political feasibility states using indicator variables. Results can be interpreted for *problem discovery* and *societal paradigm change* analyses to understand which events are of significance for further exploration, to examine pre-emptive action, or as part of contingency preparation. **Explorative strategic** exercises focus on what can happen due to sub-sequent events inclusive of endogenous policy interaction. The goal is to find a robust set of policies and their implementation path to cope with systems change, combining *instrument comparison*, *problem discovery*, and *political and societal paradigm change* analyses.

The fifth exercise **normative preserving** serves to understand how predefined target(s) can efficiently be met. The approach, suitable for *indicator assessment* and *instrument comparison*, sets an objective to find the feasibility of certain targets, or an optimum policy instrument level, assuming continuity of key socio-economic characteristics like demand growth. The use for option reduction is excluded because the necessary optimization approach sheds a substantial number of sub-optimal solutions, which are plausibly relevant. Finally, **normative transforming** exercises aim to provide insight in how predefined target(s) can be efficiently met inclusive of socio-political-technical change. The exercise uses optimization to find societal structures and policy instruments that need to change to optimally reach a target. The approach combines *instrument comparison* and *political and societal paradigm change*.

3. RESULTS

3.1 POLICY PURPOSE TO MODEL CHARACTERISTICS FRAMEWORK

The model characteristics form a classification structure of electricity system models. Eight categories are the result including the temporal structure in annual, time-slice, or continuous approaches. Each category has its own member level as chosen by the modeller and described in section 2.2, whose relevance within the model scope is indicated with a sub-system reference 1,2 and 3 (figure 6). For example, since electricity market sub-systems deal with short-term the technological change characteristic is not relevant.



Figure 6 – a classification structure of electricity system models using six model characteristics. Numbers 1, 2 and 3indicate relevance for electricity market, grid flow, and capacity expansion components.

The described model characteristics are linked to the six scenario exercises on the basis of execution requirements. Such links are made on the basis of logical reasoning constrained by presented scenario descriptions (section 2.3). For example, a predictive forecast necessitates simulation since it looks at what will happen given a set of trends, as opposed to what needs to happen given a set target in the future. It is a deterministic exercise since a single scenario run is undertaken and thereby uncertainty is ignored for simplification purposes. Similarly it is aligned to a single scenario, decision maker representation is homogeneous, decision makers are uniform or at best pluriform, and opsis is limited to cases without future knowledge due to the simulation paradigm. Technological change is exogenous and socio-technical-political aspects are excluded as endogenous variants would defeat the purpose of presenting a uniform single scenario. These links for all scenario exercises to model characteristics are presented in table 1.

Scenario type	Predictive		Explorative		Normative	
Model aspect	Forecasts	What-if	External	Strategic	Preserving	Transforming
Indicator assessment	Х	Х			Х	
Problem exploration			Х	Х		
Option reduction		Х				
Instrument comparison				Х	Х	Х
Political paradigm				Х		Х
Societal paradigm exploration			Х	Х		Х

Table 1 – Coupling between scenario exercises and their purpose for policy problem treatment

Scenario exercises have a purpose in carrying out a particular policy analysis purpose or combinations thereof (section 2.1). Some scenario exercises are better suited for particular purposes given their approach and related model capabilities detailed above. For instance, a model analysis of a societal paradigm shift in favouring a particular technology, outside of pure economic reasons, requires interactions which transform the socio-economic system and thereby can relate to explorative external, explorative strategic or normative transforming scenarios. The other scenario exercises assume relative continuity in key socio-economic characteristics barring their employment for analysing societal paradigm shifts. A potential structure of links between the six scenario exercises and their assigned purpose of policy problem treatment are shown in table 2. Finally, all three aspects of model characteristics, scenario exercises, and policy problem analysis purpose can be brought together as shown in figure 7 below. An overview of the linkage between model characteristics and scenario exercises can be found in table 2 below.

Scenario type		Predictive		Explorative		Normative
Model aspect	Forecasts	What-if	External	Strategic	Preserving	Transforming
Modelling	Simulation	Simulation	Simulation	Simulation	Optimization	Optimization
Paradigm						
Parametric	Deterministic	Deterministic/	Stochastic	Stochastic	Deterministic/	Recursive
uncertainty		Uncertainty	generators	generators	Multi-stage	dynamic
treatment		Propagation			Stochastic	stochastic
Decision maker	Uniform or	Uniform or	Pluriform or	Pluriform or	Uniform or	Uniform or
allogeneity	pluriform	pluriform	omniform	omniform	pluriform	pluriform
Decision	Homogeneous	Homogeneous/	Homogeneous/	Homogeneous/	Homogeneous/	Homogeneous/
response		Heterogeneous	Heterogeneous	Heterogeneous	Heterogeneous	Heterogeneous
Knowledge	Amblyopia/	Amblyopia/	Amblyopia/	Amblyopia/	Myopia/	Myopia/
availability	Myopia /	Myopia /	Myopia /	Myopia /	Diplopia/	Diplopia/
(opsis)	Hyperopia	Hyperopia	Hyperopia	Hyperopia	Omniopia	Omniopia
Technological	Exogenous	Deterministic	Stochastic	Productivity	Deterministic/	Productivity
change		learning	learning curve	growth based	Stochastic	growth based
		curves		R&D	learning curve	R&D
Socio-political-	Excluded	Excluded	Included	Included	Excluded	Included
technical change			dynamically	dynamically		deterministically

Table 2 – coupling between scenario exercises and model characteristics



Figure 7 - relations between policy purpose, scenario exercises, and model characteristics.

3.2 GERMAN ELECTRICITY STUDIES REVIEW

The section provides a summary of 11 German electricity system studies in relation to characteristics of employed models, scenario exercises executed, and the purpose of policy problem analyses. Study details are available in online supplement A.

Half of the studies attempt to ascertain cost, generation change, dispatch, or grid stability implications of 80% CO₂ reduction by 2050, the nuclear phase-out decision, or both. Others include electric vehicle grid integration, power-to-gas technology with high renewable penetration, and electricity plus transport interactions. Nine studies use optimization and two soft-link simulation to optimization, focusing respectively on generation investments plus electricity markets, and grid dispatch (Dallinger et al. 2013; Grave et al. 2012). Of the optimization models six operate deterministically without publication of sensitivity analyses exploring uncertainty. Two studies present uncertainty propagation using parameter variation (Bruninx et al. 2013; Knopf et al. 2014), and one incorporates multi-stage stochastic programming (Schröder 2012). The two simulation-

optimization models use stochastic generators for renewable power dispatch and market decision uncertainty.

One of the simulation-optimization models is agent-based (Dallinger et al. 2013) the other differential equation based (Grave et al. 2012), both employing a myopic approach and respectively omniform heterogenous and uniform homogeneous settings of decision makers and responses. All except one optimization model incorporates a "central planner" uniform setting with homogeneous and omniopic complete knowledge decisions. The only multi-stage stochastic optimization model used a market equilibrium approach in each period with complete firm representation and myopic knowledge limited to 5 years (Schröder 2012). Two optimization models employ passive learning curves and none R&D or productivity growth based technological change (Fürsch et al. 2012; Schmid and Knopf 2012; Schmid et al. 2012). However, an expansion of the REMIND model employs schumpeterian productivity growth (Hübler et al. 2012). The other models utilise exogenous technology cost scenarios. Finally, no models demonstrate socio-political-technical interactions, but one exercise included scenarios a-priori assuming socio-technical interactions (Pregger et al. 2013).

Eight of the eleven studies take a *normative preserving* approach to observe how renewable transition target(s) can efficiently be met, a-priori assuming trends and varying one policy decision or technology. The others are two *predictive forecasts* that investigate one scenario contingent upon technological change (Dallinger et al. 2013; Jentsch et al. 2014), and one *normative transforming* study a-priori assuming socio-technical interactions in six scenarios (Pregger et al. 2013). No analyses for option reduction, problem discovery, or political and social paradigm change were located. Exercises are thus carried out for *indicator assessment* such as GDP and CO₂ emissions, and *instrument effect* analyses like the nuclear phase-out or power-to-gas technology policy support.

3.3 MODEL CAPABILITIES TO REPRODUCE HISTORIC SYSTEM TRENDS

In this section the results are presented of an analysis on model capabilities of the 11 German electricity system models to reproduce historic German electricity system trends in relation to characteristics built into these models. Since 1990 German power plant capacity grew from 126 GW to 175 GW in 2011, primarily from onshore-wind and solar-PV, yet fossil fuel power dispatch only dropped from 67% to a 58% electricity mix share (figure 8).



Figure 8 - German generation capacity development in GW (left) and total gross electricity production in TWh (right) from 1991 to 2011. Source of data: BMWI (2013).

Six observable trends from 1991 to 2011 defined changes in Germany's electricity mix. First, slow electricity demand growth, at 0.8% average from 1991-1999, 1.6% for 2000-2008, and since a stable 620-630 TWh. Demand change is exogenously included as part of the scenarios in 10 out of 11 model studies. Endogenous demand change was incorporated in Schröder (2012) using a relation between economic output and energy service requirements. Second, end of life power plant closures, incorporated in the eleven models as a fixed or usage dependent technical lifetime of power plants. Third, fossil fuel power plant upgrades and new-builds, with 6.8, 6.1, and 3.4 GW of respectively natural gas, lignite, and bituminous coal capacity built from 2000-2013. Fossil fuel capacity development in the model studies is based on endogenous investment or least cost selection in the electricity system. Fourth, the rise of (community based) renewable energy, between 1991-2012 onshore wind grew from 0.1-31.3 GW, and between 2000-2012 solar-pv grew from 0.1-33 GW and biomass from 0.5-5.71 GW. A majority share is community owned such as onshore wind at 50.4% private citizens ownership, 39.4% by institutional and strategic investors, and 10.2% by utilities (Trend:Research 2013). The ability to endogenously incorporate this trend is limited. Nine employ exogenously fixed renewable electricity capacity developments, one uses a forced minimum 50% primary energy from renewables constraint (Nagl et al. 2011), and another a 'central' planner selection using passive learning curves interacting with capacity expansion (Schmid and Knopf 2012). Five, nuclear phase-out, after the 2011 Fukushima nuclear accident eight nuclear power plants with 8.4 GW capacity were shut-down and another nine with 12 GW are to be closed between 2015-2022. In all studies this is a scenario selection choice. Six, announced closures of peak-load fossil fuel **plants**, caused by competition of feed-in benefitting wind and solar with priority grid access. The four German utility giants have submitted closure approvals to the regulator BNetZa for 7.7 GW from 2014-2018 (PennEnergy 2014), primarily natural gas peaker plants at 6.8 GW capacity of which 2.2 GW built from 2006-2010 (see online supplement B). This trend is excluded in model studies with a perfect information approach, as this precludes unprofitable investments due to price uncertainty. The model in Schröder (2012) could capture this effect by virtue of the multi-stage stochastic approach.

4. DISCUSSION

This paper presents an analytical framework to aid thinking about the purpose of electricity system model use for policy analysis. In particular how capabilities of models based on their characteristics determine the ability to carry out scenario exercises for a specific purpose. The explication of model characteristic to policy purposes and scenario exercises aids thinking about policy relevance in constructing models and formulating model scenario exercises. First, the framework guides model selection and enhancement in light of desirable scenario exercises. Second, transparency is increased on model capabilities to carry out specific policy problem analyses. Third, the problem analysis purpose to scenario exercise relation can be used in communication with policy makers as a common entry point, used to collaboratively explore policy needs and underlying model capability requirements. The framework's limitations are its precision, or lack thereof, in formulating scenario exercises and create model characteristic and problem analysis relations. For instance, normative preserving exercises can uncover problems such as grid limitations (Bruninx et al. 2013), but their use to problem discovery is limited because of optimization constraints and few interactive elements. Notwithstanding remaining grey areas, explication serves as a richer base for discussion and model critique to be built upon. Another discussion point relates to the identification of existing capabilities of German electricity system model studies and their characteristics. The sample of 11 models is a

cross-section of the 90+ models in existence, and study findings are not directly externally valid for all electricity models, unless this sample is fully representative. However, the extent to which individual characteristics are captured has partially been captured and discussed in the overall review in absence of a complete analysis of all existing models.

5. CONCLUSIONS

The study was set out to accomplish three objectives. The first objective was to provide a framework to structure thinking about model building and use for scenario use to policy insights. The analysis was built by separately discussing each aspect: policy problem analyses, model characteristics, and scenario exercise types. And subsequently the objective was met by linking all three components into a framework in section 3.1 to provide the sought after structure.

The second objective to provide insights in what type of policy problem analyses are at present feasible was carried out by examining German electricity model scenario studies. It was found that present model studies are dominated by a-priori fixing key input parameters and strong constraints. In some cases bordering on locking in model results since the outcome becomes mentally predictable one or two key parameters, such as the relative costs of coal and gas. The implication for the present state of electricity system models is that the model purpose of policy problem analysis is limited in purpose to *indicator assessments* and *instrument analyses* under a situation of pre-selected policy instrument(s). Modelling means are not sufficiently available to explore which problems deserve policy attention, or what solutions among a range of instruments are best suited, as modelling capabilities are either in their infancy, or too recent for widespread inclusion. Model use for *option reduction, problem discovery*, and *political or societal paradigm exploration* thus at large remains out of reach.

The third objective was to examine the existing characteristics of models to analyse what improvements can be made to expand the scenario to policy insights. This was accomplished by studying the particular characteristics of the 11 German models and their scenarios, which uncovered the following specific areas of improvement:

- Lack of endogenous capacity change in renewable technologies including different policy effects as a structural model feature.
- Limited use of existing modelling techniques dealing with uncertainty, especially the lack of parameter sensitivity analyses.
- A dominant focus on "central planner" uniform approaches with perfect information, excluding market competition and knowledge limitation effects.
- Exclusion of socio-political-technical features in models through government, firm, and societal interactions, barring modelling system aspects such as technology niche creation and renewable community ownership effects.
- Dominance of exogenous technological change, minor use of passive learning by doing, and no applications of R&D investment and productivity growth approaches.

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Most limitations can be overcome by adjusting model structure with available techniques, changing model constraints, or increasing model runs and parameter variation. A major challenge for the field is the modelling of socio-political-technical interactions, necessary to enable a shift from *solution analysis*, to *solution discovery* and *problem analysis*, so as to bolster policy-relevance of electricity systems models.

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27

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