Nearly perfect and poles apart: investment strategies into the UK power system until 2050

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Abstract

United Kingdom, like several other countries worldwide, adopted an ambitious target to reduce greenhouse gas emissions until 2050 by 80%, as compared to the emissions of 1990. Energy system models, that optimize the total system costs under emissions constraint, have been extensively used to derive transition pathways and investment strategies. While these transition pathways are optimal, given the costs and emissions dimensions, they may not be optimal if further dimensions, such as supply security or stakeholder preferences, are added. State-of-the-art research argues, therefore, that near-optimal transition pathways need to be explored as well. Building on existing static approaches, this conference paper introduces a dynamic energy system model D-EXPANSE. This model is used to analyze the cost-optimal and near-optimal transition pathways of the UK power system until 2050. The model shows that investment strategies, that are nearly optimal with respect to the total system costs, are at the same time poles apart in terms of technologies and temporal distribution of investment.

1. Introduction

Several countries worldwide adopted ambitious targets to mitigate greenhouse gas emissions from their energy sectors. In 2008, United Kingdom went a step forward and adopted a legally binding target to reduce emissions until 2050 by 80%, as compared to the emissions of 1990 (Climate Change Act, 2009). The power sector is acknowledged to play a pivotal role in this mitigation effort (Williams et al., 2012). This ambition, however, requires a considerable amount of investment into new power plants and infrastructure. The ageing fleet of the UK power plants needs to be replaced in the near future as well and will require substantial investment (Ofgem, 2012). As a result, there is a growing interest in the UK in the potential investment strategies.

The energy system transition pathways in the UK and the respective investment strategies have been extensively addressed with well-established cost optimization models (Ekins et al., 2011; Strachan, 2011; Usher and Strachan, 2012). These transition pathways, derived by optimizing total costs with technical and emissions constraints, are optimal with respect to these costs and emissions dimensions. However, it is widely acknowledged that the energy system transition has multiple dimensions: at the core, it is the UK ‘trilemma’ of emission mitigation, affordability and secure supply (Hammond and Pearson, 2013), but has other

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dimensions as well (Madlener et al., 2007). In this light, the state-of-the-art research argues for exploring near-optimal space of transition pathways in addition to finding the cost-optimal pathway (DeCarolis, 2011; Trutnevyte et al., 2012a). In terms of costs, the near-optimal transition pathways deviate only a little from the optimal pathway, but they may differ substantially in other dimensions.

Building on earlier efforts with static approaches by DeDarolis (2011) and Trutnevyte et al. (2012a), this conference paper introduces a dynamic energy system model **D-EXPANSE** (**D**ynamic version of **EX**ploration of **PA**tterns in **N**ear-optimal energy **S**c**E**narios). This model provides the cost-optimal and multiple near-optimal transition pathways with the maximally different patterns in technologies and temporal distribution of the investment. This model is used to analyze the potential investment strategies into the UK power system transition until 2050, as a part of the Realizing Transition Pathways project (Hammond and Pearson, 2013).

2. Literature overview

Methodologically, D-EXPANSE builds on three trends in energy system modeling: cost optimization, exploration of the near-optimal transition pathways (scenarios) and analysis of the patterns in a large number of pathways. First, the D-EXPANSE model structure is that of a cost-optimization model (e.g. Ekins et al., 2011; Strachan, 2011; Usher and Strachan, 2012). Second, the multiple, maximally different near-optimal transition pathways are sampled in addition to the cost-optimal pathway (DeCarolis, 2011; Trutnevyte et al., 2012a). Modeling-to-generate-alternatives approach is used for this sampling (Chang et al., 1982a, b). Third, D-EXPANSE constructs a large number of transition pathways and aims to extract patterns from this large set of pathways (Kasprzyk et al., 2013; Lempert et al., 2003; McJeon et al., 2011; Trutnevyte et al., 2012a; Trutnevyte et al., 2011, 2012b). Instead of using a combinatorial set of the input parameters to produce multiple pathways as done in (McJeon et al., 2011; Trutnevyte et al., 2011), D-EXPANSE is based on the afore-mentioned modeling-to-generate-alternatives approach and in this way provides a less fragmented spread of the pathways than the combinatorial approach.

Similar to D-EXPANSE approaches were already used for constructing multiple, maximally different energy scenarios for one single year in the future (DeCarolis, 2011; Trutnevyte et al., 2012a). Such approach is in line with the wedges approach (Pacala and Socolow, 2004). D-EXPANSE is a step forward from the existing approaches as D-EXPANSE is dynamic and models the whole transition pathway from today's energy system to that in the future.

3. The EXPANSE model and the data

In the Realizing Transition Pathways project (Foxon, 2013), three storylines of the transition pathways until 2050 to a low carbon power system in the UK were developed. D-EXPANSE is applied to one of these storylines, called 'Market Rules'. The electricity demand was modeled in detail in the Realizing Transition Pathways project and these values of the annual and peak electricity demands are taken for D-EXPANSE. Thus, only the power supply mix and its transition from 2010 to 2050 are modeled.

In D-EXPANSE, the least-cost optimization is conducted first. The objective function is as follows:

$$min \sum_{i=1,j=1}^{19,9} \left[c_{ij}^{inv} x_{ij}^{ncap} + c_{ij}^{fom} x_{ij}^{tcap} + \left(c_{ij}^{vom} + \frac{c_{ij}^{fuel}}{\eta_{ij}} \right) x_{ij}^{prod} \right]; \quad (1)$$

where i - is the number of technologies considered in the Realizing Transition Pathways project (Foxon, 2013), $i = 1,2, \dots ,19$.

j - is the number of time steps. This analysis is conducted for nine time steps from 2010 to 2050, that are 5 years long, thus $j = 1,2, \dots ,9$.

x_{ij}^{ncap} , x_{ij}^{tcap}, x_{ij}^{prod} - are the variables, correspondingly representing the values of newly installed capacity in GW, the total installed capacity in GW, and the produced electricity amount in TWh/(5 years).

c_{ij}^{inv}, c_{ij}^{fom}, c_{ij}^{vom}, c_{ij}^{fuel} - are correspondingly the net present values of investment cost (M£/GW), fixed operations and maintenance cost in M£/GW/(5 years), variable operations and maintenance cost in M£/TWh, and fuel cost in M£/TWh of fuel used. The net present values were estimated assuming the discount factor of 3.5%.

η_{ij} - is the fuel use efficiency.

The above optimization task is subject to a number of equality and inequality constraints in order to account for the technical feasibility of the transition pathways and the emissions constraint. The equality constraints include:

- The balance between the annual electricity production and the annual electricity demand;
- The balance between the produced electricity amount in wind, wave, tidal, and solar power plants and their installed capacity times the capacity factors;
- The balance between the total installed capacity, newly installed capacity and the closed capacity in every time step and the capacity transfer between the time steps;
- The phasing out of the existing capacity and the capacity closure after the lifetime ends;
- The constraint, which enforces the total capacity values to be equal to the existing capacity in the initial year of 2010.

The inequality constraints included:

- The contribution of all power plants to the peak demand should exceed the required peak capacity;
- The produced electricity amount in the power plants should not exceed the maximum amount and should not be lower than the minimum amount that can be produced, given the installed capacity and the maximum and minimum availability factors;
- The upper constraint on the deployment of wind, solar, hydro power plants, electricity import and pumped storage;
- The constraint on the CO_2 emissions for meeting the climate mitigation targets.

The data for this model were taken from the well-established UK energy system model (Ekins et al., 2011; Strachan, 2011; Usher and Strachan, 2012), filling the minor data gaps from other sources. In line with the 'Market Rules' storyline of the Realizing Transition Pathways project, the targets of average CO_2 emissions from the power system were taken as 300gCO_2/kWh by 2020, 50gCO_2/kWh by 2030 and 20gCO_2/kWh by 2050.

The cost-optimal transition pathway from 2010 to 2050 and the least total system costs are found by solving the optimization task in Eq. (1) with the above-listed constraints. In line with the modeling-to-generate-alternatives techniques (Chang et al., 1982a, b), D-EXPANSE then randomly samples a wanted number of further transition pathways from the near-optimal space. This is done by solving another optimization task a wanted number of times:

$$max \sum_{i \in I, j \in J} \left[x_{ij}^{ncap} + x_{ij}^{tcap} + x_{ij}^{prod} \right]; \qquad (2)$$

where I and J - are the sets with random number of randomly selected indices i and j (Chang et al., 1982a, b). For example in the case of i, $i = 1,2,\dots,19$, a number of indices is firstly randomly drawn, which could be 5. Then, five indices are randomly drawn to form the set I, which could be $I = [1,3,11,12,18]$.

The optimization task in Eq. (2) is subject to all of the equality and inequality constraints of the optimization task in Eq. (1) and to an additional constraint on total costs in order to find solutions from the near-optimal space. This constraint is expressed as follows:

$$\left[c_{ij}^{inv} x_{ij}^{ncap} + c_{ij}^{fom} x_{ij}^{tcap} + \left(c_{ij}^{vom} + \frac{c_{ij}^{fuel}}{\eta_{ij}} \right) x_{ij}^{prod} \right] \leq C_{slack}; \qquad (3)$$

where C_{slack} is the so-called slack and defines the near-optimal space by allowing a certain deviation from the least cost value. The previous analyses assume the slack value of 10% to 30% (DeCarolis, 2011; McJeon et al., 2011; Trutnevyte et al., 2012a). In the presented analysis, the value of 20% is assumed and the results are highly dependent on this value.

Every run of the optimization task in Eq. (2) provides one transition pathway. In the presented analysis, 1000 pathways are generated by solving 1000 times the optimization task in Eq. (2). From this set of 1000 randomly generated pathways, four maximally different pathways are sampled twice: four pathways that maximally differ in the newly installed capacity in every time slice and other four pathways that maximally differ in the total investment in every time slice. The maximally different pathways are sampled using the adapted distance-to-selected method (Tietje, 2005; Trutnevyte et al., 2012a). According to this method, the first pathway is the one, whose elements of the installed capacity (or investment) have the biggest Euclidean distance from the elements of the cost-optimal pathway. The second and further pathways are found by evaluating the harmonic mean of the Euclidean distances between the elements of every randomly generated pathway and the elements of the so-far sampled pathways. The randomly generated pathway with the biggest harmonic mean of Euclidean distances is then sampled as the next maximally different pathway. This procedure is terminated, when the wanted number of maximally different pathways is sampled.

4. Results

The modeled least-cost transition pathway of the UK power system until 2050 is presented in Figure 1. The results are shaped by the constraints from the Section 2, by the demand data from the Realizing Transition Pathways project and the cost and technology data from the existing UK energy system model (Ekins et al., 2011; Strachan, 2011; Usher and Strachan, 2012). The energy system representation, used so far, was very simplistic and thus the results should be interpreted with caution. In terms of the installed capacity, the least-cost transition pathway until 2050 relies on new gas IGCC and nuclear power plants, while tidal and wind power plants are introduced after 2030. Due to the stringent emission targets after 2030, electricity is mostly produced in nuclear, tidal and wind power plants, while gas IGCC plants serve as a reserve capacity.

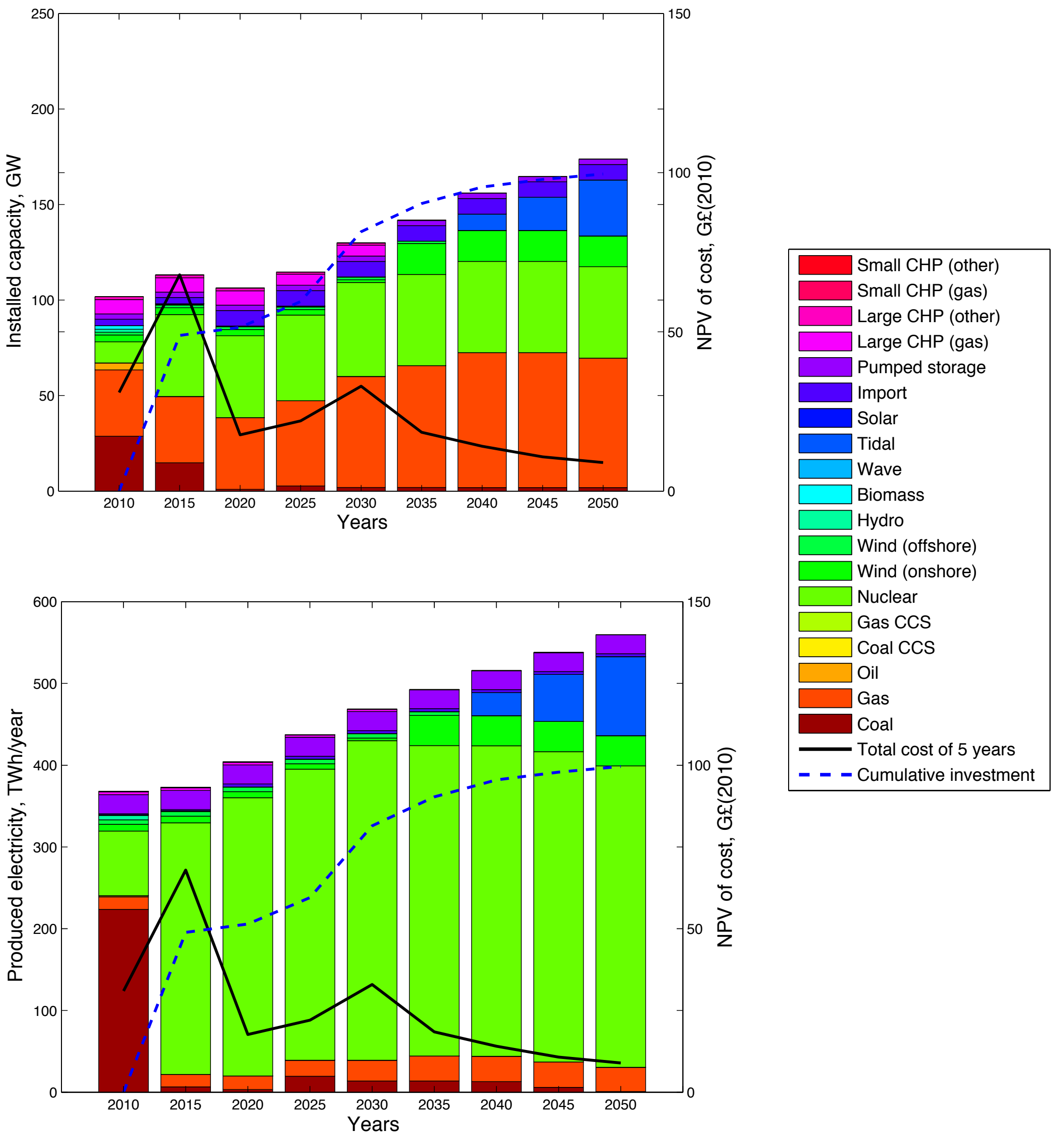

Figure 1. The installed capacity and produced electricity in the modeled least-cost transition pathway

While the used system representation was very simplistic, the modeled least-cost transition pathway is comparable with other analyses. The required investment in the power generation by 2020 is approximately £80 billion and is in the comparable range with the value of £75 billion, estimated in (Energy Bill, 2012). The power supply mix is also comparable with the runs of the existing energy system model (Ekins et al., 2011; Strachan, 2011; Usher and Strachan, 2012), which has much broader system boundaries, elaborates the technologies and the temporal supply-demand balance in more detail.

While Figure 1 presents a single cumulative investment curve of the least-cost transition pathway, Figure 2 presents 1000 cumulative investment curves of the randomly generated transition pathways. All these randomly generated pathways fall into the near-optimal space, as defined by the 20% slack from Eq. (3), but they differ in their magnitude and temporal distribution of the investment (i.e. the shape of the cumulative investment curve). Figure 3 presents the cumulative investment curves for a sample of five pathways: the cost-optimal pathway and four maximally different with respect to the investment values in every time slice. The cost-optimal pathway (Figure 1) requires a considerably high amount of investment in the year of 2015 and later the investment curve becomes flatter. The other near-optimal pathways (Figure 3) may postpone the investment peak to as far as 2035. Moreover, the cumulative investment values of the different pathways diverge considerably after 2015, but then their spread converges in 2035 and then diverges again. Overall, while all of these transition pathways are near-optimal with respect to the total system costs, their temporal patterns in investment differ and illustrate the flexibility in the investment strategies until 2050.

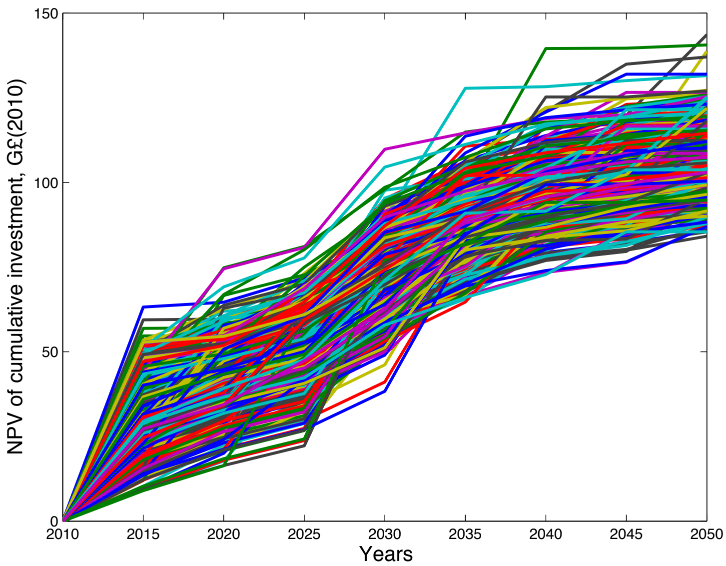

Figure 2. The cumulative investment in the 1000 randomly generated transition pathways

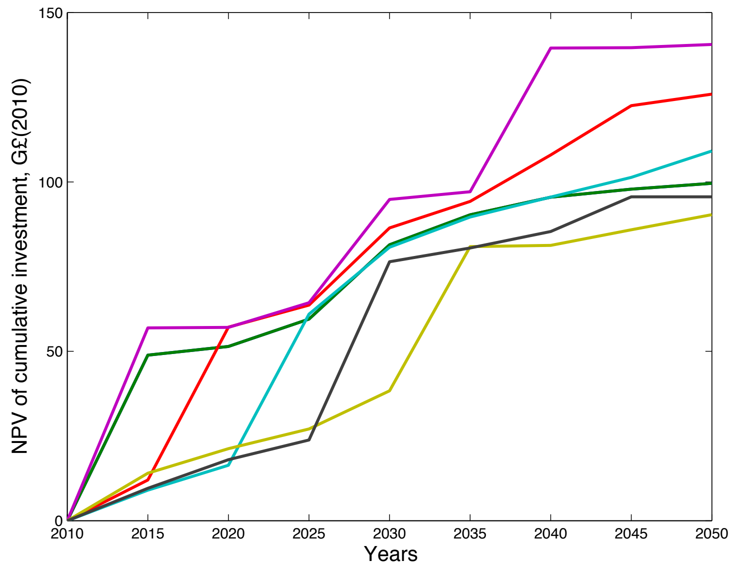

Figure 3. The cumulative investment in the cost-optimal transition pathway and four other pathways that maximally differ in the investment values in every time slice

Figure 4 presents four near-optimal transition pathways that are maximally different with respect to the newly installed capacity. All of these pathways meet the emissions constraint and fall into the space of near cost-optimal pathways, but they are poles apart in terms of technologies used. While the cost-optimal pathway (Figure 1) shows the deployment of nuclear, gas, wind and tidal power plants, other near optimal pathways indicate the possibility for large gas CHPs, wave, gas CCS and even solar power. Nuclear power appears in all of the maximally different pathways in combination with other, interchangeable low carbon options, such as wave, tidal, gas CCS or solar power. By examining the produced electricity balance of these pathways, it becomes visible that gas IGCCs, gas CHPs or coal power plants are built as a reserve capacity due to low investment cost in three of the pathways, but do not produce electricity. While a number of costly individual technologies, such as solar, can be deployed to a large extent in the different pathways, not all of the combinations of the high deployment of costly technologies are feasible in the near-optimal space. As discussed in Section 5, here further research is needed for developing methods that unravel such interdependency patterns.

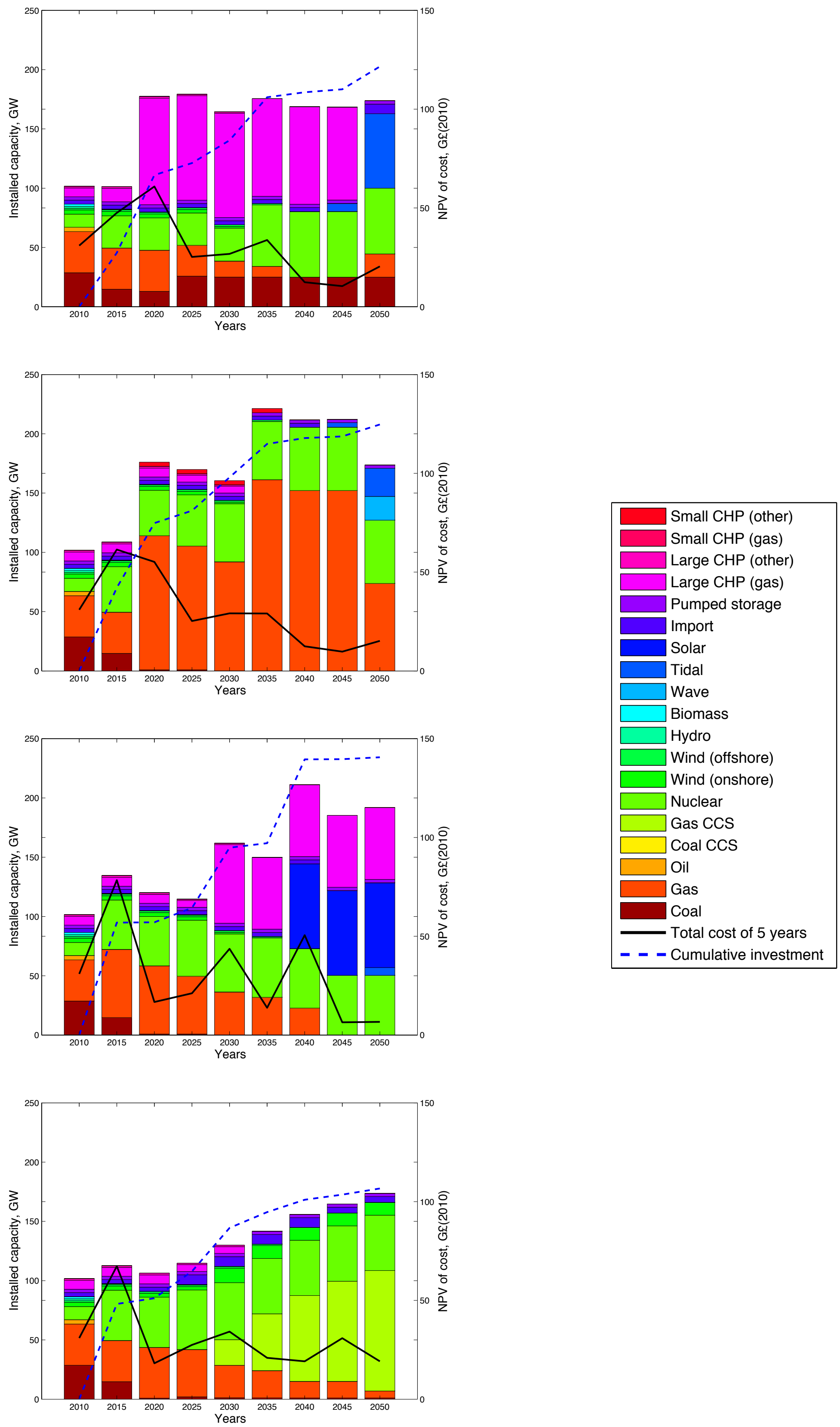

Figure 4. Four near-optimal transition pathways with maximally different patterns in newly installed capacity

5. Discussion and future research needs

As a part of the Realizing Transition Pathways project, this conference paper presented the first completed iteration of D-EXPANSE model development for analyzing the investment strategies into the UK power system until 2050. Building on earlier efforts with static models (DeCarolis, 2011; Trutnevyte et al., 2012a), the dynamic D-EXPANSE model was used to sample multiple near-optimal transition pathways with the maximally different patterns in newly installed capacity or in temporal investment distribution. While the current version of D-EXPANSE is very simple in comparison to the elaborated models such as (Ekins et al., 2011; Strachan, 2011; Usher and Strachan, 2012), D-EXPANSE shows potential for novel insights. While the large and detailed models have their own strengths, the comparatively small, exploratory models have potential for expanding the thinking about the future energy system (DeCarolis, 2011; Morgan and Keith, 2008). Rather than providing prescriptive results, D-EXPANSE exactly aims to contribute to this expanded thinking and to better understanding of the technological and temporal patterns in transition pathways.

The further iterations of the D-EXPANSE model development require improvements in three arrays: (i) better power system representation and data, (ii) further work in unraveling patterns from a large number of transition pathways, and (iii) combining this work with uncertainty analysis. Regarding the power system representation, the power system model is so far very simplistic and could be elaborated further by introducing more time slices (e.g. day and night, summer and winter loads). This would allow for a more realistic modeling of the supply and demand balance, especially during the peak and base loads. Alternatively, the transition pathways, derived with the D-EXPANSE model, could be then checked for technical feasibility by linking the D-EXPANSE model with a detailed power system model. For the analysis of the temporal investment distribution, the time aspect becomes crucial. For this purpose, more detailed data on the phasing out of the existing capacity and the building of the planned new capacity should be added to the analysis. Instead of the overnight investment, the lead times of constructing power plants could also be introduced to the model. From a broader perspective, further technologies and end-use efficiency improvements could be added to the analysis as in (Trutnevyte et al., 2012a; Trutnevyte et al., 2012b). Impacts of the energy policies, such as carbon tax, as well as the macro-economic feedbacks, such as demand elasticities, have not been considered at all and could be added.

Regarding the unraveling of patterns from a large number of transition pathways, in this conference paper four maximally different pathways were sampled and then visually inspected. In addition to such visual inspection, future research is needed in applying existing and developing new methods for formal elicitation of the patterns, e.g. (Kasprzyk et al., 2013; Lempert et al., 2003; McJeon et al., 2011; Trutnevyte et al., 2012a; Trutnevyte et al., 2012b). In particular, time series clustering could be applied to clustering the different pathways into fundamental groups and unraveling patterns in these groups (Warren Liao, 2005). Moreover, currently the sampling was conducted with respect to the differences in the newly installed capacity and in the investment values in every time slice. Other criteria could also be used for sampling the pathways, e.g. total installed capacity, produced energy or cumulative investment.

Regarding the uncertainty analysis, D-EXPANSE so far was run only with deterministic values of input parameters, such as cost. Approaches like D-EXPANSE, based on the modeling-to-generate-alternatives methods, are argued to accommodate parametric uncertainties (Chang et al., 1982a, b; DeCarolis, 2011). Yet, further research is required to investigate whether and to what extent the results from an uncertainty analysis and D-EXPANSE would overlap. For example, D-EXPANSE model could be run with different input values and the patterns could be extracted from the resulting large number of pathways. Such approach can be expected to illuminate the conditional links between the investment strategies and help to derive robust investment strategies.

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