Energy Policy 116 (2018) 95–111

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Feed-in tariffs for solar microgeneration: Policy evaluation and capacity projections using a realistic agent-based model

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ARTICLE INFO

Keywords:
Solar photovoltaics
Microgeneration
Agent-based model
Feed-in tariffs
Incentive policies

ABSTRACT

Since 2010, over 700,000 small-scale solar photovoltaic (PV) systems have been installed by households in Great Britain and registered under the feed-in tariff (FiT) scheme. This paper introduces a new agent-based model which simulates this adoption by considering decision-making of individual households based on household income, social network, total capital cost of the PV system, and the payback period of the investment, where the final factor takes into account the economic effect of FiTs. After calibration using Approximate Bayesian Computation, the model successfully simulates observed cumulative and average capacity installed over the period 2010–2016 using historically accurate FiTs; setting different tariffs allows investigation of alternative policy scenarios. Model results show that using simple cost control measures, more installation by October 2016 could have been achieved at lower subsidy cost. The total cost of supporting capacity installed during the period 2010–2016, totalling 2.4 GW, is predicted to be £14 billion, and costs to consumers significantly exceed predictions. The model is further used to project capacity installed up to 2022 for several PV cost, electricity price, and FiT policy scenarios, showing that current tariffs are too low to significantly impact adoption, and falling PV costs are the most important driver of installation.

1. Introduction

Since 2010, feed-in tariffs (FiTs) designed to encourage adoption of small-scale, decentralised renewable energy technologies have been available to households, communities, and industrial and commercial organisations in Great Britain (GB). The majority of FiT-registered installations are solar photovoltaics (PV), with tariffs paid to installation owners by their electricity supplier per unit of electricity produced or exported.

The cumulative peak capacity of small-scale (defined throughout this work as up to 10 kW) PV systems installed with support from the FiT scheme now exceeds 2 GW (Department for Business, Energy and Industrial Strategy, 2016; Ofgem, 2016a). By 2016, the total annual cost of supporting FiT-registered installations (all capacities and technology types) exceeded £1 billion (Ofgem, 2016b), and costs continue to rise as the scheme remains open to new registrations while payments to existing installations remain guaranteed for decades. FiTs are paid by electricity suppliers, but these costs are ultimately passed on to their customers. Solar PV is by far the most popular technology supported by the FiT scheme, making up 99% of the number of registered installations as of September 2016 (over 770,000 individual installations), the next most popular technology being wind power at just over 7000 installations (Ofgem, 2016a). Given the scheme's cost as well as the importance of increasing reliance on renewable energy, a review of the implementation of the FiT scheme, in terms of historical, current, and announced future policy, is relevant. Specifically, investigating if FiT policy encouraged the adoption of PV by households in an effective manner in the period 2010–2016, and predicting the outcome of future policy in the short term (up to 2022) can identify issues in the policy's implementation, and how these pitfalls can be avoided in future. To quantitatively assess policy effectiveness, this paper uses a new agent-based model (ABM) constructed to simulate the adoption of small-scale PV by households in GB.[1] While this model focuses on the effect of FiTs, it also includes other economic factors and the effect of a social network on adoption decisions.

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[1] This work and the model constructed relate specifically to policy in Great Britain, rather than the UK as a whole; while Northern Ireland does offer financial support for renewable energy, it has a separate policy. This means the model output is scaled to the population of Great Britain rather than the UK. Where relevant (e.g. regional population and load factor data), data for Great Britain were used, but for other parameters (such as household income and electricity consumption distributions), available data for the UK as a whole was used. Given the relatively small population of Northern Ireland – currently around 3% of the population of the UK (Office for National Statistics, 2015b) – using data for the UK rather than only Great Britain does not affect model outcomes significantly.

https://doi.org/10.1016/j.enpol.2018.01.060
Received 5 April 2017; Received in revised form 12 December 2017; Accepted 29 January 2018

This paper first introduces the role of ABMs in modelling energy systems in Section 2 and background on FiT policy and its outcomes so far in Section 3. Section 4 outlines model specification and operation, and results of the model for historical (2010–2016) and future (2016–2021) scenarios are presented in Sections 5 and 6 respectively, with conclusions and policy implications discussed in Section 7.

2. The role of ABMs in energy system modelling

Interest in the dynamics of innovation and technology diffusion goes back some five decades, encompassing both qualitative, explanatory theories such as Everett Rogers' *Diffusion of Innovations* (Rogers, 1962) and mathematical models for e.g. the spread of technical innovations (Mansfield, 1961) and consumer durables (Bass, 1969). The first energy system models for policy, strategy and operational planning were being developed around the same time (Hoffman and Wood, 1976). Since then, several extensive, well-established energy system modelling families have been developed, such as MARKAL/TIMES (Loulou and Labriet, 2008) and MESSAGE (Schrattenholzer, 1984). These models, often described as "bottom-up" models since they explicitly represent different technologies, use linear programming methods to find the lowest cost energy system. Another group of models, often referred to as "top-down" models, represent macroeconomic interactions robustly, but do not include the level of technological detail present in bottom-up approaches; these include DICE/RICE (Nordhaus and Boyer, 1999), GEM-E3 (Capros et al., 2013) and MERGE (Manne et al., 1995). More recently, versions of MARKAL and MESSAGE linked with macro-economic models which take into account feedbacks between the energy system and other economic sectors have been developed (Manne and Wene, 1992; Messner and Schrattenholzer, 2000). Generally, bottom-up and top-down models have produced different results for the cost or savings caused by moving to a lower-carbon energy system, with bottom-up models suggesting that moving to efficient, renewable technologies will lead to cost savings, while top-down models which endogenise economic drivers (and thus, to some extent, human behaviour) do not reproduce these large cost savings (Grubb et al., 1993; IPCC, 1996).

ABMs provide an intuitive framework to take into account explicit characteristics of both technology and human behaviour. The basic modelling elements are agents (which may represent e.g. individuals, households, or a government agency), and the collective actions of these agents leads to emergent behaviour. ABMs also address the issue of control; large-scale optimization models implicitly assume there is some centralised control over e.g. the energy system, which is often not the case, especially in the case of small-scale, privately-owned technologies such as solar PV. ABMs can address one layer of control and decision-making, focusing on the adoption of a technology by individuals or small groups (Palmer et al., 2015; Robinson et al., 2013; Sorda et al., 2013; Zhang and Nuttall, 2011) or can address multiple levels of agent interaction (e.g. regulation, forward and spot markets, and the physical load of the electricity systems), such as in the EMCAS model (Argonne National Laboratory, 2008).

According to Kiesling et al. (2012), ABMs focused on innovation diffusion can be divided into two broad categories: theoretical models, using abstract, generic representations of diffusion processes to gain insight into a particular factor influencing the diffusion process, and applied models, which often focus on a particular country or region, with the aim of providing predictions or designing and assessing support policy. A selection of models in the latter category are summarised in Table 1. Such small-scale, applied ABMs do not serve the same purpose as the large-scale models discussed above, but their ability to endogenise human behaviour may allow useful policy assessment for specific sectors, or where traditional models disagree.

3. Policy background

3.1. Feed-in tariffs in Great Britain

Great Britain's FiT scheme was set out in the 2008 Energy Act and took effect from April 2010, supporting electricity generation from anaerobic digestion, hydro power, solar PV, wind power and small-scale gas-powered CHP (Parliament of the United Kingdom, 2008) as part of the UK's climate change mitigation strategy. The FiT scheme is intended for installations under 5 MW and mainly supports small-scale generation, with the Renewables Obligation (RO) mainly supporting large-scale generation, although there is some overlap in the technologies and scales supported. This work only considers the FiT scheme, since this is by far the most common subsidy type for small-scale, domestic PV installations (see Section 3.2).

3.1.1. Aims of the feed-in tariff

The aims of the FiT scheme as stated by the Department of Energy & Climate Change (DECC) are (adapted from Nolden, 2015):

Table 1
Previous applications of agent-based models to innovation diffusion problems. This is by no means an exhaustive list; further examples can be found in e.g. Kiesling et al. (2012) and Li et al. (2015).

Reference	Model focus / sector	Decision-making strategy	Environment & network topology
Iachini et al. (2015)	Effect of social and economic factors on adoption of PV in Italy	Multi-criteria utility function: adoption when agent's threshold utility (depending on household characteristics) exceeds utility function	Small-world. Agents more likely to be linked to geographically and socio-economically proximate agents.
Palmer et al. (2015)	Effect of support schemes on adoption of PV in Italy	Multi-criteria utility function: adoption when agent's threshold utility (depending on household characteristics) exceeds utility function	Small-world. Agents more likely to be linked to geographically and socio-economically proximate agents.
Robinson et al. (2013)	Spatially-resolved adoption of PV in Austin, Texas	Theory of planned behaviour	Small-world. Agents more likely to be linked to geographically proximate agents
Schwarz and Ernst (2009)	Spatially-resolved adoption of water-saving innovations in Germany	Two methods, depending on socio-economic group: deliberate decision and a heuristic (theory of planned behaviour)	Small-world. Agents more likely to be linked to geographically and socio-economically proximate agents.
Sorda et al. (2013)	Effect of support schemes on prevalence of biogas CHP in Germany (spatially-resolved)	Decision-making algorithm considering feedstock and resource availability, heat demand and the Net Present Value (NPV) of the investment, based on simple decision rules	Relationships between two types of representative agents (e.g. banks, local and federal government, electric utilities) are pre-defined. No social network.
Zhang and Nuttall (2011)	Effect of policy on diffusion of smart metering in the UK	Theory of planned behaviour	Lattice: interaction with neighbours and random network
Zhao et al. (2011)	Effect of policy on PV adoption in the USA	Hybrid system dynamics and ABM. In ABM, multi-criteria utility function: if household's "desire level" (utility function) exceeds threshold, adoption occurs	None (only consider effects of mass advertising)

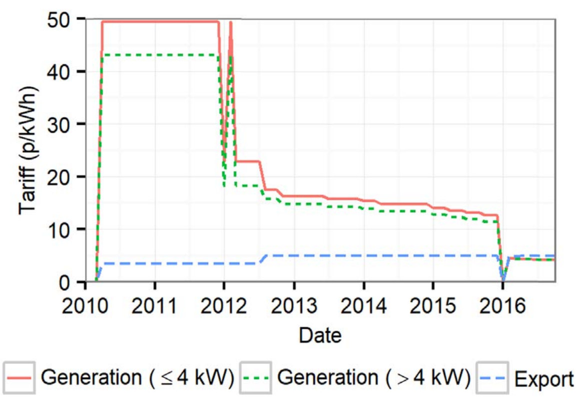

Fig. 1. Generation and export tariff levels (on a monthly basis) for small scale PV installations (≤ 10 kW) in pence per kWh. These are the 2016 levels of the FiT, adjusted for the April 2016 RPI. Data from Ofgem (2016c).

1) Encouraging deployment of small-scale (up to 5 MW) low-carbon electricity generation;
2) Empowering people and giving them a direct stake in the transition to a low-carbon economy;
3) Assisting the public take-up of carbon reduction measures;
4) Fostering behavioural change in energy use;
5) Helping develop local supply chains and drive down energy costs.

Quantitatively, the discounted costs to consumers were predicted to reach £440 million/year by 2020, with cumulative costs of £3.1 billion up to 2020 and £6.7 billion up to 2030, with a discount rate of 3.5% relative to 2008 (DECC, 2010). The cost to consumers was defined as the total generation and export tariff payments, minus the value of exported electricity to utilities; the latter value was fixed at 3p/kWh. The number of installations was predicted to reach 780,000 by 2020; this number was exceeded in 2016. The initial projections assumed a much larger fraction of non-PV installations (DECC, 2010), and did not foresee how much small-scale, domestic PV would be installed as installation costs fell while FiTs remained high (Nolden, 2015).

3.1.2. FiT scheme operation

The scheme operates by requiring electric utilities to pay owners of registered renewable energy installations for the electricity produced. The electric utility pays a generation tariff (GT) per kWh of electricity generated by the installation, and an export tariff (ET), paid only for the electricity which is (deemed to have been) exported to the grid.[2] These payments are guaranteed for 20 years for capacity registered after August 2012; prior to this, the guarantee period was 25 years. Most generators under 30 kW capacity do not have an export meter installed so their electricity exports are deemed to be half of the total production (DECC, 2015a). The model in this paper assumes this "deemed export" for all installations. Feed-in tariffs (specifically the generation tariff) have varied significantly since the introduction of the scheme in 2010, as shown in Fig. 1.

October 2011–April 2012 and August 2015–February 2016 were noticeably volatile periods for the FiT scheme. In October 2011, the government announced that FiT levels would be reduced by more than 50% from 12 December 2011 (Vaughan et al., 2011). However, a high court ruling in response to a challenge by Friends of the Earth and two PV installers judged such a drastic cut in FiT with only a few weeks' notice "legally flawed" in December 2011 (Vidal, 2011); thus, in effect, the FiT was reinstated at the higher level. This ruling was upheld on appeal in January 2012 (Carrington, 2012), which meant the change in FiT was not actually implemented until 3 March 2012.

[2] Tariffs are index-linked, meaning their value is adjusted according to the Retail Price Index (RPI), which is a measure of inflation (Ofgem, 2016f).

Table 2
Deployment caps, and corresponding FiTs, for solar PV installations with capacity less than or equal to 10 kW as originally set in February 2016 after the pause to the FiT scheme, and as adjusted for excess capacity being carried forward as of 1 October 2016 (used in the model to make projections). The export tariff is constant at 4.91p/kWh.

Year	Quarter	Original deployment cap set February 2016 (MW) (Ofgem, 2016a)	Deployment cap as of 1 October 2016 (MW) (Ofgem, 2016b)	FiT generation tariff (p/kWh) (Ofgem, 2017)
2016	1	48.4 (not reached)	n/a	4.39
	2	49.6 (not reached)	n/a	4.32
	3	50.6 (not reached)	n/a	4.25
	4	51.7	127.7	4.18
2017	1	52.8	52.8	4.11
	2	53.8	53.8	4.04
	3	54.2	54.2	3.97
	4	55.9	55.9	3.90
2018	1	57.0	57.0	3.83
	2	not set	58.0	3.76
	3	not set	59.1	3.69
	4	not set	60.1	3.62
2019	1	not set	61.1	3.55

Following the UK general election in 2015 and a public consultation on the FiT scheme (DECC, 2015b), the FiT scheme was paused from 15 January to 8 February 2016, after which FiTs for small-scale installations were reduced and deployment caps were introduced (Ofgem, 2016d, 2016e). The aim of the deployment caps is to keep the total annual cost of supporting systems installed after February 2016 below £100 million (DECC, 2015c). For every quarter, a GT and deployment cap are set (Ofgem, 2016d, 2016e), as shown in Table 2. If the deployment cap is reached before the end of the quarter, this triggers degression, which is a reduction in the GT to its next lowest level, so all subsequent successful applications will be placed on the next quarter's tariff. Excess capacity is carried forward to the next quarter's FiT rate if the cap is not reached. Even if the cap is not reached, the GT will reduce at the start of the next quarter. The phased closure of the FiT scheme is planned for 2018–2019 (DECC, 2015b), with FiTs and deployment caps for PV currently set until 31 March 2019, although the total available capacity (around 700 MW) may run out before this.

3.2. PV deployment under the FiT scheme

While some small-scale (≤ 10 kW) PV installations are registered under the RO, the majority of capacity (94%) is supported by the FiT scheme (see Fig. 2a); by 1 October 2016, 2.41 GW of capacity had been registered, with a total of 2.55 GW reported capacity consisting of small-scale installations (Department for Business, Energy and Industrial Strategy, 2016; Ofgem, 2016a). The majority of installed capacity under the FiT scheme is made up of individual installations smaller than 4 kW, but there is a significant contribution from larger systems (see Fig. 2b). However, almost all of these larger installations are non-domestic. Comparing Fig. 2c and d shows that the majority of non-domestic installations are > 10 kW, while domestic capacity is made up mostly of ≤ 10 kW installations. These observations indicate that domestic adoption under the FiT scheme is the most important category to consider in predicting small-scale PV installation rates.

The distribution of installed capacities for domestic FiT-registered installations peaks just below 4 kW, as shown in Fig. 3. In the past (2010–2015) the FiT for solar PV was capacity-dependent (Fig. 1), with larger installations (> 4 kW) receiving a lower FiT. A 'bunching up' below and at 4 kW has occurred, likely due to the fact that households could gain a higher financial return from a slightly smaller installation. This was a perverse incentive, i.e. an incentive which produces an unintended and adverse effect. Current feed-in tariffs and those

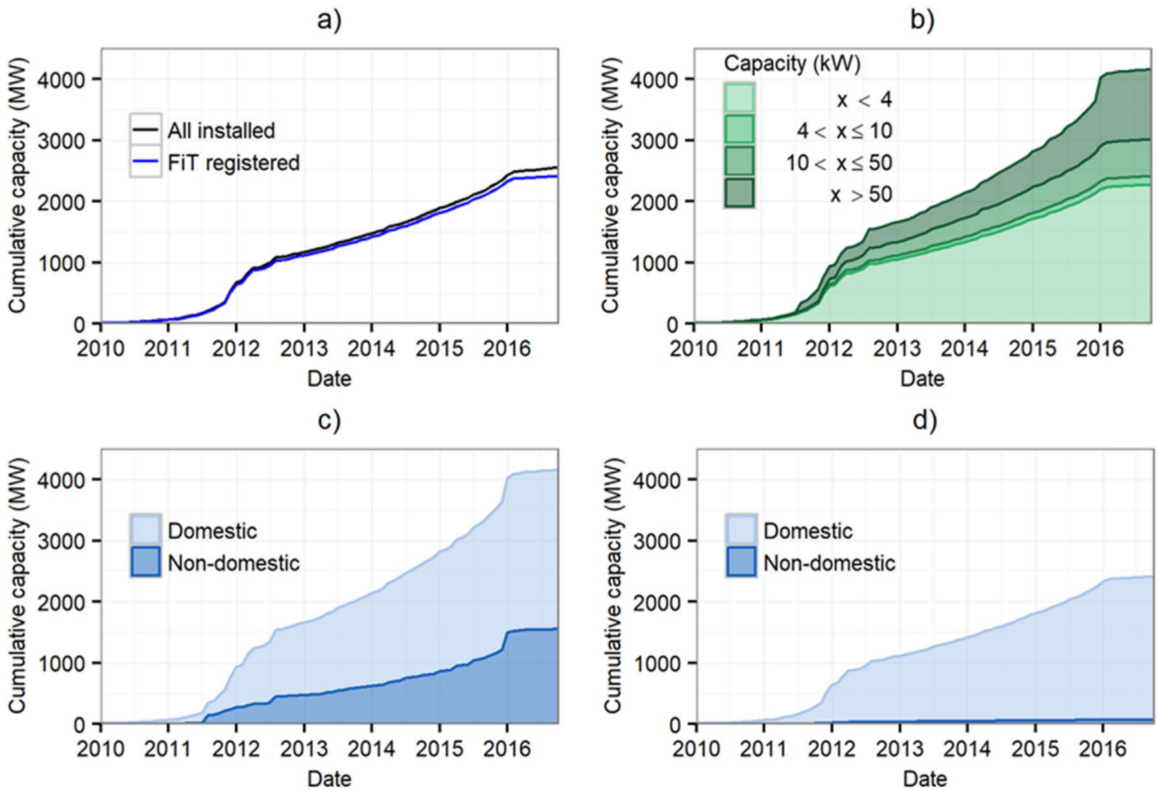

Fig. 2. a) Cumulative installed capacity of small-scale (≤ 10 kW) PV installations, including all domestic and non-domestic (industrial, commercial or community-owned) installations. Data on all installed capacity from BEIS (2016), data on FiT registered installations from Ofgem (2016a). b) Deployment of PV installations (all ownership types) registered under the FiT scheme, by capacity (Ofgem, 2016a). c) Deployment of PV installations under the FiT scheme, showing installations of all capacities, subdivided into domestic and non-domestic (industrial, commercial and community-owned) ownership type. d) Installations registered under the FiT scheme up to 10 kW capacity, subdivided into domestic and non-domestic ownership type (Ofgem, 2016a).

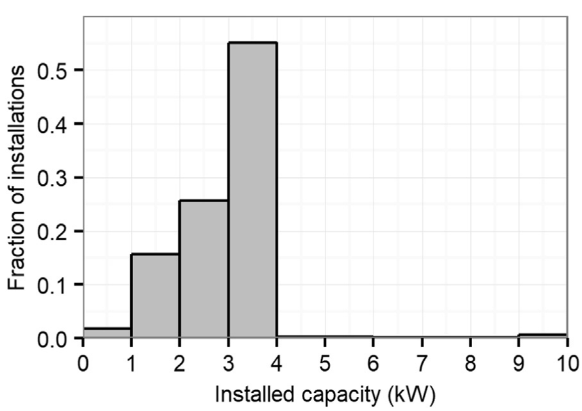

Fig. 3. The distribution of installed capacity for domestic FiT-registered PV installations up to 10 kW (Ofgem, 2016a).

announced up to 2019 are the same for all installations up to and including 10 kW capacity.

3.3. Solar photovoltaics

The market for rooftop solar PV in the UK is currently dominated by crystalline silicon, referred to as first generation solar cells (DECC, 2013). Second generation PV (the collective name for all types of thin-film cells) are also reaching maturity and are commercially available. The model described in this paper does not differentiate between different PV technologies, assuming one average installation cost per kW of peak power installed, and the same load factor for all installations in the same region. Since 2010, the average capacity installed per household (see Fig. 9b) has been increasing steadily, most likely due to both falling costs and the same amount of capacity taking up a smaller area. The cost of a small-scale PV system has fallen from around £5000/kW to £1600/kW since 2010 (see Fig. 6).

4. Model development

4.1. Modelling approach

The model introduced here uses a multi-criteria "utility function" or "desire level" for agent decision-making, detailed further in Section 4.3.2. Since the people making adoption decisions relating to small-scale, domestic PV installations are inhomogeneous and unlikely to be perfectly informed, the expected utility or usefulness of an investment is a logical modelling choice for representing individual's choices (Kiesling et al., 2012). This method was previously used by Zhao et al. (2011), Palmer et al. (2015), and Iachini et al. (2015); Table 3 summarises the factors affecting the adoption decision in these papers. Further references to specific implementations of utility methods can be found in Kiesling et al. (2012), and wide-ranging discussion of different decision-making methods in ABMs can be found there and in van Dam et al. (2013).

In this model, the agents represent individuals or households, who all make decisions independently. If an agent's total utility exceeds some threshold, they will install a PV system. This approach allows several factors to be considered in the decision-making process and gives the modeller freedom in how these are weighted, which allows for calibration to historical data. The model aims are to predict adoption decisions (if and when PV is installed, and the capacity chosen), translate the information on individual adoptions into cumulative installed capacity and production data and track associated subsidy and capital costs. The model assigns realistic agent and environment

Table 3
Previous applications of the utility function method in ABM-based investigations of the adoption of small-scale PV systems, summarising the research focus and the factors considered in the agent utility function.

Reference	Investigation focus	Factors considered in utility function
Iachini et al. (2015)	Effect of social and economic factors (Italy)	Payback period Household budget Neighbourhood influence Environmental benefit.
Palmer et al. (2015)	Effect of support schemes (Italy)	Payback period Environmental benefit Household income Communication with other agents
Zhao et al. (2011)	Effect of support schemes (USA)	Payback period Household income Word of mouth (social effect) Advertisement effect

characteristics relevant to decision-making, implements a decision-making strategy, and scales the results to the population of GB. The model was calibrated to observed PV deployment in the period 2010–2016.

The model was implemented in the R language using RStudio (RStudio Team, 2015), an integrated development environment (IDE) for R, which provides a convenient environment to handle large data sets in addition to supporting object-oriented programming, used for the ABM itself. The model code is available online.[3]

4.2. Model parameters

The following Sections (4.2.1 and 4.2.2) outline the environment and agent characteristics considered in the model, while Section 4.3 outlines model operation. A schematic of the ABM's structure is shown in Fig. 4.

4.2.1. Environment characteristics

4.2.1.1. Electricity price. The electricity price is assumed to be the same for all users, and varies annually as shown in Fig. 5. Two possible future electricity price scenarios were considered for projections (Section 6). In the high cost scenario, the increasing linear trend for the period 2010–2015 is extrapolated into the future. In the low-cost scenario, prices are assumed to remain at the 2015 level.

4.2.1.2. Solar PV capital cost. While there is data available on the average total capital cost of PV (i.e. the total system cost, including both component and installation costs), it is difficult to find information on the spread of this cost over the full time period 2010–2016. Data published by DECC (2016b) on the installation cost of FiT-registered PV installations starts in April 2014; this data was used in conjunction with average cost data for small PV systems from 2010 to 2014 (KPMG LLP, 2015). The resulting PV capital cost data is shown in Fig. 6.

It is beyond the scope of this work to attempt to accurately forecast PV prices up to 2022, as the processes driving continuing cost reduction of the technology are varied and their interplay is complex (Kavlak et al., 2016). Thus, three annual percentage cost reductions predicted by other sources were used (Fig. 6). In the high cost reduction scenario, prices fall by 10% annually (Farmer and Lafond, 2015); in the intermediate cost scenario, prices fall by 7% a year (IRENA (International Renewable Energy Agency), 2016, p. 39); and in the low cost reduction scenario, the price falls by 4% annually (International Energy Agency IEA, 2014, p. 23).

Note that this is an entirely exogenous treatment of technological change, as cost reduction is not affected by the amount of PV deployment. The percentage cost reductions are not learning rates, as they depend only on the passage of time, not cumulative production.

4.2.1.3. Owner-occupier households. Unlike the electricity and PV price, this parameter does not affect the adoption decision, but is used as a scaling factor to relate model outcomes to the population of GB. Those living in rented accommodation are extremely unlikely to install PV systems (DECC, 2015a). Thus, the model was scaled to the number of households (as given in Table 4) who own the home they occupy ("owner-occupiers") rather than the total number of households. The scale factor used is the number of owner-occupied homes in GB divided by the number of agents used.

4.2.2. Agent characteristics

Agents are represented by R objects which contain all the agent characteristics the model uses and generates. Some agent characteristics are assigned immediately upon agent creation, while others are set as the model runs.

It should be noted that the agent characteristics outlined in this section do not vary with time, with the exception of the installed capacity considered by the household. In reality, all these parameters can of course vary; it was assumed that given the relatively short total timeframe for which the model was used (2010–2021) ignoring such changes was valid. Of course, time variation for any variable can be included relatively easily, as is the case for e.g. electricity price or PV cost in this model.

4.2.2.1. Demographic data. Household income, size and region are assigned by sampling from a continuous or discrete probability distribution drawn from UK demographic data; the procedures and distributions used are detailed in Appendix A.

4.2.2.2. Technical parameters. The mean load factor (LF) or capacity factor of FiT-registered PV systems in GB is 10% (DECC, 2015d), where the LF is the average load divided by the peak load. The LF is affected by the number of hours of sunlight, i.e. the availability of fuel, and how well the system operates away from ideal conditions (e.g. lower insolation or higher temperatures, which reduce system efficiency). The load factor (LF) for all households is set to be equal to the 5-year national average (2011/12–2015/16) of the household's region, according to the data in Table A2.[4]

An agent's electricity consumption is sampled from probability distributions depending on household size and income, which are derived from real data from a large number of UK households; the procedure is described in Appendix B.

Note that while the demographic data and technical parameters are set per agent, they are set according to certain fixed probability distributions, with the distributions themselves being part of the agents' environment.

4.2.2.3. Installed capacity. The agents must have some method of deciding how much capacity to install, if they do adopt. This decision was implemented in the model by looking at both the household's income (a proxy for its budget) and its energy consumption. Households with PV installations have above-average electricity consumption (DECC, 2015a), indicating that displacing electricity purchased from the grid is a key driver for consumers installing PV.

There is a lack of data relating household income or electricity use

[3] The full model code used to generate the results presented is available at github.com/phoebe-p/FiTABM.

[4] The LF actually varies both seasonally and annually and depends on an installation's specific location and orientation. However, for the adoption decision, the important information is the *expected* LF; thus the 5 year average for each region was used as an indication of the expected level of production.

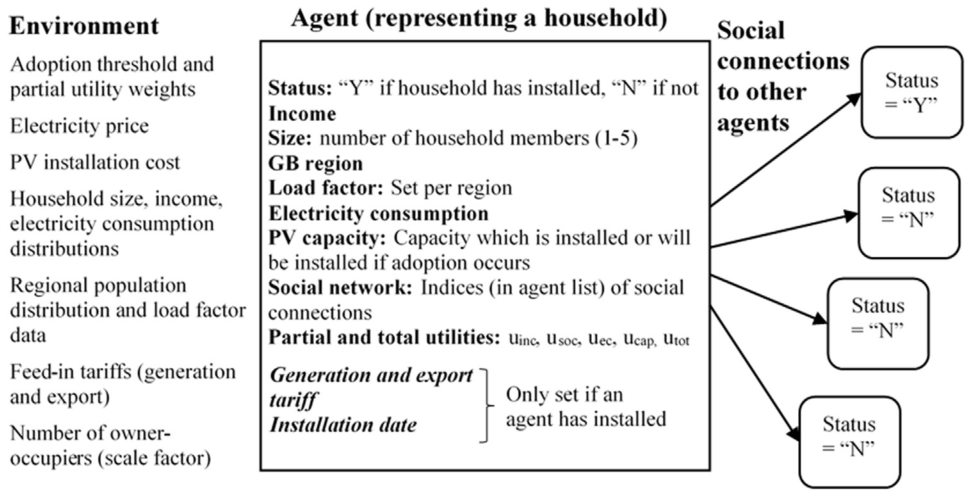

Fig. 4. Schematic diagram of one agent and its environment in the ABM. Social connections to other agents can be considered part of an individual agent's environment.

Fig. 5. Electricity prices for small consumers, including taxes, in the UK. Data for 2010–2015 is from DECC (2016a). The electricity price for 2016 was assumed to be the same as in 2015. The two electricity price scenarios used for projections are also shown.

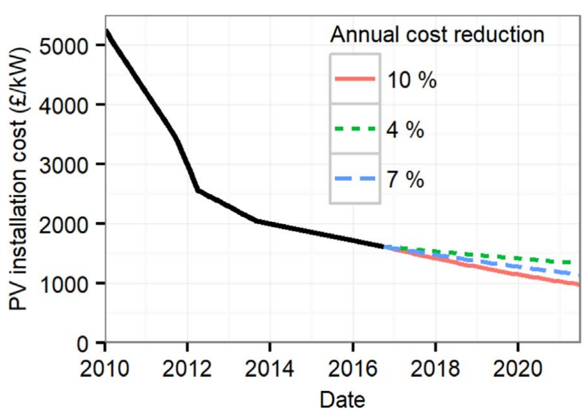

Fig. 6. The average total system cost per kW of PV capacity for small scale (around 4 kW) PV systems, as used in the model. Data from KPMG (2015) and DECC (2016b). The three PV cost reduction pathways used for projections are also shown.

to chosen capacity. It was assumed that households are willing to spend 30% of their pre-tax annual income on solar panels, which sets a capacity per household. If the expected electrical output from this capacity exceeds the expected annual consumption of the household, the installed capacity is reassigned so that its expected output is equal to the annual consumption.

If this method gives a capacity over 4 kW, the model takes into account the lower FiTs offered to installations larger than 4 kW until 2016 (Fig. 1) by considering if the household is predicted to receive a

Table 4
Number of owner-occupied homes in Great Britain (Department for Communities and Local Government, 2016), as well as projections for 2015–2016. Data was available up to 2014; the linear trend from 2014 to 2015 was used to predict values for 2015–2016.

Year	Number of owner-occupied homes (thousands)	
2010	17,463	
2011	17,388	
2012	17,276	
2013	17,205	
2014	17,199	
2015	17,193	*(projected)*
2016	17,187	*(projected)*

higher financial return if they install exactly 4 kW. If this is the case, the assigned capacity is changed to 4 kW. The model only considers installed capacities less than or equal to 10 kW; if the method described above leads to a higher installed capacity, it will default to exactly 10 kW.[5]

Note that if an agent decides to adopt a PV system, its capacity then remains static; the households in the model cannot decide to install additional capacity or remove their PV system.

4.2.2.4. Social network. A simple social network was included in the model, in which agents are randomly assigned connections to 10 other agents when an agent population is created. These social links affect the adoption decision (see Section 4.3.2.3). There are many ways a social network could be constructed more realistically, e.g. to reflect the fact that not all households have the same number of relationships, through the use of for instance a scale-free (Barabasi, 1999) or small-world (Watts and Strogatz, 1998) network. However, using a more complex social network adds significant computational complexity, meaning the model takes longer to run. Since the effect of the social network is not the main focus of the model, a very simple representation using 10 fixed connections was used.

[5] The model does not explicitly take into account the roof area available, or how much of that roof area is suitable for installing PV; in reality, these factors limit how much capacity can be installed. The model implicitly accounts for this in two ways: by scaling using the number of owner-occupiers rather than the total number of households, and by considering the electricity consumption in the capacity decision. The majority (91%) of owner-occupiers live in a whole house (Office for National Statistics, 2013) and thus will not be severely limited in the area available for PV (as opposed to those e.g. renting a room). Electricity consumption, which affects the amount of capacity installed, tends to be larger for larger houses: according to DECC (2015a), "households with solar PV are typically large, detached properties", which "tend to have higher energy consumption, and also a larger roof area".

4.3. Model operation

4.3.1. Time evolution

The model steps through the time frame under consideration in monthly intervals. For each time step, the model updates the environmental parameters and thus the corresponding agent parameters and utility functions. It then checks if any new agents will adopt under these conditions. The adoption decisions made on the first of the month in the model represent all decisions made over the course of that month.[6]

4.3.2. Decision-making

The total utility is made up of a weighted sum of partial utilities, in this case depending on household income (*inc*), the social environment of the agent (*soc*), economic attractiveness of the investment (*ec*), and the capital cost of the investment (*cap*). Adoption occurs when the total utility exceeds some threshold *t*. All the models summarised in Table 3 consider the payback period, household income/budget and some social effect. Two of these models include the effect of an environmental benefit resulting from PV installation. This model considers instead a partial utility depending on the capital cost of installation, to reflect the barrier to adoption posed by high upfront costs. The payback period (*ec*) utility can be seen, partially, as already reflecting the environmental benefit; the more electricity is produced (i.e. the more non-renewable electricity is displaced), the shorter the payback period and the higher the economic utility. In addition, there is evidence that although consumers may state that they value renewable energy adoption, this is unlikely to translate to a willingness to pay for this without additional financial support (Scarpa and Willis, 2010).

The total utility of the PV investment for a particular household *k* is:

$$u_{tot,k} = \sum_i w_i u_{i,k} = w_{inc} u_{inc,k} + w_{ec} u_{ec,k} + w_{soc} u_{soc,k} + w_{cap} u_{cap,k}$$

Where all u and w as well as t lie in the range [0, 1], and additionally the sum of partial utility weights satisfies $w_{inc} + w_{ec} + w_{soc} + w_{cap} = 1$.

The partial utility functions provide a functional form to relate the characteristic(s) under consideration (e.g. the household income) to a number which reflects the utility arising from a particular value of this characteristic; for instance, the higher the agent income, the closer to 1 we expect the income utility to be, while a higher capital cost should lead to a lower capital cost utility.

4.3.2.1. *Income utility*.

The income utility was defined in a similar way to its form in Zhao et al. (2011) and Palmer et al. (2015), with the midpoint occurring at the mean annual income of the agent population, $\bar{I}$ (this will be slightly different per generated agent population, but lies around £28,000). The steepness used in this model was $\frac{1}{5000}$,compared to $\frac{1}{1000}$ in Palmer et al. This gives:

$$u_{inc,k} = \frac{1}{1 + \exp\left(\frac{\bar{I} - I_k}{5000}\right)}$$

Where I_k is the income of agent *k*. The resulting distribution of income utilities is shown in Fig. 7a.

4.3.2.2. *Social utility*.

The social utility reflects the number of adopters an agent is connected to. When an agent is created, it is assigned L_k = 10 links to other agents. The social utility of an agent increases if an agent they are connected to adopts, and is defined by:

$$u_{soc,k}(t) = \frac{1}{1 + \exp\left(1.2 \times \left[\frac{L_k}{4} - A_k(t)\right]\right)}$$

Where $A_k(t)$ is the number of adopters an agent is connected to at time *t*. The variation of u_{soc} with number of adopters to which an agent is linked is shown in Fig. 7b.

4.3.2.3. *Economic utility*.

The economic utility is given by a straight line mapping the payback period, between 1 and 20 years, onto the range [0, 1]. While the capital cost, income, and social connections of agents have relatively narrow distributions, which either vary smoothly from one time step to the next, or stay constant over the model run, the sudden changes in the FiT within a single time step mean a logistic function mapping leads to very large, sudden changes in u_{ec}. The economic utility as a function of the simple payback period $pp_k(t)$ for the PV investment of agent *k* at time *t* is:

$$u_{ec,k}(t) = \frac{20 - pp_k(t)}{19}$$

Details of how the payback period is calculated are given in Appendix C. The variation of the economic utility with payback period is shown in Fig. 7c.

4.3.2.4. *Capital cost utility*.

The capital cost utility is included to reflect the fact that high upfront costs act as a barrier to adoption; even though the investment in PV may give high returns and be a good investment with a positive net present value, consumers may not be willing or able to invest a large sum initially. The capital cost utility is specified in terms of the household income I_k, which is taken as a proxy for available budget, and the capital cost of the investment.

$$u_{cap,k}(t) = \frac{1}{1 + \exp\left(-0.0007 \times \left[\frac{I_k}{5} - C_k(t)\right]\right)}$$

Where $C_k(t)$ is the capital cost of installation (the current PV cost multiplied by the installed capacity). The resulting distribution of capital cost utility with PV capital cost for different household income levels is shown in Fig. 7d.

4.3.3. Private and subsidy costs

One of the key aims of the model is to track the costs of deploying solar PV. Included in the model are methods for calculating the capital cost of adoption, assumed to be paid by the households, and the expected total subsidy cost incurred through payment of generation and export tariffs based on expected production, which is paid by utility companies. The model takes into account the different guarantee periods set by the government for installations installed before and after 1 August 2012 (25 and 20 years respectively).

4.3.4. Model calibration

The model was calibrated by looking for combinations of the partial utility weights $\vec{w} = (w_{inc}, w_{soc}, w_{ec}, w_{cap})$ and adoption threshold *t* which reproduce the observed small-scale, FiT-registered PV deployment in GB accurately when FiT levels, PV cost and electricity prices in the model were set to realistic values for 2010–2016 (the "realistic historical" scenario). This method of model construction, calibration and validation is referred to in van Dam et al. (2013) as "historic replay" and by Fagiolo et al. (2007) as the "history-friendly" ABM calibration approach. Approximate Bayesian Computation (ABC) was used for parameter estimation, as outlined in Thiele et al. (2014). Because a new agent population is generated probabilistically for each model run, the outcome is not deterministic, and there is more than one set of parameter values which gives an outcome close to the observed installation data. Initially, trial and error and exhaustive searching scanning the full allowed parameter space of the weights $\vec{w}$ and threshold *t* were used to identify the relevant region for the prior distribution for each

[6] In calculating the total deployment and production, it is assumed that households deciding to adopt will begin contributing to installed capacity during the following month, e.g. households adopting on 1 July 2012 in the model will be included in the cumulative installed capacity, and begin contributing to the expected electricity production, from 1 August 2012.

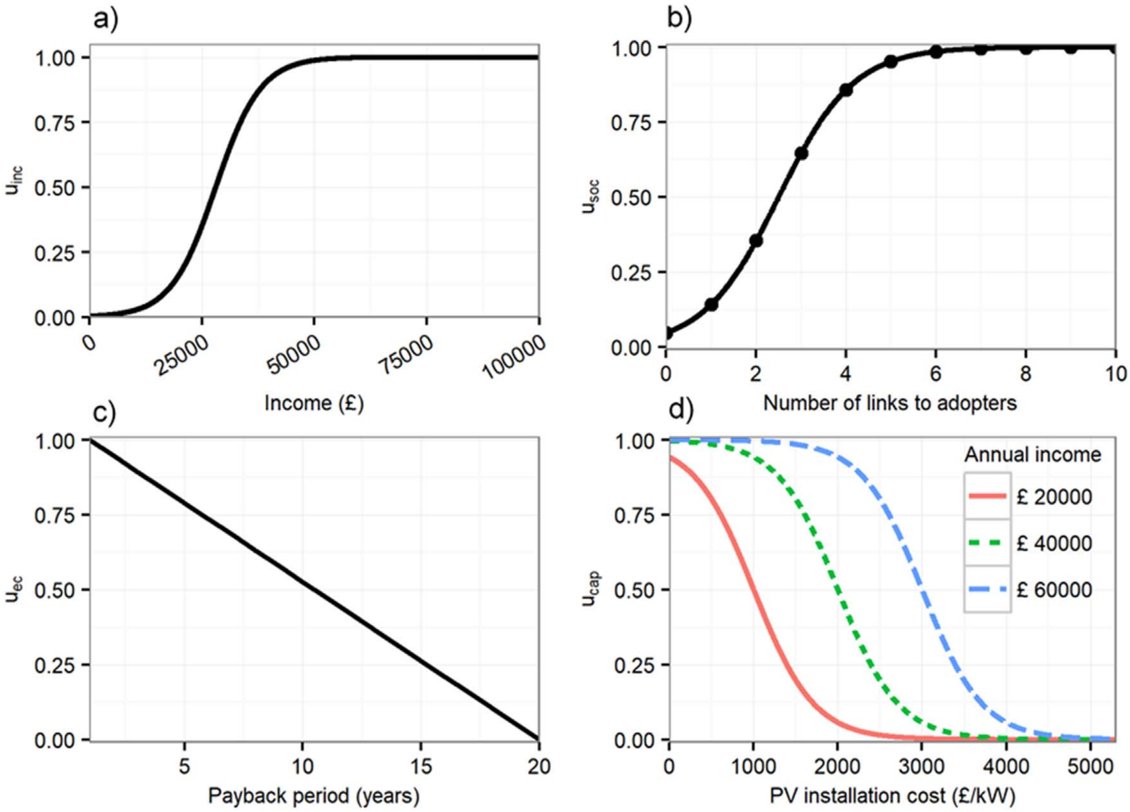

Fig. 7. Partial utilities used: a) variation of the income utility with pre-tax income, b) variation of the social utility with number of connected adopters for an agent with ten links to other agents, c) variation of the economic utility with simple payback period of the PV system, and d) variation of the capital cost utility with the capital cost of the PV system. The capital cost utility distribution depends on the agent's income, and is shown here for three different household income levels. The capacity being considered for installation is kept constant at 4 kW.

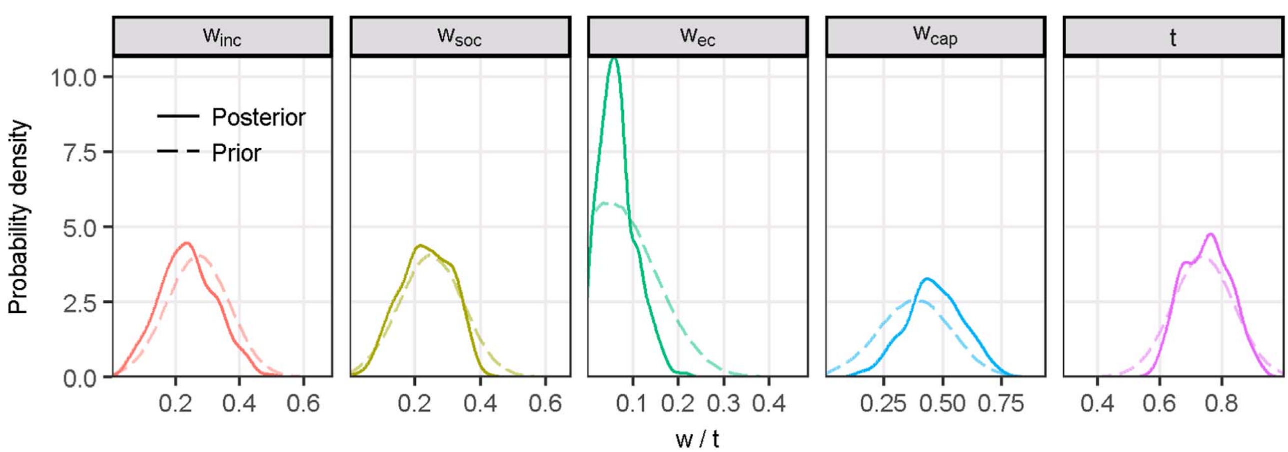

Fig. 8. Prior and smoothed posterior distributions of the model parameters. Posterior distributions were found using a rejection method with 500,000 simulations and a tolerance of 0.2%. The wider prior distribution of w_{cap} arises because it is calculated from the other parameters, and not sampled from a normal distribution itself. The prior distribution for w_{ec} is narrower than for the other parameters since many likely values on the normal distribution with mean 0.05 and standard deviation 0.1 (the prior distribution) are excluded because they are < 0.

Table 5
Summary of the 1000 accepted parameter values for the posterior distributions shown in Fig. 8. The results for w_{cap} are not shown since it was not sampled from a prior distribution but calculated from the three other weights in each case.

	w_{inc}	w_{soc}	w_{ec}	t
Min.	0.039	0.018	0.000	0.565
2.5% Perc.	0.075	0.085	0.003	0.615
Median	0.239	0.236	0.061	0.753
Mean	**0.237**	**0.233**	**0.066**	**0.751**
Mode	0.234	0.216	0.058	0.765
97.5% Perc.	0.414	0.367	0.158	0.899
Max.	0.496	0.429	0.221	0.938

parameter. The prior distributions were defined as Gaussians, centred on parameter values which were shown to give good agreement with historical data, with a standard deviation of 0.1, as shown in Fig. 8. Each parameter was constrained to lie between 0 and 1 and the partial utility weights must sum to 1; as such, w_{cap} was not explicity sampled from a prior distribution, but calculated from $w_{cap} = 1 - w_{inc} - w_{soc} - w_{ec}$. A large number of simulations (500,000) were performed using the High Throughput Computing facility of Imperial College's High Performance Computing Service, with input parameters sampled from the prior distributions using the *EasyABC* package for R (Jabot et al., 2015, 2013). The summary statistics used to identify the best fit consisted of the observed installed capacity at several points along the time evolution. The posterior

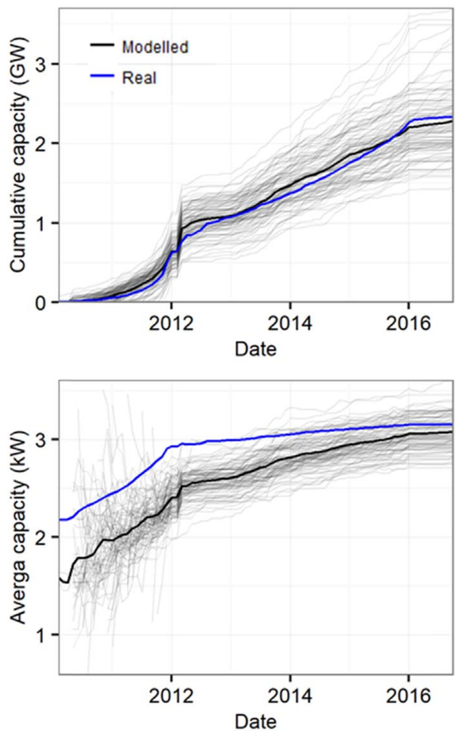

Fig. 9. Real PV capacity data (Ofgem, 2016a) and the output of the calibrated model run under a realistic scenario with 2010–2016 FiTs set equal to their actual 2010–2016 values. The thin grey lines show 100 individual model runs, each using a unique population of 5000 agents and parameters sampled from the posterior distributions shown in Fig. 8; the model result is the average of these individual runs. Top: cumulative installed capacity. Bottom: average installation capacity (cumulative capacity divided by number of adopters).

distribution is approximated by setting a tolerance value which defines which percentage of simulations which match the summary statistics best will be accepted; this was done using the rejection method implemented in the *abc* package for R (Csilléry et al., 2015, 2012). The tolerance used here was 0.2%, so 1000 sets of parameters corresponding to the best-fitting simulation runs were retained to form the posterior distributions shown in Fig. 8, and summarised in Table 5. Sampling from posterior distributions for each parameter, instead of using fixed values, also allows us to quantify the sensitivity of model outcomes to changing input parameters.

Results for the realistic historical scenario calculated using calibrated parameter values sampled from the posterior distribution are shown in Fig. 9. In addition to replicating cumulative capacity well (this being the objective of the calibration), the calibrated model also shows the correct trend in average installed capacity per household.

It should be noted that although the historical case is replicated well by the calibrated model, this does not guarantee that this choice of partial utility weights and threshold truly reflects the underlying processes driving decision-making, and validating parameters like this in an ABM is difficult (Fagiolo et al., 2007).

4.3.5. Running the model

As discussed in the previous section, the model is stochastic. This means each model run will produce different results for the same externally set conditions (see e.g. Fig. 9). In the subsequent sections, to produce results for each policy, PV cost, or electricity price scenario, the time evolution is repeated 100 times, each time using a newly generated population of 5000 agents and parameters drawn from the posterior distributions. Taking the mean of the outcomes (deployment, production, subsidy and private costs) of all model runs at each time step gives an averaged, overall result, while looking at the spread (e.g. the standard deviation) of the runs allows us to quantify the uncertainty in the model results.

The choice to use 100 runs of the model with a population of 5000 agents is somewhat arbitrary, as there are no strict rules regarding the 'correct' number of agents or runs. However, related previous work has been based on models on a similar or smaller agent scale, presenting average results of several runs. For instance, Cantono and Silverberg (2009) used a lattice of 100 by 100 agents, presenting the averaged results of ten simulations; Iachini et al. (2015) used 2000 agents (presumably over one model run, as no averaging is mentioned); Jager et al. (2000) used only 16 agents, with results averaged over 100 runs; and Robinson et al. (2013) used a population of 7700 agents averaged over 100–200 runs.

There are two distinct modes of model operation; one for historical simulations over the period January 2010–September 2016, and one for projections (October 2016–January 2022). The second category requires projections for all the time-dependent environment variables which are not required for historical runs. While historical simulations start with a new agent population with no adopters, projections require pre-generated populations reflecting the fact that around 4% of the agent population has adopted by October 2016.

5. Realistic and alternative historical scenarios

The aim of the historical scenarios considered here is to assess the implementation of FiT policy, and investigate if a similar or higher cumulative installed capacity could have been achieved at a lower cost by implementing logical, simple degression strategies (e.g. a linear or percentage reduction at regular intervals), possibly in combination with deployment caps. The FiT strategies considered were:

1. The realistic historical scenario (i.e. the calibration scenario), with the GT and ET at their historical levels (Fig. 1); this has the aim of reproducing observed installation patterns.
2. Monthly linear degression of the GT, with a constant ET. This also includes scenarios where the GT is constant.
3. Fixed percentage reduction of the GT every year, with a constant ET.
4. Quarterly linear degression of the GT in combination with deployment caps, with a constant ET.

The model includes functions to easily set FiTs and, where relevant, deployment caps, for these different degression strategies with the desired parameters (e.g. initial and final GT, ET, date until which FiTs are available, available capacity, linear or percentage degression rate). Like the realistic historical scenario, all alternative scenarios first introduce FiTs in April 2010. A large number of alternative scenarios were simulated, varying the initial feed-in tariffs between 70p/kWh and 10p/kWh and the rate at which the GT is reduced. Three different ETs (0, 5 and 10 p/kWh) and four different FiT scheme end dates (September 2013, 2014, 2015 or 2016) were tested in each case. For scenario type 4, three different constant quarterly deployment caps (50, 100 and 150 MW) were used.

Note that to implement FiT policy involving deployment caps, the model had to be modified; rather than FiTs being set at the start of a simulation and kept constant, FiTs must be dynamically updated depending on installed capacity.

5.1. Results

The mean results of around 740 simulations covering the four subsidy strategies are shown in Fig. 10, which plots the installed capacity at the end of the simulation time against the total expected subsidy cost until the end of all installations' guarantee periods. As expected, there is a general trend of increasing installed capacity with more subsidy spending; however, there is a large spread in the amount of installation achieved for a given amount of subsidy. For total spending close to £14 billion, the total cost outcome for the realistic historical scenario, the range of installed capacities is 1.5–3.8 GW.

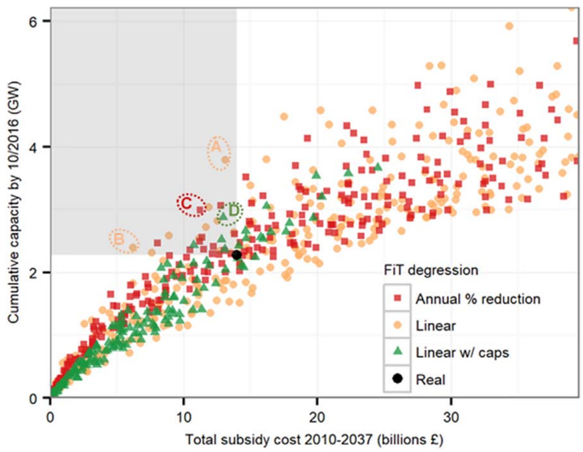

Fig. 10. Cumulative installed capacity by 1 October 2016 versus total expected subsidy cost until the end of all installations' guarantee periods, for installations installed during the period April 2010–September 2016. These are the mean results of 100 model runs for 740 different policy scenarios. The shaded area corresponds to scenarios which lead to equal or higher cumulative capacity for lower or equivalent total expected subsidy costs as compared to the simulated realistic scenario (•). Four alternative policy scenarios A-D are labelled.

The shaded area in Fig. 10 covers the region which is Pareto-optimal to the realistic scenario, i.e. achieving the same or more deployment at the same or lower total subsidy cost. However, this plot obscures some detail; it shows only final installed capacity, not electricity production up to October 2016. Increased early installation means more electricity production over the simulation period, but subsidising early installations is more expensive due to the higher incentives necessary to overcome high installation costs. Given the solar panels' expected lifetime of several decades, these initial differences in production are less significant in the long run.

Four alternative policy scenarios in the Pareto-optimal region are highlighted in Fig. 10:

A. A flat GT of 20 p/kWh, available until September 2016. The ET is zero.
B. A flat GT of 10 p/kWh, available until September 2016. The ET is 10 p/kWh.[7]
C. The GT is initially set at 30 p/kWh, and then reduced by 10% at the start of each year, ending in September 2016. The ET is zero.
D. The GT is initially set at 30 p/kWh, and is reduced linearly every quarter to 10 p/kWh by September 2016, when the scheme ends. The export tariff is zero, and the capacity available under deployment caps is 150 MW per quarter.

Fig. 11 shows how the deployment and annual subsidy cost commitment for scenarios A-D vary over the simulation period, as compared to the realistic historical case. The FiT scheme initially had no degression strategy in place, i.e. no pre-planned reduction of FiTs at a specific time and no deployment caps. This led to an escalation of the costs paid out by utilities; Fig. 11 shows that of the cost commitment of £600 million/year by late 2016, £400 million is due to the first two years of the scheme, which represents less than half of the installed capacity. Cost commitments doubled over the course of a few months (October 2011 – March 2012). If the 2011 attempt to decrease FiTs had not failed (Section 3.1.2), or if a pre-existing deployment cap or tariff reduction strategy had been in place, these cost overruns could have been limited.

[7] Note that because the export in the model is deemed to be half of total production for all installations, and the FiT is constant over the whole simulation time, scenario C is equivalent to a constant FiT of 15 p/kWh with no export tariff. In the case of changing FiTs, the export tariff essentially provides a convenient way to implement a constant "background" tariff in the model.

All the alternative scenarios end at the latest possible date (September 2016), emphasising that encouraging installation when capital costs have fallen is significantly cheaper. In alternative scenarios A and B, most of the capacity is installed later (late 2012 onwards), and thus the FiTs required are lower. Perhaps attempting to ambitiously expand PV capacity during 2010–2011 was an example of what Grubler (2012) has described as attempting to go "too fast, too big and too early" with a promising technology, by-passing essential phases in technology development and cost reduction. However, one must also consider that cost reductions are driven by more installation ("learning by doing"), so more early installation driven by the FiT would lead to lower costs later. In the model, the PV price is set externally, and is not dependent on how much has been installed (i.e. exogenous rather than endogenous learning). Scenarios C and D show alternatives which still encouraged early adoption while leading to similar or more deployment (taking into account the uncertainty in the modelling results) at a similar total subsidy cost compared to the realistic scenario, as well as similar expected production over the simulation period. Further results, including expected electricity production and private installation costs, for the realistic simulation and alternative scenarios A-D are shown in Table 6.

The alternative strategies show that there is not one clear optimal policy choice, and the same installed capacity by October 2016 could likely have been achieved in more than one way, although we must consider that the uncertainty in the model outcomes is such that some outcomes could be significantly better or worse than suggested by the mean result. Scenarios A and B have a lower, flat GT, while scenarios C and D have steady tariff reductions. A strategy for reducing the GT is especially vital if it is initially high (above ≈ 30p/kWh). Deployment caps, as in scenario D, allow a hard upper limit on cost commitment to be set, and can be goal-based. Setting a limit on cost commitment is one of the goals of the revised FiT scheme (see Section 3.1.2), and the efficacy of deployment caps in limiting costs is also apparent in the projections discussed in Section 6.

5.2. Comparison with policy aims

Section 3.1.1 introduced the stated aims of the FiT scheme. It could be argued that the first three qualitative objectives have been achieved to some extent in the case of PV; over 700,000 small-scale PV systems have been installed since 2010, giving many people a direct stake in low-carbon electricity generation. The model does not give insight into whether this has led to behavioural change (aim 4). In terms of the final qualitative aim, 2.4 GW (or 4.4 GW if larger FiT-supported installations are also included) of capacity installed over six years will not have significantly driven down global PV module prices and thus energy costs, given that the global installed capacity was estimated at 227 GW at the end of 2015, with around 50 GW of that having been installed in 2015 (IEA International Energy Agency, 2016). For comparison, Germany's FiT scheme (the EEG) supports 40 GW of capacity (Fraunhofer Institute for Solar Energy Systems ISE, 2017), or around 20% of the global total. The expansion of the UK PV installer industry required to meet demand for PV systems may have led to some decrease in labour and balance of system costs; however, the bulk of cost reduction observed is due to global decreases in module cost, rather than reduced labour or other installation costs. In addition, abrupt changes to FiT tariffs disturb the installation market, as is clear from the drastic changes in installation rates depending on available policy support.

In terms of the quantitative predictions for cost of the scheme, the unexpected acceleration in the installation rate of small-scale PV systems gave higher costs than initially calculated by the government (DECC, 2010), which assumed larger contributions from other technologies (e.g. wind, anaerobic digestion). Using the same discount rate (3.5%) relative to 2008 as the DECC report (2010) and using the metric of "cost to consumers" (subsidy cost as calculated in the model minus value of electricity exports to the utility companies), the cost to

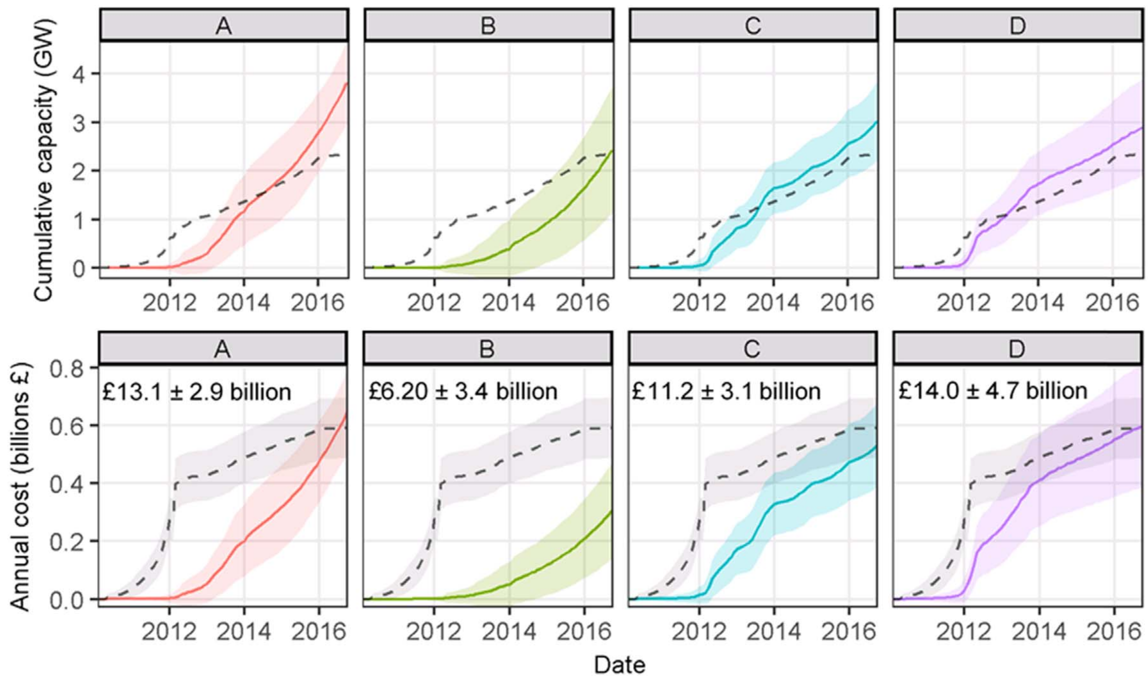

Fig. 11. Top: cumulative capacity with time for the alternative scenarios A-D. The dashed line shows the real data (Ofgem, 2016a) for comparison. Bottom: annual subsidy cost with time in the alternative scenarios. The dashed line shows the annual cost calculated for the realistic historical scenario using the calibrated model. The labels are the expected total subsidy cost to the end of the guarantee period. In each case, the lines show the mean of the 100 simulations, while the shaded area shows one standard deviation above and below the mean of the capacity/annual subsidy cost.

Table 6
Cumulative deployment by October 2016, total expected production in the period April 2010-September 2016, maximum expected annual subsidy cost over the period 2010–2037, total expected subsidy cost over the same period, and total private cost of installing PV systems in the five historical scenarios. The values reported are the mean ± standard deviation over 100 model runs.

Scenario	Cumulative deployment (GW)	Total production (TWh)	Max. annual subsidy cost (billion £)	Total subsidy cost (billion £)	Total private cost (billion £)
Realistic	2.28 ± 0.5	7.05 ± 1.2	0.592 ± 0.10	13.9 ± 2.5	5.88 ± 1.1
A	3.79 ± 0.9	6.02 ± 2.8	0.650 ± 0.15	13.1 ± 2.9	7.12 ± 1.6
B	2.39 ± 1.3	2.98 ± 2.6	0.308 ± 0.17	6.20 ± 3.4	4.30 ± 2.4
C	3.00 ± 0.8	6.28 ± 2.7	0.534 ± 0.14	11.2 ± 3.1	6.15 ± 1.7
D	2.88 ± 1.0	6.90 ± 3.5	0.592 ± 0.21	14.0 ± 4.7	6.29 ± 2.2

consumers in the realistic historical scenario was found to be £3.1 billion (standard deviation £0.6 billion) up to 2020 and £6.1 billion (standard deviation £1.1 billion) up to 2030. However, this ignores any capacity installed after September 2016, as well as all other technology types and larger PV capacity. In other words, *only* small-scale, domestic PV installed before October 2016 is already imposing a cost to consumers equal or close to the *total* predicted cost for all capacities and technologies, and thus cost predictions are being significantly exceeded.

It is somewhat unclear what the exact effect of FiT payments on electricity bills is; the method in which the cost is passed on to customers varies between utility companies. SSE Business Energy quotes a current figure of 0.5 p/kWh (SSE Business Energy, 2016), while E.ON predicted a charge of 0.35–0.4 p/kWh for 2016 (E.ON, 2014). The model predicts a current annual cost of £600 million; spread over the GB electricity market with a total size of approximately 300 TWh (Department for Business, Energy and Industrial Strategy, 2017), this gives a very rough estimate of the additional cost due to FiTs supporting small-scale PV as 0.2 p/kWh. This appears to be a good estimate as the total cost of the FiT scheme (for all technologies and capacities) is actually £1.1 billion/year (Ofgem, 2016b), suggesting a cost of 0.37 p/kWh. Compared to current electricity prices, 0.2 p/kWh represents a bill increase of ≈ 1.5%. For comparison, the effect on electricity bills in Germany due to the EEG is much larger at 6 €-cents/kWh, or 21% of the domestic electricity price (Fraunhofer Institute for Solar Energy Systems ISE, 2017). The EEG costs over £10 billion/year and supports 40 GW of solar capacity, compared to 4.4 GW (including solar installations of all capacities) in the UK.

6. Projections of future policy effectiveness

To predict the effectiveness of announced FiT policy, and explore levels of deployment depending on different external conditions (PV installation cost and electricity price), four policy scenarios were used to project cost and installation up to January 2022.

In contrast to the historical simulations starting in 2010, there are already a significant number of adopters in the agent population by October 2016; this is important because these households cannot adopt again, and contribute to the social utility (Section 4.3.2.2). To generate representative agent populations, the realistic historical scenario was repeated hundreds of times to select agent populations with a final installed capacity matching the observed installed capacity by October 2016 to within 25 MW, which are used as a starting point for future simulations.

Four subsidy strategies were explored over the period October 2016–December 2021:

a) *No subsidies:* No FiT is available for installation after October 2016.
b) *Real:* Feed-in tariffs and deployment caps are set as in Table 2, and end in March 2019.

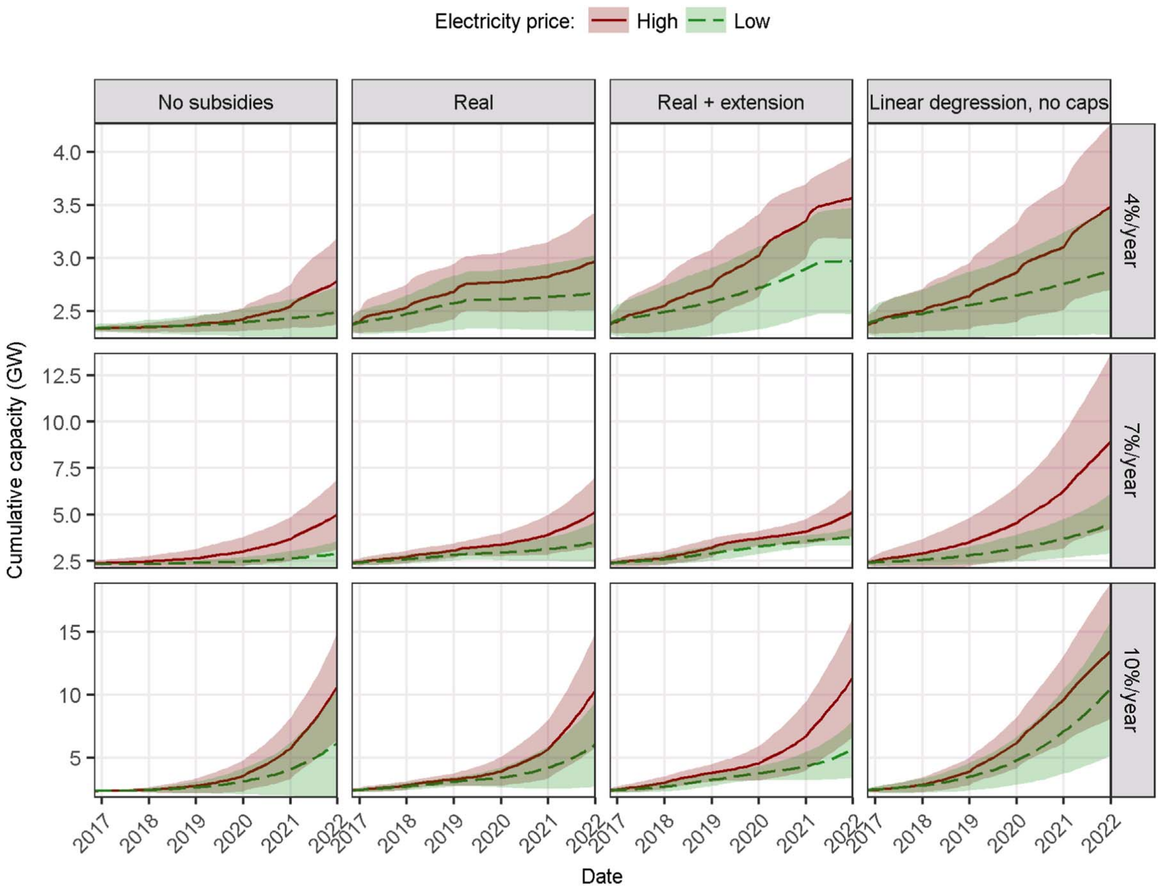

Fig. 12. Projections for the projected cumulative PV capacity up to 1 January 2022, depending on electricity and PV cost trends, for the four different future policy scenarios. The columns show the different policy scenarios, while the rows show increasing PV cost reduction from top to bottom (note the increasing range of the y-axis per row). Each combination of PV cost and policy is considered for two different electricity price trends. The lines shows the mean of the 100 simulations, while the shaded areas show one standard deviation above and below the mean.

c) *Real + extension:* Feed-in tariffs and deployment caps are set as in Table 2, but extended for a further two years until March 2021. The GT and capacity available under deployment caps are extrapolated from the announced policy; deployment caps increase by 1 MW every quarter while the GT decreases by 0.07 p/kWh. The ET is kept constant at 4.91 p/kWh.
d) *Linear degression, no caps:* An alternative, more generous subsidy system, ending in December 2021. There are no deployment caps and the GT decreases linearly every month from 4.18 p/kWh in October 2016 to zero by the end of the simulation period. The ET is kept constant at 4.91 p/kWh.

For each policy scenario, three different PV cost trends and two electricity price trends were explored, as discussed in Section 4.2.1.

6.1. Results

The cumulative deployment for each combination of policy scenario, PV cost and electricity price is shown in Fig. 12. Final deployment and total subsidy cost are summarised in Fig. 13. Both figures clearly show that decreasing PV cost is the most important driver of capacity installation; electricity price and feed-in tariffs at the levels considered here play a less significant role. Considering capacity installation for the realistic future scenario *b*, there is very little change compared to the no subsidy scenario *a* when PV costs are decreasing at 7% or 10%/year. In the slowest PV cost reduction case, we observe a clear difference in installation up to 2019 for scenario *b*, with more households installing earlier due to the additional financial benefit of FiTs. However, the final mean result by 2022 is very similar to scenario *a*, indicating that most of these households would have adopted by 2022 even without the availability of FiTs. The extended realistic scenario *c* does show a clear increase in final capacity relative to *a* in the 4%/year PV cost reduction case. However, this additional capacity is negligible compared to the effect of PV cost reduction, which can be seen clearly in Fig. 13. The key difference between scenarios *b* and *c* is that adoption occurs earlier in the simulation period compared to scenario *a*. This means more expected electricity production over the simulation period, but barely affects the final installed capacity, as is clear in Fig. 13. The total available capacity under deployment caps (just over 0.7 GW) in scenario *b* is small in comparison to the 2.33 GW installed in the period 2010–2016, especially considering the much lower cost of PV currently than in 2010, and is exceeded well before the end date of the scheme in the case of fast PV cost reduction. Between the four policy scenarios, only scenario *d* (subsidies without deployment caps) shows significantly different results, and only in the case of 7% or 10% annual PV cost reduction; however, this also comes at a significantly increased cost (Fig. 13).

The stated aim of implementing deployment caps in February 2016 (see Section 3.1.2) was limiting the additional cost of supporting post-February 2016 installations to £100 million/year. The maximum annual cost reached in scenario *b* (announced policy), with high electricity and low PV cost, is £650 million/year (standard deviation £17 million/year), compared to £590 million/year by February 2016 calculated for the realistic historical scenario. Small-scale PV installations account for 58% of the total solar capacity registered under the FiT scheme (with larger installations receiving lower tariffs), and solar technologies collectively make up the bulk of installations; this indicates that additional costs for new installations will remain below £100 million/year.

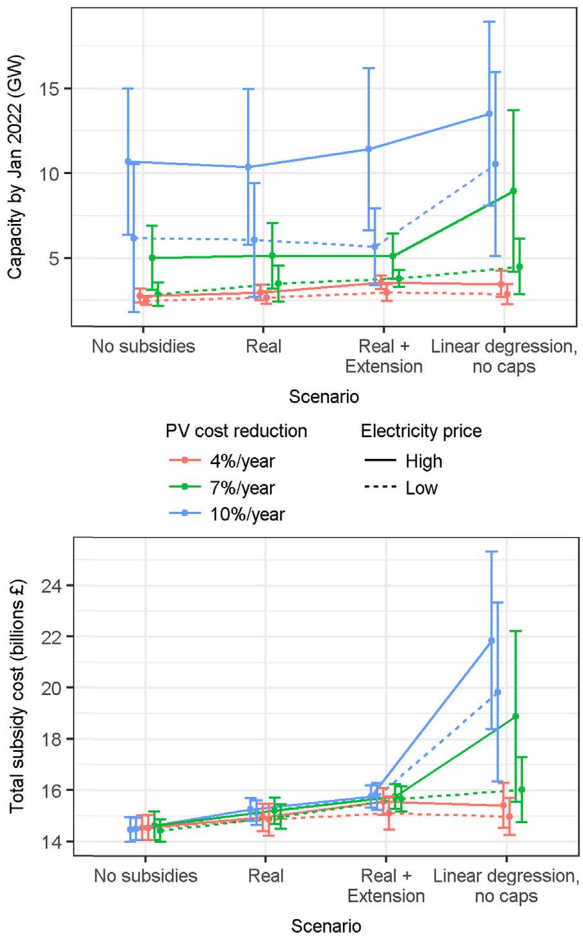

Fig. 13. Top: projected capacity by January 2022 for the four future scenarios considered, in different PV and electricity price cases. Bottom: total expected subsidy cost over the period 2010–2041 for the same scenarios. The error bars show the standard deviation over the 100 individual model runs. The points are offset slightly from one another in the x-direction for visibility.

7. Conclusions and policy implications

Adoption of small PV systems by households in Great Britain with support from the FiT scheme can be modelled successfully using an ABM calibrated to observed deployment over the period 2010–2016, and such a model provides a useful tool for policy analysis. The ABM provides a way of quantifying likely policy cost, and can provide insight into how policy could have been designed more optimally. The model presented in this paper incorporates individual agent decision-making based on household income, social connections, capital cost and payback period of the PV system investment, and takes into account statistical uncertainty using Approximate Bayesian Computation. While this model is specific to the case of solar PV in GB, it could be adapted for application to other regions or technologies. The full model code is freely available for inspection and use (see footnote 3).

Looking at FiT policy since 2010, uncontrolled policy cost escalation was a major issue – initially no degression strategy was in place, which combined with very high initial FiTs led to a rapid increase in committed cost to be paid out over the next 20 years. An initially failed attempt to decrease the GT highlights the importance of strategic planning; the alternative scenarios in Section 5 show that simple degression mechanisms, or even flat tariffs, would have been sufficient to achieve better results than those observed. If costs must be strictly limited, deployment caps provide a mechanism for doing so. Setting clear goals for deployment, setting a reasonable target subsidy cost to achieve this deployment, and making sure a mechanism to control costs (e.g. deployment caps or pre-planned tariff reduction) is in place are key requirements for successful policy. The model gives a mean predicted cost of supporting the 2.3 GW of small-scale PV installed by October 2016 of £13.9 billion; alternative scenario predictions include results of 2.4 GW at £6.2 billion or 3.8 GW for a similar cost of £13.1 billion.

The low FiTs as of 2017 have little effect, only encouraging slightly earlier adoption, which is likely to be achieved before 2022 in any case as long as PV installation costs continue to fall. Apart from the stated aim of limiting the additional cost of post-February 2016 installations to £100 million/year, which the deployment caps are projected to do successfully, it is thus unclear what the purpose of the continued existence of the FiT scheme is.

While the model does not take into account the dynamics of the PV installer industry, it highlights the effect that fluctuations in available financial support have on the rate of installation, and thus on the PV market. Actions which damage the stability of this market, such as sudden, sharp reductions in the FiT, will have serious repercussions for the installer industry. Gradual, pre-planned reductions lead to a more constant rate of installation, and less market volatility. The model did not incorporate policy (un)certainty into agent decision-making, but it is likely that confusing and erratic policy reduces the likelihood of installation.

In addition to the broader issues discussed above, several clear, specific issues with (past) FiT policy were identified. Paying a lower generation tariff for larger installations, as was done prior to 2016, with an abrupt FiT decrease at a still relatively small capacity of 4 kW, offered a perverse incentive for households to install less capacity to receive more money. While there are reasons (e.g. cost control and grid stability) to disincentivize larger installations, an abrupt cut-off at a small capacity is a crude mechanism for doing so; alternatives are a cut-off at higher capacities, or a slowly decreasing capacity-dependent FiT. While the government makes FiT policy, it does not actually pay the subsidy; electricity suppliers do, meaning additional costs incurred by these companies will ultimately be reflected in customers' bills. The fact that the government is not directly responsible for paying out subsidies means the incentive to make policy as cost-effective as possible is somewhat reduced. Although almost all small-scale systems have only a generation meter and no export meter (and export is assumed to be half the total generation), the FiT scheme uses separate export and generation tariffs for all installations. For the vast majority of small-scale systems, and thus the vast majority of domestically-owned systems, these two tariffs could be replaced by one single tariff. Alternatively, export meters could be installed for everyone. This is the case in Germany, where the label of "feed-in tariff" is more accurate, as the tariff is only paid over electricity exported to the grid.

Acknowledgements

The authors would like to thank Dr. N. J. Ekins-Daukes for his insightful comments and assistance in proofreading, and the Imperial College High Performance Computing Service for the computational resources provided.

Funding

Raphael Slade was supported by the Engineering and Physical Sciences Research Council, UK, through the SUPER-GEN Bioenergy Hub project Bioenergy value chains: whole systems analysis and optimisation (EP/K036734/1).

Appendix A. Data used in agent creation

A lognormal distribution was fitted to real UK income data (HM Revenue and Customs, 2016), and incomes are assigned by sampling from this continuous probability distribution, shown in Fig. A1.

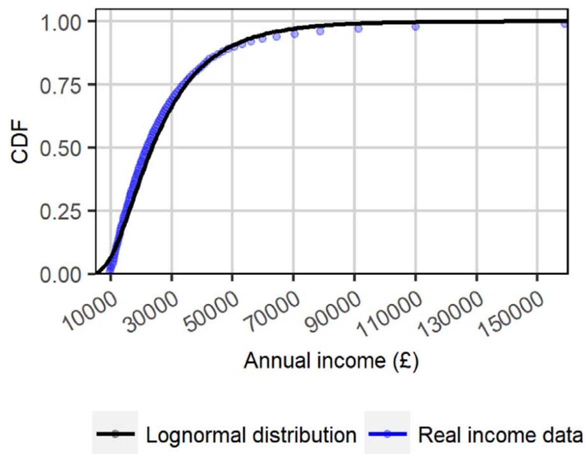

Fig. A1. First to 99th percentiles of pre-tax income for UK households (HM Revenue and Customs, 2016), and the cumulative distribution function of the lognormal distribution fitted to this data with $log\ \mu = 10.07$ and $log\ \sigma = .57$, where μ and σ are the mean and standard deviation of the underlying normal distribution. Incomes for agents in the model are generated by sampling from this normal distribution.

The household size is assigned by sampling from a discrete probability distribution, reflecting the fraction of households with a certain number of members, according to the probabilities shown in Table A1. For simplicity, it was assumed that the largest possible household size was five people, since very few households are larger than this.

The agents were divided between regions with probabilities corresponding to the fraction of the total population living in each region in 2012 (see Table A2), and are also assigned the corresponding load factor. Note that this implicitly assumes that household size distribution is the same over all regions.

Table A1
Household size in the UK. Data on the number of one, two, three or four or more person households from Office for National Statistics (2015a); data on the proportion of 4+ member households comprising 5 or more people from Office for National Statistics (2014).

Household size	Fraction of households
1	0.29
2	0.35
3	0.16
4	0.13
5	0.07

Table A2
Mid-2012 population per region of GB (Office for National Statistics, 2014) and mean load factor of FiT-registered PV installations in the region recorded in the period 2011–2015 (DECC, 2015d). Agents are assigned to a region with probabilities equal to the fraction of the population in the region.

Symbol	Region	Mid-2012 population (thousands)	Fraction of population	Mean load factor 2011–2015 (%)
A	East Midlands	4567.7	0.074	9.53
B	East of England	5907.3	0.095	10.2
C	London	8308.4	0.134	9.28
D	North East	2602.3	0.042	9.72
E	North West	7084.3	0.114	9.33
F	Scotland	5313.5	0.086	9.04%
G	South East	8724.7	0.141	10.3%
H	South West	5339.6	0.086	10.4%
I	Wales	3074.1	0.050	9.84%
J	West Midlands	5642.6	0.091	9.84%
K	Yorkshire & the Humber	5316.7	0.086	9.70%
	Great Britain (total)	61881.3	1	9.98%

Appendix B. Predicting household electricity consumption

While electricity consumption is not straightforward to predict, there are some indicators which can help predict a household's consumption, including income level and household size (Druckman and Jackson, 2008). Electricity use data from the National Energy Efficiency Data-Framework (NEED) was used to model to effect of these two variables on annual electricity consumption. The NEED data includes the median and mean electricity consumption varying with income level and household size (DECC, 2015e). The probability distribution of electricity consumption is positively skewed so it has a long tail at high consumptions and the median is lower than the mean (Fig. B1). In addition, electricity consumption must be positive, indicating that it is reasonable to model the distribution of electricity consumption as lognormal.

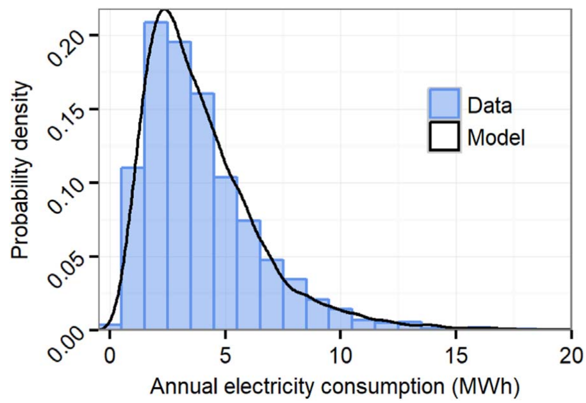

Fig. B1. Electricity consumption data from 4 million UK households in 2014 (from DECC, 2016c) and modelled electricity consumption for a population of 5000 agents, using sampling from lognormal distributions based on income and household size.

One can fully specify a lognormal distribution if the mean m and median $\widetilde{m}$ of the data are known, using the two equations:

$$m = e^{(\mu+\sigma^2/2)}$$

$$\widetilde{m} = e^{\mu}$$

These can be solved for μ (the mean of the variable's natural logarithm) and σ (the standard deviation of the variable's natural logarithm). For each agent/household, the model checks into which size and income category it falls, and thus which μ and σ are appropriate. The model then samples randomly from the corresponding lognormal distribution, and assigns a consumption value. The resulting distribution of electricity use reflects the real UK distribution well (see Fig. B1).

Appendix C. Calculation of the simple payback period

Symbols:
$pp_k(t)$ Simple payback period (years)
$R_k(t)$ Annual return of agent's PV system (£/year)
$PV(t)$ Total system cost of PV per installed kW (£/kW)
$IC_k(t)$ Agent's installed capacity (kW)
$O_k(t)$ Annual electricity output of the agent's PV system (kWh/year)
LF_k Load factor of the agent's PV system (%)
$GT(t)$ Generation tariff (p/kWh)
$ET(t)$ Export tariff (p/kWh)
$EP(t)$ Electricity price (p/kWh)
The k subscript indicates that a value is specific to an agent, and time-varying values are explicitly denoted as functions of time.
The simple payback period is given by:

$$pp_k(t) = \frac{PV(t)IC_k(t)}{R_k(t)}$$

i.e. the initial capital cost divided by the annual return to the installer. The annual return is made up of three components: from generation payments, export payments, and savings on electricity bills. Thus, $R_k(t) = R_{gen}(t) + R_{exp}(t) + R_{sav}(t)$. The generation payments are simply equal to the expected annual output $O_k(t) = LF_k IC_k(t)\times 24 \times 365$ times the current GT. Since the model is considering small systems, it is assumed that all export is deemed rather than measured, and thus the ET is paid on half the amount of electricity generated. The other half of the electricity generated is used by the household, leading to avoided electricity costs. These assumptions give the annual return as:

$$R_k(t) = O_k(t)\left[GT_k(t) + \frac{1}{2}ET_k(t) + \frac{1}{2}EP(t)\right]$$

The payback period obtained from these calculations may not be the “true” payback period which is affected by e.g. annual variations in electricity production, rebound effects, price fluctuations, annual variations in load factor and electricity consumption and how much purchased electricity is displaced by the PV panels, but it does reflect the kind of simple calculation a consumer or PV installer could feasibly make before deciding to install solar panels. Obtaining the exact payback period is not the aim of the calculation; the aim is reflecting the decision-making behaviour of households through the information which would be available to them.

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