Coping with Uncertainties in the Electricity Sector - Methods for Decisions of Different Scope

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ABSTRACT

Decision-making in the energy sector and notably the power industry has to cope with multiple uncertain factors such as renewable forecasts, technology developments or demand growth. At the same time, multiple methods are available to support decision-making under uncertainty. The focus of the present review is to identify the merits of different optimization modelling approaches regarding various types of decision problems under uncertainty with a focus on the electricity system. Stochastic optimization and robust optimization are scrutinized along with other, less known methods like information gap decision theory (IGDT) or modeling-to-generate-alternatives (MGA). Also, simple deterministic equivalents, scenario and sensitivity analyses are considered when it comes to solving operational decision problems, investment decisions and policy choices regarding regulatory settings. The latter deserve particular scrutiny in a context of decarbonization and energy system transformation which embraces several decades and multiple decision makers in a multi-level governance context.

Keywords: Electricity system, Stochastic optimization, Robust optimization, Information gap decision theory, Modeling-to-generate-alternatives, Scenario analysis, Sensitivity analysis

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1. INTRODUCTION

Uncertainties are ubiquitous in everyday life and in business - there are even theories of the firm that conceptualize firms and other organizations as institutions to reduce revenue uncertainties (Schneider 1995). At the same time, the standard models for energy markets and energy decision support frequently do not deal explicitly with uncertainties (for an overview cf. e.g. Ventosa et al. 2005) - while there is a burgeoning stream of research over at least the last three decades trying to develop decision support models that explicitly deal with risk and uncertainty in the energy context. As many of these models are optimization models, the subsequent discussion focuses on this model category. We therefore leave aside for future review the further categories discussed by Ventosa et al. (2005), namely equilibrium and simulation models. Optimization models are especially used to analyze pathways for the decarbonization of the energy system at different scales (e.g. Balyk et al. 2019; Gerbaulet et al. 2019; Huppmann et al. 2019) - which implies time horizons of several decades and correspondingly large

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uncertainties. Against this background, the present contribution primarily aims to bridge the gap between the specialist literature and the general and political debate on uncertainties related to energy systems and their transformation with a focus on the power system as a key sector for decarbonization. The question to be addressed is thereby less of the order on how to do things right but rather on how to do the right things, i.e., what are adequate models for different types of decision problems.

In this perspective, we subsequently first provide a typology of decisions in the energy sector and also discuss different types of uncertainties (Section 2). Based on these typologies, we then provide an overview of different methods to incorporate uncertainties in various decision support models (Section 3). We thereby distinguish operational and investment decisions at the company level as well as political decisions on regulatory settings. Uncertainties are particularly challenging in the latter context - and yet the way forward is not necessarily through using the most advanced decision theoretical models. Nevertheless, improved conceptual framings may be helpful to address the still largely unresolved challenges of energy and climate policy - as is discussed in the concluding Section 4.

2. ENERGY-RELATED DECISIONS AND UNCERTAINTIES

The energy and especially the electricity sector are characterized by long-lived investments along with considerable political interference - the latter being related both to the networks being monopolistic bottlenecks and to the energy sector being the by far most important contributor to Greenhouse Gas emissions and also other air-borne emissions. An obvious classification of energy-related decisions is thus according to the type of decision makers and the degree of commitment. This leads to three basic types of decisions (cf. also Fig. 1):

1. Political decisions on regulatory settings
2. Corporate investment decisions
3. Corporate operational decisions

It is worth noting that at all three levels, different types of decision makers have to be distinguished. In many cases, decisions are also not taken by single decision makers as frequently assumed in normative decision theory but by groups of decision makers, e.g., the members of the board of a company or the members of parliament.

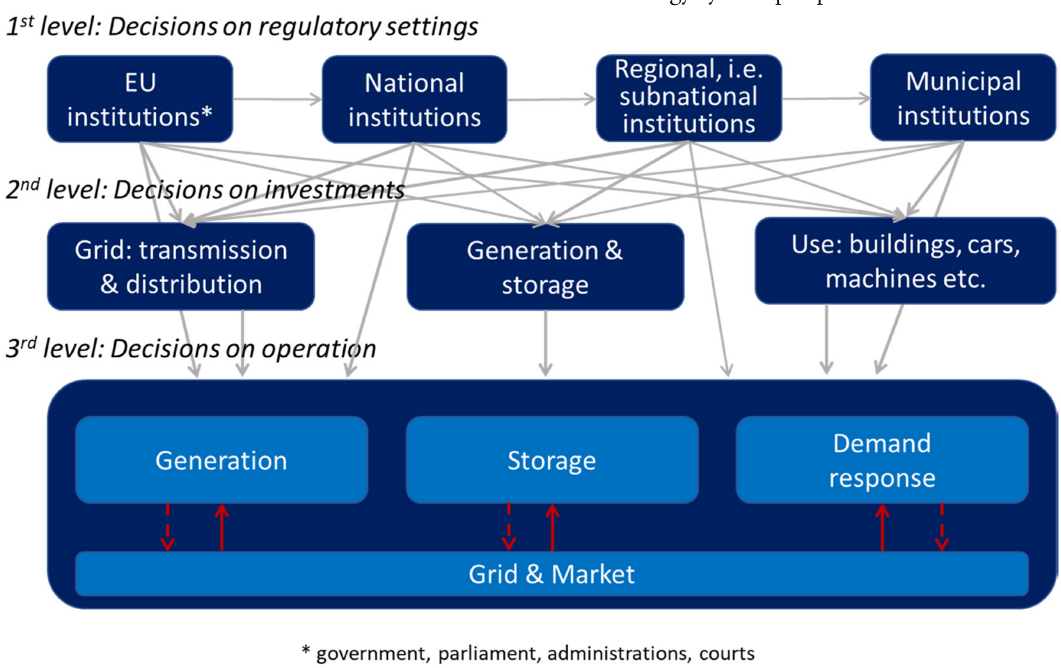
As depicted in Fig. 1, political decisions are made at the supranational, national, regional, and even local level. The latter are for example relevant when it comes to defining priority areas for the installation of new wind turbines. In general, political decisions involve multiple stakeholders and are taken under consideration of multiple objectives. In addition, cause-effect relationships and interactions for many policy instruments are uncertain. This applies especially to the case of price-based instruments and support mechanisms such as CO_2 taxes.

The second level of decisions comprises investment decisions. They do not only have long-lasting effects, but they are frequently lumpy (e.g., construction of a certain line or not). Consequently, they typically also have a high financial impact on the companies requiring thorough risk assessments. In terms of riskiness, it is important to distinguish between investments in regulated network businesses and investments in other parts of the energy value chain. For the former, corporate risk remains limited even under so-called incentive regulation (Littlechild 1983; Jamasb and Pollitt 2000) given that prices are regulated, and customers are unable to change the service provider. In deregulated markets, risks are prima facie much larger, as various uncertain and stochastic factors influence profitability. For instance, investment decisions in generation facilities are based on anticipated revenues earned on the electricity markets for up to several decades in the future which are subject to uncertain future conditions like the development of electricity demand, CO_2 and fuel prices or the evolution of generation and storage capacities (cf. e.g. Weber 2005; Hasani and Hosseini 2011). Obviously, both the risk and the return of these investments may be strongly affected by political decisions such as support mechanisms for renewables or phase-out decisions.

On the third level are the operational decisions. These decisions are made by market participants as well as network and system operators. Examples of operational decisions in the European market context are the submission of bids to energy and reserve markets by power plant operators or portfolio marketers. Grid operators have to determine the commercial transaction constraints for market coupling or decide on switching operations. A distinctive feature of operational decisions compared to investment decisions is that they are taken repeatedly, e.g., daily. The specific circumstances for the decisions may vary from day to day, yet the type of decision to be taken remains the same. Still, important short-term uncertainties may arise from various operational factors such as infeed of renewables, demand, power plant and line availabilities, etc.

FIGURE 1

Decisions and decision-makers in a national energy system perspective.



Source: Own illustration.

In normative decision theory, decisions under uncertainty are generally subdivided into decisions under risk and decisions under ignorance (Peterson 2009; Bamberg et. al. 2019). Decision-making under risk refers to a setting where objective probabilities for the outcomes of uncertain factors are available and known, e.g., from past observations of weather.[1] In this case, the basic decision rule according to normative decision theory is to maximize the expected

1. As a consequence of climate change, probabilities obtained from past observations may yet be adjusted.

utility of the decision maker (e.g. Peterson 2009, 65s.). Under ignorance (also referred to as Knightian-uncertainty, cf. Knight 1921), no objective probabilities are available. Following Savage (1954), subjective probabilities might be used in such a case and the corresponding decision rule then is the maximization of subjective expected utility. In a multi-person decision making context, agreeing on subjective probabilities is yet challenging.

Regarding the description of uncertainties themselves, more detailed classifications have been proposed inter alii by Soroudi and Amraee (2013) and Aien et al. (2016). They classify uncertainty modeling methods into six categories, which in fact refer partly to the characterization of the uncertain parameters itself and partly to the corresponding decision-support models: Besides the probabilistic, possibilistic, and hybrid possibilistic-probabilistic methods they identify the information gap decision theory, interval-based analysis, and robust optimization as approaches to cope with uncertainties.

Subsequently we yet rather take the decision situations as starting point for classifying the multiple available methods. In view of energy-related decision support, we may distinguish decisions according to:

1. The type of decisions,
2. The type of uncertainties present,
3. The characteristics of the decision makers.

Subsequently we primarily use the first distinction but will come back to the other two where appropriate. Regarding the characteristics of the decision makers, the number of decision makers is particularly important, since a common consistent preference ordering may not exist in the case of multiple decision makers. Also risk aversion is an important characteristic of many decision makers.

3. METHODS TO SUPPORT DECISION-MAKING IN POWER SYSTEMS UNDER UNCERTAINTIES

Given the previous considerations, we subsequently discuss the methods available for energy-related decision support by type of decision. We start with operational decisions, even though the regulatory settings and the investment decisions are usually a prerequisite for operational decision-making. Yet taking the last decisions first is conceptually in line with Bellman's principle of optimality (Bellman 1957), which implies that the last decisions should be considered first and then solutions for preceding stages may be induced. Another reason for discussing operational decision-making first is that there is a very broad body of literature available in that field regarding the treatment of uncertainties. When it comes to giving examples we subsequently focus on the electricity system for two reasons: on the one hand, forecast uncertainties are most relevant in that field given the limited storability of electricity, on the other hand there is also the largest body of literature in this field, notably in connection with optimization models.

Thereby it is worth noting that the introduction of competitive electricity (and gas) markets has led to a much more dynamic market environment and this has also increased both the number of uncertain factors and their relevance. Notably electricity market prices at the wholesale level are an important yet uncertain factor when it comes to both operational decision-making and investments. Ventosa et al. (2005) present an overview of methods for electricity market modeling. They categorize the existing approaches into three main classes, namely optimization models, market equilibrium models and simulation tools. Subsequently, the focus will be on optimization models as they reflect the ambition of decision makers to make the best possible decisions. At the same time, they are also frequently used to describe market outcomes in settings with perfect or at least working competition.

3.1 Operational decision-making

Most deregulated electricity markets are characterized by a sequence of markets, supporting the planning and coordination of system operation under uncertainty. Major operational decisions like unit commitment are usually done with a certain lead time, e.g., on a day-ahead basis. Subsequent market timeframes like intraday, balancing, or real-time markets support dispatch decisions and serve to balance and operate the system in real-time. Besides the buy and sales decisions on the different markets, corresponding operational decisions are taken repeatedly on a day-to-day, hour-to-hour or even intra-hour basis.

The most well-studied operational decision problem in the energy sector is without doubt the unit commitment and dispatch problem, i.e., the problem of determining the optimal power plant operation schedule. In European style electricity markets with self-scheduling of generators, the problem is solved by each generation company individually whereas in the U.S. and in similar centrally organized markets it is solved by the system operator jointly with the market clearing and congestion management problem. Traditionally, the unit commitment and dispatch problem is formulated as a deterministic mixed-integer problem (e.g. Sheble and Fahd 1994; Baldick 1995; Padhy 2004).

Even before the liberalization of the electricity sector, uncertainties such as failures of generation units and demand forecast errors have been considered in several models (e.g. Dillon et al. 1978; Bunn and Paschentis 1986). While demand forecasts have been improved over time, the increasing feed-in of intermittent renewable energy sources has led to new sources of uncertainty and has spurred the development of new approaches.

In the deregulated market context, the following major approaches have been put forward to cope with uncertainties in unit-commitment and dispatch (cf. the reviews by Zheng et al. 2015; van Ackooij et al. 2018):

- Use of the deterministic equivalent
- Stochastic optimization
- Chance-constrained optimization
- (Stochastic) (Dual) Dynamic Programming
- Robust optimization

3.1.1 Deterministic equivalent

This approach corresponds to a continued use of the traditional deterministic approaches - considering that some or all parameters in the model may be uncertain but can be represented by their ex-ante expected values (cf. Birge and Louveaux 2011). This approach is straightforward and rather rapid and may be complemented by sensitivity calculations to cope e.g., with major unforeseen events such as line outages. This is still the common practice in the North American ISO markets (cf. Litvinov et al. 2019) and also in many self-scheduling European utilities. In the North American ISO markets, deterministic day-ahead unit commitment is thereby frequently complemented by network security checks (so-called security-constrained unit commitment SCUC, e.g. Fu et al. 2005).

3.1.2 Stochastic optimization

Stochastic optimization, also known as stochastic programming, explicitly considers the future uncertain values of some parameters. With emphasis on the unit commitment problem under uncertainty, Zheng et al. (2015) and van Ackooij et al. (2018) discuss the basic structure of the underlying problem and review main contributions with regards to stochastic methods. Zheng et al. (2015) also emphasize that the modelling of the uncertainties themselves is key for the obtention of good results in stochastic optimization.

This notably requires the selection of the stochastic factors to be considered explicitly and an appropriate modelling and empirical estimation of the corresponding stochastic processes. The most important uncertain factors in future energy systems will be probably wind and solar forecasts (cf. the reviews by Zhang et al. 2014; Antonanzas et al. 2016) along with demand uncertainty for electricity (cf. Hong and Fan 2016) and possibly also heat (in case of combined heat-and-power systems). But power plant and line outages may also be considered explicitly and in hydro-dominated systems, inflow uncertainty may be a major driver of system operation. In the case of European-style power markets, unit commitment and dispatch are handled at the level of individual generation companies. They are thus less interested in the system-wide infeed from renewables and electricity demand levels but rather take forecasts of electricity prices (cf. Nowotarski and Weron 2018) as inputs for their bidding and generation scheduling.

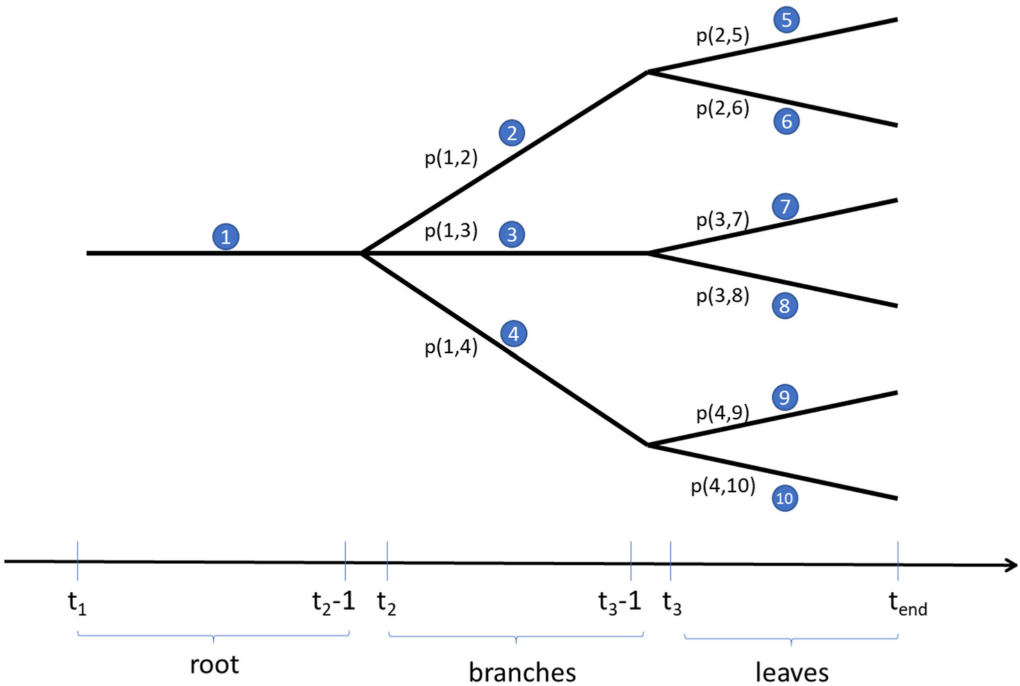
Based on empirical estimates of the stochastic process parameters, usually Monte-Carlo simulations are performed to obtain multiple possible realizations of the uncertain factors. These need then to be condensed into a limited number of scenarios to make stochastic optimization programs manageable. Two basic approaches are in use for scenario reduction, on the one hand iterative scenario reduction techniques based on probability metrics (e.g. Dupacova et al. 2003; Heitsch and Römisch 2009) and on the other hand moment-matching approaches (e.g. Høyland et al. 2003). Recent research suggests that instead of the Wasserstein distance underlying the previously mentioned scenario reduction approaches, the so-called energy distance may be more appropriate for scenario reduction when it comes to preserving statistical properties like the mean or variance of the original simulations (cf. Ziel 2020).

The resulting scenarios then form a scenario tree as depicted in Fig. 2. As shown in Fig. 2, the distribution of uncertain parameters is approximated by a finite number of possible situations, or scenarios. A scenario tree is composed of one root node (1) followed by several branches (2 to 4), which have their termination points in leaves (5 to 10). The transition between the nodes is described by transition probabilities (p(1,1) etc. in Fig. 2). The root stands for first-stage decisions. An example for a typical root decision is the unit commitment for large conventional power plants, which has to be decided day-ahead.

The branches and leaves correspond to further decision stages, with decisions being made after the arrival of new information, e.g., update of demand forecasts. Based on this information, the root decisions are modified whenever beneficial and possible. In this terminology, a scenario is a path from the root to one leaf. Decision stages correspond to different moments in time where decisions are taken. In early stages, several scenarios share the same information and the same decisions as depicted by the successive bifurcations of the scenario tree. Note that in many energy modelling applications, each stage may comprise several time steps as depicted in Fig. 2.

Considering the typical decision structure of liberalized electricity markets with day-ahead markets and subsequent intraday or real-time markets, a two-stage stochastic program seems a natural choice. Two-stage stochastic programs have been extensively studied theoretically

FIGURE 2
Representative sketch of a scenario tree.



Source: Own illustration.

(e.g. Carøe et al. 1997; Birge and Louveaux 2011), as well as regarding applications to power systems (e.g. Nürnberg and Römisch 2002; Bouffard and Galiana 2008; Garcia-Gonzalez et al. 2008). Notably Papavasiliou and Oren (2013) model the unit commitment of slow generation units in the first stage and the unit commitment of fast units and dispatch of all units in the second stage. Their model considers uncertain wind production and failures of generation units and transmission lines.

Considering continuous updates of uncertain parameters like wind production, various authors also develop multi-stage stochastic programs. Both Carpentier et al. (1996) and Takriti et al. (2000) focus on the unit commitment problem and consider random failures of generation units through scenario trees. They find that the stochastic models lead to significant cost savings compared to a deterministic model, where inherent uncertainties like generation outages are considered by reserve margins. The WILMAR model, as presented notably in Tuohy et al. (2009) and Meibom et al. (2011), implements a three-stage recursive approach, which allows to model uncertain forecast errors of wind and other renewable production for large-scale systems. Accordingly, the day-ahead market and unit commitment problem is solved (root decision) and decisions are reoptimized after the arrival of new information, i.e., more accurate wind power forecasts (recourse decision). For the simulation of future operational decision-making, the model is combined with a rolling-horizon approach that allows to analyze the operation for entire years in the future.

Instead of minimizing the expected costs, stochastic programming may also be modified to include risk-aversion by decision makers (e.g. Schultz and Tiedemann 2006; Carrion et al. 2007; Lima et al. 2018). Thereby usually the conditional Value-at-Risk (cVaR) or first-order lower partial moments (LPM) are used, since these are coherent risk measures (cf. Artzner et al.

1999) and preserve a (mixed-integer) linear program formulation. Yet with respect to repeated operational decisions like unit commitment and dispatch, decision makers are likely to be only mildly risk averse - as the potential losses for each single decision sequence are limited and losses on one day are likely to be compensated by gains on other days.

3.1.3 Chance-constrained programming

In the case of stochastic programming, the uncertainty in parameters translates into an objective function that reflects a weighted sum of the different possible scenarios. Chance-constrained programming rather considers the probabilities of different outcomes by defining probabilistic constraints, i.e., constraints that have only to be fulfilled with a certain probability. This may be seen as an appropriate way to handle some technical constraints like minimum up and minimum downtime constraints or ramping constraints which are in fact rather engineering estimates than strict physical system constraints. Violating them with a small probability may be tolerable. Applications in the field of unit commitment and dispatch may be traced back to Ozturk et al. (2004). Other contributions include Wang et al. (2012) and Pozo and Contreras (2013). A major drawback of chance-constrained programming is that probabilistic constraints may lead to non-convex problems which are both computationally demanding and with global optimality of solutions being difficult to prove.

3.1.4 Stochastic dynamic programming and stochastic dual dynamic programming

In hydro-dominated power systems, the natural variation in rainfall and other weather variables introduces a source of uncertainty that impacts the reservoir levels and corresponding available energy strongly at time scales of weeks and seasons. Implementing this as a stochastic program would require multiple stages and correspondingly a huge number of decision variables - implying very long solution times for the resulting stochastic program. If only the reservoir levels are included in time-coupling constraints and the number of such time-coupling variables is hence limited, an alternative formulation and solution approach is possible. This is a stochastic version of the dynamic programming approach going back to Bellman (1957). Thereby the reservoir filling levels as key decision variables are discretized and decisions are determined starting from the final stage of the planning horizon and solving the problem recursively backwards in time. At each stage, the optimal decisions are taken considering the expected value of water remaining in the reservoirs ("cost-to-go") which has been derived from the following time step. Turgeon and Charbonneau (1998) study the hydropower system of Quebec (Canada) while Wolfgang et al. (2009) analyze the Nordic power system applying stochastic dynamic programming to find the optimal strategy of hydropower generation.

As an alternative to stochastic dynamic programming, Pereira (1989) and Pereira and Pinto (1991) develop an approximate algorithm called stochastic dual dynamic programming. The algorithm aims at providing efficient solutions for large-scale systems. It has been first used to determine optimal short- and mid-term storage strategies for hydro-dominated power systems like Brazil or Norway (e.g. Rougé and Tilmant 2016). Later, the algorithm has been extended to long-term problems covering planning horizons over several years (e.g. Gjelsvik et. al. 2010). A piece-wise linear approximation of the expected-cost-to-go function is obtained from the dual solutions of the optimization problem at each stochastic stage, making use of the so-called Benders decomposition (cf. Benders 1962). Guigues and Römisch (2012) consider risk-averse formulations of multistage stochastic linear programs and use stochastic dual dynamic programming to approximate the recourse function.

3.1.5 Robust optimization

One of the basic requirements of the discussed stochastic programming approaches is the knowledge of the relevant uncertainties and their stochastic characterization, i.e., the probabilities of occurrence. Where this information is not or only partly available, other uncertainty modelling techniques like robust optimization can support operational decisions.

Robust optimization is based on the idea that parameters subject to uncertainty are not described by their probability density function but modelled through an uncertainty set. This set, also called ambiguity set, allows to consider all possible realizations of the uncertain parameters and then the optimum is sought for the worst-case realization. The standard security-constrained unit-commitment and dispatch problem (SCUC) may be considered as a particular case of robust optimization with a finite uncertainty set corresponding to the contingencies (line outages) considered (cf. Street et al.2011). Yet generally, continuously valued uncertainty sets are considered in robust optimization, in the simplest case based on value ranges for all uncertain parameters (so-called uncertainty box model). A robust optimization approach to solve the security-constrained unit commitment problem considering uncertainty sets of nodal net injections is developed in Bertsimas et al. (2013). Other applications of robust optimization to the unit commitment problem include Jiang et al. (2012) and Zhao et al. (2013).

Information gap decision theory (IGDT) may be seen as a reverse-engineered version of robust optimization. It also does not consider the probability of uncertain parameters, but rather focuses on the differences between parameters and their best estimate. Then the impact on decisions is evaluated and for a given maximum deviation from the optimal outcome, the allowable deviation in the input parameters is estimated. The concept is often applied in fields like biodiversity or water resource management (e.g. Hipel and Ben-Haim 1999), yet Mohammadi-Ivatloo et al. (2013) and others provide applications to the unit commitment and dispatch problem for self-scheduling generation companies. It is particularly useful if no empirical observations are available to estimate parameter uncertainty.

Distributionally robust optimization on the contrary aims at using available empirical observations and a corresponding distribution estimate for the uncertain parameters like renewable infeed. Yet it considers the possibility that the actual distribution may deviate from the estimated one, e.g., due to data errors, lack of observations or inadequate distributional a-priori assumptions. Therefore, decisions are robustified against possible deviations from the estimated distribution. The size of the deviation is often evaluated using the so-called Wasserstein metric, which provides an integral measure of the distance between two distributions. A first application to the unit commitment and dispatch problem can be found in Xiong et al. (2017), further applications include Duan et al. (2018) and Zhao and Jiang (2018).

For both robust optimization and information gap decision theory, the solutions obtained are rather conservative since the optimization focuses exclusively on the worst-case outcome. Robust optimization is therefore also labelled a min-max strategy since it minimizes the maximum of all possible cost outcomes (or max-min in case of profit maximization). It corresponds hence to highly risk-averse decision making. This contrasts with stochastic optimization which minimizes the expected value of costs in its standard version. By including a risk term such as CVaR or LPM, varying degrees of risk aversion may also be included in stochastic optimization (cf. section 3.1.2). Yet when using the same uncertainty set, robust optimization yields more risk averse outcomes since it exclusively considers the worst case. Distributionally robust optimization is to some extent less conservative than standard robust optimization as the considered uncertainty set contains only possible parameter distributions that do not deviate "too much" (in the Wasserstein metric) from the best guess.

3.1.6 Other approaches

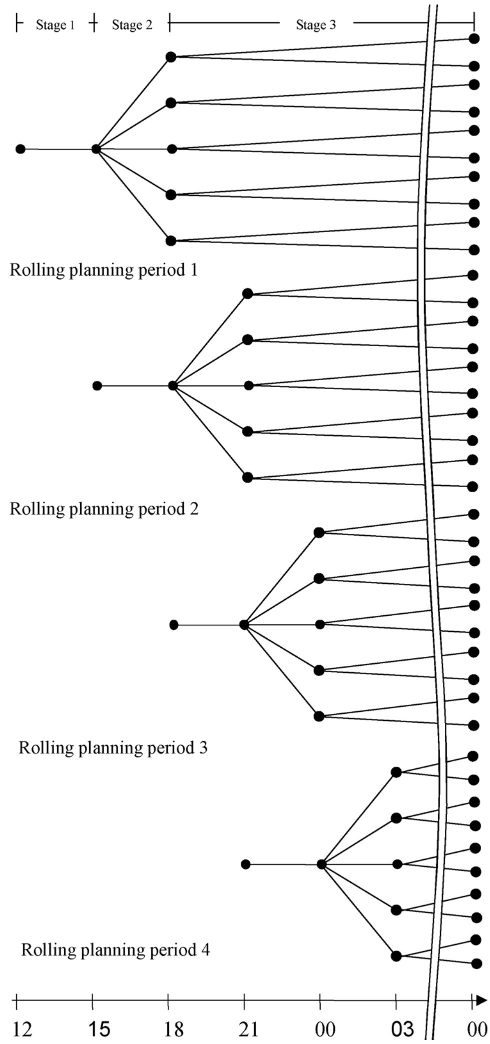
Besides the aforementioned approaches rooted in classical optimization and decision theory, also various (meta-)heuristic approaches have been applied to unit commitment and dispatch problems under uncertainty. These include fuzzy sets (e.g. Wang et al. 2018), particle swarm optimization (e.g. Man-Im et al. 2017) as well as evolutionary and genetic algorithms (e.g. Reddy et al. 2015). For these approaches, generally no proof of convergence towards the optimal solution is available, yet they may provide possibilities to tackle non-convex problem instances or multi-objective settings. Yet the unit commitment and dispatch problem under uncertainty has been abundantly studied using classical optimization approaches and powerful numerical solvers are available for these problem instances. Therefore, the added value of non-conventional approaches seems rather limited.

3.1.7 Challenges for application of stochastic methods in operational planning

The discussion in the preceding sections has illustrated that there are multiple methods and applications available for including uncertainties in operational decision support tools, notably when it comes to the unit commitment and dispatch problem that is at the heart of the operational planning in the electricity industry. Still the broad application of stochastic methods in this field faces at least three challenges: 1) the large number of potential uncertainties to be considered, 2) the curse of dimensionality and 3) the necessity to provide valid estimates of the probability distributions as input to the formulated stochastic problem. The rapidly growing availability of data, methods and tools certainly alleviates challenge 3) to some extent. Yet still the high dimensionality of comprehensive stochastic models provides a computational challenge - the more since the solutions have to be computed within minutes to be useful for operational decision-making. But even without this time constraint, the sheer problem sizes may rapidly get discouraging. With T time steps, K stochastic factors and N possible realizations of the stochastic factors per time step, we end up with $(N^K)^T$ paths through the scenario tree. With 24 timesteps in day-ahead unit commitment, 4 stochastic factors and just 3 possible realizations per factor this means $(3^4)^{24}=3^{96}\approx 6\cdot 10^{45}$ scenarios - compared to just one single scenario in case the deterministic equivalent is used. Hence a major effort has to be devoted to identifying the most important stochastic factors and their realizations and to limit the number of stochastic stages to a few. Computational experience with the WILMAR model and results reported by Sturt and Strbac (2012) suggest that for standard applications, two stochastic stages may be enough, yet extreme events need to be appropriately represented.

Rolling planning as implemented for example in the WILMAR model is a possibility to circumvent the aforementioned curse of dimensionality. The basic principle is illustrated in Fig. 3. Rolling planning consists of repeated optimization runs which follow on information updates (e.g., new renewable forecasts). In Fig. 3, these updates occur every three hours. Without information updates (i.e., in the absence of uncertainties), rolling planning can be seen as an approximate decomposition of a longer-term planning problem. As such it suffers of the difficulty of assigning appropriate terminal values, e.g., to storage filling levels or to unit operation statuses - also in the presence of uncertainties. Yet in the presence of uncertainties, it is often the only possibility to assess the effects of repeated decisions taking into account these uncertainties. With regular information updates, the longer-term problem would not be solv-

FIGURE 3
Sketch of rolling planning over a half day with replanning every three hours.



Source: Weber et al. (2009).

able as a stochastic program due to the aforementioned curse of dimensionality. Also for other approaches like robust optimization or chance-constrained programming, the impacts in the longer run may be assessed using a rolling-planning approach.

3.2 Investment decision-support

Compared to operational decisions, investment decisions have implications over much longer time periods as mentioned in section 2. Models for investment decision support must hence consider the short-term uncertainties during the later operations along with the long-term uncertainties related to all the preceding years. This implies that potentially more uncertain factors become relevant and for each uncertain factor the range of possible values is larger. E.g., day-to-day changes in fuel and CO_2 prices are mostly in the order of 2 % or less. But over one or two years, these prices may well change by 50 % or more - even outside the specific situation of a pandemic. At the same time, over periods of several years, structural breaks such as new technologies, policy changes, etc. are more likely. This implies that historical observations and relationships may not that easily be extrapolated to the future.

Correspondingly, the empirical foundations for the application of stochastic optimization or others of the previously discussed approaches are weaker. Yet with increasing computational capabilities and recent conceptual advances, various approaches have been developed to incorporate uncertainties explicitly into longer-term models (e.g. Fürsch et al. 2014; Seljom and Tomasgard 2015; Ioannou et al. 2017; Xu and Hobbs 2019). In any case, the consideration of uncertainties is an important issue for successful businesses.

In large companies, the standard business practice for investment decision support is to use the discounted cash flow (DCF) approach (e.g. Brealey et. al. 2016) to compute the net present value of an investment. Uncertainties and risk aversion are only indirectly reflected in this approach namely through the applied discount factor that should reflect the average capital cost of the firm - which in turn depends on the risks the firm is exposed to.[2]

An important input to the DCF approach is the cash flows over the lifetime of the project. These cash flows depend on future market prices and those are in turn impacted by various uncertainties. Both practitioners and academics then frequently use scenarios to describe future uncertainties more explicitly and apply bottom-up electricity market models to derive corresponding price scenarios (e.g. Keles et al. 2011; Spiecker and Weber 2014).

These longer-term techno-economic models are known in the power systems literature as generation expansion planning (GEP) models. Koltsaklis and Dagoumas (2018) provide a detailed review of recent developments in that field, including also stochastic modelling approaches - these basically fall into the same categories as discussed above for operational decision-making. Another review is provided by Oree et al. (2017) with a particular focus on renewable energies and the uncertainties they are inducing. Yet it is important to state that system-wide generation expansion models are not useful in deregulated markets for direct decision support to investors. Rather the generation investment decisions are taken by individual market players who base their decision on expected market prices (cf. above) rather than on an optimal system development path.

The GEP models may then inform the investors and other stakeholders on potential developments of the generation mix and the market prices. In particular, investors may use them as stated before to derive input for the DCF-based investment valuation.

An alternative to the use of the DCF approach are real option methods (cf. Dixit and Pindyck 1994). Thereby it is important to distinguish the valuation of operational flexibilities as real options (as e.g. in Tseng and Barz 2002; Weber 2005) from the use of the real options approach to evaluate investments (cf. e.g. Kumbaroğlu et al. 2008; Yang et al. 2008; Boomsma et al. 2012). In the latter case, the main optionality considered is the possibility to delay an investment. This provides incentives to investors to purchase land or exploration licenses upfront, yet then to wait with the actual investment until prices and other conditions are particularly advantageous. Such modelling provides interesting insights, yet legal constraints and the sensitivity of the approach to the assumed stochastic processes may be invoked as reasons why

2. According to the standard textbook model, the so-called capital-asset pricing model (CAPM), only systematic risk, i.e. risk correlated with the general (asset) market risk, impacts the capital costs (cf. Sharpe 1964; Lintner 1965; Mossin 1966). Yet both advanced theoretical models (cf. Goyal and Santa-Clara 2003; Acharya et. al. 2013) and applications in the energy sector (cf. Schober, Schaeffler, and Weber 2014; Kitzing and Weber 2015) suggest that also idiosyncratic, non-systematic risk matters. Cf. also the empirical studies by Polzin et al. (2019) on factors influencing capital costs for renewable investments.

it has only found limited application in practice. The general idea incorporated in real options that early commitments reduce flexibilities and that later decisions can be made based on improved information has also been implemented in stochastic programming approaches to the generation and/or transmission expansion problem (e.g. van der Weijde and Hobbs 2012; Munoz et al. 2014; Konstantelos and Strbac 2015). A discussion of the role of "real options thinking" in energy modelling is provided by Schachter and Mancarella (2016) who also emphasize the challenges when making practical use of real option approaches.

Practitioners as well as academia instead frequently use the scenario approach to consider long-term uncertainties - and this in various economic sectors. It allows to describe interdependent uncertainties and makes them more tangible by focusing on a limited number of possible alternative developments (cf. Gausemeier et. al. 1998; Börjeson et. al. 2006; Höjer et. al. 2008). According to Schoemaker (1991), the use of scenarios is particularly advantageous for managerial decision-making in a context, where costly surprises have been experienced or significant change and uncertainty are ahead. This is certainly true for the energy sector, and correspondingly the scenario approach has been an important field for the use of scenarios all throughout the last decades, e.g. Bentham (2014), Rogelj et al. (2018), ENTSOG/ENTSO-E (2019), IEA (2019) and Shell (2019). In the context of energy-related decision making, the distinction between normative and descriptive scenarios (cf. Ducot and Lubben 1980; van Notten et al. 2003) is particularly important.[3] Whereas the former aim to show pathways towards a predefined future as e.g. defined through decarbonization goals, the latter are not purposeful. They are therefore more appropriate when it comes to exploring the uncertainties and risks that decision-makers are facing, e.g., when it comes to investment decisions. To illustrate the difference, think about investments in a new hydrogen infrastructure. Normative scenarios will provide an indication how much hydrogen pipelines and electrolyzers are needed (or are efficient to install) when e.g., climate neutrality is to be achieved by 2050. Descriptive scenarios instead describe possible futures, which as seen of today may also include the possibility that policy priorities shift away from climate neutrality. Correspondingly they may inform a potential investor into electrolyzers that there is a risk that the future may not be as bright for electrolyzers as it shines under a climate-neutrality scenario.

Yet one should note that scenarios - at least as commonly applied - do not include probabilities of occurrence. Hence a full quantification of risks is not possible. The extent of losses (or gains) might be computed using the prices obtained in a certain scenario, yet the expected losses/gains or a risk measure like the conditional Value-at-Risk cannot be computed unless probabilities are assigned to the scenarios. A robust optimization may however be performed by selecting the decision alternative that performs best under the worst-case scenario - this is an extremely risk-averse decision behavior, as mentioned above. It correspondingly does not reflect a typical economic risk-return tradeoff.

To summarize, five basic alternatives may be distinguished on how to account for uncertainties when it comes to investment decisions:

1. Base the investment appraisal on expected future prices and corresponding cash flows and apply (sufficiently) high discount rates to account for the uncertainty of these cash flows.
2. Make use of the real options approach to include the value of waiting in the investment appraisal.

3. For further scenario classifications cf. the above-mentioned sources as well as Börjeson et al. (2006).

3. Use scenarios to inform the decision makers about the possible risks associated with an investment.
4. Apply stochastic optimization, possibly accounting for risk aversion in the objective function, based on longer-term scenarios that have been assigned (subjective) probabilities.
5. Proceed as under 1., but additionally apply risk analysis using a combination of qualitative and quantitative methods.

Note that alternative 3) does not include by itself an unequivocal decision rule. But it may be complemented by a robust optimization, which would select the investment alternative that performs best under the worst conditions (i.e., max-min). Alternatively, also some other decision rule as defined for decisions under ignorance (cf. Peterson 2009; Bamberg et al. 2019) may be used.

Alternative 5) deserves some more attention as it has not been discussed earlier and seems also underresearched.[4] It is rooted in the institutional rulings applicable to large companies under most legislations. Those impose obligations on stock-listed companies regarding corporate risk management (e.g., through the KonTraG in Germany, the LSF in France or the SOX in the U.S).[5] Although the requirements for corporate risk management are typically rather unspecific in these general laws, they oblige companies to monitor all major risks threatening the existence of the company and to identify suitable countermeasures. This implies also that major investments have not only to be assessed in view of their expected returns but also regarding the financial and other risks they may induce for the company. In this vein, risk assessment should complement standard investment assessments. In line with standard enterprise risk management practices (e.g. Collier 2009; Chapman 2012), this should include phases of risk identification, risk analysis and risk evaluation. Especially financial risks may be assessed using quantitative models for a worst-case (or at least low performance) scenario. If risk exceeds the prespecified corporate risk appetite, the investment should not be carried out.

Even though this approach also considers the worst-case scenario, it has distinct features compared to robust optimization: in the case of robust optimization, the optimization itself focuses on the worst-case scenario, whereas in the mean plus risk assessment framework, the worst-case scenario is only evaluated as a constraint. This makes it also distinct from the mean-risk frameworks used in stochastic programming where a risk term is included in the objective function.

3.3 Political and regulatory decision-making

Whereas for some it is self-evident that policymaking is fundamentally different from decision-making in firms, others tend to argue that they should be guided by the same principles and that similar mechanisms may be observed. It is beyond the scope of this paper to provide a detailed analysis of these diverging perspectives and the different corresponding schools of thoughts.

Yet even if economists, engineers, and many others tend to agree that decision-making in both areas should be guided by the same principles (notably of rationality), political de-

4. A risk-constraint is introduced explicitly in the operational unit commitment model by Li et al. 2007) as well as a few follow-up papers, yet there it is formulated using a downside risk measure which requires scenario probabilities.
5. Cf. KonTraG (1998), LSF (2003), SOX (2002).

cision-making is much more than its corporate counterpart characterized by the following aspects:

1. Multiple objectives,
2. Multiple stakeholders,
3. Cause-effect relationships for many policy instruments uncertain,
4. Multi-level decision making.

In the tradition of utilitarian ethics, economics tends to consider maximization of welfare as the ultimate and unifying objective of political decision-making. Yet in practical policymaking, multiple objectives are postulated more or less side-by-side, such as the famous energy policy trilemma of (1) security of supply, (2) affordability (or economic efficiency) and (3) environmental protection (e.g. Doukas et al. 2008; Heffron et al. 2015). And obviously multiple stakeholders are involved when it comes to energy policy making, including among others both regulated and non-regulated firms, local communities, and NGOs. A further challenge to political decision-making is that there is often considerable uncertainty regarding the strength (or even the nature) of cause-effect relationships for policies. This is rather an epistemic uncertainty, related to the limits of scientific (and other) model representations (e.g. Oberkampf et al. 2004; Kiureghian and Ditlevsen 2009; Roy and Oberkampf 2011), that is added on top of the aleatory uncertainties that also investors are facing when it comes to the longer-term effects of their investment decisions.[6] A last point, that has in fact already been made in Fig. 1, is the multiplicity of decision makers at different levels from local to international. Above the national level (and sometimes even below), there is no clear political hierarchy of decision making. This is reflected in the concept of "multi-level governance" developed in political science (e.g. Liesbet and Gary 2003; Bache and Flinders 2004).

Regarding the implications of these observations, we first state that there is no comprehensive review available that provides a concise overview on the way uncertainties may be handled when it comes to political and regulatory decision support. This is probably reflective of the broad range of methods and models that is applied for energy and climate policy decision support. Even as far as the focus is limited on optimization models, the question is only partly addressed. (Pfenninger et al. 2014) in their widely cited overview paper are rather focusing on challenges for modelling energy systems than energy policies and they consider uncertainties along with a perceived lack of transparency regarding energy system model formulations and input data. This call for open-source model and open data has been answered since then with numerous open data and open model initiatives emerging, yet this does not per se solve the issue on how to cope with uncertainties. And also, the link between model results and actual policy decision making remains as challenging as before with open data and open models.

In another somewhat earlier paper, Bazmi and Zahedi (2011) are very optimistic regarding the potential of optimization models to support energy planning and energy policy making. To fully capture their potential, they call for a holistic, system-based approach that among others should also include an "optimization under uncertainty strategy", yet they are not more specific on this. On the other hand, there has also been a strand of literature rather critical about

6. It is worth noting that the distinction of epistemic and aleatory uncertainty is most frequently used when risks in predominantly physical and technical systems are analysed (cf. the context and application examples of the references cited). In social and economic systems, there is a further relevant aspect: the interference between objects and subjects of the analysis – human beings (may) react to results published on human behavior. A well-known example in finance is the so-called "Monday effect" on stock market returns. It disappeared on major stock markets after having been observed (cf. e.g. French 1980; Cho et. al. 2007; Doyle and Chen 2009).

optimizing energy system models with regard to their contribution to the energy transition, including among others Trutnevyte (2016). She argues that optimizing energy system models are not good in foreseeing actual developments and illustrates this with an ex-post analysis of the UK energy transition.

This paper is embedded in a research stream that explicitly considers multiple possible outcomes in energy system models. A key paper hereby is DeCarolis (2011) that introduces the "modeling to generate alternatives" (MGA) approach to optimizing energy system models. The MGA approach itself has been developed and applied to problems in land and water management from the 1980ies onwards, cf. Brill et al. (1982). It consists in searching for near-optimal solutions, i.e., solutions that exceed the best (cost-minimizing) objective function value only by a prespecified gap, but where the decision variables (primal variables) are as different as possible from the original optimum. Hence different possible outcomes are identified that all meet a certain "close-to-optimality" criterion.[7] This approach is also used e.g. in Li and Trutnevyte (2017) where it is combined with Monte Carlo simulations to additionally cope with parametric uncertainty. DeCarolis et al. (2017) build on this research stream and provide a best-practice guide to energy system optimization which among others also covers various ways to deal with uncertainties including scenarios, sensitivity analyses, stochastic optimization, and MGA.

We subsequently focus on two core dimensions regarding the treatment of uncertainties in models for political decision support: 1) the use of scenarios (and related to that sensitivity analyses) and 2) the use of linear optimization models in particular and optimization models in general. Obviously, other methods like computable general equilibrium models may also be used to support political decision making - and some of the subsequent reflections also apply to these models. Yet for a concise presentation and discussion, we focus on optimization approaches. For similar reasons, we mostly leave aside considerations on procedural and communication aspects, although they are also of considerable relevance.

3.3.1 Use of scenarios and sensitivity analyses

As in the case of investment decisions and even more so, the added value of stochastic or robust optimization has to be scrutinized given the limited empirical support for not only probabilities but also ranges of possible outcomes. Consequently, and in view of keeping the multitude of potentially uncertain factors tractable, the scenario approach has been and continues to be the most frequently used approach to reflect uncertainties.

One important point for truly descriptive scenarios in the policy realm is that the choice of scenario drivers depends on the political decision level: everything that is truly exogenous to the decisions under study may be included as scenario driver. On the other hand, all factors that may be influenced by the political decision makers themselves should not be treated as exogenous. E.g., the choice of carbon budgets (or alternatively carbon prices) may be considered as exogenous when dealing with German energy policy decisions, but it is part of the policy choices when it comes to European-level decision making.

Yet another issue is relevant in the context of political decision-making and the multiple stakeholders involved therein: Even if everyone agrees that scenarios are intended to inform

7. The MGA approach has some similarities to the information gap decision theory (IGDT) approach discussed in section 3.1.5. Yet the IGDT aims at providing bounds on allowable parameter uncertainty for a certain objective function gap, i.e. it is interested in bounds on some type of aleatory uncertainty. The MGA approach rather focuses on structural uncertainty, which may be seen as a type of epistemic uncertainty, by considering given parameter values and looking how far solutions may be pushed away from the original optimum.

decision makers and to enlighten decisions, there are two competing views on this enlightenment:1) an idealistic concept of enlightenment and 2) a partisan concept of enlightenment.

The idealistic concept of enlightenment is rooted in the normative decision theory as taught in undergraduate business courses and reflected in textbooks like Peterson (2009) or Bamberg et al. (2019). Scenarios serve here to elucidate uncertain, possible future states of the world. They are exploratory by nature, although ideally the set of scenarios considered reflects the key uncertainties driving the system outcomes (as e.g. intended in Spiecker and Weber 2014). And based on the analysis of these scenarios and the consequences of alternative choices therein, decision makers are expected to make rational, well-founded decisions that serve best the common good (or welfare for mainstream economists). The underlying, idealistic credo of the scenario developers may be characterized as "let us contribute to the rising of the sun of knowledge".

In the partisan concept of enlightenment, the credo sounds similar at first audition: "let us carry the torch of knowledge to shed light on the good cause." Yet the twist is different here: the scenario developers use them to disseminate knowledge and to convince other people instead of seeing the scenarios as instrument to discover knowledge.

First empirical analyses suggest that experts indeed make a distinction between these two types of scenario usages: the majority of the surveyed experts supports the statement that scenarios are used inside their own institution predominantly to gain insights, i.e., to discover knowledge along the lines of the first concept. For multi-stakeholder interactions in the policy debate, the same experts preponderantly agree to the statement that scenarios are used according to the partisan concept of enlightenment, i.e. to support the own vision of the future.[8] Put differently: scenarios and the results of corresponding model runs are used to support a certain "framing" (cf. Tversky and Kahneman 1981; Chong and Druckman 2007) for energy decisions (cf. Bickerstaff et al. 2008; Wolsink 2020).

As applied energy analyses frequently are intended to support the policy debate, this ambiguity in scenario construction and usage is almost inevitable. It is yet already helpful if it is reflected in scientific publications on the subject.

An alternative or rather a complement to scenario-based analysis for decision support are sensitivity analyses. While scenarios reflect future world views and encompass complementary assumptions on multiple parameters, sensitivity analyses rather focus on the variation of single parameters (cf. Refsgaard et al. 2007; Spiecker and Weber 2014). This enables a detailed assessment of input assumption variations on scenario outcomes. In a simple energy system model for 2050, Droste-Franke et al. (2015) report that the installed PV capacities increase by almost 100 % when PV costs are modified by merely 20 %. Similar findings are described by Lopion et al. (2019) for offshore wind energy.

Sensitivity analyses may be particularly relevant in the case of epistemic uncertainty, notably regarding the future behavior of humans in the presence of (rather) new technologies. E. g. the adoption of electric vehicles by customers is still difficult to predict given the limited observations available and the continuous change, the technology is undergoing. It is even more difficult to assess the diffusion of vehicle-to-grid concepts. The previously discussed MGA approach provides a systematic way to identify such potential variations.

8. Results of a survey held among participants from industry and academia on July 13, 2018 in the context of the project LKD-EU with about 70 participants. Details on the survey are available from the authors on request.

3.3.2 Use of linear (and other) optimization programs

The results reported at the end of the previous section pinpoint at a key issue with linear optimization models applied to energy policy decision making, namely so-called penny-switching: If two alternative technologies differ by only one cent or one penny in their cost, the linear program will always choose the slightly cheaper technology for a market share of 100 %. This certainly is a rational choice for a single decision maker with abundant knowledge and a single objective of cost minimization. But when it comes to modelling the energy system several decades ahead, this is unlikely and misleading. Notably for distributed technologies like PV panels, electric vehicles, heat pumps, building retrofit or even wind turbines, there are multiple decision makers with at least partly diverging preferences as well as heterogenous siting and financing conditions. Modelling the corresponding decisions using a linear optimization program with a single objective function and a limited number of technology classes does not reflect the heterogeneity of investors and investment opportunities and thus is likely to underestimate the diversity of future technology choices.

Kallabis et al. (2016) propose a piecewise linear function for the marginal costs of an ensemble of (conventional) generators. This corresponds to the formulation of a quadratic optimization problem and allows to describe the heterogeneity of conventional units regarding their efficiency in a parsimonious short-term model of the German electricity market. Lopion et al. (2019) present an energy system model with a quadratic cost term for investment costs and show that this leads to a broader technology mix while reducing at the same time the sensitivity of results with respect to changes in the (medium) cost estimate for a technology.[9]

These findings suggest that the outcomes of linear programs have to be considered with prudence when it comes to modelling the future optimal mix of generation and application technologies. Quadratic approaches deserve here further and more detailed investigations as well as iterative model couplings between linear optimization models for subsectors (e.g. power generation) with discrete choice models (cf. McFadden 1973; Hensher et. al. 2005) applied to energy related choices (e.g. Dubin and McFadden 1984; Weber 1999; Banfi et al. 2008; Hackbarth and Madlener 2013).

Given the aforementioned caveats, the use of linear programs may provide relevant insights to support political and regulatory decision making. Yet the results should not be taken at their face value. Rather they have to be complemented by reflections on the heterogeneity of decision makers and decision contexts and on the uncertainty of cause-effect relationships for policy instruments.

As the development of modern solvers enables also quadratic programming problems to be solved efficiently, this may be a way forward beyond linear optimization problems. Notably this may allow to address parametric uncertainty e.g., in efficiencies or investment cost. Also, other convex optimization formulations may be scrutinized to cope with the heterogeneity of technologies, sites, and decision makers in future rather distributed energy systems.

4. CONCLUSION

After several decades of research both on the decarbonization of energy systems and on the appropriate modelling of uncertainties in the context of decision support models, there is obvi-

9. Note that in optimal power flow models, quadratic cost functions for single generators are frequently used (cf. Momoh et. al. 1999; Zimmerman et. al. 2011)

ously not one silver bullet nor one single solution that fits all problems. The long-time horizon for the system transformation together with the multiplicity of involved investors and policy makers gives rise to multiple uncertainties and makes decision support in the field challenging.

A first step to cope with uncertainties is certainly to identify and assess them thoroughly. This may be done outside any optimization model used for decision support, by enumerating possible sources of uncertainty and estimating their range. By varying then parameters in the optimization model, the sensitivity of the reference model results with respect to changes in the assumptions may be identified.

Another standard approach to address uncertainties is to identify scenarios and compute the corresponding model outcomes. Compared to multiple sensitivity analyses, the computational burden is certainly lower, and the gathered insights may be connected to the scenario storylines underpinning the scenarios. On the other hand, the aggregation of uncertainties into a limited number of scenarios may induce a considerable loss in information.

Stochastic and robust optimization as well as chance-constrained programming are mathematically demanding approaches. These are generally more appropriately applied in operational planning where more empirical evidence on the uncertain parameters is available.

Like sensitivity analysis, the modeling to generate alternatives (MGA) approach is a computationally demanding approach for large optimizing energy models. Yet it enables not only insights into the impact of changes in single parameters but also on the bandwidth of potential solutions that are "within reach" of the computed optimum for a certain tolerated gap in the objective function.

A particular challenge to modelling is the intertwined decision making in a multi-level governance setting. Further research efforts may be devoted to developing transparent modelling approaches that enable an in-depth analysis of the interdependencies without imposing strong theoretical priors like in Nash equilibria. Dealing with decisions of other institutions as part of the structural uncertainties may be a way forward to identify "robust" or rather error-tolerant strategies for decarbonization in a multipolar setting.

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