The Shape of Future Electricity Demand: Exploring Load Curves in 2050s Germany and Britain

T. Boßmann^{(a)*} and I. Staffell^(b)

^(a) Fraunhofer Institute for Systems and Innovation Research ISI, Karlsruhe, Germany.

^(b) Imperial College Business School, Imperial College London, South Kensington, UK.

*Corresponding author. Tel.: +49-721-6809257. E-mail address: tobias.bossmann@isi.fraunhofer.de.
Fraunhofer ISI, Breslauer Str. 48, 76139 Karlsruhe.

Originally published in Energy, Elsevier B.V.

<http://dx.doi.org/10.1016/j.energy.2015.06.082>

Abstract

National demand for electricity follows a regular and predictable daily pattern. This pattern is set to change due to efficiency improvements, de-industrialisation and electrification of heat and transport. These changes are independent of renewable infeed and are not well understood: contemporary studies assume that electricity load curves will retain their current shape, scaling equally in all hours. Changes to this shape will profoundly affect the electricity industry: increasing the requirements for flexible and peaking capacity, and reducing asset utilisation and profitability.

This paper explores the evolution of load curves to 2050 in Germany and Britain: two countries undergoing radically different energy transformations. It reviews recent developments in Europe's electricity demand, and introduces two models for synthesising future hourly load curves: eLOAD and DESSTinEE. Both models are applied to a decarbonisation scenario for 2050, and consistently show peak loads increasing by about 23% points above the change in annual demand, to 103 GW in Germany and 92 GW in Britain. Sensitivities around electrification show that a million extra heat pumps or electric vehicles add up to 1.5 GW to peak demand.

The structure and shape of the future load curves are analysed, and impacts on the national electricity systems are drawn.

1 Motivation and Aims

The electricity sector is a capital intensive business with long planning and operation periods of several decades. In order to meet long-term strategies and targets for a secure, affordable and low carbon energy system, the right investment decisions have to be taken imminently in terms of electricity generation capacity, grid infrastructure, and system flexibility. Energy system modelling serves as basis for making strategic and investment decisions; however, the majority of models focus on the supply and demand of electricity only in terms of annual consumption. This neglects the features of electricity which make it a unique and challenging commodity to trade: the need to balance supply and demand over extremely short timescales, limited options for storage, inflexibility in the quantity demanded at any given time, and almost no communications between supplier and the majority of consumers (flat-rate pricing and infrequent metering of consumption).

The predictable and repetitive pattern of hourly electricity demand is fundamental to the current design of our power systems. However, most studies which project the future of this demand neglect the evolution of the hourly electricity consumption pattern (also referred to as system load curve) and simply scale a historic load curve according to an assumed future electricity demand. This is seen in both academic reports [1]–[6], and studies by system operators and government departments [7]–[11], which are directly shaping national energy policies.

Many of the broad roadmaps and pathways to 2050 further simplify the hourly pattern of electricity demand, considering only the annual level of consumption or dividing the year into a limited number of time slices (e.g. [12]–[15]). The nature of energy systems models such as MARKAL, TIMES, MESSAGE or PRIMES means they cannot represent the intricacies of electricity sector transformation [16]. Hourly unit commitment of power stations is simulated under specific framework conditions, such as emission or energy demand reduction targets to better understand which investments are required.

In the future the diffusion of new as well as the phase-out of existing technologies may imply substantial transformation of the load curve. These changes may have important implications, for example greater need for managing peaks (storage, demand-side management, interconnection, peaking capacity) and of troughs (curtailment of excess renewable energy). Hence, it is crucial to integrate this issue in the context of energy-system modeling.

This study aims to explore the extent to which future electricity load curves will be transformed by structural changes on the demand side, drawing out simple relationships that can be easily implemented in future research, and highlighting the importance that these often-overlooked changes will have on the future electricity supply system.

This paper begins by analysing the current composition and past changes in national load curves, highlighting the influence of technology shifts and temperature. It then reviews current efforts in projecting future load curves and introduces two state of the art models: eLOAD and DESSTinEE. These models are then used to project load curves for Germany and Britain in 2050, using a

scenario to achieve 80% decarbonisation. The key features of these load curves are analysed, including sensitivities to future investment in electric heat pumps and battery electric vehicles. Finally, the wider implications of these changes are discussed, including the impacts on system flexibility, peak capacity requirements and asset utilisation.

2 Composition of Today's Load Curves

In this paper, the term "load curve" is used to mean the annual 8,760 hour time-series of demand, and "load profile" is used for the repetitive 24-hour distribution of load from a given sector or appliance.

2.1 Background

Load curves in major European countries changed dramatically as new technologies came into usage, existing ones further penetrated the market and old ones were phased out. Figures 1–3 look at the three largest economies (Great Britain¹, Germany and France) to highlight some of the major trends seen in the past.

*Figure 1: Evolution of load in Great Britain, 1991–2013 (left), and in Germany, 2006–2013 (right).
Data from [17], [18].*

Figure 1 shows that over the course of twenty years British peak and minimum load did not evolve in the same manner as overall annual electricity demand (average load). Germany has also experienced an uneven evolution of load, although these trends cannot be observed over such a long time frame due to lack of data. Figure 2 shows also that load did not evolve equally across all hours of the day in Germany and the UK, due to changes in the technology mix of electricity

¹ Note the distinction between Great Britain and the United Kingdom. When considering annual energy demand the whole United Kingdom is considered, whereas for hourly electricity load Great Britain is considered. The latter is made up of England, Wales and Scotland only, as Northern Ireland is served by a different electricity grid.

consuming processes and appliances. The rise of computers and other electronic devices with stand-by modes altered the balance of morning, evening and night-time demand, implying a load shift from midday hours into these periods.²

Figure 2: Change in mean daily load distribution on summer Wednesdays in Germany (left) and throughout the entire year for the UK (right). Each year's load profile is normalised against the daily minimum to highlight changes in shape, and the evolution of annual demand over this period is shown to the right. Data from [17], [18].

This argument is backed by the rising temperature-sensitive peak load in France over the past ten years, shown in Figure 3. The significant growth of electric heating systems resulted in the sensitivity of peak load increasing by 50% over the last decade, from a 1.7 GW increase per degree centigrade drop in temperature in 2003/04 to a 2.6 GW increase in 2011/12. This has contributed towards peak load in France increasing from 85 to 100 GW during this period, driven by the adoption of both heat pumps and conventional resistance heaters (both ~150,000 per year) [19].

² Solar PV panels have the same effect of reducing apparent demand during daylight hours; however, this demand data is not affected by renewable outputs, and their effect would only become visible from the mid-2000s as opposed to the late 1990s.

Figure 3: The temperature sensitivity of peak load in France, in 2003 and 2012. Data from [20], [21].

This development should serve as an important warning to other countries which are planning a large transition to electric heating. In particular, the UK has ambitious plans³ for heat pumps to deliver a third of all heat by 2030, which will have a profound impact on peak load and may prove problematic given the current worries around capacity shortage. Whilst there is no official target for heat pump uptake in Germany, new installations have increased strongly in recent years [19], which could introduce similar problems with peak load at a time when large amounts of nuclear capacity are being retired.

In February 2012, France was hit by an exceptional cold wave lasting for about 13 days with temperatures averaging -4°C , compared to the norm of 5°C for that time of the year. Due to the elevated degree of electrified space heating French electricity consumption set a new record of 102.1 GW, exceeding the previous peak from December 2010 by more than 5 GW and the peak of 10 years before by 22.4 GW [22]. Around 9 % of French electricity consumption during the cold wave was covered by electricity imports from neighbouring countries. Contrary to France's usual role as a net electricity exporting country, it had to import up to 9 GW (whereof up to 3 GW were provided by Germany and 2 GW by the UK), pushing French electricity transfer capacities to their limits [22]. If France's neighbouring countries follow the same path of electrifying heat, then these imports may not be available during such a cold spell in the future, potentially leading to power outages across Europe.

³ Based on the 4th Carbon Budget: 6.8 million homes plus around 60% of commercial and industrial heat demand [64].

2.2 Measures for Defining Load Curves

To get a complete representation of national electricity demand, load curves are defined here to measure the active power absorbed by all consumers on the network, including those served by autoproducers (e.g. industrial demand met by on-site generation) and small distribution-connected renewables. This is equivalent to the total net generation of electricity (gross generation minus power station self-consumption), including network losses, excluding consumption for pumped storage.

Historic hourly load curve data were sourced from Entso-E [18] and National Grid [17], and autoproducer load (which is invisible to system operators) was estimated and added back using Entso-E monthly statistics [18].⁴

Several measures can be used to evaluate and define national load curves, a selection of which are given in Table 1, following [23].

In Table 1:

- L_t is the hourly mean load (measured in GW) at time t ;
- Δt is the duration of load remaining within specific boundaries, relative to the maximum load
- rr is the ramp rate between adjacent time periods (i.e. $\partial L / \partial t$);
- rrf is the ramp rate factor, defined as the mean absolute change in load relative to the maximum load;
- ΔL is the unbroken series of load change in a single direction (i.e. the extent from a local minima to maxima);
- T is temperature (measured in °C); and
- t_{peak} is a definition of which time periods contain the peak load – taken to be 18:00 and 19:00 on weekdays.
- Temperature sensitivity is represented by the negative differential of load with respect to temperature, as it is conventional to think of demand rising as more heating is required, which is as T falls. This can be thought of as the average slope of the data on the left side of Figure 3, for temperatures below 15°C.

⁴ We used the assumption that autoproducers run baseload to primarily serve heavy industry and CHP, so for each month, the constant power output from autoproducers was estimated and added on to the load curves. In Britain the 4.6 GW fleet [88] was calculated to serve on average 2.2 GW during summer and 2.8 GW in winter; and in Germany, the 10.0 GW fleet [89] produced 7.0 GW and 9.0 GW respectively.

In 2010			DE	GB
Load duration curve	Total demand [TWh]	D	547	340
	Minimum load [GW]	$\min(L)$	40.2	21.1
	Maximum load [GW]	$\max(L)$	88.3	61.4
	Min/max load ratio	$\min(L) / \max(L)$	45.5 %	34.4 %
	Capacity factor	$\text{mean}(L) / \max(L)$	70.7 %	63.1 %
Stable load situations	Mean duration of maximum load [h]	$\text{mean}(\Delta t_{90\%-100\%})$	4.09	2.70
		$\text{mean}(\Delta t_{70\%-100\%})$	15.8	8.95
	Total number of hours with maximum load [h]	$\sum(\Delta t_{90\%-100\%})$	286	192
		$\sum(\Delta t_{70\%-100\%})$	4733	2511
Load change between consecutive hours	Ramp rate factor	$\text{mean}(rr)/\max(L)$	1.97 %	2.66 %
	Mean ramp rate [GW]	$\text{mean}(rr _{rr>0})$	1.96	1.88
		$\text{mean}(rr _{rr<0})$	-1.57	-1.44
	Maximum load change [GW]	$\max(rr _{rr>0})$	9.91	7.90
		$\min(rr _{rr<0})$	-6.82	-5.35
Continuous load change sequences	Maximum load change [GW]	$\max(\Delta L_{pos})$	29.0	24.6
		$\max(\Delta L_{neg})$	-26.4	-25.2
	Nb. of load alternations	n_{altern}	1,800	1,920
Temperature sensitivity	Mean temperature sensitivity [GW/°C]	$-\text{mean}(\partial L / \partial T _{T<15})$	0.49	0.81
	Peak temperature sensitivity [GW/°C]	$-\text{mean}(\partial L / \partial T _{T<15, t_{peak}})$	0.60	1.14

Table 1: Evaluation criteria for historic German and British load curves.

Table 1 contains the assessment of the German and the British load curve from the year 2010. The same criteria are calculated for the 2050 load curves later in the results section.

German demand in 2010 equaled nearly 550 TWh, with the hourly load ranging between 40.2 and 88.3 GW,⁵ compared with 340 TWh in Britain. While Britain's annual demand is 62% that of Germany's, the hourly load ranges from 52% of the German minimum to 70% of the German maximum load. This more pronounced load variance is confirmed by the British capacity factor being 10% lower than Germany's. The capacity factor is an indicator for the average usage (and hence the profitability) of installed power plants. More detailed insights about the share of base, mid-merit and peak load may be gained by plotting the load duration curve (see, for instance, Figure 11).

The length of peak load situations and the ramp rate factor assist in identifying the technical requirements for peak load capacity and generation flexibility. The 8.8 GW of German capacity which meets the top ten percent of load is expected to run for an average of 4 hours per plant start, and for a total of 286 hours per year. In Britain, peak loads are shorter and "spikier", so the

⁵ One should note that the present analysis is based on mean hourly data. Maximum and minimum load may actually have exceeded the outlined figures for fractions of an hour.

top ten percent (4.1 GW) runs for just 192 hours per year, in blocks of 2.7 hours per start. British power stations must therefore recoup their fixed costs (e.g. capital) from fewer running hours, potentially giving rise to higher price spikes during peak times.⁶

With regard to the hourly load alternation, in absolute terms the British ramp rates are slightly smaller (1.66 cf. 1.77 GW per hour), however this represents a greater proportion of capacity changing output (2.7% cf. 2.0%). The same trend is seen with the maximum ramp rates, which required 10.8% of British, and 9.5% of German capacity to change output over one hour; and with the maximum continuous load changes.

British demand is 40% more sensitive to temperature than German, with peak evening load rising by over 1 GW for every degree that temperature falls. This mirrors the share of electric heating in both countries, 10% in the UK households and 4% of Germany's [24][25]; and the relative inefficiency of the British housing stock, which means a greater percentage of energy is used for space heating. However, both countries pale in comparison to France, where peak temperature sensitivity is 2.6 GW/°C (based on the slope in Figure 3).

3 Modelling Techniques

3.1 State of the Art

As mentioned beforehand, the majority of studies apply simple scaling of a historic load curve according to an annual demand projection in order to estimate the future load. This approach is inadequate in the context of long-term energy system modelling where new technologies penetrating and existing ones leaving the market may imply significant change to the future load shape.

An important number of publications deal with individual aspects of hourly load projection. Most of the studies focus on the load curve projection of single sectors or consumers [26]–[33]. Others limit themselves on regional load curves [34]. Further works address single characteristics of the future system load, such as the load duration curve [35]–[37] or system peak load [9], [38]–[40].

However, when it comes to the continuous hourly projection of national system load curves over the duration of an entire year, to the extent known, there are only three types of approaches currently described in literature:

The first type equals a trend-extrapolation of the historic evolution of load shape transformation. Filik *et al.* assess historic load curves regarding their daily, weekly and seasonally occurring periodicity [41]. The resulting insights are integrated in a load curve trend-extrapolation,

⁶ Holding other factors constant (fuel prices and having no market for capacity), some peaking generators would lose money and close down in the long-run, causing peak prices to rise due to greater reliance on demand side response.

considering assumptions about the overall annual demand evolution. Macro-economic effects, technological innovations or temperature related impacts on the load curve are not taken into account, as this assumes that past technology shifts will continue unaltered into the future. Sotiropoulos further develops this approach in [42] by running a regression analysis based on hourly German load data from 2006–2011, integrating economic trends, public holidays and vacation, unpredictable events and population growth. The market penetration of new technologies is not explicitly taken into account.

A specific focus on individual appliances or events is set on in the second group. Koreneff *et al.* assess the evolution of future load curves considering the extensive diffusion of electric vehicles and heat pumps [43]. Their consumption pattern is represented by hourly synthetic load profiles. The degree of load curve transformation primarily depends on the respective annual electricity demand. A potential load curve transformation related to changes in electricity demand in other sectors and the impact of the outdoor temperature are not taken into account.

The third group extends the use of representative load profiles to the full composition of the future load curve. Hainoun and Pina *et al.* determine user specific load profiles of representative customer groups, within the industry, tertiary and residential sector, based on empirical data [44], [45]. These profiles are scaled according to an annual electricity demand projection and put together in order to generate the overall load curve. As the diffusion of new technologies is not explicitly taken into account, Andersen *et al.* [46] apply the same approach but set a particular focus on the impact of the increasing market penetration of electric vehicles and heat pumps. Gobmaier *et al.* carry out a regression analysis on historic load measurements considering typical days, temperature and day light [47]. Generated load profiles are further adjusted according to future changes in consumer behaviour, such as adjusted working times or opening hours in the commercial sector.

All these approaches come with the common drawback of neglecting stochastic outliers and characteristic irregularities. The two models used in this paper (eLOAD and DESSTinEE) take two different approaches of incorporating the anomalies based around partial decomposition.

3.2 eLOAD Model Description

The eLOAD (electricity Load curve Adjustment) model⁷ projects the long-term evolution of hourly electricity load curves at national level for all EU27 countries up to 2050. eLOAD consists of two modules. The first addresses load curve transformations due to structural changes on the demand side and the introduction of new appliances (such as electric vehicles), while the second module addresses active changes due to demand response (DR) activities [48].

The first module combines the approach of [44] for specific and particularly relevant applications and the option of scaling; giving a partial decomposition approach (PDA, cf. Figure 4). Technology-

⁷ Further information about the model is available from <http://www.forecast-model.eu/forecast-en/content/methodology.php>

specific annual demand projections are provided by the bottom-up simulation model FORECAST7 and used to identify all “relevant applications” that feature a significant increase or decrease in electricity consumption over the projection horizon. eLOAD uses appliance-specific hourly load profiles from field surveys, simulation models and official data bases, which are assembled as in [49] to generate load curves for all relevant appliances for the base year, according to the respective annual demand in the base year. The residual load curve (from all other applications not explicitly modelled) is deduced from the historic metered load curve, and then the appliance-specific and residual load curves are scaled for all projection years according to the evolution of annual demand. Reassembling these scaled load curves gives the total national load curve of the projection year.

Figure 4: Overview of the calculation procedure of the Partial Decomposition Approach, showing an example for two appliances (night storage heater and heat pumps) over a 48 hours load curve excerpt.

To select “relevant applications” we calculate the change in annual demand between base and projection year for each application and express it relative to the total national demand in the projection year. If this ratio exceeds a certain threshold (the selection criterion, taken here to be 1%), the application is labelled as relevant. Depending on the individual scenario this can be translated into about 30 relevant applications covering approximately 80% of the total change in demand between base and projection year (see Figure 5). Sensitivity calculations prove that selecting a higher number of relevant applications has only a marginal impact on the projected shape of the load curve.

Figure 5: Relation between selection criterion, number of relevant applications and cumulated share of change in demand (for an exemplary scenario).

The main advantage of partial decomposition is that it properly takes into consideration structural changes in overall annual demand by explicitly modelling the main drivers for load curve transformation while preserving stochastic outliers and characteristic irregularities from historic load curves. Limiting the number of required load profiles by selecting only the most relevant applications minimizes research effort for data collection and susceptibility. Using the results from the FORECAST model entails the benefit of integrating the assets of bottom-up demand simulation modelling, that is the appropriate representation of a large variety of appliances, the diffusion of new technologies, the evolution of techno-economic characteristics, macro-economic drivers and political measures.

The second module of eLOAD, dealing with DR modelling, aims to smooth the net load, which is defined as the system load less the generation of renewable energy sources. A smoothed net load ensures efficient use of existing electricity generation and grid infrastructure, increased operational security as well as a reduced need for investments in new electricity generation and transportation assets [50], [51].

For appliances that are suitable for demand response the related load curves, techno-economic parameters and restrictions (e.g. load availability, storage capacities, activation costs) are taken into account in the framework of a mixed-integer optimization which determines the least-cost scheduling of the appliances' load from a consumer perspective. That is, based on a day-ahead price/net-load signal⁸ the appliances' load is scheduled from hours of high prices to hours of low prices.

⁸ Empirical data shows a linear relationship between net load and wholesale prices, which serves as a basis to estimate future hourly wholesale prices based on the projected net load evolution.

3.3 DESSTinEE Model Description

DESSTinEE (Demand for Energy Services, Supply and Transmission in Europe) is a model of the European energy sector in 2050, going from demand for energy services through to the hourly profiles of demand and generation of electricity. It is used to test assumptions about the technical requirements for energy transport (particularly for electricity), and the economic challenges around developing the necessary infrastructure for this. The DESSTinEE model is implemented in Microsoft Excel and VBA.⁹ It includes forty countries in Europe and North Africa, considering 10 forms of primary and secondary energy. Energy demand and supply in each country is modelled in three stages:

1. macroeconomic projection of demand for energy services and modal shares, giving final demand for each energy vector in 2050;
2. synthesis of hourly electricity demand profiles for 2050; and
3. simulation of the least-cost dispatch and transmission of electricity across the continent.

The annual energy projection begins with a calibration to the energy system of each country in 2010, an example of the UK is shown in Figure 6. The 2050 energy system is then projected 'backwards', reading from right to left in the figure. Following Deng, each country's demand for energy services (such as the distance people travel or the value added by industry) is projected to 2050 using macroeconomic relationships with population, income, energy prices and sector-specific details [52]. These service demands are then allocated to final energy demands using inputs on the technology mix and efficiencies in 2050, and then translated into primary energy requirements for each fuel.

DESSTinEE is a simulation model for exploring future energy system transition pathways (similar to DECC's 2050 calculators [53]) rather than an optimisation model that is used to find the least-cost path to reducing carbon emissions (such as MARKAL or TIMES). Such normative scenarios can however be used by DESSTinEE as a source of input parameters. The IEA's Energy Technology Perspectives [12], IIASA's Global Energy Assessment [13], and European Commission's Low Carbon Economy 2050 Roadmap [14] are currently implemented and, where necessary, extended with country-specific information to account for differences in the current national energy systems and expected trajectories.

⁹ The model is available from sites.google.com/site/2050desstinee.

Figure 6: Historic snapshot of the UK energy system in 2010, used for calibrating the DESSTinEE model, showing the flow of modelling logic for (1) annual projections and (2) hourly load curve synthesis.

The synthesis of hourly demand profiles uses a similar, but simpler, approach to eLOAD. Each country's load curve is decomposed into major economic sectors (residential, commercial, agriculture, industrial, road and rail), with built sectors being split further into space heating, water heating, cooling, and all other appliances. Daily profiles (24 periods) are specified for each sector and end-use, with summer/winter and weekday/weekend variants to account for differences in human and economic activity. The model generates annual profiles (8,760 periods) for each sector, scaling space heating demands by the number of heating degree days (HDD) experienced. Stochastic variation is added to each profile to mimic the natural variability of human behaviour, and the sector profiles are summed to give the national load profile.

To preserve the unique and anomalous features of historic load curves, the residuals between actual and simulated load of the year 2010 are calculated, then scaled up and applied to the 2050 profiles. Figure 7 shows an example of the model's ability to replicate historic load curves from 2010. When validating the simulated load curves for 2010, the residuals for both Britain and Germany were normally distributed with a standard deviation of 7% (± 2.6 and ± 4.3 GW respectively). The correlation between the simulated load curve (before residuals were applied) and historic data was 0.96 for Britain and 0.91 for Germany.

Figure 7: Validation of the DESSTinEE model, showing two weeks of historic demand in 2010 in Germany and Britain against the model's simulation before residuals are added back.

The final stage of the DESSTinEE model is to simulate the electricity sector of each country, calculating the least-cost dispatch for a specified mix of power stations and transmission across a constrained network. This functionality is not used in this paper.

4 Scenarios for Future Load Curve Projection

This section introduces the scenario used for projecting hourly electricity load curves to 2050. To briefly summarise, this study:

- Looks at two countries which are undergoing different energy sector transformations;
- Focusses on a core decarbonisation scenario, with sensitivities around the electrification of heat and transport;
- Uses two independent models to understand the influence of different calculation methods.

4.1 Case Studies: Germany and Great Britain

Germany and the UK are interesting to study as they are both going through quite different revolutions and facing divergent future prospects, while aiming at the same time for a transformation towards a more sustainable national energy system. In particular, the stark contrast between national visions for the electricity has drawn interest, ranging from a 25% reduction in Germany to a doubling in Britain [54].

The German economy is still characterized by a strong presence of energy intensive industry, whereas the UK has undertaken an important shift towards the service sector¹⁰. Furthermore, Germany faces a declining birth rate and a decrease in population whereas the UK has one of the

¹⁰ Manufacturing contributes 20% of German GDP and 10% of UK GDP [90].

highest birth rates in the EU and strong immigration. Finally, both countries have designed a long term pathway towards a sustainable energy future: Germany's *Energiewende* and Britain's *Carbon Budgets*, which will both be very demanding on the electricity sector. Germany seeks to limit electricity consumption through extensive energy efficiency measures, whereas the UK seeks to expand it by shifting transport and heating into the electricity sector.

In order to represent these trends and objectives, we base our load curve calculations on an energy demand projection provided by the Energy Systems Analysis Agency (ESA2) [55]. The underlying explorative scenario assesses the impact of ambitious shares of renewable electricity generation, a broad diffusion of energy saving technologies as well as the comprehensive penetration of new technologies such as heat pumps and electric vehicles. The analysis concludes that energy efficiency and renewables could deliver a 90% emission reduction of the European power sector, compared to 1990.

The penetration of new technologies in particular is subject to uncertainty. We therefore analyse a set of sensitivity cases around the diffusion of heat pumps and electric vehicles, and their usage profiles (the use of heat storage and altered patterns of vehicle charging).

4.2 Assumed Evolution of Annual Electricity Demand

4.2.1 Drivers of Demand

Annual electricity demand in the two countries was projected from the 2010 baseline to 2050 using both the FORECAST and DESSTinEE models. These projections were disaggregated at the appliance- or sector-level, and used as an input for the subsequent load curve synthesis. This annual demand projection was initially conducted using FORECAST as part of the preparations of the ESA2 report [55]. DESSTinEE was set up to use these FORECAST parameters so that the two models could be comparable.

The key socio-economic drivers for annual demand (e.g. fuel prices, population and income growth) are based on a breakdown of the assumptions made in the EU Energy Roadmap 2050 [56], as summarised in Table 2.

The countries' population projections move in different directions, and the gradual shift towards smaller household sizes means the housing stock is assumed to grow slightly relative to population. The UK economy grows to exceed Germany's by the mid-2030s and its population by the 2040s, while the standard of living continues growing at a similar rate in both countries, following the long-term historic trend. The resulting GDP projections give broad agreement with those from financial institutions [57], [58] and other energy systems models [59], [60].

Following the European Commission [56], we assume that fuel prices continue increasing until 2030, after which concerted global climate action reduces demand for fossil fuels, and thus their prices. Prices in 2050 end up 10–17 % above 2010 prices: €3.00/GJ for coal, €10.40/GJ for oil, €6.90/GJ for gas and €346/t_{CO2} (in 2008 Euros).

Three of the technical drivers for the total demand of electricity are energy efficiency and the electrification of heat and transport. We assume relatively strong improvements in efficiency, particularly in the thermal performance of the housing stock. By 2050, German houses require two-fifths as much delivered heat per m² of floor space as today, implying that all new homes are built to PassivHaus standards (15 kWh/m²/yr), and the existing stock is extensively retrofitted with insulation, ventilation and smart control systems. The reduction is slightly lower in the UK (55% of 2010 levels) despite a greater proportion of new-build, due to technical and cultural difficulties in introducing these technologies [61]–[63].

		Germany			UK		
		2010 value	Annual growth	2050 value	2010 value	Annual growth	2050 value
Macro economy:							
Population		82.1m	−0.3%	72.1m	62.0m	0.5%	74.5m
National GDP	[€2008 bn]	2,280	1.1%	3,530	1,880	2.0%	4,130
GDP per capita	[€2008]	27,770	1.4%	49,060	30,370	1.5%	55,400
Residential heating:							
Housing Stock		38.4m	0.0%	38.4m	27.0	0.7%	36.2m
Share of useful heat provided by electricity		3.9%	4.3%	21.3%	9.4%	4.7%	59.0%
Electric heat pumps*		0.4m	7.8%	7.5m	0.0m	21.6%	19.2m
Other electric heating [†]		1.1m	−5.3%	0.1m	2.5m	−0.4%	2.1m
Specific heat demand	[kWh / m ² / yr]	132	−2.3%	51	132	−1.5%	73
e-Mobility:							
Electric vehicles ^Δ		0.0m	19.2%	23.4m	0.0m	19.8%	14.7m
Share of passenger fleet		0.0%	20.1%	60.1%	0.0%	18.5%	41.1%
Annual utilisation	[p-km / yr]	14,300	0.2%	15,730	12,700	0.2%	14,000

Table 2: Main economic and technical assumptions from the FORECAST model, showing the historic and future values with compound annual growth rates.

** The efficiency of heat pumps is temperature dependent, and is outlined in Section 4.3.*

† Some households use electricity for additional as opposed to their main heat source, so the share of households with electric heating is greater than the share of heat delivered by electricity.

Δ Electric vehicles (whether battery electric or plug-in hybrid operating in electric mode) have a specific consumption of 0.20 kWh/km in 2010, improving by 0.3% per year to 0.18 kWh/km in 2050.

The uptake of heat pumps in the UK is based on the CCC's 4th Carbon Budget [64], which projected that 7 million homes and 60% of non-residential buildings would use heat pumps by 2030. The CCC's central projection has since been lowered to 4 million homes [63], but this increases to 8.5 million homes if technical lifetimes reach 20 years, and hybrid heat pumps (i.e. heat pumps installed with a gas boiler backup) are included. Extrapolating these numbers to 2050 gives 19.2 million

residential heat pumps. Germany has not stated a specific target for the diffusion of heat pumps; however, more than half of today's newly constructed buildings rely on a heat pump system [65]. This trend is continued into the future, implying that by 2050 heat pumps cover 21% of the useful residential heat demand.

The uptake of electric vehicles in the UK is also based on the CCC projection for 60% of new vehicles to be electric (either EV or PHEV) from the 2020s onwards [63], leading to a total of 14.7 m electric vehicles on the road in 2050. The German government pursues the target of having one million electric vehicles on German streets by 2020 and up to 6 million by 2030 [66], [67]. Under the given scenario, this number is assumed to rise up to 23.4 m vehicles by 2050.

4.2.2 Demand Projections to 2050

Figure 8 shows the future evolution of demand as calculated by the two models, set against historic growth and projections made by other institutions. These results are not intended to be an accurate forecast of the future. Rather they explore one potential scenario with an ambitious transition towards decarbonised energy systems.

FORECAST provides results for each year to 2050, whereas DESSTinEE produces a single snapshot for 2050. The projections from FORECAST and DESSTinEE are very similar, showing the importance of using common assumptions relative to using different calculation methods. The end results differ by 2–3% because of using different calibration, growth models for economic sectors and disaggregation levels. In particular, technology diffusion is endogenously calculated by FORECAST, but exogenously specified within DESSTinEE.

Figure 8: Annual electricity consumption in Germany and Britain over the last 40 years, and projected over the next 40 years using the FORECAST and DESSTinEE models. The projected 2050 electricity demand from other studies are shown at the right of the chart, labelled a–f.

These results can be put into context by comparing them with the 2050 electricity demands projected in other studies. As shown in Figure 8, the ESA2 projection sits at the lower end, because it assumes that a greater contribution to decarbonisation comes from energy efficiency measures.

Our projections for both countries are around 38% lower than the IEA 4 Degrees Scenario, and 46% below their 2 Degrees Scenario (not shown). The German result is closest to the Energiekonzept Reference Scenario [68], and remains similar to the European Commission's Reference Scenario [60], which models the development of the EU energy system under current trends and adopted policies¹¹. The UK result agrees with both the EC's Reference and DECC's Core Decarbonisation scenario to within $\pm 10\%$ [69].

A notable feature in Figure 8 is the turn-around in German electricity demand, which decreases by 4% from 2010 to 2050. This is partly due to its falling population; however, the main drivers for this result are a strong commitment to energy saving across all sectors (in line with the German government's aims to reduce electricity demand by 25% until 2050). The decrease is not as strong as anticipated by the German government because of the increased electrification in the heating and transport sector (to ensure decarbonisation), which wipes out energy savings in other sectors.¹²

Whereas the German government plans for decreasing consumption, the UK government expects electricity demand to expand rapidly in coming decades. Electricity has been placed at the centre of its climate change strategy, as it is perceived to be the cheapest sector to rapidly decarbonise. With the power sector largely carbon-neutral by 2030, heat and transport are rapidly electrified, leading government to speak of electricity demand doubling between 2010 and 2050 [71]. The scenario used here assumes this will be offset by large efficiency improvements, to yield an 18% increase over 2010 levels.

4.2.3 Sectoral Breakdown of Demand

A key assumption common to both results is that economic growth and energy demand will continue to decouple in the future due to the accelerated uptake of energy efficiency measures. Historic demand has been strongly linked with GDP, as seen by the downturns during the early 1980s recession, the German reunification in 1990, and the recent recession in 2009.

This decoupling can be seen in Table 3, as the energy intensity of the two economies declines by 2.3% and 0.7% per year. All sectors other than transport fall in Germany and rise more slowly than GDP in the UK, driven by the diffusion of efficient lighting and electric devices. However, the increase in electric heating and personal transport means that electricity consumption per capita

¹¹ It includes policies and measures adopted in the Member States by April 2012 as well as policies, measures and legislative provisions (including on binding targets) adopted by or agreed in the first half of 2012 at EU level, including the Energy Efficiency Directive.

¹² A recent study carried out on behalf of the German Ministry for the Environment states that the planned 25% reduction may not comprise new electricity consuming end-uses such as electric vehicles, heat pumps or electricity based methane production (also referred to as power-to-gas) [91].

continues to increase, bringing the overall demand change to 0.2% annual decrease in Germany and 0.5% increase in the UK.

		Germany			UK		
		2010 value	Annual growth	2050 value	2010 value	Annual growth	2050 value
Total electricity demand	[TWh]	547	−0.2%	512	340	0.5%	423
- Industry	[TWh]	230	−0.1%	224	102	0.6%	130
- Commercial & others	[TWh]	161	−1.4%	91	112	0.0%	114
- Residential	[TWh]	139	−0.5%	115	122	0.2%	134
- Transport	[TWh]	16	4.1%	83	4	6.2%	44
Demand per capita*	[kWh / year]	2,160	0.6%	2,740	2,210	0.2%	2,400
Electricity intensity†	[Wh / € GDP]	188	−2.3%	75	87	−0.7%	64.4

Table 3: Electricity demand evolution of selected sectors and related indicators, showing the historic and future values with compound annual growth rates.

** 'Personal' consumption from the residential and transport sectors divided by population.*

† 'Economic' consumption from the commercial and industrial sectors divided by GDP.

4.3 Assumed Appliance Load Profiles

Both eLOAD and DESSTinEE make use of synthetic load profiles, describing the hourly load of individual sectors and end-uses, distinguished by season and day of week. eLOAD considers technology-specific load profiles for all end-uses and technologies featuring a significant change in annual demand between base year and projection year. DESSTinEE is more coarse-grain, using load profiles for each economic sector as a whole, plus heating technologies and electric vehicles. In both models these profiles are taken from historic data, except for electric vehicles, where we use a range of proposed charging patterns.

Based on the technology discrete annual demand projection provided by the FORECAST model it turns out that residential electric heating systems (i.e. heat pumps and storage heaters), residential water heating, electric vehicles and lighting in the residential and commercial sector feature the strongest change in demand. The load profiles of space heating technologies and electric vehicles are common to both models and, thus, explained in more detail in the following.

Figure 9a depicts the normalized load profiles for different heating technologies in Germany and the UK. eLOAD uses the individual technology profiles (solid lines), whereas DESSTinEE uses the sector-average profiles for conventional technologies (dotted lines). The German profiles are based on data from the German DSOs Vattenfall Hamburg [72] and Eon Bayern [73], and DESSTinEE used the average of these, weighted by the number of installations. The UK standard heating profile was based on metered consumption data from DEFRA [74], and the UK heat pump profile is taken from [75].

Figure 9: Normalised load profiles of residential space heating technologies (left) and the relationship between outdoor temperature and space heating demand for a single household (right).

The level of heating demand is temperature dependent, and was assumed to vary with daily average temperatures so that the load shape within each day remains unchanged. National-average temperature profiles were extracted from the MERRA database [21] by taking the population-weighted average temperature. Above a set temperature (15.5°C in DESSTinEE, 17 °C in eLOAD) there was assumed to be no demand for space heat, and below this point demand increased linearly with temperature (i.e. heating demand is proportional to degree days).

The electrical demand from conventional heating technologies is therefore scaled linearly with temperature. However, when using air-source heat pumps (ASHP) the coefficient of performance (COP)¹³ falls during lower outdoor temperatures. Based on industry-wide data from dozens of manufacturers, typical COPs for ASHPs are 3.0 at 10°C external temperature, falling to 2.4 at 0°C and 1.9 at –10°C [75]. More electricity is required per unit heat delivered during the coldest days when buildings have their highest demand for heat. The electricity consumption of air-source heat pumps (and their impact on peak load) therefore increases as a quadratic, rather than linearly, with falling temperature (see Figure 9b).

¹³ COP is the ratio of heat produced to electricity consumed, analogous to efficiency. It can be greater than 1 because ambient heat is harvested from the environment.

Figure 10: Normalised load profiles of electric vehicles under (a) static, and (b) smart charging strategies.

The other major technology profile is for electric vehicles. Figure 10 illustrates the charging profile of passenger electric vehicles under different charging strategies. The “home” profile (from [76]) considers uncontrolled charging after the last journey of the day, resulting in a pronounced evening peak, especially on weekdays. The “home and work” profile (derived from [77]) also assumes that charging is uncontrolled, but that charging facilities are widely available at workplaces, giving a profile that is more equally spread over the day, with a slight peak in early morning and a reduced evening peak. As working schedules in Germany and the UK differ by approximately one hour [78], an offset is introduced between the countries’ weekday profiles.

In the context of smart grid deployment, one may assume that vehicle charging patterns may become price sensitive in the long run, and will differ from day to day according to price signals. In order to quantify the impact of such a flexible profile, we consider a sensitivity case which uses an optimised charging load profile for electric vehicles. In the literature, “smart” or “managed” charging profiles are based on the current supply-demand interaction with all charging occurring at night (e.g. [77], [79]–[83]). However, with continued deployment of solar PV and wind, the system minimum is likely to occur during daytime in summer, and shift dramatically from day to day, making for a more dynamic “smart” charging profile.

For this scenario, smart charging is based on the net load to be met by thermal power stations, which is the projected 2050 load curve minus the output from renewables, which were based on [84]. The “smart” charging profile (Figure 10b) is determined using the demand response module of eLOAD, which determines the most favourable hours for battery charging, distinguished by season, considering the predefined electricity generation mix for the UK and Germany in 2050. This capacity mix is taken from the ESA² scenario [55] to be consistent with our macro demand projection, and is given in Table 4. Wind and solar capacities are seen to have grown rapidly in recent years, and are assumed to continue expanding by 1.7–2.8% per annum in Germany and 6.5–7.6% per annum in the UK.

	Germany						UK					
	Wind			Solar			Wind			Solar		
	2010	2013	2050	2010	2013	2050	2010	2013	2050	2010	2013	2050
Installed capacity [GW]	27.2	34.3	65.2	17.5	35.9	99.0	5.4	11.0	112.8	0.1	2.9	43.8
Annual generation [TWh]	37.8	53.4	159.1	11.7	30.0	112.2	10.2	27.4	285.8	0.0	2.0	43.8
Share of total demand	7%	10%	31%	2%	6%	22%	3%	9%	70%	0%	1%	11%

Table 4: Renewable electricity capacities and generation in 2050. Historic generation data from [85], demand data from [17], [86], [87], and 2050 projections from [55].

5 Results and Discussion

The load curves produced for this study are available to download as supplementary data – see the published version of this paper at <http://dx.doi.org/10.1016/j.energy.2015.06.082>.

5.1 Evolution of Hourly Load Curves until 2050

Table 5 evaluates the projected 2050 load curves from both models, using the same criteria as were presented for historic load curves in Table 1. The comparison between these criteria in 2010 and 2050 gives detailed insights about the potential evolution of hourly load over the course of the next four decades. It is notable that the two models are in broad agreement despite being developed independently and using different methods for load curve synthesis.

In this Core scenario (which includes uncontrolled charging of 15–23 million electric vehicles) peak load is projected to grow significantly in both countries: to 101–105 GW in Germany and 91–92 GW in Britain. Peak growth in Germany is limited to about 15% due to the reduction in annual demand, whereas in Britain it is projected to rise by 50%, which is double the growth in energy demand. A 30 GW increase in peak load will require (very approximately) €25 billion to be invested in Britain over and above that needed to cover existing plant retirements;¹⁴ compared with €12.5 billion if a more successful integration of heat pumps and electric vehicles meant that peak load grew at the same pace as annual demand. In Germany, the change in load shape adds 20 GW to peak load compared to the situation where all hours scale down equally, requiring (again, very approximately) €17 billion additional investment in capacity.

¹⁴ This very rough calculation, intended to give a sense of the scale of this challenge, is based on the current average investment costs for CCGT and OCGT plants in 2010 Euros, taking no account of technology learning or other developments. Other technologies such as coal, oil or hydro have higher capital costs, and so this is possibly a conservative estimate.

In 2050			DE			GB		
					Change from 2010		Change from 2010	
			2010	2050		2010	2050	
Load duration curve	Total demand [TWh]		547	512 512	−6% −6%	340	423 423	+25% +25%
	Minimum load [GW]		40.2	31.1 33.6	−23% −16%	21.1	22.1 26.2	+5% +24%
	Maximum load [GW]		88.3	101.0 104.6	+14% +18%	61.4	91.4 92.3	+49% +50%
	Min/max load ratio		45.5%	30.8% 32.1%	−32% −29%	34.4%	24.4% 28.4%	−30% −17%
	Capacity factor		70.7%	57.9% 55.9%	−18% −21%	63.1%	52.9% 52.3%	−16% −17%
Stable load situations	Mean duration of maximum load [h]	>90%	4.09	1.87 1.88	−54% −54%	2.70	1.96 2.21	−28% −18%
		>70%	15.8	5.40 4.58	−66% −71%	8.95	6.49 5.71	−27% −36%
	Total duration of maximum load [h]	>90%	286	127 139	−56% −51%	192	45 73	−77% −62%
		>70%	4733	1599 1291	−66% −73%	2516	1091 873	−57% −65%
Load change between consecutive hours	Ramp rate factor		1.97 %	3.20% 3.22%	+62% +63%	2.66 %	2.98% 2.77%	+12% +4%
	Mean ramp rate [GW]		1.96	2.81 2.58	+43% +32%	1.88	2.50 2.11	+33% +12%
			−1.57	−3.79 −4.84	+141% +208%	−1.44	−2.98 −3.25	+107% +126%
	Maximum load change [GW]		9.91	12.9 11.6	+30% +17%	7.90	10.8 7.79	+37% −1%
			−6.82	−13.0 −13.1	+91% +92%	−5.35	−11.6 −9.52	+117% +78%
Continuous load change sequences	Maximum load change [GW]		29.0	50.8 59.5	+75% +105%	24.6	33.9 42.8	+38% +74%
			−26.4	−55.1 −60.2	+109% +128%	−25.2	−39.3 −44.1	+56% +75%
	Nb. of load alternations		1,800	1,642 936	−9% −48%	1,920	2,702 1,004	+41% −48%
Temperature sensitivity	Mean temperature sensitivity [GW/°C]		0.49	0.48 0.41	−2% −16%	0.81	1.55 1.29	+90% +59%
	Peak temperature sensitivity [GW/°C]		0.60	0.64 0.85	7% 42%	1.14	1.81 1.84	58% 61%

Table 5: Evaluation criteria for the projected 2050 load curves in Germany and Britain, set against the historic perspective. For 2010, historic load data is used; for 2050, each cell presents the results from eLOAD (top) and DESSTinEE (bottom).

The load duration curves in Figure 11 show what happens during the rest of the year. Whilst peak load increases, minimum load remains similar in Britain and falls by around 8 GW in Germany due to reduced utilisation of night storage heaters. Asset utilisation therefore decreases significantly in both countries, *in addition* to reductions caused by increasing penetration of zero marginal cost renewables. For example, in Germany load is projected to fall below the 2010 level for 7,500 hours of the year. In the absence of greater demand side flexibility, with fewer MWh sold per MW of capacity, electricity prices will have to increase in order for power stations and transmission infrastructure to remain profitable, either through peak pricing or capacity payments.

Figure 11: Load duration curves for Germany and Great Britain in 2010 (historic) and 2050 (projected). The system peaks are highlighted in the inset figure top right.

Figure 12 shows the average daily profiles for the two countries in 2050, relative to the historic profiles for 2010. This clearly depicts the size of the evening charging peak for electric vehicles, and the relative reduction in night-time demand due to the switch from night-storage heaters to electric heat pumps. These changes mean that ramp rates become much stronger, particularly downward ramps after the evening charging peak. Ramp rates in both countries grow both in absolute terms (GW per hour) and relative to peak load (a greater portion of the generating fleet starting or stopping).

Figure 12: Comparison of the average weekday load curves projected by eLOAD and DESSTinEE for 2010 and 2050.

Figure 12 demonstrates how scaling historic load profiles by a linear factor would lead to substantial deviations from the eLOAD / DESSTinEE projections. Simple rescaling yields deviations with an RMS error of 9 GW in Germany and 5 GW in Britain, with strong diurnal and seasonal components.

Some discrepancies can be seen between the two models in Figure 12: for example, in the British summer profile eLOAD projects a reduced level of 3 to 4 GW between 11:00 and 19:00 relative to DESSTinEE. This can be traced to different assumptions for the increase in efficiency, highlighting the importance of drilling down into sub-sector and individual technology profiles, rather than focussing solely on the 'prime suspects' of heat pumps and electric vehicles.

The drivers behind load curve transformation are identified in Figure 13, which shows how the changes in individual technology profiles come together to form the overall shift from the 2010 to 2050 load profile in Germany. For example, efficiency improvement leads to reduced growth in morning time, and the phase-out of German storage heaters gives a reduction in night time load. The most substantial change is the evening charging peak for electric vehicles, which contributes 30 GW to peak load on an average weekday. In winter, heat pumps add a solid band of 5 GW load on top.

Figure 13: The contribution that different technologies make to changes in the load profile from 2010 to 2050 in Germany, based on results from eLOAD.

The temperature sensitivity of load in Germany falls slightly even though the share of heat produced from electricity increases five-fold (see Table 2). The total demand for heat falls by 60% due to extensive insulation improvements, and inefficient resistance heaters are almost entirely replaced with heat pumps. The temperature sensitivity of peak-time load (weekdays 18:00–19:00) increases (albeit by differing amounts in the two models) as this electric heat is provided all-day round rather than predominantly during the night-time with current storage heaters.

The situation is very different in Britain due to the combination of expanding housing stock, less effective uptake of insulation, and a larger assumed penetration of heat pumps. Both mean and peak-time sensitivity are expected to increase by at least 60%, with the latter rising to around 1.8 GW per degree centigrade. This would put Britain into a similar position as France, with both countries experiencing sharp peaks in demand during cold weather. If a cold spell were to affect both countries simultaneously, this is likely to be a source of stress and potential failure in the system.

5.2 Sensitivity to Electric Vehicle Charging Profiles

In the core scenario, transformation of the load curve and evolution of peak load are primarily driven by the extensive diffusion of electric vehicles and their assumed load profile (battery charging after the last journey). Figure 14 compares the mean system load curve on weekdays from the Core scenario with the two alternative charging strategies (averaged across the results of the two models). Extending vehicle charging to work hours prevents the evening load peak from

emerging and implies instead a more balanced profile which is relatively close to the current shape.¹⁵ As indicated by Figure 15, German peak load can be preserved at the level of 2010 while the increase in the UK peak load is reduced from 30 to 22 GW.

Figure 14: Mean system load curve on weekdays under different charging strategies for electric vehicles (averaged across the two models)

This profile changes substantially with smart charging. Germany's evening load peak shifts towards midday hours in order to bring power consumption in line with PV electricity generation, and the system shifts from being winter to summer peaking. Peak load experiences an increase compared to 2010 to a level of 96 GW (vs. 103 GW under the Core scenario). As the major part of British electricity generation in 2050 relies on wind power that features a weaker diurnal generation profile, the system load therefore has a less pronounced midday peak in summer, and a more balanced winter profile. With respect to peak load and load duration curve, the results are similar to those under the *home+work* charging strategy, as shown by Figure 15; however, both strategies result in different utilisation for conventional generation.

To assess the impact of the different charging profiles on the electricity supply, Figure 16 depicts the mean net load (the difference between system load and generation from PV and wind) to be met by conventional generators. The smart charging profile not only shaves the peaks (from >90 to about 64 GW for Germany and from 80 to about 64 GW for Britain) but also fills the net load troughs (from -70 to -43 GW and from -70 to -58 GW). This reduces the amount of excess renewable energy which must be curtailed:¹⁶ from 22 to 7 TWh and from 51 to 44 TWh per year. Controlling the charging of electric vehicles can have substantial impact on the utilisation and

¹⁵ The detailed assessment of the results using the evaluation criteria of Table 5 is available from the authors upon request.

¹⁶ Assuming that renewables are curtailed when net load decreases below zero. Conventional generators have a must-run element and so more than this may be curtailed in practice, in the absence of storage.

profitability of existing power plants and reduce the need for flexible and peaking capacities. These aspects will be considered further in future research activities.

Figure 15: Load duration curves of Germany (left) and Great Britain (right) for different charging strategies of electric vehicles, averaged across both models.

Figure 16: Mean net load under different charging strategies for electric vehicles

5.3 Sensitivity to Electricity Intensity

Great uncertainty surrounds any projection for uptake of new technologies in 35 years' time. We therefore consider a set of sensitivities around the number of heat pumps and electric vehicles (using the Core assumption: charging after the last journey of the day) in operation in each country. From the Core figures presented earlier in Table 2, we consider two cases with ± 4 million residential heat pumps ($\pm 53\%$ in DE, $\pm 21\%$ in GB), and then separately two cases with ± 4 million EVs in each country ($\pm 17\%$ in DE, $\pm 27\%$ in GB). Figure 17 shows the range of load curves produced from these sensitivities, averaged across the two models.

Figure 17: The range seen across load duration curves across both models and all sensitivity cases (i.e. with more/fewer heat pumps or electric vehicles)

Figure 17a depicts the load duration curve for both countries across the different sensitivity cases, illustrating that the changes in electricity intensity primarily affect peak load situations. Figure 17b illustrates the difference between the various sensitivities and the Core scenario, showing that the bulk of electricity consumption of electric vehicles and heat pumps coincides with peak load situations. For example, 4 million additional electric vehicles in Germany adds 6 GW to peak load, at least 2 GW during the 2,000 highest load hours, and makes almost no change to the system minima. In Britain, the same number of vehicles raises peak load by 5 GW, and the 2 GW load increase affects only the top 1,000 hours.

4 million more heat pumps likewise drive an increase in peak load of 5 GW and 3 GW in both countries. However, additional load is more equally spread throughout the year, resulting in a simultaneous rise of base load (lasting for at least 6,000 hours per year) by 2 GW and 1 GW, respectively. This is due to heat pumps providing hot water all year round, as well as space heating. The impact on the temperature sensitivity of load is consistent across both models and countries, with ± 4 million heat pumps altering the average and peak sensitivity by ± 0.14 GW/ $^{\circ}\text{C}$.

An additional 4 million heat pumps therefore raises the average temperature sensitivity to 0.59 and 1.56 GW/°C in Germany and Britain, and the peak sensitivity to 0.90 and 1.97 GW/°C.

6 Conclusions

This study demonstrates how the shape of the electric load curve will change substantially in the coming decades due to the evolving structure of electricity demand. Two independent methodologies are presented for examining this issue, and the robustness of this result is confirmed by their general agreement.

In a scenario where Germany and the UK transform towards sustainable energy systems through energy efficiency and electrification, the major drivers behind load curve transformation are identified as new demand-side technologies (heat pumps and electric vehicles), efficiency improvements and macro-economic factors (GDP and population).

Electricity demand of heat pumps and electric vehicles without smart management strongly coincides with current peak load hours, increasing the system load peak more strongly than annual demand. By 2050, German demand may fall 6% whilst peak load rises by 15%, leading to a 20% fall in the capacity factor of the load curve, and thus in asset utilisation. In the UK, the increase in peak load is double that of demand, requiring 30 GW of additional capacity by 2050, compared to 15 GW if the load shape remained unchanged from today. A simplistic estimate suggests that unfavourable changes to the load shape will require €17 and €12 billion of additional capacity within the German and British electricity systems between now and 2050. These impacts are being missed by studies which assume that load will scale up equally in all hours.

Sensitivities around the level of transport and heat electrification reveal that an additional million electric vehicles increases demand by 2.8 TWh and peak load by 1.5 GW in Germany and 1.3 GW in Britain. A million extra heat pumps adds 4.3 TWh in Germany and 3.1 TWh in Britain, with an extra 1.2 and 0.8 GW peak load, respectively.

Energy efficiency is able to partly compensate for the increase in load, particularly through savings in lighting. However, the order of magnitude and the distribution throughout the day differ from electric vehicles and heat pumps, giving only a limited impact on peak load.

The combination of increased peak load, reduced minimum load, decreased utilisation and stronger ramp rates means that balancing supply and demand will become more challenging in the future, especially when considered alongside the growth in variable renewable energy sources. Either a substantial amount of low cost, flexible power generation capacity, or a reinforcement of daily storage capacity is required.

Alternatively, explicit charging strategies for electric vehicles can assist in reducing peak load, by spreading the charging process across the entire day. However, charging at both home and workplaces requires the widespread availability of public charging infrastructure, and disregards

the availability of renewable electricity generation. Smart charging strategies have immense potential for net load smoothing and the integration of renewables. However, they cannot rely on simple repetitive profiles for charging (e.g. always recharging overnight) and must be matched to the instantaneous output from variable renewables, requiring 'smart' communication and control infrastructure. Large-scale market entry of electric vehicles should be accompanied by sophisticated charging strategies to ensure a sustainable and cost-efficient integration.

Future research activities could expand the focus on this demand response aspect, assessing the transformation of net load, how other demand side technologies (e.g. heat pumps, white appliances or industry processes) can contribute to peak load shaving and RES integration, and how this affects the electricity supply side.

7 Acknowledgements

Iain Staffell was funded by the EPSRC Grand Challenge: Transforming the Top and Tail (topandtail.org.uk) (EP/I031707/1) and UKERC Phase III (ukerc.ac.uk) (EP/L024756/1), and wishes to thank Robert Staffell and Richard Green for comments and insights. The supporting research data is available to download from the publisher at <http://dx.doi.org/10.1016/j.energy.2015.06.082>.

8 References

- [1] Consentec and r2b, "Voraussetzungen einer optimalen Integration erneuerbarer Energien in das Stromversorgungssystem," Aachen, 2010.
- [2] DLR, IZES, Ecofys, S. Klinski, and Wuppertal Institut, "Vorbereitung und Begleitung der Erstellung des Erfahrungsberichtes 2011 gemäß § 65 EEG - Vorhaben V: Integration der Stromerzeugung aus Erneuerbaren Energien und konventionellen Energieträgern," Stuttgart, 2011.
- [3] Fraunhofer IWES, "Dynamische Simulation der Stromversorgung in Deutschland nach dem Ausbauszenario der Erneuerbaren-Energien-Branche," Kassel, 2009.
- [4] W.-P. Schill, "Residual Load, Renewable Surplus Generation and Storage Requirements for Renewable Integration in Germany," *DIW Discuss. Pap.*, vol. 1316, 2013.
- [5] I. Staffell, R. Green, and K. Kendall, "Cost targets for domestic fuel cell CHP," *J. Power Sources*, vol. 181, no. 2, pp. 339–349, Jul. 2008.
- [6] R. Green, I. Staffell, and N. Vasilakos, "Divide and Conquer? k-Means Clustering of Demand Data Allows Rapid and Accurate Simulations of the British Electricity System," *IEEE Trans. Eng. Manag.*, vol. 61, no. 2, pp. 251–260, May 2014.
- [7] SRU, "Climate-friendly, reliable , affordable: 100 % renewable electricity supply by 2050," Berlin, 2010.
- [8] UBA, T. Klaus, C. Loreck, and K. Müschen, "Klimaschutz und Versorgungssicherheit - Entwicklung einer nachhaltigen Stromversorgung," Dessau-Roßlau, 2009.
- [9] National Grid, "UK Future Energy Scenarios - UK gas and electricity transmission," Warwick, 2013.
- [10] Ofgem, "Electricity Capacity Assessment," London, 2012.
- [11] DECC, "Electricity Market Reform," London, 2013.

- [12] IEA, "Energy Technology Perspectives 2012 - Pathways to a Clean Energy System," OECD Publishing, IEA, Jun. 2012.
- [13] IIASA, *Global Energy Assessment - Towards a Sustainable Future*. Cambridge, New York, Laxenburg: Cambridge University Press and the International Institute for Applied Systems Analysis, 2012.
- [14] European Commission, "Impact Assessment - A Roadmap for moving to a competitive low carbon economy in 2050. SEC(2011) 288 final," Brussels, 2011.
- [15] K. Ramachandran and H. Turton, "The Swiss TIMES Electricity Model (STEM-E) Updates to the model input data and assumptions," Villingen, 2012.
- [16] S. Pfenninger, A. Hawkes, and J. Keirstead, "Energy systems modeling for twenty-first century energy challenges," *Renew. Sustain. Energy Rev.*, vol. 33, pp. 74–86, 2014.
- [17] National Grid, "Metered half-hourly electricity demands," 2014. [Online]. Available: <http://www.nationalgrid.com/uk/Electricity/Data/Demand+Data/>.
- [18] ENTSO-E, "Hourly load values of a specific country for a specific month," 2013. [Online]. Available: <https://www.entsoe.eu/db-query/consumption/mhlv-a-specific-country-for-a-specific-month/>.
- [19] EHPA, "Outlook 2012 - European Heat Pump Statistics," 2012.
- [20] RTE, "Record of power consumption," 2014. [Online]. Available: http://clients.rte-france.com/lang/an/visiteurs/vie/vie_stats_conso_inst.jsp.
- [21] NASA, "MERRA Data Holdings," 2014. [Online]. Available: http://disc.sci.gsfc.nasa.gov/daac-bin/DataHoldings.pl?LOOKUPID_List=MAT1NXSLV.
- [22] RTE, "La vague de froid de février 2012," Paris, 2012.
- [23] T. Boßmann, R. Elsland, F. Lickert, and M. Wietschel, "The German load curve in 2050: structural changes through energy efficiency measures and their impacts on the electricity supply side," in *ecee 2013 summer study*, 2013, pp. 1199–1211.
- [24] DECC, "United Kingdom housing energy fact file," London, 2013.
- [25] J. Kockat and C. Rohde, "The challenges , dynamics and activities in the building sector and its energy demand in Germany - D2.1 of WP2 from Entranze Project," 2012.
- [26] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," *Renew. Sustain. Energy Rev.*, vol. 13, no. 8, pp. 1819–1835, Oct. 2009.
- [27] I. Richardson, M. Thomson, D. Infield, and C. Clifford, "Domestic electricity use: A high-resolution energy demand model," *Energy Build.*, vol. 42, no. 10, pp. 1878–1887, Oct. 2010.
- [28] J. Dickert and P. Schegner, "A Time Series Probabilistic Synthetic Load Curve Model for Residential Customers," in *2011 IEEE Trondheim PowerTech*, 2011.
- [29] A. Grandjean, J. Adnot, and G. Binet, "A review and an analysis of the residential electric load curve models," *Renew. Sustain. Energy Rev.*, vol. 16, no. 9, pp. 6539–6565, Dec. 2012.
- [30] P. Esslinger and R. Witzmann, "Entwicklung und Verifikation eines stochastischen Verbraucherlastmodells für Haushalte," in *12. Symposium Energieinnovation*, 2012.
- [31] R. Elsland, T. Boßmann, R. Hartel, T. Gnann, M. Genoese, W. Fichtner, and M. Wietschel, "Analysis of structural changes of the load profiles of the German residential sector due to decentralized electricity generation and e-mobility," in *Fourth International Conference on Sustainability in Energy and Buildings*, 2012.
- [32] M. Wiest and M. Finkel, "Lastflussberechnung unter Verwendung statistischer Methoden zur Nachbildung probabilistischer Last- und Einspeiseprofile," in *VDE-Kongress 2012*, 2012.

- [33] M. Muratori, M. C. Roberts, R. Sioshansi, V. Marano, and G. Rizzoni, "A highly resolved modeling technique to simulate residential power demand," *Appl. Energy*, vol. 107, pp. 465–473, Jul. 2013.
- [34] F. M. Andersen, H. V. Larsen, and R. B. Gaardestrup, "Long term forecasting of hourly electricity consumption in local areas in Denmark," *Appl. Energy*, vol. 110, pp. 147–162, Oct. 2013.
- [35] N. D. Uri and J. S. Maybee, "Forecasting the load duration curve using Box Jenkins time series analysis," *Eng. Optim.*, vol. 3, no. 4, pp. 193–199, 1978.
- [36] A. Poulin, M. Dostie, M. Fournier, and S. Sansregret, "Load duration curve: A tool for technico-economic analysis of energy solutions," *Energy Build.*, vol. 40, no. 1, pp. 29–35, Jan. 2008.
- [37] EIA, "The Electricity Market Module of the National Energy Modeling System - Model Documentation Report," Washington, 2011.
- [38] R. J. Hyndman, "Extended models for long-term peak half-hourly electricity demand for South Australia," Melbourne, 2007.
- [39] R. J. Hyndman and S. Fan, "Forecasting long-term peak half-hourly electricity demand for South Australia," Melbourne, 2009.
- [40] C. Pout, F. MacKenzie, and E. Olloqui, "Final Report: The impact of changing energy use patterns in buildings on peak electricity demand in the UK," 2008.
- [41] Ü. B. Filik, Ö. N. Gerek, and M. Kurban, "A novel modeling approach for hourly forecasting of long-term electric energy demand," *Energy Convers. Manag.*, vol. 52, no. 1, pp. 199–211, Jan. 2011.
- [42] E. Sotiropoulos, "Modeling of German Electricity Load for Pricing of Forward Contracts," ETH Zürich, 2012.
- [43] G. Koreneff, M. Ruska, J. Kiviluoma, J. Shemeikka, B. Lemström, R. Alanen, and T. Koljonen, "Future development trends in electricity demand," Espoo, 2009.
- [44] A. Hainoun, "Construction of the hourly load curves and detecting the annual peak load of future Syrian electric power demand using bottom-up approach," *Int. J. Electr. Power Energy Syst.*, vol. 31, no. 1, pp. 1–12, Jan. 2009.
- [45] A. Pina, C. Silva, and P. Ferrão, "Modeling hourly electricity dynamics for policy making in long-term scenarios," *Energy Policy*, vol. 39, no. 9, pp. 4692–4702, Sep. 2011.
- [46] F. M. Andersen, H. V. Larsen, and T. K. Boomsma, "Long-term forecasting of hourly electricity load: Identification of consumption profiles and segmentation of customers," *Energy Convers. Manag.*, vol. 68, pp. 244–252, Apr. 2013.
- [47] T. Gobmaier, W. Mauch, M. Beer, S. von Roon, and T. Schmid, "Simulationsgestützte Prognose des elektrischen Lastverhaltens," München, 2012.
- [48] J. Torriti, M. G. Hassan, and M. Leach, "Demand response experience in Europe: Policies, programmes and implementation," *Energy*, vol. 35, no. 4, pp. 1575–1583, Apr. 2010.
- [49] C. Fünfgeld, "Die 'Repräsentativen VDEW-Lastprofile' - Ziele und Hintergründe," *VEÖ J.*, vol. 9, pp. 33–36, 2001.
- [50] B. Tarroja, F. Mueller, J. D. Eichman, and S. Samuelsen, "Metrics for evaluating the impacts of intermittent renewable generation on utility load-balancing," *Energy*, vol. 42, no. 1, pp. 546–562, Jun. 2012.
- [51] M. Huber, D. Dimkova, and T. Hamacher, "Integration of wind and solar power in Europe: Assessment of flexibility requirements," *Energy*, vol. 69, pp. 236–246, May 2014.
- [52] Y. Y. Deng, K. Blok, and K. van der Leun, "Transition to a fully sustainable global energy system," *Energy Strateg. Rev.*, vol. 1, no. 2, pp. 109–121, Sep. 2012.

- [53] DECC, "The UK 2050 calculator," 2015. [Online]. Available: <http://2050-calculator-tool.decc.gov.uk/>. [Accessed: 27-Apr-2015].
- [54] F. Kirsch, "Reducing electricity demand in the transition to a low-carbon Germany - is it realistic," in *12th IAAE European Energy Conference*, 2012, vol. 2050, no. Decc.
- [55] ESA2, "Shaping our energy system - combining European modelling expertise. Case studies of the European energy system," Karlsruhe, 2013.
- [56] European Commission, "Energy Roadmap 2050, Communication, COM(2011) 885/2," Brussels, 2011.
- [57] J. Hawksworth and G. Cookson, "The World in 2050," 2008.
- [58] K. Ward, "The world in 2050," London, 2011.
- [59] W. Graus, E. Blomen, C. Kleßmann, C. Capone, and E. Stricker, "Global technical potentials for energy efficiency improvement," in *IAEE European Conference September 2009*, 2009.
- [60] European Commission, "EU Energy, Transport and GHG Emissions Trends to 2050 - Reference Scenario 2013," Brussels, 2014.
- [61] B. Boardman, S. Darby, G. Killip, M. Hinnels, C. N. Jardine, J. Palmer, and G. Sinden, "40% house," Oxford, 2005.
- [62] J. Rosenow and R. Galvin, "Evaluating the evaluations: Evidence from energy efficiency programmes in Germany and the UK," *Energy Build.*, vol. 62, pp. 450–458, Jul. 2013.
- [63] CCC, "Fourth Carbon Budget Review - technical report," London, 2013.
- [64] CCC, "The Fourth Carbon Budget - Reducing emissions through the 2020s," London, 2010.
- [65] N. Diefenbach, T. Loga, J. Gabriel, and M. Fette, "Monitoring der KfW-Programme 'Energieeffizient Sanieren' 2010 und 'Ökologisch / Energieeffizient Bauen' 2006-2010," Darmstadt, 2011.
- [66] Bundesregierung, "Leitmarkt und Leitanbieter für Elektromobilität," 2014. [Online]. Available: http://www.bundesregierung.de/Webs/Breg/DE/Themen/Energiewende/Mobilitaet/podcast/_node.html. [Accessed: 12-Dec-2014].
- [67] NPE, "Fortschrittsbericht 2014 - Bilanz der Marktvorbereitung," Berlin, 2014.
- [68] Prognos, EWI, GWS, M. Schlesinger, D. Lindenberger, and C. Lutz, "Energieszenarien 2011," Basel, 2011.
- [69] HM Government, "The Carbon Plan: Delivering our low carbon future," London, 2011.
- [70] HM Government, "2050 Pathways Analysis," London, 2010.
- [71] DECC, "Electricity Market Reform: keeping the lights on in the cheapest, cleanest way," 2011. [Online]. Available: <https://www.gov.uk/government/news/electricity-market-reform-keeping-the-lights-on-in-the-cheapest-cleanest-way>. [Accessed: 12-Dec-2014].
- [72] Stromnetz Hamburg, "Informationen für Stromverorger, SLP, TLP," 2014. [Online]. Available: <https://www.stromnetz-hamburg.de/de/stromversorger.htm>.
- [73] E.ON, "Standardlastprofile," 2014. [Online]. Available: http://www.eon-bayern.com/pages/eby_de/Netz/Stromnetz/Netzzugang/Lastprofilverfahren/Standard_Lastprofile/index.htm.
- [74] DEFRA, "Household Electricity Study - EV0702," 2014. [Online]. Available: <http://randd.defra.gov.uk/Default.aspx?Menu=Menu&Module=More&Location=None&Completed=0&ProjectID=17359>.

- [75] I. Staffell, D. Brett, N. Brandon, and A. Hawkes, "A review of domestic heat pumps," *Energy Environ. Sci.*, vol. 5, no. 11, p. 9291, 2012.
- [76] D. Dallinger, G. Schubert, and M. Wietschel, "Integration of intermittent renewable power supply using grid-connected vehicles - a 2030 case study for California and Germany," Karlsruhe, S 4/2012, 2012.
- [77] K. Parks, P. Denholm, and T. Markel, "Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory," Golden, 2007.
- [78] Statistika Centralbyran, "Harmonised European Time Use Survey," 2014. [Online]. Available: <https://www.h2.scb.se/tus/tus/>.
- [79] E. Larsen, D. K. Chandrashekhara, and J. Ostergard, "Electric Vehicles for Improved Operation of Power Systems with High Wind Power Penetration," in *2008 IEEE Energy 2030 Conference*, 2008.
- [80] J. Mullan, D. Harries, T. Bräunl, and S. Whitely, "Modelling the impacts of electric vehicle recharging on the Western Australian electricity supply system," *Energy Policy*, vol. 39, no. 7, pp. 4349–4359, Jul. 2011.
- [81] P. Finn, C. Fitzpatrick, and D. Connolly, "Demand side management of electric car charging: Benefits for consumer and grid," *Energy*, vol. 42, no. 1, pp. 358–363, Apr. 2012.
- [82] M. Metz and C. Doetsch, "Electric vehicles as flexible loads – A simulation approach using empirical mobility data," *Energy*, vol. 48, no. 1, pp. 369–374, Dec. 2012.
- [83] D. Madzharov, E. Delarue, and W. D'haeseleer, "Integrating electric vehicles as flexible load in unit commitment modeling," *Energy*, vol. 65, pp. 285–294, Feb. 2014.
- [84] G. Schubert, "Modeling hourly electricity generation from PV and wind plants in Europe," in *9th International Conference on the European Energy Market*, 2012.
- [85] BP, "BP Statistical Review of World Energy - June 2014," London, 2014.
- [86] Enerdata, "ODYSSEE database on energy efficiency data & indicator," 2014. [Online]. Available: http://odyssee.enerdata.net/nrd_web/site/.
- [87] AGEB, "Energieverbrauch in Deutschland im Jahr 2013," Berlin, 2014.
- [88] DECC, "Digest of United Kingdom Energy Statistics," London, 2013.
- [89] DIHK and VEA, "Faktenpapier Eigenerzeugung von Strom," Berlin, Hannover, 2014.
- [90] Worldbank, "Services, etc., value added (% of GDP)," 2014. [Online]. Available: <http://data.worldbank.org/indicator/NV.SRV.TETC.ZS>.
- [91] Öko-Institut and Fraunhofer ISI, "Klimaschutzszenario 2050 - Zusammenfassung," Berlin, Karlsruhe, 2014.