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Does cost optimization approximate the real-world energy transition?

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ABSTRACT

Bottom-up energy system models rely on cost optimization to produce energy scenarios that inform policy analyses, debates and decisions. This paper reviews the rationale for the use of cost optimization and questions whether cost-optimal scenarios are adequate proxies of the real-world energy transition. Evidence from ex-post modeling shows that cost optimization does not approximate the real-world UK electricity system transition in 1990–2014. The deviation in cumulative total system costs from the cost-optimal scenario in 1990–2014 is equal to 9–23% under various technology, cost, demand, and discount rate assumptions. In fact, cost-optimal scenarios are shown to gloss over a large share of uncertainty that arises due to deviations from cost optimality. Exploration of large numbers of near-optimal scenarios under parametric uncertainty can give indication of the bounds or envelope of predictability of the real-world transition. Concrete suggestions are then made how to improve bottom-up energy system models to better deal with the vast uncertainty around the future energy transition. The paper closes with a reflective discussion on the tension between predictive and exploratory use of energy system models.

1. Introduction

Jeremy Bentham (1748–1832), thought leader of classical utilitarianism, first used the words 'maximize' and 'minimize' to describe societal goals of maximizing utility and minimizing suffering [1]. These concepts were operationalized in the early 20th century, when mathematical optimization was invented. Since then, optimization was used extensively in mathematics, engineering, economics, and computer science. Since 1970s [2–5] and 1980s [6,7] bottom-up energy system models that rely on cost optimization for modeling global, national and local energy systems underpin many policy analyses, debates, and decisions. Such models have a detailed representation of energy service demands, energy resources, technologies and infrastructures, and they minimize total discounted system costs under technology, environmental and policy constraints. Often perfect foresight of future costs, technology availability, and service demands is assumed. The solutions of such models are energy scenarios for decades ahead. For example, National Energy Modeling System in the US [8] or MARKAL in the UK [9] are used to produce energy scenarios to assess national-level policy proposals or inform infrastructure planning decisions. Open-source OSeMOSYS [10] reaches experts in developing countries. Half of 30 integrated assessment models of climate change that inform the latest Fifth Assessment of the Intergovernmental Panel on Climate Change [11] are based on cost optimization; four fifths of these cost-optimization models rely on perfect foresight. The other half of these models implicitly use cost optimization rationale by prioritizing least cost technologies in their simulations. Other examples of widely used cost optimization models are TIMES/TIAM [12], MESSAGE [7], LEAP [13], TEMOA [14,15], Calliope [16], and many others.

Many of these bottom-up, perfect-foresight cost-optimizing models have evolved into large-scale, complex models that rely on thousands of parametric and structural assumptions. Although widely used, they have been criticized too. These models have been argued or shown to have systemic biases [17–19], to be based on value-laden [20,21], fragile [18] or narrow assumptions [22,23], to lead to irreproducible scenarios [24], and to have insufficiently broad system boundaries [25]. Retrospectively, the models did not capture structural changes in real-world transitions [23,26,27]. Detailed scenarios developed with such bottom-up models have been argued to be inadequate for anticipating long-term phenomena in face of deep uncertainties in technology, economy, and society [28–30]. When described in detailed narratives, such scenarios also tend to induce overconfidence because detailed

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scenarios seem more probable that the ones that have not been shown in detail [31]. As a result, there has been an increasing interest in model evaluation to assess the performance of models, cf. [32]. One of the unresolved critiques is the use of cost optimization [25]. This papers aims to assess the adequacy of cost optimization for modeling energy transitions.

Ever since the first bottom-up energy system models were developed, there has been a tension between exploratory and predictive use of energy scenarios. Nowadays modelers frame energy scenarios resulting from the models as possibilities what might happen and not predictions—that is, as scenarios “for insights, not numbers” [p. 449, 33]. But whether used for predictions or insights, scenarios generated with models are implicitly assumed to be able to give some indication of what is possible in the future and, in this way, are implicitly used as proxies of the future. From the multidimensional space of possible futures that is defined by technical, economic, environmental and other constraints, bottom-up models use cost-optimization to narrow down this space to one scenario to analyze further. But even intuitively one senses that real-world energy system transition may not be cost optimal. To date the bottom-up modeling community has been struggling to make the bridge between the need for scenarios that are reasonable proxies of the real-world transition and the models that cannot provide such proxies.

With the aim to resolve the aforementioned tensions and lack of ex-post evidence in bottom-up energy system models, this paper gathers historic evidence and conducts an ex-post modeling exercise in order to understand whether cost optimization approximates the real-world energy transition. The UK electricity system from 1990 to 2014 is modeled, using bottom-up electricity system model D-EXPANSE. With hindsight, the actual (real-world) transition is known and can be compared to the modeled cost-optimal scenario. As historic data on the model parameters, such as technology and fuel costs, are collected, the parametric uncertainty can be nearly eliminated in order to enable exploration of the cost optimization rationale. Due to its ex-post modeling approach, this study is the first of its kind.

This paper is structured as follows: Section 2 provides an overview why cost optimization is used in bottom-up energy system models and why it may be limited; Section 3 introduces the bottom-up energy system model D-EXPANSE; Section 4 describes the case and data of the UK electricity system transition in 1990–2014; Section 5 presents the ex-post modeling results; Section 6 discusses the results and proposes future research needs; Section 7 lists the implications for modeling the future energy transition with bottom-up energy system models; and Section 8 concludes.

2. Rationale for cost optimization and its limitations

Costs are among the key drivers of the energy system transition. On this basis, there are two interlinked arguments why cost optimization is used in bottom-up energy system models: the social planner's approach and the partial equilibrium argument. The social planner's approach originates in planning and public policy and assumes that there is a single decision maker, who aims at achieving the best outcome for the society as a whole. Such an outcome is reached by maximizing the sum of the energy supplier's and consumer's surpluses in the case of elastic demands. This surplus maximization is transformed into an equivalent of minimization of the total system costs that represent the negative of the surplus [12]. With fixed demands, only the total costs for suppliers are minimized. In reality, however, such a single social planner does not exist and, especially after market liberalization, multiple interacting energy suppliers and consumers with heterogeneous decision powers and stakes shape the energy transition [30].

The partial equilibrium argument assumes that energy supply-demand equilibrium is reached, when the total surplus, as in the social planner's approach, is maximized [12]. However, the general equilibrium assumption is not shared by institutional and evolutionary economists [34], while the partial equilibrium assumption does not account for the interaction between the analyzed sector and the wider economy.

In addition to these critiques of both the social planner's and partial equilibrium arguments, the heterogeneous actors in the real world do not always act rationally as assumed in models [35,36] and, if they do, there are other factors than only costs that they may consider [37]. Decision may be made using the principle of satisficing rather than optimizing, especially in face of multiple stakes. Energy transition is actively shaped by policy makers and other decision makers, who in the process require several alternatives to consider and choose from [15,38,39]. Neither posing one cost-optimal alternative for discussion nor expecting that it will be prescriptively followed is realistic. After all, the energy system is highly complex and it cannot be steered to a single least cost state anyway [40].

In light of such critiques, the bottom-up energy system modeling community has attempted to improve the models to deviate from cost optimal scenarios under perfect foresight to the ones that are believed to be more realistic. Such attempts include the myopic instead of perfect foresight versions [41], multi-objective optimization [42], analysis of parametric uncertainty [43,44], inclusion of external costs in addition to direct costs [45], models of multifaceted nature of behavior and decisions [30,46], second-best policy scenarios [47], near-optimal scenarios [39,48–50], or modeling constraints that enforce the deviation from cost optimality [51]. In addition, simulation rather than cost optimization models have been developed. Simulation models rely on historic evidence or theory-informed description of model variables to simulate the future scenarios, e.g. [52].

Even if ex-post validation and broader evaluation of models has been repeatedly called for [27,53], the handful of existing studies compared past scenarios and real-world transition on a generic level [17,23,26,27,31,54,55]. With the exception of McConnell and colleagues [56], no ex-post modeling studies exist that enable unpicking the reasons behind the mismatch of the modeled energy scenarios and the real-world transition. For example, such reasons could be cost optimization, parametric assumptions, structural assumptions, model boundaries, or others.

Recently, three-decades-old techniques [37,57] for exploring near-optimal solutions of optimization tasks have been applied to bottom-up energy models [39,48–50]. All these studies have showed that a small deviation in total system costs leads to a very diverse set of near-optimal energy scenarios. Keepin and Wynne [18] have already pointed out to this limitation of bottom-up energy system models, when small differences in input parameters, such as technology costs, cause large differences in solutions. Such limitation may not be resolved by multi-objective optimization. For example, Hara [50] has conducted vehicle mix optimization using two objectives of carbon emissions and costs. The resulting Pareto optimal solutions are less diverse than the near-Pareto optimal solutions, i.e. solutions that have up to 0.5% higher emissions (or costs) as compared to their respective Pareto optimal solution. In sum, the use of optimization tends to gloss over the diversity in possible near-optimal energy scenarios.

Even if the real-world energy system may not evolve in a cost-optimal way, costs are still among the key drivers. It is thus meaningful to assume that the energy system will not evolve in the most expensive and irrational way. Instead, the real-world transition will likely be somewhere close to the cost-optimal scenario, but not necessarily exactly the optimal one. Several modeling studies, with bottom-up or other types of models, allowed higher than optimal system costs in energy scenarios, e.g. a deviation of 10–30% in total system costs [39,48–50,58,59]. However, there is little evidence of what level of deviation from cost-optimality could be adequate. Empirical evidence from interviews in Switzerland, reported by Trutnevyte and colleagues [60], showed that various stakeholders would accept 30% higher total system costs if the system would reach other goals, e.g. related to environmental concerns or energy independence. This is the only existing evidence, but it originates in the stated preferences approach and thus may also not be an adequate representation of the real world.

3. D-EXPANSE model

In order to understand whether cost optimization approximates the real-world energy transition, the D-EXPANSE model is used to model the UK electricity system transition from 1990 to 2014. According to the typology of Hourcade and colleagues [61], D-EXPANSE (Dynamic version of EXploration of PAtterns in Near-optimal energy ScEnarios) has the structure of the conventional, bottom-up, technology rich, cost optimization model with perfect foresight. Alternative typologies of bottom-up and top-down models exist [62]. D-EXPANSE is considered bottom-up because it does not have macro-economic completeness.

In addition, D-EXPANSE has two state-of-the-art features. First, it systematically explores near-optimal energy scenarios [39,48–50]. Even with a single set of input assumptions, the model produces a wanted number of different scenarios that are either cost-optimal or near-optimal. Near-optimal scenarios are scenarios, whose total system costs do not exceed the predefined upper limit that is higher than the costs of the cost-optimal scenario. Second, in order to understand the influence of the parametric uncertainty Monte Carlo technique is used to sample sets of various inputs. Other existing models that explore near-optimal energy scenarios [39,48–50] have been limited to deterministic versions and, in line with the wedges approach [63], modeled only one single year in the future. D-EXPANSE thus substantially extends the current models. It models the transition from today to the future rather than adopting the wedges approach and it conducts Monte Carlo runs to address parametric uncertainty. D-EXPANSE complements other versions of the EXPANSE model that adopted wedges approach [39], was spatially explicit [49], and included optimization of other objectives beyond costs [64].

Fig. 1 summarizes the procedure that is used for the ex-post UK electricity system modeling. D-EXPANSE and its mathematical formulation are introduced in detail in Appendix A. In brief, the deterministic D-EXPANSE run and Monte Carlo runs are conducted in parallel in order to compare them for better understanding of the role of parametric uncertainty. D-EXPANSE is at first run in cost optimization mode to find the least cost solution (scenario), under a set of supply-demand, technology and resource constraints. Then, the total system costs of the cost-optimal scenario are evaluated and used as the anchor point for generating the near-optimal scenarios. The maximum deviation, called slack and expressed as $(C_{near\text{-}optimal} - C_{optimal})/C_{optimal}$, is allowed from the total costs of the cost-optimal scenario. Costs then become a constraint and not the objective function in D-EXPANSE. The technique of efficient random generation [37,57] is used to produce 500 scenarios that all meet the model constraints and do not exceed the total systems costs plus the slack. The cost-optimal and near-optimal scenarios are then compared to the real-world UK electricity system transition, for which the historical data are available. In Monte Carlo runs the randomly drawn technology costs, electricity demands and some technology parameters also produce variation in the real-world transition and its costs.

The large ensembles of cost-optimal and near-optimal scenarios are then analyzed for additional insights. There are 501 scenarios (one cost-optimal and 500 near-optimal scenarios) in the set of the deterministic D-EXPANSE run and 250'500 scenarios in the Monte Carlo version (501 optimal and near-optimal scenarios times 500 Monte Caro runs). These large ensembles are analyzed using descriptive statistics and scenario visualization. Nine maximally-different scenarios, which differ from each other in installed capacity per technology as much as possible, are extracted for detailed inspection using the adapted distance-to-selected technique [49,65].

D-EXPANSE has a rather stylized reference energy system, but with all its essential elements. Such a stylized representation is an advantage for reducing the computing time of thousands of model runs and for clarity, when extracting patterns from the large and diverse ensembles of near-optimal scenarios. D-EXPANSE models the electricity generation mix, electricity import through interconnectors and pumped hydropower storage to supply the UK electricity demand. The electricity demand is exogenously assumed in line with the historic data and is not modeled as elastic. The electricity dispatch is based on three-stage load curve, including baseload, shoulder and peak loads. Transmission and distribution are not modeled and these losses are included as exogenous assumptions, since D-EXPANSE is not spatially explicit and thus cannot account for transmission and distribution costs and efficiency differences due location of power plants. Technology costs are assumed exogenously too in line with the historic data; technology learning effects are not endogenously modeled.

4. UK electricity system transition in 1990–2014 and the model input data

The D-EXPANSE model was used to model the UK electricity system transition from 1990 to 2014 (five time steps of 5 years). Since energy system modeling activities have been shown to mirror the policy discussions of their time [23,66], discussions from early 1990s were used to set up the model. The UK Energy Act 1983 and subsequent White Paper 1988 initiated the privatization process in the UK electricity sector. This privatization was completed in 1991, whereas the subsequent six years were spent "in search of the full discipline of the market" [p. 12, 67] until the market was fully opened to competition in 1999. With this aim to open the market that was previously dominated by coal, oil and nuclear power, policies targeted new market players, such as combined cycle gas turbines (CCGTs). After the oil crises in 1973 and 1979, beliefs that oil prices were on the upward trend led to stronger focus on non-fossil fuel alternatives, such as renewable energy. For example, first commercial wind power park started operating in the UK in 1991.

The electricity generation technologies that are included in D-EXPANSE are taken from the studies of early 1990s [23]. The annual supplied electricity requirement, peak demand and baseload demand are available from statistics. Reconstruction of the historical investment costs, operation and maintenance, and fuel costs have proved to be the biggest challenge. While the fuel and investment costs are relatively easier to find [54,67], hardly any data is available on the operation and maintenance costs. Thus, these costs are assumed as in various energy modeling studies in the 2000s.

The modeling data and uncertainty ranges for Monte Carlo runs are summarized in Appendix B. Uniform distributions are used in Monte Carlo runs, because the aim is to understand the spectrum of uncertainty rather than deliver probabilistic modeling outcomes. The D-EXPANSE runs are conducted for two discount rates: 3.5% and 8%. The rate of 3.5% is the social discount rate used in recent

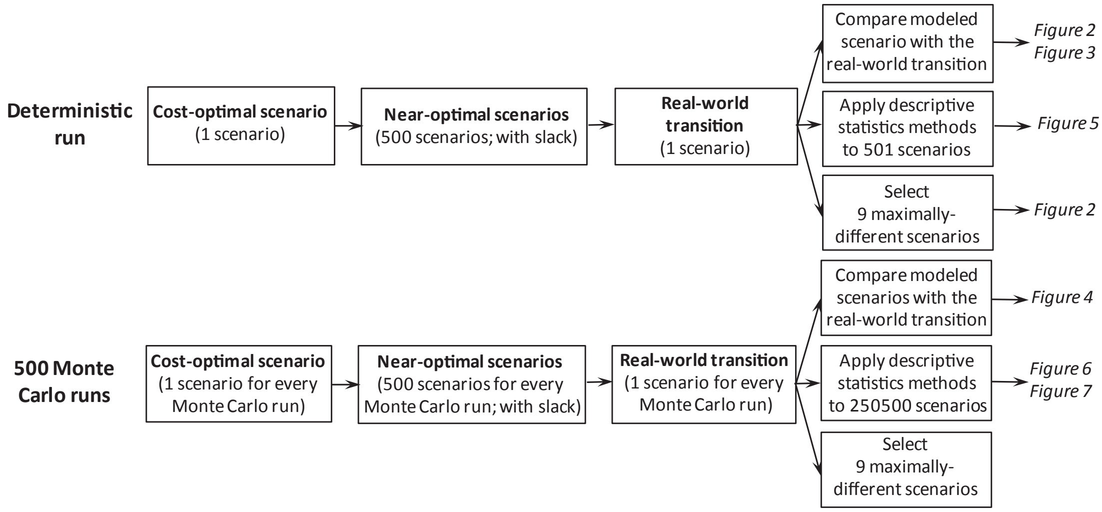

Fig. 1. D-EXPANSE procedure for ex-post UK electricity system modeling.

modeling and policy appraisal studies [68]. The rate of 8% was used in the UK energy modeling studies in 1990s [69,70].

In 1988 UK accepted the targets of European Union Large Combustion Plant Directive (88/609/EEC), which aimed at limiting sulfur dioxide, nitrogen oxides and particle emissions. Implementation of this directive imposed emission reduction from existing power plants above 50 MW capacity as well as set a pollution ceiling for new plants. In D-EXPANSE it is assumed that all newly built plants are in line with the directive, because the pollution ceiling was mandatory for new plants. Since the retirement of existing plants is reconstructed from the historical statistics, it is assumed that existing plants either retire or are refurbished to meet the directive's reduction requirements.

In terms of greenhouse gas emissions, in 1990 Margaret Thatcher spoke to the Royal Society about climate change for the first time. In 1992 UK signed the United Nations Convention on Climate Change at Rio de Janeiro. However, the climate mitigation action had been maturing until 2008, when the Climate Change Act was released [67]. Although the period after 2008 is towards the very end of the modeled timeframe, atmospheric pollution policies and constraints are not included in D-EXPANSE. But greenhouse gas emissions of the generated scenarios are calculated in order to gain insight on the interactions between cost optimization and emissions.

5. Ex-post modeling results

5.1. Cost-optimal scenario vs. real-world energy transition

The modeled cost-optimal scenario of the deterministic D-EXPANSE model run with 3.5% discount rate is compared to the real-world transition in terms of installed capacity in Fig. 2. The cost-optimal scenario is not identical to the real-world transition. First, in the early 1990s the so-called ‘dash for gas’ happened in the UK, when gas CCGTs were rapidly deployed. In the modeled cost-optimal scenario the ‘dash for gas’ happens to a lesser extent. Due to perfect foresight D-EXPANSE anticipates the gas price increase after 2000, related to the peak of the UK own gas production in 2000 and the subsequent net import of gas after 2004. In the real world neither policy makers nor investors have such perfect foresight. This lack of perfect foresight contributes to this difference between the modeled cost-optimal scenario and real-world transition. In fact, the real-world transition has been argued to follow the most investable path rather than the path with the lowest total costs in the long run [71]. If real options thinking is adopted, then other management decisions, such as option to wait, commit to a follow-on investment. or abandon activity, are also considered.

Winskel [72] explained the ‘dash for gas’ in the UK as a result of a combination of factors, such as electricity market liberalization policies, resource availability, falling prices at the time, improving turbine performance, atmospheric pollution legislation, and institutional tensions from the nationalization period. Pearson and Watson [67] argued that the primary cause for the ‘dash for gas’ was the policy to bring new players into market dominated by coal: “The RECs [Regional Electricity Companies], wanting to limit the major player's market power, contracted for electricity from CCGTs, part owned by RECs themselves and the oil companies. The regulator, keen to encourage new company entry to promote competition, allowed the RECs to include power purchase costs from IPPs [Independent Power Producers] in their regulated price caps and so, to pass them through to costumers. This was a controversial decision — and was taken despite evidence that the new CCGTs could be more expensive than the plants they were replacing” [p. 12, 67]. Especially the last sentence shows that a deviation from the sole focus on costs was acceptable to achieve another objective of increasing the diversity of market players and fostering competition.

Instead of CCGTs, the modeled cost-optimal scenario has a higher share of new coal and nuclear power plants than the actual transition. In reality, the construction of new nuclear plants was under debate in the UK at that time and thus delayed. Even though the Government gave the green light to Sizewell B nuclear plant in 1986, it was commissioned only in 1994 due to uncertain public support and the debts of the nuclear industry. The estimates of the levelized costs for nuclear electricity in 1990s were also higher than the estimates for gas CCGT, although the cost out-turns, in the subsequent years dropped [54]. The deployment of new coal plants was limited due to the aforementioned atmospheric pollution regulations as well as due to the coal miners' strikes in 1984–1985, leading to more than a half of deep coal mines being closed by 1992. The indirect or lifecycle costs related to coal and nuclear, such as for air pollution or long-term nuclear waste storage, were not accounted for in D-EXPANSE.

After 2005 an increasing share of renewable electricity technologies has been deployed in the UK, as a result of stronger climate change-related policies. Such tendency, however, is not reproduced in the modeled cost-optimal scenario because climate change

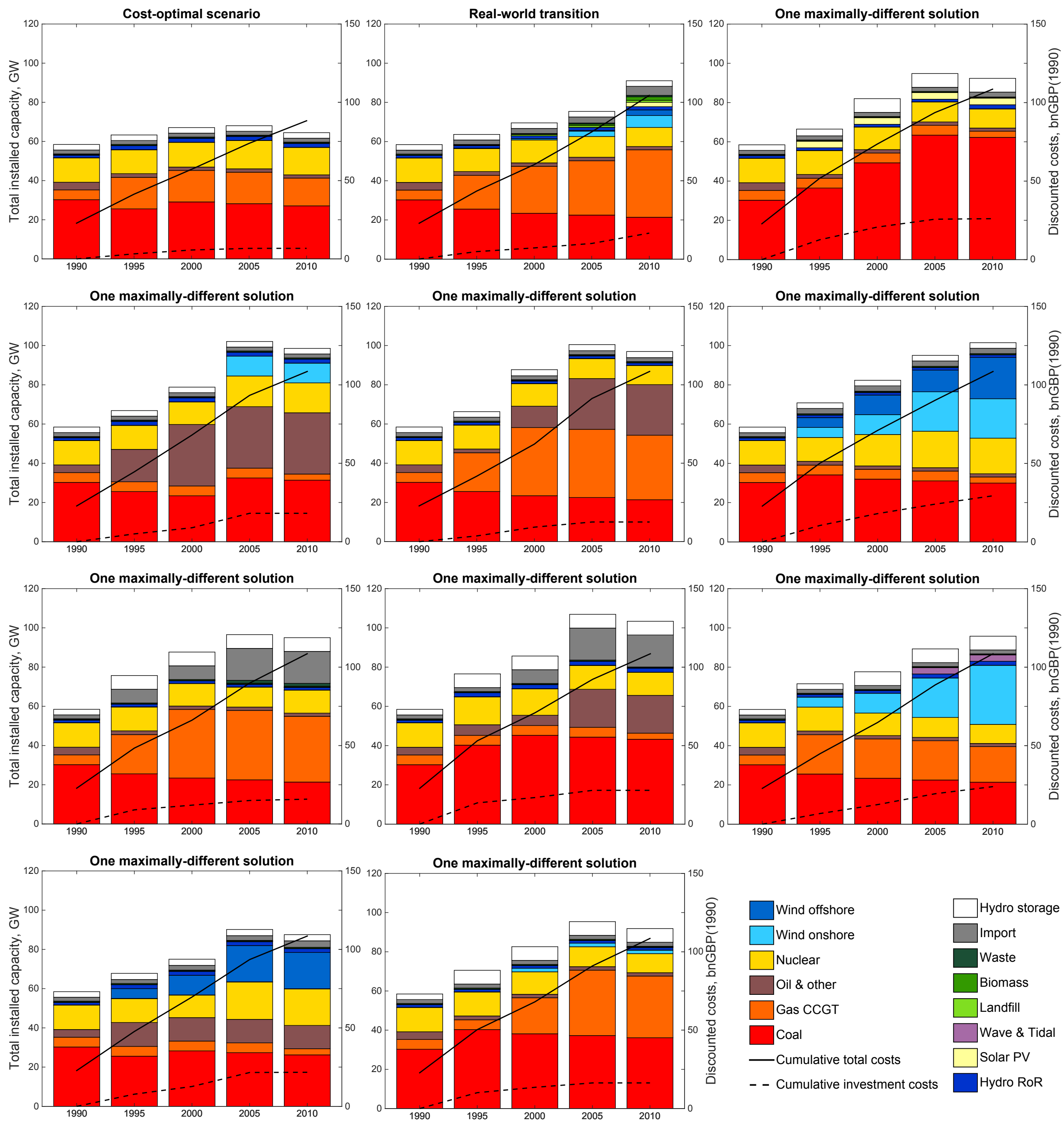

Fig. 2. Comparison of the modeled cost-optimal scenario, real-world transition, and nine maximally-different near-optimal scenarios (deterministic run; 3.5% discount rate; 23% slack).

policies and other atmospheric pollution constraints have not been included. Due to its focus on costs, the cost-optimal scenario does not include costlier renewable technologies.

Due to perfect foresight the model also anticipates the decline in electricity demand after the economic crisis in 2008. The installed capacity in the cost-optimal scenario thus decreases in the final time step. In the real-world transition, however, new capacities are built. A large share of this new capacity are renewable energy sources that have lower contributions to the peak equation and thus lead to a substantial difference between the total installed capacity of the optimal scenario and the real-world transition.

Fig. 3 compares the evolution of cumulative total system costs in the case of the modeled cost-optimal scenario and the real-world transition. In order to make a consistent comparison, the costs of the real-world transition are evaluated using the same technology and fuel costs and system boundaries as in D-EXPANSE. The costs of the real-world transition can be seen not to follow the cost-optimal path. When 3.5% discount rate is used, the cumulative total system costs in 1990–2004 exceed the costs of the cost-optimal scenario by 5% and in 1990–2014 – by 16%. When 8% discount rate is used, the deviation in 1990–2004 is 5% and in 1990–2014 – by 12%.

In order to examine whether this deviation originates in parametric uncertainty in energy demand, technology data and costs, 500 Monte Carlo runs are conducted for each case of 3.5% and 8% discount rates. The spread of deviations in 1990–2004 and 1990–2014 are shown in Fig. 4. With both 3.5% and 8% discount

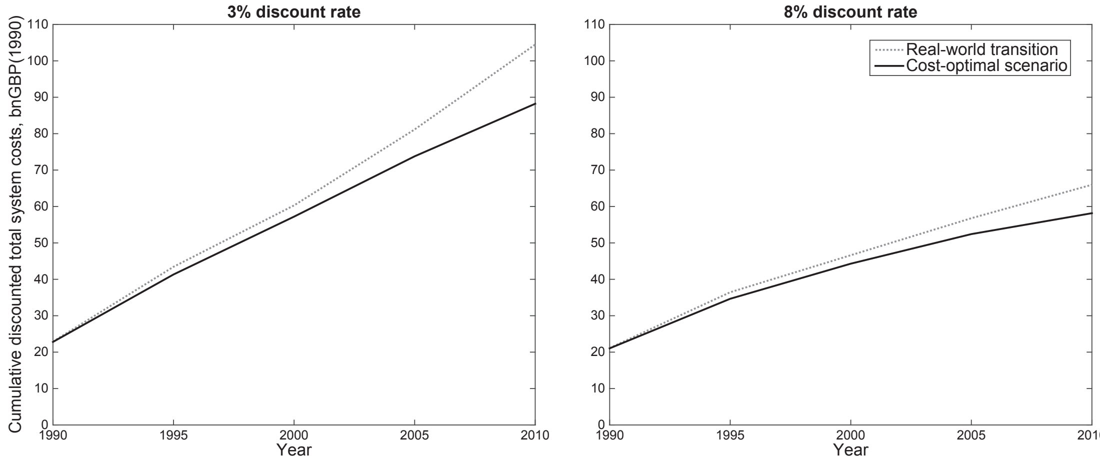

Fig. 3. Comparison of the cumulative total system costs of the modeled cost-optimal scenario and the real-world transition (deterministic run).

rates, the deviation in cumulative total system costs of the real-world transition from the cost-optimal scenario in most Monte Carlo runs is about 5%. In 1990–2014 the deviation increases and varies from 13 to 23% (3.5% discount rate) and from 9 to 17% (8% discount rate). These findings confirm that the modeled cost-optimal scenario does not approximate the real-world transition and that the reason is not only rooted in the parametric uncertainty. There is a very small number of model runs for 3.5% discount rate, where the deviation is 0% or negative in 1990–2004, meaning that the costs of the real-world transition are equal or below the cost-optimal scenario. As the cost-optimal scenario in D-EXPANSE has the least cumulative total costs in the whole period 1990–2014, it can occur that some feasible energy scenarios could have lower cumulative costs in the shorter term (1990–2004), but eventually their costs exceed those of the cost-optimal scenario in the whole period 1990–2014.

5.2. Near-optimal scenarios and technology deployment

The deterministic D-EXPANSE version is used to produce 500 near-optimal scenarios, i.e. scenarios whose cumulative total system costs do not exceed the predefined slack. The slack is chosen as

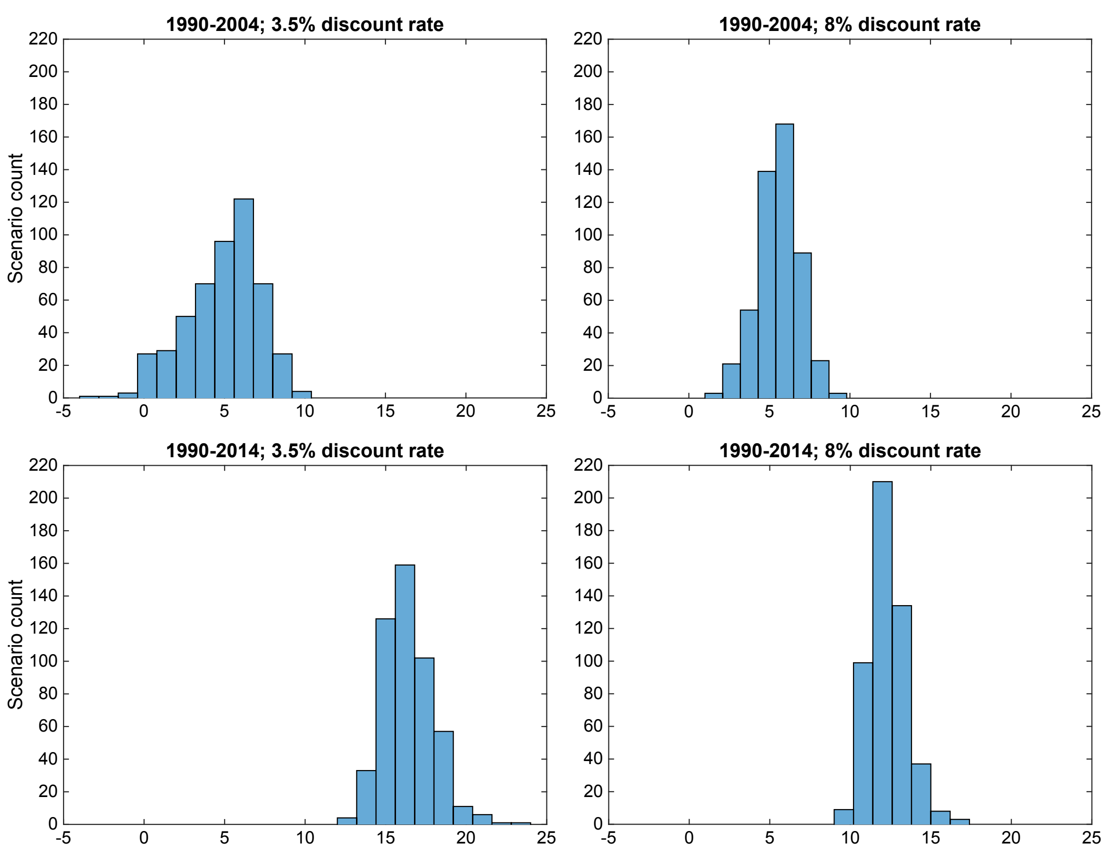

Figure 4. The deviation in cumulative total system costs of the real-world transition from the modeled cost-optimal scenario (500 Monte Carlo runs).

23% (3.5% discount rate) and 17% (8% discount rate), according to the maximum deviation found in Fig. 4. Fig. 5 shows the ranges, upper and lower quartiles, and medians of the installed capacity in these near-optimal scenarios in 2000 and 2010. It can be seen that, when the model includes several technologies with comparable and low costs, deployment of these technologies in the near-optimal scenarios can vary substantially. For example, the installed capacities of coal, gas, oil, nuclear, and electricity import vary by a magnitude of 10–40 GW. This is a known bias of cost-optimization models, where small differences in technology costs can produce very different energy scenarios, as Keepin and Wynne [18] illustrated with tilting planes. Costly renewable technologies, as a rule, appear only in a very small number of near-optimal scenarios, mainly in mixes that deploy other cheap technologies so that the overall scenario costs would not exceed the predefined slack. However, if the rest of the generation mix is relatively cheap, there is a possibility even for costly technologies to get deployed. The findings in Fig. 5 again support the argument that analysis of cost-optimal scenarios glosses over the possible variety in technology deployment. Analysis of near-optimal scenarios helps to systematically deal with such a bias.

In addition to the contributions of the individual technologies in Fig. 5, nine maximally-different scenarios in terms of installed capacity are sampled to reveal technology combinations and are shown in Fig. 2. A vast variety of technology deployment patterns can be observed: from the cost-optimal scenario with coal, oil and CCGTs to a coal-dominated scenario, a scenario with oil and CCGTs, a scenario with another dash for gas, and even several scenarios with deployment of onshore or offshore wind power. As the maximally-different scenarios are sampled by maximizing the difference in installed capacity per technology (see Appendix A for method), the resulting scenarios are at extremes. Such analysis can thus be useful to explore the bounds or extremes of the near-optimal space of energy scenarios.

5.3. Near-optimal scenarios and system costs

Fig. 6 presents the spread of cumulative investment costs and total system costs in the cost-optimal scenario, real-world transition, and near-optimal scenarios for the Monte Carlo runs. The near-optimal scenarios cover a sufficiently wide area to encapsulate the real-world transition, but the spread of costs of near-optimal scenarios is wider. Since the cost-optimal scenarios and especially the real-world scenario exhibit less variation in technology mixes, they are not as widely distributed as near-optimal scenarios, whose technology mixes vary significantly.

The cost-optimal scenarios, however, fall outside the area covered by near-optimal scenarios and this points to a bias in D-EXPANSE. When the space (polyhedron) of feasible scenarios is described by supply-demand, technology and other constraints, cost-optimal scenario ends up in one of the vertices of this space. When the additional slack constraint is added to form the near-optimal space, a smaller sub-space of near-optimal scenarios is formed; [64] provide a graphical illustration. This new constraint

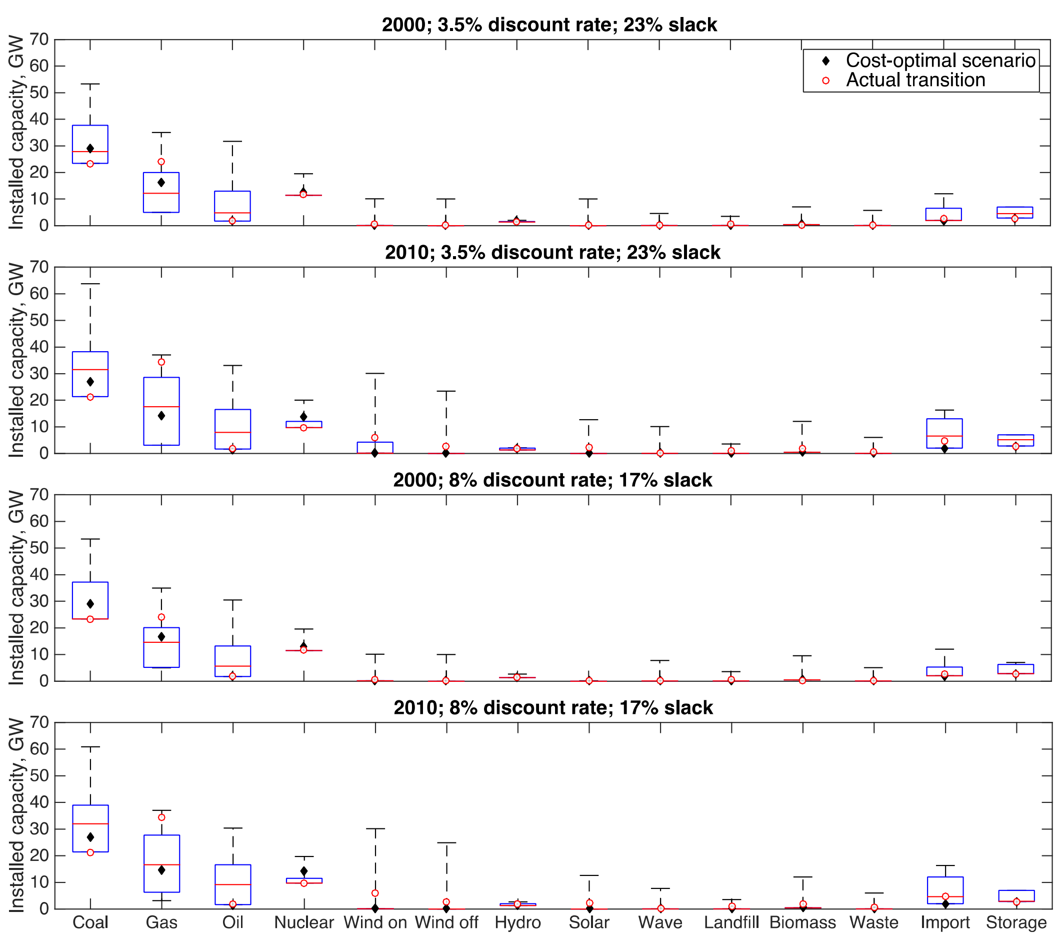

Fig. 5. Technology deployment in 500 near-optimal scenarios (deterministic run). The boxplots present the ranges, upper and lower quartiles, and medians of installed capacity in near-optimal scenarios.

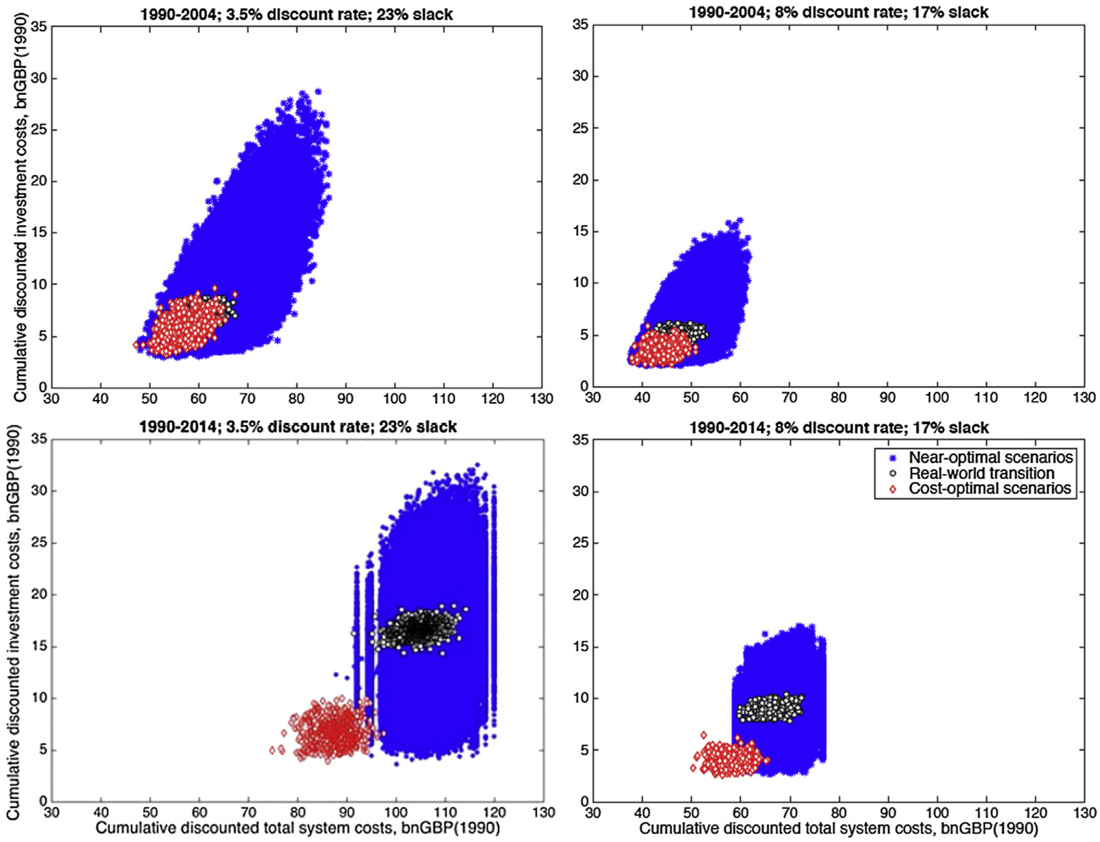

Fig. 6. Comparison of cumulative investment costs and total system costs by 2014 (500 Monte Carlo runs; 500 near-optimal scenarios).

creates a new facade and many new vertices in the sub-space, where the new slack constraint intersects with the other constraints. The random generation technique samples a wanted number of these vertices from this near-optimal space. A large share of these vertices fall on the polyhedron's facade, defined by the new slack constraint. As a result, D-EXPANSE results in many near-optimal scenarios that are exactly on the slack constraint's intersection with other constraints, i.e. scenarios with total costs that are equal to the maximum deviation allowed. Despite this bias, Fig. 6 still shows that near-optimal scenarios are better able to encapsulate the real-world transition than the cost-optimal scenarios.

5.4. *Near-optimal scenarios and greenhouse gas emissions*

Fig. 7 shows the cumulative greenhouse gas emissions in the modeled cost-optimal scenario, real-world transition and the near-optimal scenarios. In order to make a consistent comparison, the emissions of the real-world transition are evaluated using the same emission factors and system boundaries as in D-EXPANSE. Fig. 7 shows that both cost-optimal scenarios and near-optimal scenarios exhibit a vast spread of cumulative emission patterns and encapsulate the emissions from the real-world transition. The emissions of the real-world transition have only a narrow range of uncertainties because the emission factors are not varied in Monte Carlo runs, but some uncertainty originates in the Monte Carlo variations in technology deployment in the real-world transition. The cost-optimal scenarios in Monte Carlo runs at times capture the emissions of the real-world transition and at times – not. It can thus be concluded that both cost-optimal and near-optimal scenarios with Monte Carlo runs perform best together in capturing the real-world emission patterns.

6. Discussion of the results and future research needs

The ex-post modeling of the UK electricity system transition in 1990–2014 shows that cost optimization in a bottom-up model D-EXPANSE does not approximate the real-world transition. Neither cumulative total system costs, investment costs nor technology deployment or greenhouse gas emission patterns of the real-world transition could have been captured by cost-optimal scenario only. Monte Carlo D-EXPANSE runs show that this phenomenon does not originate in the parametric uncertainty. The detailed comparison of the cost-optimal scenarios and the real-world transition in Section 5.1 reveals purposeful reasons for deviation from cost optimality. Thus, bottom-up energy system models in the future should analyze near-optimal scenarios.

In the period of 25 years the total cumulative costs of the UK real-world transition exceed the costs of the cost-optimal scenario by 13–23% (3.5% discount rate) and 9–17% (8% discount rate). This deviation shows that cost optimization may not be a completely inadequate proxy for the real-world transition and costs are still one of the key drivers of the transition. But even such 9–23% deviation in cumulative total system costs leads to a large variety of near-optimal scenarios (e.g., Figs. 2 and 5). Even in combination with Monte Carlo runs, analysis of cost-optimal scenarios only glosses over the spectrum of the uncertainty. Near-optimal scenarios that seem as likely as the cost-optimal one are not analyzed, preventing energy systems modeling to develop a more comprehensive picture of the potential futures.

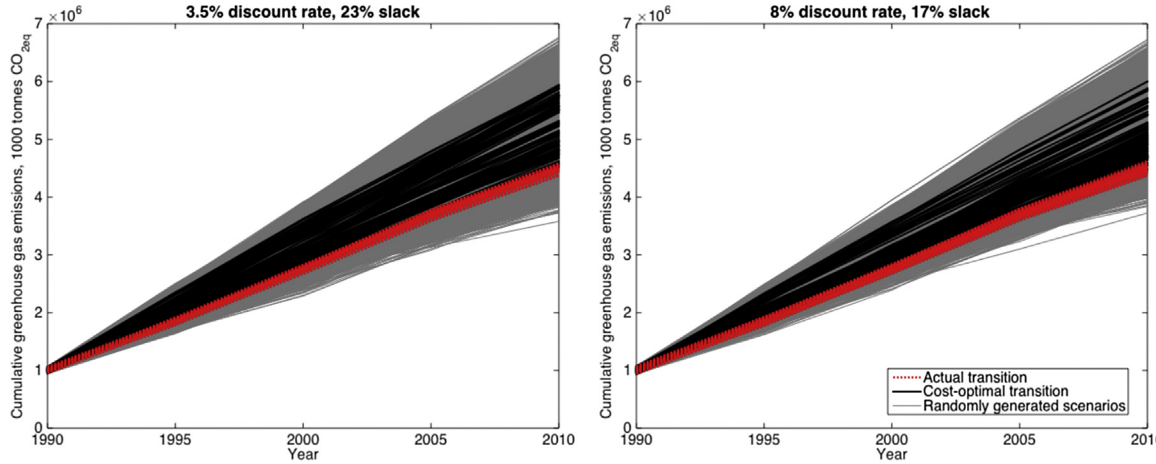

Fig. 7. Comparison of cumulative greenhouse gas emissions in modeled cost-optimal scenario, real-world transition, and near-optimal scenarios (500 Monte Carlo runs; 500 near-optimal scenarios).

As shown in Sections 5.2–5.4, the near-optimal scenarios can encapsulate the real-world energy transition. Yet, the width and multidimensionality of this near-optimal space means that a very large number of diverse near-optimal scenarios shall be sampled and analyzed. Only by sheer luck one of the sampled scenarios may turn out to mimic the real-world transition. It is thus more important to treat such analysis of near-optimal scenarios as a way to extract generic insights or as bounding analysis, answering questions such as: what are the minimum and maximum deployment levels of a specific technology or what are the minimum and maximum emission levels? For such types of questions, D-EXPANSE is especially suitable because it generates near-optimal scenarios that are on the vertices or extremes of the near-optimal space.

The presented ex-post modeling exercise with D-EXPANSE is not without limitations, which can influence the findings. D-EXPANSE is limited by its structural assumptions, such as representation of the electricity system, system boundaries, absent environmental policy constraints, and perfect foresight. First, the current D-EXPANSE version models the transition in 5-year time steps, without detailed annual modeling. The electricity dispatch module has three stages only: baseload, shoulder and peak load. While more detailed temporal resolution is preferable in the future, it might not substantially change the finding about the real-world deviation from cost optimality, since the deviation primarily arises from the choice of CCGT over coal or nuclear.

The current system boundaries of D-EXPANSE consider only electricity generation, import and storage, while electricity demand is given exogenously and is not elastic. Interaction with others parts of the whole energy system are not considered, for example, domestic natural gas exploration, electricity transmission and distribution, heating, transportation, and industrial sector, c.f. [12,73,74]. Extension of D-EXPANSE to cover the whole energy system is preferable in the future. This extension should also include an ex-post analysis of how well cost optimization approximates the real-world transition of the whole energy system, beyond electricity generation. D-EXPANSE does not account for macro-economic feedbacks.

The current D-EXPANSE version does not model environmental policy constraints on local air pollution and greenhouse gas emissions. As argued in Section 4, it was sufficient to assume that all new coal power plants after 1990 would anyway meet the pollution requirements according to the Directive 88/609/EEC and thus constraining the model for local pollution was not necessary. The significant climate change action started only towards the very end of the modeled timeframe with the Climate Change Act in 2008 and thus was also not included. If the greenhouse gas constraint after 2008 would be modeled in the D-EXPANSE, it would not much influence the comparison of the cost-optimal scenario and the real-world transition, because D-EXPANSE anticipates the electricity demand decrease after 2008 and no new capacity is built anyway.

The D-EXPANSE model, as many other current models overviewed in Section 1, at the moment has perfect foresight. For example, it anticipates gas price increase after 2000 or electricity demand decrease after 2008. Such situations may not have been thought about at the time, when the investments were planned. Future D-EXPANSE versions could test the performance of the perfect versus myopic foresight.

Another group of D-EXPANSE limitations revolve around the definition and modeling of costs. First, the ex-post analysis is conducted with the historical cost out-turns, as far as they are available. Such approach is useful to illustrate that cost optimization does not approximate the real-world transition not only due to imprecise model parameters, such as costs. In the future, ex-post modeling could be conducted with the expected future costs rather than historical cost out-turns. Second, the best definition of slack (deviation from cost optimality) needs to be reflected on. Currently, D-EXPANSE defined slack in terms of cumulative total system costs at the end of the modeling timeframe. Yet, testing of alternate slack definitions should be done in the future. Third, the current D-EXPANSE version considered only direct costs. It could be argued that cost optimization that includes external costs, multi-objective optimization that reflects multifaceted policy agenda, or even simulation based on history-informed relationships may lead to narrower deviation of the real-world transition from the optimal scenario. Ex-post evaluations of alternative energy system optimization and simulation approaches are essential to understand what performs better and under what circumstances. Since bottom-up models that rely on optimization of direct costs are widely used in energy modeling community, this ex-post analysis still makes a novel contribution to improving these models.

To what extent are these ex-post modeling findings applicable to other contexts, subsectors, or spatial scales is a question that requires future research. The UK electricity sector underwent a liberalization process in 1990s and thus findings cannot be directly extended to the cases with other governance types, e.g. in a mature liberal market. Evidence can only be gathered by repeating ex-post modeling exercises in other contexts.

7. Implications for modeling the future

Since bottom-up cost optimization energy system models are widely used today, the reported ex-post modeling indicates concrete ways how to improve the existing models. First of all, such models shall navigate the space of cost-optimal and near-optimal energy scenarios under parametric uncertainty. This will come at a cost of new modeling efforts, failed experiments, and increased computing time. But the resulting approaches, as demonstrated with D-EXPANSE, can better embrace the vast future uncertainty that is inherent in energy transition. In fact, the deviation from cost optimality in the future may become even bigger in light of the radical energy system change that is aspired today.

Such navigation of cost-optimal and near-optimal energy scenarios under parametric uncertainty requires new techniques to deal with the resulting very large and diverse ensembles of energy scenarios. Examples of such techniques are:

- Techniques that elicit insights from large scenario ensembles or help choose small sets of scenarios that are fit for specific purpose; the overview is provided in [75];
- Story-and-simulation approach [76,77]. This approach could help anticipate some socio-political reasons for deviation from the cost-optimal scenario, e.g., as in the storylines of governance and policy changes [78]. At the same time, it must not be forgotten that these storylines would enable consideration of several fragments of the space of future energy scenarios only.
- Robust decision making [52,79,80]. This approach helps finding policy or decision alternatives that are robust against the variety of future developments. An initial policy alternative is tested against the large ensemble of modeled scenarios in order to assess in which cases the policy alternative fails to meet its goals or succeeds and what are the vulnerabilities. Further policy alternatives can then be formulated and tested for robustness.

The variety in cost-optimal and near-optimal energy scenarios under parametric uncertainty means that the chance of selecting one scenario that will exactly match the real-world transition is extremely low. The approaches of **bounding analysis** [29] or **'envelope of predictability'** [53] are thus recommended. These approaches argue that the multi-dimensional space of future scenarios shall be explored by learning from the extremes or bounds of this space. Optimization framework of D-EXPANSE and other bottom-up energy system models becomes an advantage here. As discussed by Keepin and Wynne [18] with tilting planes and in Section 5.3, optimization and random generation technique result in scenarios that automatically are on the vertices (extremes) of the cost-optimal and near-optimal scenario space, i.e. where several model constraints intersect. When combined with elicitation of smaller numbers of maximally-different scenarios, such analysis can provide succinct insights into the bounds of the scenario space or the 'envelope of predictability'.

Analysis of cost-optimal and near-optimal scenarios under parametric uncertainty is not an answer to all structural assumptions in the bottom-up models. Multi-model multi-scenario exercises, e.g. [81], can help cancel out some of the limitations of individual models. Ex-post evaluation will be key to understanding what modeling approaches work best under what circumstances.

Last, but not least, opening up to a wider consideration of uncertainty may be challenging for both scenario modelers and especially scenario users. Practitioners at times prefer straightforward answers, even if they are over-simplistic [82,83]. Since the communication of modeling assumptions and several modeled scenarios has already proven to be difficult [20,21,66], the challenge will likely be even bigger when communicating uncertainty around near-optimal scenarios. More research and evaluation is necessary to ensure effective communication.

8. Conclusions

Cost-optimizing bottom-up energy system models are widely used to produce global, national and local energy scenarios that inform energy policies and discussions. Although the use of cost-optimization can be theoretically grounded, this paper provides evidence from ex-post UK electricity system modeling in 1990–2014 that cost optimization does not approximate the real-world transition. The deviation in total cumulative system costs in 1990–2014 is found to be equal to 9–23%, under various technology, cost, demand, and discount rate assumptions. This analysis showed that cost-optimal scenarios also gloss over a substantial share of uncertainty that arises from deviations from cost optimality. Large numbers of near-optimal scenarios could be used instead, because such scenarios encapsulate the real-world transition. A range of concrete suggestions how to improve bottom-up energy system models to embrace both parametric and structural uncertainty due to cost optimization are made.

For the first time this paper provides evidence to yet unresolved debate, whether cost optimization is a suitable proxy for modeling the energy system transition. The findings serve as food for thought about the tension between predictive and exploratory use of energy system models. In the last decades, scenario community became increasingly cautious with their confidence in ability to forecast the future [27]. Historical studies tended to have a poor track record, but modeling was also at the early stage of development. Interestingly, this ex-post analysis shows that, if near-optimal scenarios are considered, the models may not be able to predict the real-world transition exactly, but they could provide the 'envelope of predictability' or serve as a bounding analysis. It is challenging to say whether with improving models and increasing experiences the energy community could become a little more confident again. The presented ex-post modeling results provide some hints in this direction. Finding the answer requires further experimentation with various models, necessarily followed by ex-post evaluations and continuous iterative learning process.

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Appendices A and B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.energy.2016.03.038.

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