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

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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.

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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)