Sustainable Cities and Society 31 (2017) 173–182

Contents lists available at ScienceDirect

Sustainable Cities and Society

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

Engineering advance

A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency

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ARTICLE INFO

Article history:
Received 28 November 2016
Received in revised form 7 February 2017
Accepted 11 March 2017
Available online 14 March 2017

Keywords:
Agent-Based Modelling
Diffusion of innovation
HVAC
Lighting
Appliances

ABSTRACT

Residential energy efficiency is an important strategy for reducing greenhouse gas emissions. There are many technologies that help improve residential energy efficiency, and in fact, increased energy efficiency has already helped reduce global greenhouse gas emissions significantly in the past. However, with greater innovation, further improvements can be made and improving energy efficiency is an ongoing activity. Policymakers around the world are putting strategies in place to speed up the adoption of energy efficient technologies and practices, but ultimately this process is based on choice by residents themselves. Human decision making and choice however is a very complex issue, and complex computational tools are required in order to analyse and/or predict the impact of various policies. Traditionally, equation-based models such as Bass and Choice models have been used to describe the diffusion of technologies in a population, but certain limitations have been identified. This article explores what these limitations are in the context of energy efficient residential technologies and how an alternative computational and empirical paradigm, Agent-Based Modelling (ABM), can help resolve some of these limitations. As such, this is a review article into how ABM can support analysis of strategies to catalyse greater uptake of energy efficiency in the residential sector.

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1. Introduction

Globally there are significant concern over climate change impacts, which has created the need to address climate forcing mechanisms; particularly reducing greenhouse gas emissions from human activities. Since industrialisation, human activities have lead to an increase in the levels of atmospheric CO_2 and other greenhouse gases. The burning of fossil fuels for energy is the largest source of greenhouse gas emissions from human activities, with energy use in the residential sector estimated to contribute 11% of total CO_2 emissions in the EU (Drummond & Ekins, 2016) and 21% of CO_2 emissions in the United States (Estiri, 2015). Globally, the residential sector has been estimated to represent 31% of the total energy use (Swan & Ugursal, 2009). Furthermore, some argue that unless the residential sector becomes more energy efficient, greenhouse gas emissions associated with residential energy use will increase significantly going into the future. For example, in a sta-

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http://dx.doi.org/10.1016/j.scs.2017.03.006

Table 1
Behavioural tendencies influencing the adoption of EE technology (adapted from Frederiks et al., 2015; Knobloch & Mercure 2016; Sorrell, Mallett, & Nye, 2011).

Behavioural tendency	Description	Implication for policy
Inertia	People have a tendency to want to stick with the status quo rather than having to change, for practical reasons and for convenience; as they like to avoid hidden costs associated with a switch	Until new solutions become the norm, people are likely to resist change and may require considerable convincing
Satisficing	People don't tend to optimise their decision but rather aim to satisfy a small set of criteria, i.e. the minimum requirements	This means that the availability of products is critical because as long as these fulfil the minimum requirements, they will be chosen
Being loss and risk averse	People weight losses more than gains when making decisions and people tend to avoid the prospect of a loss even with the prospect of certain gains, and tend to accept a gamble in order to avoid a loss	It is important to address concerns about losses and any potential risks as these will disproportionately influence the adoption decision
Persisting with sunk costs	Once people have invested in something, in terms of time and/or money, they tend to become fixated on 'recovering losses'	Take care to frame communications around energy efficiency in a way that does not amplify any concerns about sunk costs
Social comparisons	People tend to follow the behaviour of others, i.e. following the norm	This reinforces dominant technologies and creates inertia at the start of an adoption curve, but conversely, amplifies uptake when adoption rates cross certain thresholds
Irrational response to monetary incentives	People's response to incentives are often short-lived and unpredictable and may crowd out intrinsic motivations	Non-monetary incentives often work more effectively than monetary incentives
Free-riding effect	People tend to look for ways that they can gain benefits without paying for them	Build social cohesion and capital as a counterpoint to the free-riding behaviour and appeal to people's desire to benefit the greater good
Trust	People seek information and judgments from those that they trust	Work with trusted sources of information
Availability bias	People primarily draw on knowledge and information that is easily accessible. Lack of information may mean that some opportunities are missed.	Create heuristics (such as efficiency ratings) and make them easily accessible, and create communications that appeal to this sentiment. Make sure information is well-known.
Split incentives	Opportunities may not be taken if it is not possible for individuals to appropriate the benefits of the investment	Target information and incentives at those decision-makers who are likely to benefit from adoption.
Bounded rationality	There is a cognitive effort in analysing which option is better, and humans often opt for simpler way of making decisions such as through imitation or inquiry.	Don't assume that residents will always make decisions based on rigorous analysis but will sometimes be swayed by friends or other information sources' recommendations.

tus quo scenario with a projected growing population, Australia's CO_2 emissions from residential energy use are expected to grow by 38% by 2050 (Hetherington, Roetzel, & Fuller, 2015). Residential energy efficiency, i.e. reducing energy use in the residential sector, is viewed as an essential part in many national strategies to reduce CO_2 emissions in order to mitigate the potential impacts of climate change (Drummond & Ekins, 2016; Hetherington et al., 2015).

This article reviews the applicability of Agent-Based Modelling (ABM) for understanding technology diffusion of residential energy efficient technologies, specifically with the purpose of evaluating how different policy approaches are likely to increase the adoption of energy efficient technologies. These ABM can provide decision support that informs scenario analysis and improves the efficacy of policies designed to reduce residential energy demand. Whilst it is recognised that there is significant merit in more traditional approaches to diffusion modelling, this article explores the hypothesis that ABM provide some unique benefits to supporting policy development for reducing residential energy demand, and subsequently explores the types of ABM approaches that may be suitable.

There are two general approaches to reducing the CO_2 emissions from the residential sector, namely improved energy efficiency and the adoption of renewable energy technologies. In turn, increased energy efficiency can be achieved either based on improvements in technology or based on behavioural/lifestyle change. van Sluisveld, Martínez, Daioglou, & van Vuuren (2016) found that lifestyle changes can potentially achieve about 13% emissions reduction over the long term. van Sluisveld et al. (2016), as well as Yan et al. (2014), argue that a holistic approach to emissions reduction is required that includes both demand side measures (energy efficiency) as well as supply side measures (substitution of fossil fuels with renewable energy sources). Despite the uptake of renewable energy, it is likely that energy for the residential sector for the foreseeable future will still result in significant CO_2 emissions, which means there is a continuing need for improved energy efficiency in the residential sector as a fundamental component of mitigating human-induced climate change.

The impact of more energy efficient technologies was evidenced by the fact that over a 30 year time period, ending in 1998, the OECD nations would have used 49% more energy than they actually did without improvements in energy efficiency (Geller, Harrington, Rosenfeld, Tanishima, & Unander, 2006). In the residential sector, there has been trend for improved energy efficiency in technologies such as: lighting, space heating and cooling, cooking, refrigeration, and water heating (Fan, MacGill, & Sproul, 2015). In fact, there are many new technologies that contribute to significant reductions in energy use, such as LED lighting (Aman, Jasmon, Mokhlis, & Bakar, 2013) and energy efficient appliances (State of New South Wales and Office of Environment and Heritage, 2013). To meet emissions reductions targets, governments around the world are implementing various strategies to speed up the adoption rates of these technologies, and the New South Wales Energy Efficiency Action Plan is a good example of this type of plan (State of New South Wales and Office of Environment and Heritage, 2013).

This article follows a number of steps to explore the types of modelling that can support the analysis of policies designed to increase the adoption of energy efficient technologies in the residential sector. Firstly, more traditional approaches to diffusion modelling are discussed. Secondly, we discuss the factors and processes that are believed to lead to the uptake of energy efficient technologies in the residential sector. Thirdly, we explore the various types of ABM approaches (both theoretical and empirical) that may be applied to this problem and discuss their applicability and limitations for the purpose of modelling the uptake of energy efficient technologies in the residential sector.

2. Equation-based approaches to diffusion modelling

In Physics, diffusion is a process in which particles intermingle, as well as the process of heat transfer between objects that are in contact with each other. Borrowing on this, the term technology diffusion, or innovation diffusion, is a metaphor that refers to the process by which technology spreads and is adopted in human populations. The concept of innovation diffusion was first introduced by Rogers (1962) who described how innovation is communicated in a social system, reinforcing how the communication aspect is an essential part of the process of technology adoption. Computationally, the uptake of innovation is thought to follow an S-curve where uptake starts slowly and speeds up to a more linear rate, and

Table 2
Generic factors thought to influence consumers' decision to purchase different energy efficient technology. Adapted from (Hall et al., 2013; Hicks & Theis 2014; Newton & Meyer 2013; Noonan et al., 2013; Rosenberg, 2011; Wilson et al., 2015).

Purchasing consideration	Description
Social norm and influence of others	Clearly, when others adopt a technology this means that there is greater social pressure to follow what others do; especially when the adoption occurs in the same social network of an individual (Hall et al., 2013; Hicks & Theis 2014; Noonan et al., 2013; Rosenberg 2011). Specifically, residents' social communication, and in recent times, social media, plays a key role here (Wilson et al., 2015).
Monetary factors: purchase cost, operating cost, cost benefits	People tend to be influenced by monetary factors, but it is argued that the cost benefits and operating costs are difficult to estimate, requiring cognitive effort, plus behavioural economics tell us that the initial cost is likely to weigh more heavily for many people. The importance of this is influenced by socio-economic factors (Hall et al., 2013).
Lifestyle	Some argue that aesthetics and taste anxiety, as identity creation and as a kind of residential ethics is a key driver for home renovation or upgrade decisions (Rosenberg 2011). Simplistically, this can be branded as 'lifestyle' considerations, i.e. how the purchasing of an energy efficient product can help to create a personalised identity, aesthetic and way of living.
Energy savings & associated environment benefits on reduced greenhouse gas emissions	Not everyone is motivated by energy savings and environmental benefits, but some certainly are and this is seen as a function of environmental attitudes and awareness (Hall et al., 2013; Liu, Chang, & Den, 2013; Newton & Meyer, 2013)
Knowledge of how to achieve energy savings	Whilst residents may have good intentions to reduce energy, they don't always know how to achieve this. Knowing what to do, and what to purchase in order to reduce energy use is critical for change to occur (Hall et al., 2013)
Availability of capital	As many energy efficient technologies tend to come at a higher initial cost, access to capital can be an important limiting factor in the adoption process (Wilson et al., 2015).
Breakdown of the previous system	This inevitable driver for an upgrade is a key trigger point for all types of energy efficient technologies.

Table 3
Technology specific factors thought to influence consumers' decision to purchase different lighting options. Adapted from (Aman et al., 2013; Di Maria et al., 2010; Hicks & Theis 2014; Khan & Abas 2011).

Purchasing consideration	Description
Light qualities (i.e. aesthetics)	This relates to the ability to render colours naturally, and the level of illumination (Aman et al., 2013). The perception of light quality, based on hearsay and past experience, is likely to be as important as the actual and current light quality.
Expected useful life of bulb	The useful life of a lighting product varies considerably and impact on the environmental impact as well as the lifecycle costs of the product. There is also a nuisance element related to products that break down more often. The lifetime of lighting equipment is typically measured in hours, as the expected time until the amount of light (lumens) has dropped to about 50% of initial values. LED lighting typically has longer lifetime compared to incandescent, fluorescent, or halide lamps.
Toxicity of materials	Some lighting types emit levels of mercury (Hg) which have been banned in some countries, but the sale of these persist in other locations (Aman et al., 2013).
Overall environmental impacts of lighting technology	Probably not generally considered by laypeople, this includes consideration of the lifecycle impacts of different options, and as per Aman et al. (2013), modern options (such as LED) vastly outperform more traditional options such as incandescent lights, in all environmental dimensions, i.e. soil, water, air and resource impacts.
Total Harmonic Distortion	A measure of the amount of electrical distortion created by the equipment and this aspect is mostly a concern for electrical engineers or electricians rather than residential users of lighting products.
Temperature emission	Some lights emit less heat than others, which is considered a selling point in some cases (Hicks & Theis, 2014)

then as greater saturation rates are reached it slows down again (Rao & Kishore, 2010). The theory of innovation (Rogers, 1962) also divides the uptake-phases into 'innovators', 'early adopters', 'early majority', 'late majority' and 'laggards'.

Common equations-based explanations for this curve is an epidemic model (Gupta & Jain, 2012) or a logistics model (Gruber & Verboven, 2001), or the Bass diffusion model (Bass, 1969, 2004). Rao and Kishore (2010) reviewed diffusion modelling approaches and proposed a number of refinements from the fundamental equation-based models where parameters are constant and assumptions are rigid, which included:

- Dynamic parameters, e.g. where the parameters in the equation change over time;
- Consideration of multiple innovations simultaneously, potentially competing with each other;
- Spatially sensitive adoption models that accommodate spatial variability in socio-demographic differences, and other attributes;
- Multi-phase adoption models, where the adoption of a technology is a gradual or multi-step process rather than a binary process; and,
- Consideration of adoption as a function of technology-specific coefficients.

An example of a highly refined model is described by Higgins, Paevere, Gardner, and Quezada (2012). In this innovation diffusion model based on the Bass equation, the uptake of solar photovoltaics and electric vehicles is described based on a typology of households where complex criteria are taken into account within a multi-criteria choice model. This, in turn, is applied to a set of four different vehicle types; each representing a sequentially higher level of adoption (i.e. an increasing degree of the vehicle being an electric car). This is done in a way that takes into account spatial variability in demographics, geographic attributes as well as based on specific attributes of different electric vehicles. Thus, this model pushes the boundaries of what can be achieved with traditional diffusion modelling approaches as it is able to capture important

Table 4
Technology specific factors thought to influence consumers' decision to purchase different HVAC systems. Adapted from (Chua, Chou, Yang, & Yan, 2013; Noonan et al., 2013; Wilson et al., 2015).

Purchasing consideration	Description
Thermal comfort	A comfortable home is a key consideration for the investment in HVAC systems, especially if this comfort can come with less guilt of using energy and emitting greenhouse gases, plus different systems perform differently in this respect (Chua et al., 2013; Wilson et al., 2015).
The inconvenience of making the change	Installing HVAC systems can lead to significant inconvenience and this, in turn, may be a deterring factor when choosing to upgrade (Noonan et al., 2013)
Increase in the resale price of a property	The HVAC system is a significant part of the infrastructure of a home, and an upgrade is likely to make the property more attractive and thus quite likely create higher resale values (Noonan et al., 2013)
Split incentives	This occurs when those who pay the energy bills are not those who would need to invest in energy efficient technology (Noonan et al., 2013). For example, renters may pay energy bills whilst it is the owner of the property would purchase the HVAC technology.
Sound pollution	Some HVAC systems are associated with noises and sounds that may be unappealing to potential customers (Chua et al., 2013).

aspects of the process. The model has proven useful in evaluating policies (in relation to electric vehicles in this case) however the authors note that a difficult issue with the model is the limited ability to capture explicit social behaviour and model geographical relationships between potential adopters such as different household types. The model also does not capture some of the highly non-linear relationships and the influence of irrational social pressures and thresholds on adoption.

Another example of a highly refined equation-based technology adoption model is described by Noonan, Hsieh, and Matisoff (2013), where an equation similar to the Bass model was used to simulate the adoption of energy efficient Heating, Ventilating and Air-Conditioning (HVAC) technology. This approach was based on the statistical analysis of house sales data that revealed the adoption determinants for both homeowners and developers, based on factors like housing type, house values, and location. However, they concluded that whilst the approach has merit and provides insights on the variability of adoption rates across a city, the approach is unable to consider social context or socio-psychological factors which they concluded influence on decisions to adopt energy efficient HVAC technology.

It would appear that these refined models, described above, have reached the limits for equation-based approaches in modelling the process for the uptake of energy efficient technologies across a city. Therefore, the question is what other approaches are available to overcome some of the limitations of the equation-based approaches. However, before reviewing the alternatives, we first explore the particular factors that influence the uptake of energy efficient technologies.

3. Factors that influence the uptake of energy efficiency technologies

A key approach to reducing energy use in the residential sector is for householders to adopt more energy efficient technologies such as energy efficient lighting (i.e. LED lighting), refrigeration and HVAC. HVAC is responsible for nearly a third of all residential energy use, making it the largest end-use category (Noonan et al., 2013). The Australian Government (2013) reported the following breakdown of residential energy use in Australia: HVAC 40%, water heating 21%, lighting 6% and appliances (including for refrigeration and cooking) 33%. A large array of policies are in place in different countries to increase residential energy efficiency. The OECD recommends improving awareness of energy efficiency technologies by educating the public about the need for environmental action, and that grants and subsidies for energy efficient technologies should focus on low-income households (OECD, 2014). Policies have included introducing mandatory minimum energy efficiency standards in new homes (Berry & Marker, 2015), providing energy price signals via emissions taxes or cap and trade programs (Jacobsen, 2015), improving product information such as by energy star labels and ratings (Jacobsen, 2015), low-interest loans, third party financing or tax credits (Wilson, Crane, Chryssochoidis, 2015), working with suppliers and tradespeople to help them supply and promote energy efficient products (OEH NSW, 2014), and providing subsidies for purchasing energy efficient products (Noonan et al., 2013). There are also various interventions and policies that focus on behavioural change rather than technology for reducing residential energy demand, such as for example being vigilant about turning off lights when not needed, or ensuring dishwashers and washing machines are only used when full (Hall, Romanach, Cook, & Meikle, 2013). The focus of this article is on the special case of technology adoption as a one-off behaviour rather than understanding incremental changes in people's habitual behaviour, i.e. changing the way people use their existing technologies.

Consumer behaviour, i.e. the choice to purchase a particular technology over another, is often argued to be complex and not very well-represented by a rational choice model of human behaviour (Frederiks, Stenner, & Hobman, 2015). In the rational choice model of human behaviour, a person objectively weighs up the benefits and costs of different options and chooses whatever option maximises their net benefits. In fact, in studies of pro-environmental behaviours, it has been found that there is often a gap between what people say they value and what they do (Kollmuss & Agyeman, 2002; Newton & Meyer, 2013). It is argued that there are knowledge-action gaps, value-action gaps, attitude-action gaps, and/or intention-action gap (Frederiks et al., 2015). For example, this means that whilst a consumer may understand and place value on the need for improved energy efficiency, there is no guarantee that these pro-environmental attitudes lead to the adoption of energy efficient technology. In the extension this means that simply promoting pro-environmental knowledge and attitudes does not necessarily lead to the enduring results and changes in behaviour that are sought (Frederiks et al., 2015). It is worth noting however that even when energy-savings are clearly cost-effective, i.e. monetary investment is less than the cumulative monetary benefit over time, this is also no guarantee of uptake, and that monetary incentives, in fact, can be counterproductive and reduce the sought after behaviour (Frederiks et al., 2015). This shows that models of human behaviour, other than the rational choice model, are required.

Frederiks et al. (2015) argue that whilst consumer behaviour is not "rational", it is in fact to a large extent predictable. This is on the basis that behavioural economics has been successfully studying behavioural tendencies and cognitive biases in relation to economic decision-making, and the field has been reaching maturity to the point that Daniel Kahneman won a Nobel Prize in Economics

Table 5
Technology specific factors thought to influence consumers' decision to purchase different appliances, including fridges, dishwashers and washing machines. Adapted from (Mills and Schleich 2010; Newton and Meyer 2013; Ward, Clark, Jensen, Yen, & Russell, 2011).

Purchasing consideration	Description
Energy star rating	Consumers have been shown to be willing to pay extra for a higher energy star rating of appliances and/or fridges (Ward et al., 2011).
Functionality of the fridge/appliance	Particular design features of appliances or fridges play a key role in decision making. For example, the purchase of a fridge is considerably dependent on the volume of the food compartments, as well as the freezer compartment volume (Ward et al., 2011).
Water and/or other resource use	Residents may be concerned not only about conserving energy but also about conserving water or other resources (Newton & Meyer, 2013).
Family structure	Especially the presence of children influences the demand for larger appliances, such as washing machines (Mills & Schleich, 2010)

in 2002, and the popularization of this knowledge in books such as *Predictably Irrational* (Ariely, 2008) and *Thinking Fast and Slow* (Kahneman, 2011). In fact, behavioural economics through rigorous experimentation has shown that people's economic decision making is more often based on common rules-of-thumb, heuristics, and mental short-cuts than considered and balanced deliberation on the relative benefits and costs of different options. For example, Di Maria, Ferreira, and Lazarova (2010) noted that in relation to adoption of energy efficient light bulbs that "*consumers' fuzzy perception of operating costs [is] one of the key barriers to adoption: the difficulty to estimate such costs by consumers without adequate technical background allows for anchoring and adjustment biases*". Frederiks et al. (2015) have described some key points based on behavioural economics that are particularly important for adoption of energy-efficient technology, as shown in Table 1.

Clearly, behavioural economics has something to contribute to the understanding of the adoption of energy efficient technology in the residential sector. Specifically, it tells us to consider the following: that residents will consider satisficing minimum requirements; how residents seek information and recommendations for their decisions; the importance of social comparison and social norms; how to frame communication to residents in order to not trigger unproductive responses, such as the tendency to persist with sunken costs or to seek free-rider opportunities. However, the way that people make decisions about HVAC systems, refrigerators, household appliances or lighting is not only a function of the resident, but naturally also dependent on the particular products on offer, and the particular attributes of these products. Residents consider a number of issues when choosing a technology and that the types of issues being considered tend to be specific to the type of technology that is considered. In fact, a different set of parameters is considered for different technologies in different reports and articles, as per Table 3 (for lighting), Table 4 (for HVAC systems), and Table 5 (for fridges and appliances). There are also a number of factors that are generic across the three types of energy efficient technologies, as shown in Table 2.

4. Synthesis: challenges in equation-based diffusion modelling of residential energy efficient technology

As a synthesis of the information on what factors can influence adoption of energy efficient technology in the residential market, it can be concluded that:

- Householders will attempt to satisfy a limited number of criteria when they choose whether to invest in energy efficient technology. The types of criteria that householders will consider depend strongly on what type of technology that is being considered, as illustrated in Tables 2–5 .
- There is clear evidence from a number of studies that environmental concerns or even financial matters may not feature in the criteria that householders use. This raises the topic of preference, i.e. different householders have different preference profiles which will influence what criteria they use when purchasing lighting systems, HVAC systems or appliances.
- Behavioural economics tells us that rather than evaluating criteria themselves, the way that householders are often likely to evaluate technologies against criteria is based on communications and judgments from trusted information sources, and/or friends.
- Householders are likely to be strongly influenced by social norms and others behaviours, and the 'social pressure to adopt' is likely to be diffused through social networks.

Equation-based diffusion modelling can to a limited extent take some of these issues into account:

- **Variability in preferences**: It may be possible to use 'household type preference profiles' if the population is considered to be made up of different 'types of households'. This high-level aggregation of preference profiles may be problematic, both in terms of data requirements, as the computational complexity will increase significantly with an increase in a number of household types; as well as in terms of still being unable to disaggregate preference profiles to an individual level and thus a high level of aggregation will remain.
- **Communication**: the role of communication and individual householders seeking judgments and recommendations on different technologies would be difficult if not impossible to describe in an equation based diffusion model. Specifically, differential (rather than aggregate) trust is harder to gauge in these models. In theory, the judgments from key sources could be included as predictive parameters and weighed somehow into the equations, but it may be cumbersome and not ideal because it would primarily operate at an aggregate level rather than at an individual level.
- **Householder choices**: In equation based models, it would be difficult to describe how decision are being made, i.e. how heuristics, rules of thumb are applied and how residents apply personal satisficing criteria, and how residents adapt the way they make decisions based on social influence and/or recommendations they receive. Based on calibrating models, equation-based models may still be able to describe the aggregate behaviour of the population, but it would be hard to judge how interventions in the complex procedure of decision making would play out.

As a summary, equation based approaches aggregate individuals or households into groups (e.g. household size, location) and lose most of the heterogeneous nature. Also equation based approached apply a probability or proportion of a group that makes a decision at a time step. Therefore, it does not capture specific decision made by individuals, and does not capture who or why. Another problem is that recent research has added additional variables (e.g. economic, demographic) to better represent the groups of individuals or households. The more variables that are added, the more that the effect of each variable to the decision making is diluted. So the whole diffusion trend is averaged out. Therefore, dramatic changes to adoption are not well-described.

Thus, we argue that whilst equation-based diffusion models can to some extent predict aggregate adoption behaviour in a population, they are limited when it comes to evaluating complex policies and targeted interventions that aim to increase uptake. Therefore, alternatives to equation-based modelling ought to be explored, with Agent-Based Modelling one option that can address the limitations of equation-based modelling.

5. ABM approaches potentially suitable for modelling diffusion of residential energy efficiency technologies

Behavioural economists or cognitive scientists explore how individuals behave and make decisions, but ABM explores how groups of individuals create emergent patterns and how they interact with each other when they make decisions (Goldstone & Janssen, 2005). Technically, ABM emerged from the fields of Artificial Intelligence (AI) and Cellular Automatons (CAs), combining the 'cognitive models' of agents as described in AI including how agents interact with each other in a computational environment; with agents also spatially located in a network of CAs, allowing agents also to interact with representations of their environment.

In other words, ABM allows for software representations of agents behaviour and decision making in interaction with each other and with their environment (Gilbert & Troitzsch, 2000). ABM usually describes the decision making of individuals within a population, but sometimes for computational and empirical reasons, there are software agents that represent groups of people's behaviour (Moglia, Perez, & Burn, 2010). ABM has become a widely used approach and as such has been used in a large array of applications. One of the first models that were developed was *Sugarscape* created by Epstein and Axtell (1996) which described fairly straightforward interactions of agents operating on a resource landscape. This approach was part of a move towards a bottom-up approach to doing social science, where the interactions and interdependency of individual agents was used to understand emergent behaviour, such as norm formation, cultural diffusion and cooperation at a societal level. Being essentially a style of software architecture for undertaking simulations of agent behaviour, ABM has subsequently found applications in as diverse fields as the biological sciences, ecology, social science, economics, financial analysis, archaeology, transport systems, water management, electricity market analysis, among others (Macal & North, 2005; Moglia et al., 2010; Macal, 2016). The approach has been widely used to explore policies or interventions in a system to achieve a particular goal, such as reducing energy consumption in office buildings (Zhang, Siebers, Aickelin, 2011), policy responses to reduce carbon emissions in an economy (Natarajana, Padget, Elliott, 2011), coordination of airline operations (Bouarfa, Blom, & Curran, 2016), reducing car crashes in heavy vehicle transport systems (Thompson, Newnam, & Stevenson, 2015), increasing the number of environmental behaviours within an educational organisation (Sánchez-Maroño et al., 2015) and many others. As stated by Johnson (2015) ABM allows for analysing a set of problems where you need to account for '*complexity in varied contexts, on varied scales, and with an interrelated and interdependent environment*'. Heckbert, Baynes, and Reeson (2010) further argue that ABM has found a large number of applications in urban environment, at least in part because '*Cities provide rich territory for research into the complex relationships between decision-making and landscapes affected by human activity. In cities there is a concentration of features that match well with the strengths of ABM: heterogeneity (in households, businesses, neighbourhoods, land use); autonomous decision making (e.g., by residents, industry, utilities); direct and indirect interactions (e.g., in property markets, planning and policy); and cross-scale effects (from local development choices to urban expansion).*' Many of these features are also present in the problem of understanding diffusion of energy efficient technologies in an urban population.

Kiesling, Günther, Stummer, and Wakolbinger (2012) provided a rigorous review of different ABM available to model innovation diffusion modelling, which discussed the relative advantages of different approaches when it comes to representing population heterogeneity, social influence and cognitive strategies. In relation to diffusion of residential energy efficient technology, it is notable that the limitations of equation-based diffusion modelling are particular strengths of ABM, which are: the ability to represent heterogeneity of householder preferences (Brown & Robinson, 2006; Kiesling et al., 2012; Zhang, Gensler, & Garcia, 2011), the ability to more realistically represent human decision making based on empirical data (Birks, Townsley, & Stewart, 2012; Haase, Lautenbach, & Seppelt, 2010; Jackson, Forest, & Sengupta, 2008), and capacity to model communication and social influence (Canessa & Riolo, 2006; Zhang, Gensler et al., 2011). Furthermore, a comparison of predictive accuracy and performance of ABM versus equation-based diffusion modelling for transportation behaviour studies shows that ABM has had a similar capacity for prediction as equation based diffusion modelling (Mao, Zou, Liu, Xue, & Li, 2015). The main difference appears to be that ABM has greater flexibility in exploring specific policy interventions; as illustrated by Sopha, Klöckner, and Febrianti (2015). Whilst it can be argued that Randomised Controlled Trials (RCT) are designed to be 'policy-specific' as well, these are costly and limited, and so ABM provides a virtual laboratory to inform RCTs by understanding which specific policies to be explored in the trials. In terms of prediction accuracy, it is noted that ABM has the same limitations of all modelling approaches, i.e. it provides conditional prediction in the sense that it provides prediction but only under the conditions set out in the model (Boschetti, Grigg, & Enting, 2011). This shows the importance of being able to set out the conditions for which the model predicts. It also highlights the need for making sure ABMs are empirically based, and there are numerous methods for empirical parameterization of ABMs as laid out by Smajgl, Brown, Valbuena, and Huigen (2011), including based on surveys, census data, field or lab experiments, role playing games, interviews, direct observation and expert knowledge.

Recognising that there are many types of ABMs, the question is: what type of ABM approach is suited to modelling the adoption of energy efficient technology in the residential sector? To judge the suitability of different types of approaches, we evaluate a select number of approaches (chosen on the basis of relevance to the problem) to explore the theoretical and empirical basis for decision rules of agents in the model, as well as the empirical basis of the initiation of agents and social network structures; as well as the type of problems that the different ABMs have been applied to.

Rai and Robinson (2015) described an ABM that simulated the adoption of residential solar Photo-Voltaic (PV) Systems. The theoretical basis for the decision applies the Theory of Planned Behaviour (Ajzen, 1991). Empirically, the model is based on policy data from the local utility company on rebates, a longitudinal survey of householders, publically available data on house parcels and land values, LIDAR data about site specific conditions relating to the likely effectiveness of solar PV. Agents are initialized based on city-wide survey data. Specific attributes that were considered in the decision making and feeding into the Theory of Planned Behaviour model, were: the financial payback, a household's financial resources, attitude towards PV, and social influence. The social influence occurs over a small-world network structure and the distances between households were considered when assigning the networks. Subsequently, the model was tested using the sensitivity of components as well as the system as a whole. The model was written in the R and Python programming languages. Finally, the model was fitted against historical PV uptake data and the predictive accuracy is shown to have 86.6% correct predictions, which is quite good. A limitation is that it focuses primarily on financial attributes as well as a social influence rather than a range of other potential parameters. The model also assumes that the supply of PV systems is straightforward for householders, and does not consider the influence of any sales campaigns.

Sopha et al. (2015) described an ABM to explore policy options supporting adoption of natural gas vehicles in Indonesia. They embeded a model of decision maker psychology within an ABM; that took into account a set of adopter categories, a range of technology attributes, a process for decision making as well as the social network of decision makers. Inspired by the Consumat metamodel for decision making, the model considered imitation and deliberation as the only modes of decision making. The model was parameterised based on two surveys of vehicle owners, including the definition of adoption thresholds. After undertaking successful validation of different varieties, including against historical data, scenarios were developed on which conclusions could be inferred that informed policy. In fact, based on the flexibility of the model, very specific policy recommendations could be made, and this capacity is the greatest strength of this model. Carrillo-Hermosilla (2006) describes an ABM of generic technology adoption, and focuses on how the adoption of technology leads to replicator behaviour (i.e. householders copying others), and how an agent's imperfect information on technology performance (the perceptions of performance) gets closer to actual performance as the number of adopters grows, and how new producers of the technology emerge as adoption grows. Technologies are described according to generic criteria: relative advantage, compatibility, complexity, trialability, observability, and sustainability. The model also allows users of the technology to communicate with each other. As a model to illustrate policy dynamics, the focus on empirical data is low but is primarily based on judgments and literature. Ultimately the model explores ways to get out of technological lock-in situations and allow transitions from traditional technologies towards more environmentally sustainable technologies, and finds that endogenous changes within the industry can enable a transition between dominant technologies. This model has some very interesting features but lacks in the empirical foundation.

Schramm, Trainor, Shanker, and Hu (2010) described an ABM of the diffusion and adoption of different brands in a population of consumers. It incorporated elements of social influence, perceived characteristics of the brand, and how brand managers develop communications to influence perceptions. The theoretical basis of the agent decision making is the consumer diffusion paradigm (Gatignon & Robertson, 1985) where the decision is based on 'personal traits', 'perceived innovation characteristics', and 'social influence'; as well as the 'social system'. Adoption for a given householder occurs when an adoption threshold is crossed. Consumers are classified into four categories (innovators, early adopters, and late adopters), and they choose between four different brands. A synthetic and heterogeneous set of customers is created. Ultimately, this model allows for the exploration of competition between different brands and targeting communications at different parts of the adoption curve. The model is written in NetLogo, a software platform for creating ABMs.

An increasingly mature approach to ABM modelling of the adoption of technology is the Consumat approach (Janssen & Jager, 1999, 2001, 2002, 2003; Janssen & Viek, 2001; Jager, 2006; Jager, Janssen, & Bockarjova, 2014; Van Vliet, Jager, De Vries, Faaij, & Turkenburg, 2009; Vliet, Vries, Faaij, Turkenburg, & Jager, 2010) that was developed by the early desire to build ABMs on the basis of state-of-the-art behavioural science (Jager, Janssen, De Vries, De Greef, Vlek, 2000; Jager & Janssen, 2003). The Consumat II represents an update of the approach based on lessons learnt and updated understanding of cognitive processes (Jager & Janssen, 2012). The Consumat model, however, is primarily a theoretical framework for agent decision making so to evaluate its use in practice, we explore the application of the Consumat theoretical structure in an ABM to model uptake of electric vehicles (Jager et al., 2014). The model was framed around two key concepts, i.e. need and uncertainty. Need has two sub-components, existential need and social need, where the existential need relates to travel needs for which empirical data had been collected via a household survey. Financial needs are also considered, based on price differences between electric vehicles and fuel cars, as well as the prices of fuel and electricity. In this way, based on empirical data from a survey, different agents in the model are assigned an 'existential need' and 'need satisfaction' with different options. Furthermore, agents also consider the 'social need', i.e. the interaction with others, belonging to a group, and having a social status. This becomes the need to be like others (conformity), and the need to be different (anticonformity). This is operationalized on the basis of how similar your behaviour is to others, and empirical data exists on the relative importance of the two drivers (conformity and non-conformity). Another important factor that is considered is the 'uncertainty' in the existential and social needs. For existential uncertainty, this relates to the variability in the information provided on existential needs satisfaction; and for social needs, this relates to the proportion of friends using a different fuel, i.e. electric vehicles. Depending on the level of needs satisfaction and uncertainty, agents operate according to different modes of decision making (based on cognitive science). There is no evaluation of the prediction accuracy of this model, nor any sensitivity analysis. There is also no formalised method for empirically defining the model, however, there is no reason for why this general structure can't be adjusted to any particular problem. One difficulty perhaps is that it involves a rather large number of parameters that need to be empirically established.

6. Discussion

There is a clear and present need to improve residential energy efficiency if we are to significantly reduce global greenhouse gas emissions, and it has been shown that reducing residential energy will be mostly achieved through greater uptake of more efficient technology. There are many technologies available to support a more energy efficient residential sector; many which are cost-effective yet uptake is often slower than would be expected based a rational choice model of human behaviour. In fact, what is clear is that purchases of residential technologies are subject to human cognitive limitations and we can learn much from behavioural economics when thinking about how to increase uptake. Furthermore, there are many issues that influence the decision of when to purchase these efficient technologies other than economic or environmental aspects. However, we have also seen that technological transitions can happen rapidly when conditions are right, and therefore the need to understand how policy makers can catalyse such transitions is evident. In order for policymakers to catalyse such transitions, they need appropriate tools in order to make sense of what seems like sometimes irrational consumer behaviours. For this purpose, we have seen that equation based diffusion modelling has been rather successful in helping policy makers, and these models can often boast good predictive accuracies. However, the limitation of such models is that they struggle to incorporate behavioural science and agent decision making, heterogeneity

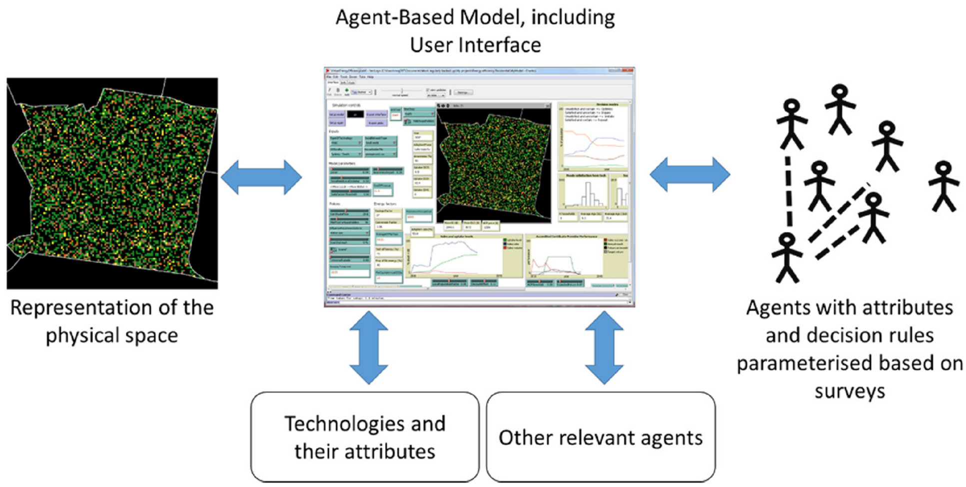

Fig. 1. Diagram of key components of an ABM for describing the adoption of energy efficient technology.

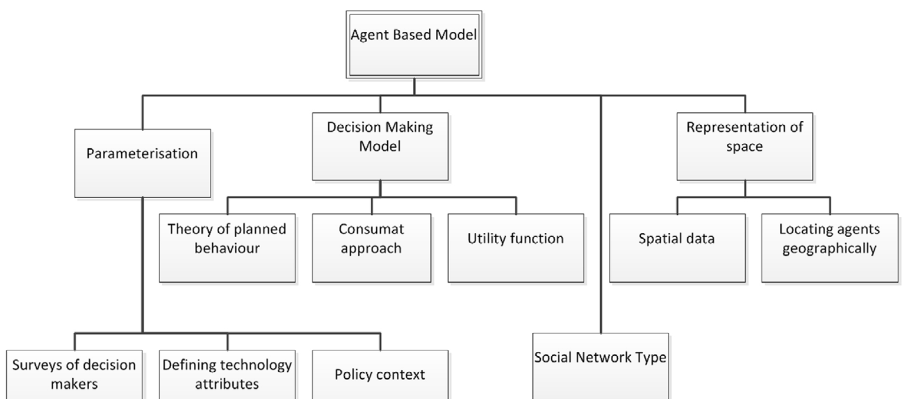

Fig. 2. Key decisions when intending to simulate the uptake of residential energy efficient technology using ABM.

of agents, the complexities of communication and perceptions of technologies, and to some extent also the social influence on agents. ABM has emerged as a viable alternative to equation-based diffusion modelling, which can model technology diffusion with at least the same accuracy as equation-based modelling when appropriately parameterized based on empirical data, calibrated based on macro-level data, and validated using sensitivity analysis. There is, however, a sense that there is more of an art in building ABMs, and the approach requires more data. Nonetheless, these issues can be addressed by transparency in assumptions and modelling design, as well as by adaptively building the empirical basis of the model towards greater accuracy. A description of the common elements of an ABM for uptake of energy efficient technologies is shown in Fig. 1, with the following elements:

1. A user interface by which a user can enter assumptions, parameter values and explore outputs, including exploring adoption rates spatially over a geographic region and graphical representations of uptake over time.
2. A computational representation (i.e. as objects in a special case of object oriented programming) of a number of agents, with each agent being attributed with unique values and that are able to make individual decisions in each time step. There is also likely to be a computational representation of the social network between agents.
3. A computational representation of the technology options that agents can choose between, including values on key attributes that will have some kind of influence on adoption decision making
4. A computational representation of the space on which agents are located, and this may include attributes that impact on technology performance or agent decision making.
5. Computational representations on any other relevant agents, such as when appropriate, sales agents (like retailers), information sources that provide recommendations, or government policy makers.

As for the types of ABMs that may be appropriately used, we have found that there is a strong preference for using household surveys as the key empirical basis of models. It is also strongly advised to use some kind of theoretical framework for agent in providing a rigourous framework for the development of an ABM to simulate technology diffusion, which are: the Consumat model (Jager et al., 2014; Vliet et al., 2010); as well as the Theory of Planned Behaviour (Rai and Robinson, 2015). The Consumat model captures several aspects of the Theory of Planned Behaviour, but also includes the aspect of behavioural control, i.e. feeling like you are able to carry out a certain behaviour. So far, compared to the extensive list of factors that we have seen influence the adoption of energy efficiency, ABMs have focused on relatively limited set of factors although this may be due to the type of technologies that have been explored (i.e. many of the factors we have identified are irrelevant for residential PV systems or electric vehicles).

We have also found that key aspects of designing an ABM to describe technology uptake are:

- Technology specificity: being specific about what factors that householders consider, as these are strongly technology dependent.
- Heterogeneity of agents: representation of variability of preferences and personalities, and this ought to have some empirical basis such as a householder survey.
- The mechanism for an update of perceptions: transparent representation of the mechanism by which householders update their perceptions of technology performance. It is clear that there is often a significant gap between perceptions and actual performance, and it is unusual for householders to spend the required cognitive effort in order to get an accurate estimate. It has also been shown that this gap reduces as uptake grows.
- Social network diffusion: representation of the social networks between agents along which recommendations and imitative behaviour can be transferred. Small-world network structures have been found useful to generate synthetic social network data, recognising that collecting empirical social network data is expensive.
- Supply side dynamics: representation of the supply side of technology uptake. Another key aspect that was raised as being important (OEH NSW, 2014), although rarely modelled except for by Carrillo-Hermosilla (2006) who has shown that this is a key aspect of technological transitions. The model by Carrillo-Hermosilla (2006) is however very simplistic and no further advanced model of this aspect of technological transitions was found.

Fig. 2 shows some of the key decisions that a modeller has to make when developing an ABM to describe the uptake of energy efficient technology amongst householders, which include: how to represent the geographical space, how to represent householder decision making, and how to parameterize the model; including how to define the policy context and technology attributes. There are a range of possible decision making models to choose from and the list here is by no means exhaustive. The Consumat approach, the Theory of Planned Behaviour and Rational choice based on utility function are all meta-decision making models that can be adapted to different context. It is recommended to select a model based on a deep understanding of the decision making context based on information such as qualitative social research. It has also been found that surveys are a useful means of parameterize agent decision making, but to design a survey it is good to first know the decision making model.

Finally, the Consumat modelling framework appears to be appropriate for incorporating all of the aspects of decision making that behavioural economics and cognitive science indicate are important, although that is not to say that other frameworks couldn't achieve the same thing.

7. Conclusion

Energy efficiency in the residential sector is urgently needed in order to reduce greenhouse gases globally. The decision by a householder on when to adopt a more energy efficient technology is influenced by a wide array of factors that include previous experiences, social networks and the maturity of the technology. Decision-making in this context is complex and whilst equation based diffusion modelling has some merits in describing diffusion of energy efficient technology, the adoption of ABM, which are underpinned by theoretical frameworks such as the Consumat, have the capability to overcome some of these limitations and provide insights about the behavioural dynamics of how different households adopt more efficient technology. In particular, the use of an ABM can better represent diversity in the population as well as incorporate behavioural aspects and how social network influence when different types of people are likely to adopt a new technology. This gives policy makers a powerful tool for targeting programs for the uptake of more energy efficient household appliances and fittings to those most likely to be early adopters, who then influence adoption across their social networks and therefore mass adoption. It can also identify how habits that may impede adoption even if an economically rational assessment would identify that there are net benefits. These insights can enable the development of focused programs that address current impediments in policy analysis and thus support the diffusion of new technologies. However, the application of ABM to understand the dynamics of technology diffusion is still limited by lack of empirical data. There is the need for longitudinal studies across population cohorts to better understand the factors and dynamics of how different types of people adopt new technology.

Acknowledgments

This research was jointly funded by the Commonwealth Scientific and Industrial Research Organisation, a federally funded research organisation in Australia, and the Low Carbon Living CRC.

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