Smart grids, local adoption of distributed generation and the feed in tariff policy incentive

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Abstract

Smart Grids are often proposed as a means make the most efficient use of available network infrastructure. To deliver such benefits, Smart Grids rely on the adaptation of various consumption practices on the part of the domestic consumer. In addition, the concept requires the adoption of various enabling technologies. The diffusion of these innovations, in both practice and technology, are crucial to the success of the Smart Grid as a means of decarbonisation and efficient infrastructure usage.

This paper focuses on the role of domestic users of the electricity network as potential adopters of renewable micro-generation. Data on UK household adoption of micro-generation in the UK in response to national Feed in Tariff policy are analysed from both a temporal and spatial perspective. An Agent Based Model is presented and used to investigate the speed and scale of technology adoption in the presence of policy incentivisation. Heterogeneous agent behaviour is simulated, using parameters from prior research and the data analysis presented to simulate different users' patterns of consumption and consumers' adoption strategies, including peer effects.

We illustrate the impact that micro-generation adoption, in particular photovoltaic panels, will have on energy consumption, particularly the geographic location of distributed generation as compared to consumption and urban centres. We explore how such adoption may change the typical consumption pattern of both individual households and aggregated groups of households directly and consider research findings on indirect impacts of micro-generation on householder consumption. We discuss the implications of these findings for visions of the electricity network as a Smart Grid and for energy policies designed to promote both adoption of micro-generation and change of consumption behaviour in the Smart Grid context.

Introduction

Commitments to reducing carbon emissions to limit anthropogenic climate change have been made around the globe. To meet these commitments, without compromising the quality of life and economic prosperity that result from use of energy, strategies incorporating two interlinked methods are proposed: Increasing technical efficiency to reduce overall demand, and reducing the use of fossil fuels to provide energy in usable form. In the UK, strategies (Ofgem 2008) to meet legislative targets (UK Parliament 2008) for emissions involve, amongst other things, switching to electricity as the primary fuel for heating and transportation, particularly in the domestic sector. For such a strategy to deliver a reduction in carbon emissions, a concomitant decarbonisation of electricity generation is required. To achieve the objective of decarbonised electricity generation, policies have been developed throughout Europe to encourage the penetration of low Carbon generators at scales both large, such as wind farms, and small, for instance distributed generation such as domestic photovoltaic (PV) installations or micro CHP. Electrification of heating and transport and efficiency measures at the demand side in combination with *partial* decarbonisation do not *guarantee* a reduction in carbon emissions, as is well documented in studies on the rebound effect (e.g. Druckman et al. 2011; Chitnis et al. 2013). However, despite concerns about the rebound effect, the strategies put forth in the UK (and many other countries) rely on a move to substitution of fossil fuels for heating and transportation by electricity, increased energy efficiency in the demand side, increased renewable generation and efficiency of supply.

Increased reliance on electricity for heating and transportation and a substantially increased share of renewable generation have some major consequences for the electricity network. Firstly, there will be an increase in overall quantity of energy that must be delivered via electricity, estimated at up to 2.5 times today's supply (e.g. Winser 2010). Secondly, there will be an increased unpredictability of generation as it becomes reliant on weather conditions. In order to address these consequences, mechanisms are needed to ensure that the increased load and variability do not cause interruptions to electricity supply.

The research presented has been carried out in the context of wider research into the effects of householder behaviour on the Smart Grid. The Smart Grid is a term used to describe an electricity network that can operate efficiently given the problems outlined in the previous paragraph and can achieve the goals of security and decarbonisation of electricity supply. Although there is no universally accepted definition of the smart grid, a useful (and widely adopted) description is given by the European Technology Platform "electricity networks that can intelligently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies" (ETP 2006). The success of such a grid depends upon its users adopting both new technologies and behaviours to provide information to allow such intelligent integration and act on information provided to them.

One particular pattern of adoption that will influence the nature of the smart grid is already under way: the adoption of micro-generation by domestic users. The influence of the UK Feed in Tariff (FiT) policy, designed to encourage the adoption of distributed generation, is analysed and used to inform a model of PV micro-generation adoption. The observed data on micro-generation adoption in the UK is analysed from both temporal and spatial points of view.

A computational model of technology adoption incorporating household behaviour is described. The simulation uses a model derived from large scale studies to generate profiles capturing household consumption behaviour (Stokes et al. 2004). Adoption (investment) behaviour is modelled dynamically, with the decision making process being evaluated repeatedly through the model run. We characterise the agents in the model as prosumers – a term coined by Toffler (1981) to describe the qualitative change as some consumers become actively involved in the production of those goods that they consume. This term has been adopted in the electricity literature to describe those actors who gain the ability to produce electricity having previously only consumed. For example, households acquiring micro-generation such as micro-CHP or PV panels would be aptly described as prosumers. This model has been implemented and used to model localised domestic PV (PV) adoption. The model parameters are informed by the data on micro-generation adoption to date.

In the final section, we synthesize the analysis of empirical adoption data, model outputs and literature on the effect of micro-generation on consumption behaviour to draw conclusion on the extent of PV adoption to date, the potential effects on the efficiency of network utilisation and therefore future policy.

Analysing data on behaviour in response to FiT policy

Data from the UK since the FiT became available (01/04/2010) show a strong adoption of micro-generators, particularly solar PVs (Figure 1). However, if the data on the *rate* of adoption is examined, for instance for PV installations (Figure 2), it is clear that the rate of adoption is neither constant nor steadily increasing.

It is clear that there is a mechanism at work causing large spikes in the rate of adoption. In the UK, the rate of PV capacity increase is characterised by repeated periods of gradually rising adoption, followed by a large spike after which the rate drops to a lower level than previously (Figure 2). An examination of the events that happen around each spike clearly indicate that any announcement of a change to the policy (in these cases a reducing, or degression, of the tariff) has triggered a rush to adopt before the tariff is changed. This effect has also been observed in Germany (Bundesnetzagentur 2012). In both countries, changes in policy designed to limit the cost of FiTs in fact triggered a rush to install PVs and thus guarantee the higher tariff would be paid for those installations.

SPATIAL ASPECTS

The geographical distribution of installation density throughout the UK displays some interesting features (Figure 3). The country wide increase of installation density is consistent with the temporal increase in adoption already described. On a regional scale, areas of high adoption density before the FiT remain relatively high throughout the time period. For instance, even before the FiT (when the UK had a patchwork of capital subsidy schemes), the South West of England had a higher density of installations (lighter shade) than the rest of the country and this remains true at the end of 2011. On smaller scale still, the rate of increase of density is tangibly different across the country. By the end of 2011, it is clear that there are fairly large areas of low adoption density particularly around large cities. In particular, areas that remain black are postcodes which still have no installations. It can be seen that a number of cities exhibit "black holes" in the centre.

Some of these effects are likely to be due to obvious physical differences between urban, suburban and rural environments. In urban environments, buildings are often packed densely together causing shading of each other from the sun, they may well be medium or high-rise, meaning that the ratio of sun-facing roof space to occupants is very low. Buildings, both residential and commercial, are often occupied by multiple tenants, none of whom have authority to install micro-generation on the building. These conditions militate against the installation of PV generators on these buildings.

Economic considerations, in combination with socio-economic demographics, are also likely to strongly influence spatial distribution of adoption. The structure of incentivisation in the UK is such that the capital investment required to install PV is not subsidised, with the FiT designed to recoup that investment and provide a profit over time. Therefore installation is far easier for owners who either have access to the capital required to install PV generators on their roofs or the capacity to enter into contracts with a third party to lease the roof over a long time period. Leicester et al (2011, Figure 6) show that this effect is observed, with the number of PV installations being strongly negatively correlated with high indices of multiple deprivation (i.e. the most deprived areas have least installations – roughly half the PV installations are in the top 3 indices). In the UK, as a rather crude generalisation, wealthy house owners tend to live in suburban, peri-urban or rural settings – another factor in the socio-economic structure which points toward PVs being adopted more in non-urban environments.

These patterns of local adoption are likely to have significant effects on proposals to balance local demand with local distributed generation via a Smart Grid. If the Smart Grid is to increase efficiency of electricity network infrastructure use by effectively limiting load on large sections of the distribution network, it is necessary that large volumes of distributed generation be situated near large (and potentially increasing) demands. On the face of it, the inverse of this distribution is observed in the adoption patterns to date.

Modelling PV adoption and the impact on consumption profiles

The data shown in the previous section show patterns of adoption that are irregular across the UK. Temporally, the influences of announcements, which we might characterise as policy "shocks", are pronounced. Spatially, macroscopic patterns of adoption density are apparent – for instance the lack of installations in cities – while at a much smaller (postcode district) level, differing levels of adoption in ostensibly similar situations. Traditionally, models of technology diffusion (e.g. Rogers 1983; revised edition of 1962) and their mathematical formalizations (e.g. Bass 1969; Norton & Bass 1987; Mahajan et al. 1995) characterise adoption with a very few parameters. For example, in the domain under consideration, the adoption of PV panels prior

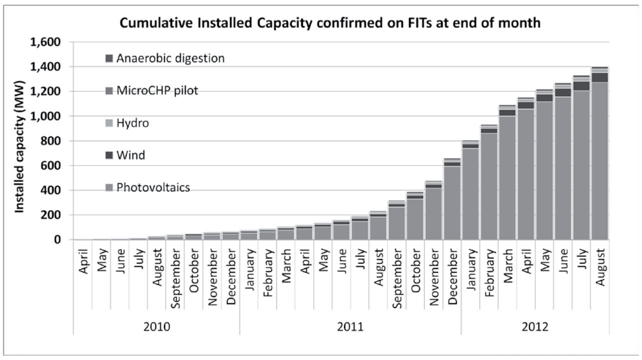

Figure 1. Renewable technology capacity installed under FiTs per month in UK (Source: DECC 2012).

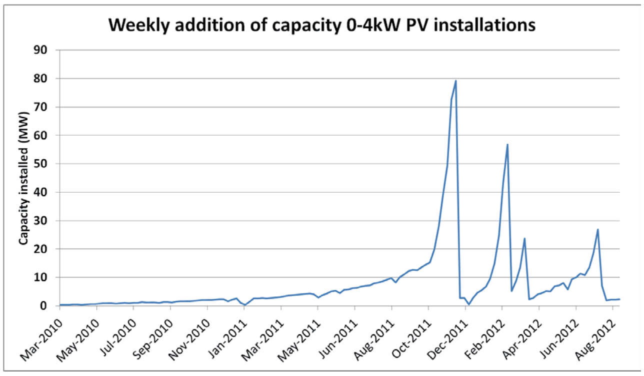

Figure 2. Detailed view of small scale PV capacity installed per week in the UK (Source: DECC 2012).

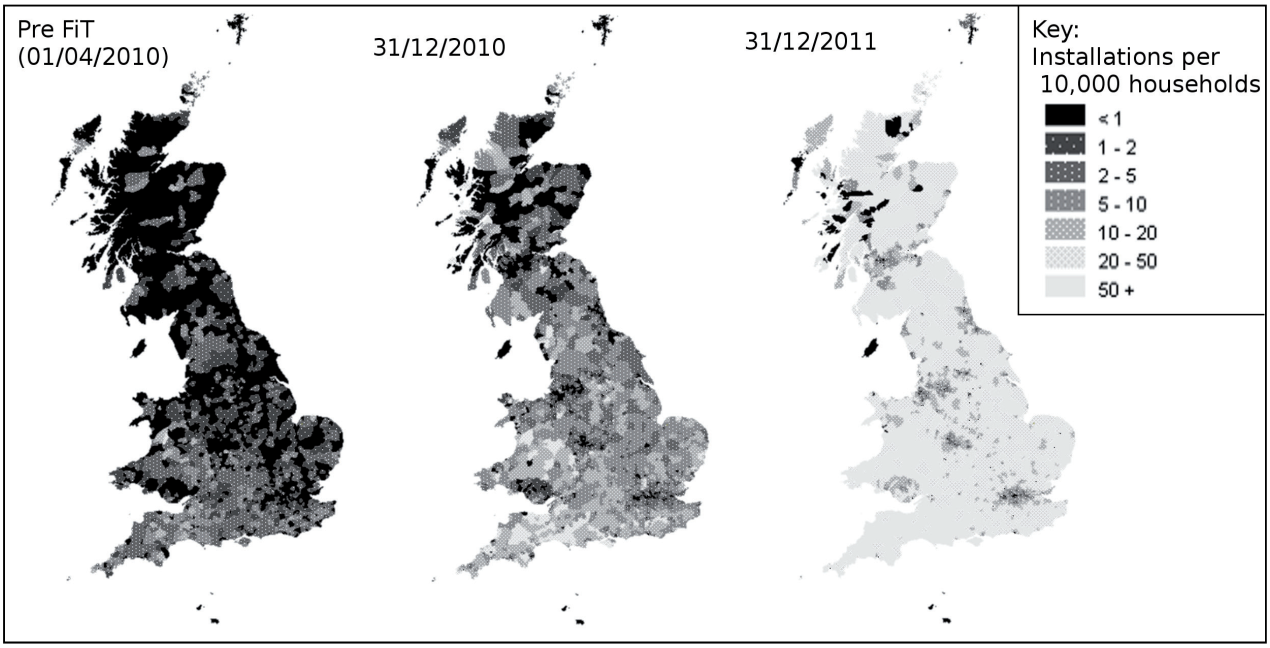

Figure 3. Visualisation of DECC data on FiT installations per 10,000 households. Source: (Snape & Rynikiewicz 2012).

to 2007 has been studied across a range of countries, with the Generalised Bass Model being used to allow for incorporation of time delay in the adoption process (Guidolin & Mortarino 2010). However, the traditional diffusion of innovation does not easily incorporate changing contextual variables, spatially specific effects such as social learning by observation or short timescale events (such as the changing of FiT policies). One approach is to further partition and parameterise equation based diffusion models and this has indeed been done in the context of adopting emission reducing technology (e.g. Higgins et al. 2011; 2012). However, this approach cannot overcome the inability of equation based macro models to capture the effects of social and geographical connections between potential adopters.

A useful technique to overcome such modelling limitations is Agent Based Modelling (ABM). ABM is a methodology for building a computational model based upon specification of behaviours of actors within a system (agents) and their interactions with each other. The overall system behaviour is not pre-defined or characterised by equations, but emerges as a consequence of the combination of agent behaviours and interactions. An approach to modelling the Smart Grid using such a technique is described by Snape et al (2011). In the implementation for this paper, the ABM technique is combined with insight from the FiT data previously described, theory from both Psychology and Science and Technology studies and empirical data about the factors which influence adoption of micro-generation (e.g. Carley 2009; Faiers & Neame 2006). Predispositions are assigned to households based on empirical studies about attitudes to micro-generation adoption (adapted from DEFRA 2008) and are combined with vicarious social learning (observations of other agents' actions). In addition, the facility to give agents access to external variables as time series is incorporated – in this implementation, for instance, time-varying weather is incorporated to give realistic PV generation profiles as is a time series representing the announcement of changes to the FiTs and the levels announced by the UK government. Agents choose the time at which they consider PV adoption at random intervals (chosen from a Poisson distribution, mean 30) and calculate the economic benefit of adopting, the number of their neighbours who have adopted and the urgency of the decision, based on the imminence of a tariff change, all tempered by their predisposition to each factor allocated as described above. If these factors combined give a desire to adopt greater than a certain threshold (again based on predisposition to adopting micro-generation), the prosumer adopts PV. This gives a rich model which can simulate both rates of adoption under steady state conditions and reactions to externally imposed shocks such as policy changes. Some sample results are presented for one particular postcode to the end of 2011, just after the first policy shock when an early review of the energy tariffs was announce (Figures 4 & 5). The postcode in question is LE2, a suburban postcode in Leicester with a mixed socio-economic demographic. Qualitative features in the simulated adoption which correspond to those observed in the real data – particularly the long period of slow adoption, followed by a spike in adoption as the change to FiT is announced.

Adoption has typically reached around 1–1.5 % of households with PV generation across the UK. Such levels of adoption have a direct effect on the total demand profile for a group of households. At 1 % adoption of PV, the effect is modest but noticeable and will become more pronounced as that fraction increases (Figures 6 & 7)

The model may be used to simulate different localities by changing the initialisation data for agents, for instance socio-demographic data, physical characteristics of households and population density, but without changing the model itself. Importantly, the model can also run "what-if" scenarios with different policy incentives in order to examine the potential impact of future policies, or to look at counter-factual questions to consider what the effect of alternative policies may have been. A wider exploration of the range of outputs across different areas of the UK and for potential alternative policy scenarios is in progress.

Discussion

FiTs have been shown to be effective means of encouraging diffusion of distributed renewable generation. There has been particular success in diffusing PV generation at the household level. Adoption of other distributed generation technology such as micro or mini wind generators, micro or community CHP, mini-hydro or anaerobic digesters has been notably less widespread. Installations by firms, industry and community projects have been scarce. Such schemes remain notably unusual – constituting only 0.05 % of total installations (Ofgem 2012) – raising questions about the efficacy of FiTs, perhaps in combination with UK culture, in promoting community energy schemes.

When considering the scale of micro-generation adoption (and therefore its impact on future electricity networks), it should be noted that although the number of installations is large and spread over the population, due to the overwhelming dominance of very small scale PV among those installations, the capacity remains relatively small. In 2011 PV generation produced just 104 GWh – less than 0.1 % of total electricity sales of 308 TWh (DECC 2012a). To put this another way – in 2011, the average UK household used ~4,200 kWh of electricity per year and the average PV installation output was ~303 kWh, or around 7 % of the annual usage (DECC 2013). Of course, in individual cases, the PV installation may provide a far greater percentage of the consumption.

In particular, there is a large impact of *announcement* of FiT degression as analysis shows that this causes a "rush" in adoption which is outside the steady pattern of increasing adoption before such an announcement. This can be easily observed in the data for the UK and Germany. This is an unwanted effect – the effect of such degression should be to slow the rate of adoption as it comes into force, but there is a large and opposite unwanted side effect of the announcement. Grubler (2012) has identified this as a problem with policy to incentivise energy innovation more generally, saying of policy to stimulate energy innovation, "Persistence and continuity of policies are key … Innovation 'impatience' and erratic stop-and-go policies … are therefore detrimental and preordain failure in triggering transitions."

The adoption patterns will cause a direct impact of PV adoption on demand profiles, similar to that shown in Figures 6 & 7 for ~1 % of households owning PV, across almost all localities. As the fraction of households with micro-generation increases, the overall demand profile will show increased variability and unpredictability. The geographical location of distributed generation in comparison to demand gives some cause for concern when considering smart grid solutions as a method to manage demand in order to minimise peak loads on the infrastructure. Policy makers have identified faster than anticipated adoption and rapidly rising numbers of registered installations and acted to try to slow this. Despite these concerns, as noted above, the total generation from these installations is still a small fraction of the overall consumption in the UK.

In addition the direct impact of micro-generation adoption on the electricity system, there may be an indirect effect on the demand profiles due to changes in consumption habits and practices made by householders (or community members) who own a renewable energy generator. This effect merits further research and the model presented is well placed to incorporate such effects into the behavioural models of prosumers. As yet, evidence on the energy behaviour of people in response to ownership of a micro-generation device which qualifies for the FiT is scarce. Keirstead (2007) suggests that ownership of PV generators influenced patterns of consumption, noting that "Two notable changes were seen: a 6 % saving in the overall amount of electricity used and load-shifting to times of peak PV generation". Bergman and Eyre (Bergman 2009; Bergman & Eyre 2011) are perhaps less optimistic, stating that striving for maximum adoption does not lead to householders making best use of renewable generators in their home, nor to such householders maximising the potential energy and emission savings. Bergman makes the link between this phenomenon, socio-technical lock-in of energy practices, and the lack of connection between personal energy use and global phenomena such as Climate Change. The evidence for change of practice due to the adoption of distributed generation is mixed.

One tangible, although not particularly desirable, example of a small change in practice resulting from the adoption of PV generators is evident in the UK. There is evidence of an emerging niche market for devices which schedule electrical immersion water heaters to switch on at times when PVs[1] generate. This has the potential to create a sizeable rebound effect. The use of such a device may be economically efficient for the individual householder, it is highly undesirable from an energy point of view, where electrical energy which may be used for a variety of purposes is being converted into low-grade heat energy and stored as hot water rather than exported to the grid. The energy will often be entirely lost to the atmosphere as the hot water cools if it is not needed – e.g. on a hot summer's day when surplus PV generated electricity is likely to be at a maximum.

There is some evidence that policy makers are considering the adoption of distributed energy generation in a wider context of a suite of energy efficiency policies to reduce carbon emissions. For instance, in the UK, the most recent announcement of changes to the FiT scheme, in addition to an overall degression, introduces an energy efficiency qualification for the highest bands of the tariff (although this requirement is waived for community installations – perhaps in an effort to address the relatively slow rate of community installations). The evidence to date, though, indicates that distributed generation has a scale and geographic dispersion that could make visions of a smart grid which balances energy supply and demand locally, regionally and nationally difficult to achieve.

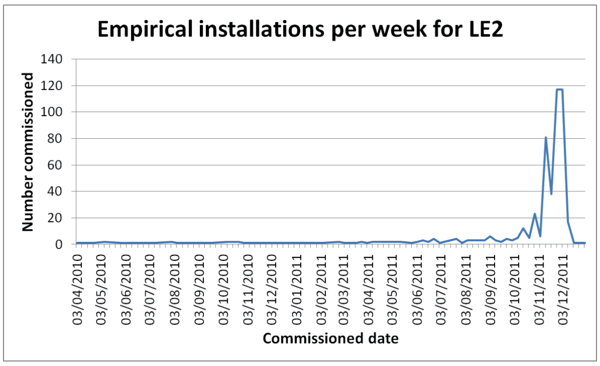

Figure 4. Data for installations per week in LE2 postcode. (Source: Ofgem 2012; via REF 2012.)

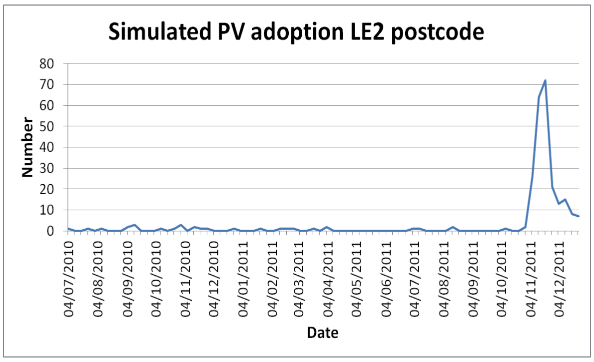

Figure 5. Simulation results for adoptions per week in LE2.

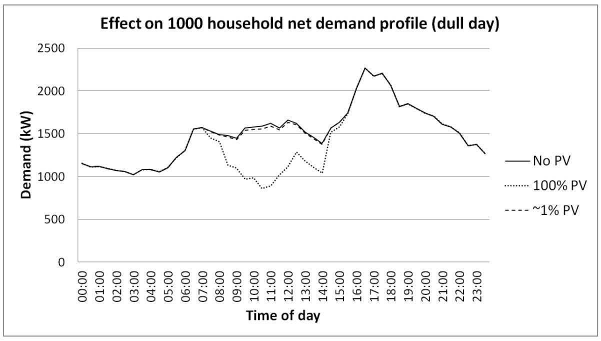

Figure 6. Direct effect of PV adoption on overall demand profile for 1,000 prosumers (dull day). Generated from simulation run with 1 year typical weather.

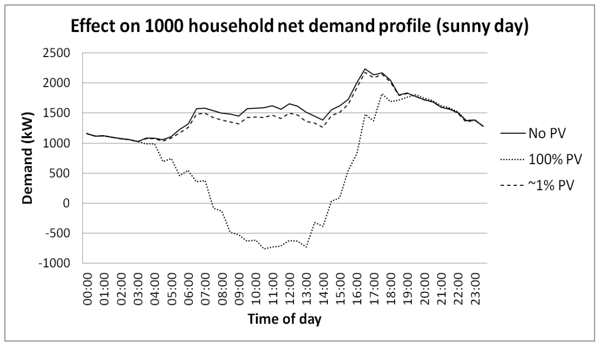

Figure 7. Direct effect of PV adoption on overall demand profile for 1,000 prosumers (sunny day). Generated from simulation run with 1 year typical weather.

Conclusion

Distributed renewable generation on a local (indeed individual household) scale has undoubtedly increased markedly in the UK over the last two and a half years. A similar trend is evident across many European countries. However, due to the combination of physical factors (e.g building ownership, geographical location) and the economic structure of FiT incentives, patterns can be observed which are not particularly conducive to an overall vision of smart grid innovation having a dual benefit of facilitating carbon emission reduction and avoiding investment in electricity distribution infrastructure.

In terms of the first smart grid goal – carbon emission reduction – the structure of FiTs (in the UK at least) has led to the vast majority of installations being very small scale, typically on individual households. This means that, despite the rapid increase in distributed generation capacity installed, the *total* capacity installed and, crucially, the amount of traditional generation displaced is relatively small. There are relatively few larger scale (for instance community based) renewable installations. The combination of these factors calls into question the efficiency of the scheme in terms of investment (which is ultimately shared between the bills of consumers) and the ongoing cost of administrating many hundreds of thousands of installations set against the scale of benefit.

In terms of the second goal – avoiding investment in electricity distribution infrastructure – the picture is rather less good. A large amount of the network reinforcement required to cope with increased electricity demand is required in cities and large towns. However, the adoption we see is largely not in towns. For instance, in the UK, there are pronounced "black holes" of adoption in large conurbations including London, Birmingham, Manchester/Liverpool and Newcastle. Adoption has been strongest in highly rural areas – for instance the South West of England including Cornwall and Central Wales. Thus, in total, we see that the generation is generally far from the centres of high consumption. Therefore, any Smart mechanism to match demand to supply will tend to relieve pressure only in already low consumption areas while high consumption areas remain

FiTs have proved to be a successful incentivisation mechanism for the installation of local distributed generation. However, a deeper analysis shows that distributed generation adoption is neither at the scale nor in the geographical areas that would best suit a Smart Grid future where demand may be matched to supply at a variety of physical scales.

Bibliography

Bass, F.M., 1969. A new product growth model for product diffusion. *Management Science*, 15(5), pp. 215–227.

Bergman, N., 2009. Can micro-generation catalyse behaviour change in the domestic energy sector in the UK? In *Broussous, C. and Jover, C., (eds) Proceedings of the eceee 2009 summer study*. ECEEE 2009 summer study. La Colle sur Loup, France: ECEEE, pp. 21–32.

Bergman, N. & Eyre, N., 2011. What role for microgeneration in a shift to a low carbon domestic energy sector in the UK? *Energy Efficiency*, 4(3), pp. 335–353.

Bundesnetzagentur, 2012. Increase in the number of photovoltaic systems. *Bundesnetzagentur Press Releases*. http://www.bundesnetzagentur.de/SharedDocs/Pressemitteilungen/EN/2012/120109IncreaseNumberPhotovoltaicSystems.html [Accessed January 7, 2013].

Carley, S., 2009. Distributed generation: An empirical analysis of primary motivators. *Energy Policy*, 37(5), pp. 1648–1659.

Chitnis, M. et al., 2013. Turning lights into flights: Estimating direct and indirect rebound effects for UK households. *Energy Policy*, 55, pp. 234–250.

DECC, 2012. Feed-in Tariff statistics. *Department of Energy and Climate Change*. Available at: http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/source/fits/fits.aspx [Accessed January 14, 2013].

DEFRA, 2008. *A Framework for pro-environmental behaviours*, Uk Government, London: Department for Environment, Farming and Rural Affairs.

Druckman, A. et al., 2011. Missing carbon reductions? Exploring rebound and backfire effects in UK households. *Energy Policy*, 39(6), pp. 3572–3581.

ETP, 2006. Definition - SmartGrids: European Technology Platform for the Electricity Networks of the Future. Available at: http://www.smartgrids.eu/?q=node/163 [Accessed December 22, 2010].

Faiers, A. & Neame, C., 2006. Consumer attitudes towards domestic solar power systems. *Energy Policy*, 34(14), pp. 1797–1806.

Grubler, A., 2012. Energy transitions research: Insights and cautionary tales. *Energy Policy*, 50, pp. 8–16.

Guidolin, M. & Mortarino, C., 2010. Cross-country diffusion of photovoltaic systems: Modelling choices and forecasts for national adoption patterns. *Technological Forecasting and Social Change*, 77(2), pp. 279–296.

Higgins, A. et al., 2012. Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. *Technological Forecasting and Social Change*, 79(8), pp. 1399–1412.

Higgins, A., Foliente, G. & McNamara, C., 2011. Modelling intervention options to reduce GHG emissions in housing stock – A diffusion approach. *Technological Forecasting and Social Change*, 78(4), pp. 621–634.

Keirstead, J., 2007. Behavioural responses to photovoltaic systems in the UK domestic sector. *Energy Policy*, 35(8), pp. 4128–4141.

Leicester, P.A., Goodier, C.I. & Rowley, P., 2011. Evaluating the impacts of community renewable energy initiatives. In *Proceedings of the ISES Solar World Congress 2011*. ISES Solar World Congress. Kassel, Germany: International Solar Energy Society.

Mahajan, V., Muller, E. & Bass, F.M., 1995. Diffusion of new products: Empirical generalizations and managerial uses. *Marketing Science*, 14(3 supplement), pp. G79–G88.

Norton, J.A. & Bass, F.M., 1987. A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products. *Management Science*, 33(9), pp. 1069–1086.

Ofgem, 2012. Central Fit Register Report Viewer. *Ofgem*. https://www.renewablesandchp.ofgem.gov.uk

Ofgem, 2008. *Long-Term Electricity Network Scenarios (LENS) – final report*, Available at: http://www.ofgem.gov.uk/Pages/MoreInformation.aspx?docid=5&refer=Networks/Trans/Archive/ElecTrans/LENS [Accessed July 1, 2011].

REF, 2012. Installed Renewable Energy Generators database. *Renewable Energy Foundation*. Available at: http://www.ref.org.uk/fits/ [Accessed January 14, 2013].

Rogers, E.M., 1983. *The Diffusion of Innovation (3rd Edition)*, New York: The Free Press.

Snape, J.R., Irvine, K. & Rynikiewicz, C., 2011. Understanding energy behaviours and transitions through the lens of a smart grid Agent Based Model. In *Energy efficiency first: The foundation of a low-carbon society - Proceeding of eceee 2011 Summer Study*. eceee 2011 summer study. Belambra Presqu'île de Giens, France: ECEEE, pp. 1919–1930.

Snape, J.R. & Rynikiewicz, C., 2012. Peer effect and social learning in micro-generation adoption and urban smarter grids development? *Network Industries Quarterly*, 14(2&3), pp. 24–27.

Stokes, M., Rylatt, M. & Lomas, K., 2004. A simple model of domestic lighting demand. *Energy and Buildings*, 36(2), pp. 103–116.

Toffler, A., 1981. *The third wave*, Bantam Books New York.

UK Parliament, 2008. Climate Change Act.

Winser, N., 2010. Hunter Memorial Lecture 2010: Britain's Energy Mix and the National Grid, 2010–2030. Available at: http://tv.theiet.org/technology/power/10204.cfm [Accessed January 8, 2013].

Endnotes

1. See, for instance, www.rudgerenewables.co.uk.

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