Applied Energy 138 (2015) 150–159

Contents lists available at ScienceDirect

Applied Energy

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

Energy and complexity: New ways forward

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HIGHLIGHTS

- Review application of complexity methods to energy systems and systems change.
- Attributes: self-organisation, path dependency, emergence, co-evolution, adaptation.
- Modelling approaches: agent-based models, dynamic network models.
- Long-term energy systems change: co-evolutionary framework.
- Policy challenges: systemic interactions, decision-making under uncertainty.

ARTICLE INFO

Article history:
Received 27 August 2013
Received in revised form 16 September 2014
Accepted 21 October 2014

Keywords:
Complexity science
Energy systems
Modelling
Complex adaptive systems
Agent-based modelling
Energy policy

ABSTRACT

The purpose of this paper is to review the application of complexity science methods in understanding energy systems and system change. The challenge of moving to sustainable energy systems which provide secure, affordable and low-carbon energy services requires the application of methods which recognise the complexity of energy systems in relation to social, technological, economic and environmental aspects. Energy systems consist of many actors, interacting through networks, leading to emergent properties and adaptive and learning processes. Insights on these type of phenomena have been investigated in other contexts by complex systems theory. However, these insights are only recently beginning to be applied to understanding energy systems and systems transitions.

The paper discusses the aspects of energy systems (in terms of technologies, ecosystems, users, institutions, business models) that lend themselves to the application of complexity science and its characteristics of emergence and coevolution. Complex-systems modelling differs from standard (e.g. economic) modelling and offers capabilities beyond those of conventional models, yet these methods are only beginning to realize anything like their full potential to address the most critical energy challenges. In particular there is significant potential for progress in understanding those challenges that reside at the interface of technology and behaviour. Some of the computational methods that are currently available are reviewed: agent-based and network modelling. The advantages and limitations of these modelling techniques are discussed.

Finally, the paper considers the emerging themes of transport, energy behaviour and physical infrastructure systems in recent research from complex-systems energy modelling. Although complexity science is not well understood by practitioners in the energy domain (and is often difficult to communicate), models can be used to aid decision-making at multiple levels e.g. national and local, and to aid understanding and allow decision making. The techniques and tools of complexity science, therefore, offer a powerful means of understanding the complex decision-making processes that are needed to realise a low-carbon energy system. We conclude with recommendations for future areas of research and application.

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http://dx.doi.org/10.1016/j.apenergy.2014.10.057
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Contents

1. Introduction

Current systems of energy provision and demand need to change significantly in order to address the so-called energy 'trilemma' – how to consistently provide affordable energy services, achieve security of energy supplies and reduce greenhouse gas emissions from energy conversions to mitigate climate change. This will require substantial deployment of low-carbon technologies and energy-efficiency measures, the costs and benefits of which are often highly uncertain. Moreover, energy systems consist of a range of actors – producers, generators, suppliers and end users who will frequently have conflicting objectives. These actors and technologies interact through physical and social networks governed by institutional and political structures, the development of which is also uncertain. Together, these features make energy systems examples of complex systems, the study of which has become a fruitful area of research and application over the last 30 years, particularly since the founding of the Santa Fe Institute in 1984. However, the concepts developed in the complexity domain are only just beginning to be applied to the understanding of energy systems. This paper aims to set out the ways in which complex systems thinking and modelling could be useful in understanding the complexity of energy systems and how these systems change, in order to address current and future policy challenges.

In the United Kingdom (UK), there are energy policies aimed at addressing all three aspects of the trilemma: the 2008 Climate Change Act sets a legally-binding target of reducing the UK's carbon emissions by 80% from 1990 levels by 2050 [1]; the Warm Homes and Energy Conservation Act [2] places a duty on government to make sure no person lives in fuel poverty by 2016; and there are several policy actions to support energy security in the UK [3]. Policy measures enacted to achieve these targets and objectives, such as Electricity Market Reform [4] and the Green Deal [5], lead to multiple interactions between changes in actors' behaviours and further technological and institutional changes, which may serve to help or hinderthe achievement of policy goals. However, analysis of policy measures and instruments tends to be dominated by techno-economic models that do not reflect the full complexity of energy systems, particularly in relation to systems interactions and actor behaviours. Hence, we argue that there would be great value in applying approaches and models that incorporate complex systems thinking by reflecting both interactions between actors, networks and institutions in energy systems that give rise to emergent system properties and the limited or 'bounded' rationality of those actors in relation to decision-making under uncertainty. Complexity science and its associated modelling methods enable the study of how interactions between different elements of a system give rise to the collective emergent behaviour of that system and how the system interacts and responds to its environment and evolves over time. In this paper, we review recent advances in complexity science and modelling, and examine the ways in which these would enable those working in the energy domain to better understand and model the complexity within energy systems for the purpose of advancing adoption of new technologies, policies and behaviours.

Some of the insights reported here are drawn from a workshop coordinated by the UK Energy Research Centre (UKERC) and held in the UK in July 2012 that drew together academics across multiple disciplines who were interested in complexity and energy modelling [6].

In Section 2 we outline the characteristics of complexity science and the energy system, and examine how complexity science offers an alternate approach to understanding energy system change. In Section 3 we discuss the purpose of computational modelling of complex systems and briefly summarise some of the modelling methods available. We also briefly highlight the realities of modelling complex systems including the data requirements and discuss the advantages that complexity modelling methodologies can bring to the energy domain over traditional modelling methods. In Section 4 we give examples of the application of complexity modelling reported in recent research work in the areas of transport, user behaviour and infrastructure. In Section 5 we discuss how complexity and coevolutionary ideas can be applied to understanding long-term energy systems change. We conclude in Section 6 with recommendations for areas of future work.

2. Synergies between energy systems and complex systems

Systems theory is well-established in engineering and in biological and physical sciences because it is a convenient and useful way to see a whole as a collection of its interacting parts. Systems dynamics is a branch of systems theory that recognises the role of positive and negative feedback, in which systems can spin out of control, as in virtuous or vicious cycles, and in which systems can be kept within bounds, respectively. The general principles of systems theory [7] allow consideration of any phenomena at any nested level as an open system. The body of knowledge that is complex systems theory particularly developed from the founding of the Santa Fe Institute to study common features of a range of systems that exhibit complexity. This builds upon systems theory by recognising further principles of the manifestation of systems, such as self-organisation, non-linearity, emergence and co-evolution [8–10].

Understanding these features and principles can aid the management of complex systems. A complex system is typically adaptive or evolutionary and influenced by social and political, as well as physical, processes. In 1948, Weaver [11] set out one of the first defining papers on science and complexity, in which he categorises problems of simplicity (e.g. two variables in physical sciences), problems of disorganised complexity (e.g. thermodynamics) and problems of organised complexity. Problems of disorganised complexity can be addressed using statistical methods to look at the aggregate properties of the system. In organised complexity there are "a sizeable number of factors which are interrelated into an organic whole" [11] and the behaviour of the system cannot be predicted by an understanding of the elements within it; statistical methods are no longer appropriate.

Complexity science is now a widely accepted multidisciplinary field of research with roots in dynamical-systems theory and chaos theory [12] and an increasing body of researchers and associated literature. The concepts and methods are beginning to be applied in several disciplines (by both academics and to a lesser extent practitioners), including economics [13–17], health care [18], technology and innovation [19], and management [20], yet it is only really an emerging area of interest in the energy domain.

In the following sections we discuss in more detail the characteristics that are common to both complexity science and energy systems. We also explain why we think understanding energy systems requires an alternative approach and how we can use complexity science to do this.

2.1. Characteristics of energy systems

Energy systems can be understood as complex adaptive systems in that they have interrelated, heterogeneous elements (agents and objects). In addition, there is no autonomous control over the whole system, and, in that sense, self-organised emergent behaviour arises that cannot be predicted by understanding each of the component elements separately. For example, the introduction of a new technology (an object) will influence the behaviour of one or more people (agents), which leads to direct and indirect effects (such as resilience, security) on other parts of the system.

Energy systems exhibit complex social and technological dynamics. These include the complexity inherent in the technological systems and infrastructures by which energy is converted, transmitted and distributed in order to provide useful energy services to households, industry and businesses, and in the related actors and social institutions, policies and practices that influence these systems. As we discuss below, current modelling approaches tend to focus only on some aspects of this complexity. From a complexity perspective, energy systems are made up of (1) agents, interacting through networks under the influence of institutions, which gives rise to emergent properties and co-evolutionary dynamics, (2) objects, such as technologies and infrastructures, which are relatively stable in the short term, but whose adoption is dynamic, and (3) the environment, which provides resources and also establishes social, political, and cultural scenarios in which the energy system operates.

The key agents in energy systems include household and business energy users, energy conversion and supply companies, economic and environmental regulators, and governments (local and central). These agents are able to adapt and respond to other agents and objects, but are heterogeneous and lack the perfect rationality and foresight of 'representative agents' in many economic models [21]. They interact through physical and social networks, by sharing information or learning from one another, influenced by social norms and institutional rules. This may lead to self-organisation and emergent properties, such as common practices for energy use or particular market frameworks governing energy supply. These interactions change over time according to dynamical rules which emerge with the availability of new objects, policies and so on, but, as both technologies and institutions are subject to non-linear increasing returns (positive feedbacks) to adoption, change is path-dependent and systems are subject to lock-in [22–24]. This means that potentially advantageous innovations may not be adopted if they do not fit with the current system.

2.2. Current energy systems analysis approaches

The field of energy systems analysis is inherently interdisciplinary and energy modelling aims to take an integrated approach. Energy modelling holds a key position owing to "the central role of energy projections in policy decision-making and the political importance of modelling results in policy debates" [25]. Current modelling approaches tend to draw on economic and technical aspects of energy systems, but other social science and natural science insights are starting to be incorporated [25]. A single model may focus on the economy (whole economy), some part of the energy chain, or key sectors such as residential or industrial [25]. However, there are significant challenges to the incorporation of complexity and uncertainty into current energy systems models.

The most widely used model for understanding energy-system change to date is arguably the MARKAL model and its derivatives [26]. Briefly, MARKAL is a generic model that can represent the evolution over a period of usually 40–50 years of a specific energy system at different geographic levels (e.g. national or state). It is a 'bottom–up', reductionist model for techno-economic assessment of technology options. There are limitations in using this type of model to understand energy systems change, as bottom–up models are more suitable for studying specific technical opportunities and their energy, cost and emission implications, although exogenous forecasts of economic activity may be used. A recent review recognised that most large scale energy models "provide normative optimised scenarios, in which real implementation bottlenecks are ignored (e.g. uncertainty, heterogeneity of decision makers and market imperfections)" [27]. A number of hybrid approaches are under development to link the macro-economic and technological approaches to energy modelling [25]. Whilst this type of energy systems and hybrid modelling can provide useful insights for policy makers [28–32], we argue that they are limited in relation to representing the drivers and barriers to long-term change in energy systems.

One limitation is that agents in real energy systems rarely act as rational economic actors; they lack perfect foresight, may be

Table 1
Main characteristics of complex systems and examples of their application to energy systems.

Term	Definition	Example in energy systems
Agents	Agents are actors (individuals or groups) in the system that take decisions or influence others. Agents interact and are coupled in the system and, importantly, are able to adapt, learn and respond to other agents or the conditions of the environment	The energy system includes a diverse cast of heterogeneous agents, e.g. households, businesses, government organisations, suppliers, generators, investors, regulators Agents interact with and are influenced by each other, e.g. households are influenced by their supplier or other households with which they are in contact Interactions between the agents in the system shape the system but may be constrained, e.g. by legislation, infrastructure or technology
Networks	Networks are the physical and social structures through which agents interact, and which are defined by directionality and tightness of coupling, which has implications for resilience, robustness and inter-dependency	Physical and social networks occur in the energy system, e.g. the physical electricity distribution network and social networks operating between households and energy utility companies
Dynamics	Complex systems are dynamic and move around in an attractor basin; they are not in equilibrium	Energy systems change structurally over time, e.g. with changing populations, lifestyles, technologies, costs Feedback mechanisms also operate
Self-organisation	A self-organising system adapts autonomously and organisation arises in the system despite there being no agent with overall control	While some aspects of the energy system can be influenced, there is no overall control held for planning or use of energy systems. Decisions are taken at multiple levels, e.g. individuals, households, communities, local and central government and internationally. Agents at each level will respond to the changing environment around them An organised system emerges which supplies our demand for energy
Path dependency	A system is where it is today based on many past interacting decisions that have driven the evolution of the system in particular directions Systems may be similar but they are individual, each has a unique history and a current make up which varies in many ways, e.g. spatial locations, ages, and distribution of skills	We are locked-in to many aspects of our energy systems by historical decisions, e.g. we cannot rebuild the entire domestic housing stock, and are reliant on aging infrastructure
Emergence	The macro nature of the system emerges from the micro behaviours and interactions of agents within the system and its environment, and cannot be predicted with an understanding of the constituent parts of the system	We cannot, for example, accurately predict future energy demand based on historical information and knowledge of individual users because we cannot know the effect of multiple non-linear feedbacks due to new interactions or changed behaviours
Co-evolution	Each system co-exists with other systems, competing for resources and survival, whilst also relying on each other in different ways Sub-systems within the system will coevolve as they have interdependencies. For example, the energy system is itself made up of sub-systems and is also interdependent on the water, transport, ICT and food production systems	Energy systems consist of technologies, institutions, business strategies, user practices and ecosystems that mutually coevolve. For example, new technologies may bring the need for new business models, policy and regulation. Consumer behaviour may bring demand for new technologies, or conversely technologies may change consumer behaviour
Learning and Adaptation	Complex systems can learn and adapt through experimentation and use of novelty in the system whilst also being able to retain certain structures and functions despite changes to their environment. Complex systems may be able to adapt to improve functionality to take advantages of particular changes to their environment	Consumers can learn the effects of unconstrained demand, for example, through information provided by smart meters, and so they can change their usage and influence systemic features such as efficiency and value for money. Systems around particular fuel sources or technologies, e.g. shale gas or nuclear power, can adapt to take advantage of external technological or political changes

motivated by other drivers (e.g. environmental concern or peer influence) and are heterogeneous in their preferences. As such the economic assessment aspects of energy-systems modelling may not adequately represent the real system of agents. Real energy systems exhibit dynamical properties of feedbacks, inertia and lock-in that are not well-represented in models in which system evolution is driven by simple decision rules, such as cost optimisation. Furthermore, under conditions of uncertainty, how actors within the system envisage the future evolution of the system will influence their decision-making at any point in time. This means that it is virtually impossible to predict the future evolution of a complex system. However, drawing on the study of a range of complex systems, complexity science does enable useful understanding to be developed of higher-level systems properties, such as resilience and adaptability, and modelling can be used to simulate complex systems change involving boundedly rational agents acting under conditions of uncertainty. Thus, incorporating characteristics of complex systems into large scale energy system modelling could provide useful insights for decision makers into the implementation bottlenecks associated with uncertainty, actor heterogeneity and market imperfections that are not addressed in existing models. The next section sets out key systems features and examples of these in energy systems.

2.3. Characteristics of complexity science and relevance for energy systems

In Table 1, we give definitions of the following main characteristics of complex (adaptive) systems [8,12], and examples of their application to energy systems:

- Agents
- Networks
- Dynamics
- Self-organisation
- Path dependency
- Emergence
- Co-evolution
- Learning and adaptation.

Modelling approaches that have investigated the implications of these complex-systems characteristics could usefully be applied to energy systems. In the next section, we review the main features of current complex-systems modelling approaches.

3. Complexity modelling approaches

A common method for making sense of a system which cannot be easily or safely experimented upon is to create a computational model of the system. As with all methods of scientific research, computational models aim to achieve the following:

- Answer one or more specific research questions (be purposeful).
- Use a predefined methodology to answer the question (be repeatable).
- Collect evidence (be unbiased).
- Produce findings unknown beforehand which may be beyond the boundary of the research (make a novel contribution).

3.1. Simplifying assumptions

By definition, a model is a representation. In the creation of any representation we make simplifying assumptions about the system which is represented. We argue that the assumptions made in non-complex systems models create limits to what might be understood from such models but may be relevant if they suit the purpose of the model. When more assumptions are made we find it easier to understand the representation, but we limit what we can learn [33].

In energy systems modelling we typically want to answer questions such as how to change the system to provide affordable energy services or reduce carbon emissions, or to make the system more resilient to disturbances or robust to security threats. Through the use of models we attempt to address the energy trilemma.

Creating a model requires us to define the system under investigation. The facts we observe from our models and our evaluation of these depends on how we bound the system [34]. A boundary provides the modeller with a scope for the model and for the range of data that will need collecting. If we make only this one assumption we can embrace a system holistically – all its components, all its interactions, all its contexts, and all its interpretations. We make no assumptions about the structure of the system. Models in this area are generally qualitative and descriptive, such as Checkland's soft-systems modelling approach [35].

Often, however, computational models demand further simplification because their scope is large or because the manipulation of large data is onerous (see Fig. 1).

The second assumption a modeller makes is to classify the components of the system. The use of normative classifications, i.e. those deemed appropriate, desirable, valuable and good, usually reflects the history of the system and its specific ideologies and contexts. Classification provides an initial structure for the components of the system in the model but it ignores other potential classifications; for example, there are some 17 choices available for clustering of components [36], giving rise to very large numbers of potential classifications. A model which assumes a classification provides strategic insight into longer-term change, as successive structural changes (reconfiguration of components) emerge driven by the interactions of diverse components. Different and novel structures give rise to different evaluations of systemic properties, for example efficiency, resilience, and security. The models also provide a record of how the structure has changed from its initial conditions.

The third assumption made is that of average types, which limits the capacity of the model to evolve. The only change possible within the model is in the relative numbers of the average types. Structural stability can be investigated particularly by using the addition of noise (random variation) to the model. We say that the outcome of the model is deterministic, as in chaos theory, or systems dynamics, where probabilistic outcomes can be identified through modelling. Calculations of robustness and resilience are also possible. The model with assumptions about average types is suitable to test contingencies.

By assuming average interactions, a mechanical model is created from which we can predict the outcome of the system's operations. This assumption removes the capacity of the model to try out new combinations of interactions which might be higher-performing. Structural stability is assumed. Models of this kind exist for real-time, autonomous control of engineering systems, such as active multi-models [37]. Non-linear dynamical models are also in this category. Models without dynamical capability are essentially static and most simple of all.

The number of assumptions imposed will depend on the system in focus and the questions being investigated, in order to assess the appropriate balance of complexity and simplicity. For example, whilst an equilibrium model may be appropriate for examining the balance of energy supply (provision) and average population demand, an adaptive evolutionary model with fewer assumptions will be necessary to examine energy systems change over a 50-year period.

Models can be used to aid decision-making at multiple levels, e.g. national and local, and to aid understanding and decision-making [38,39]. Complexity modelling can be used to aid decision-making in three main ways: (1) strategically: to explore

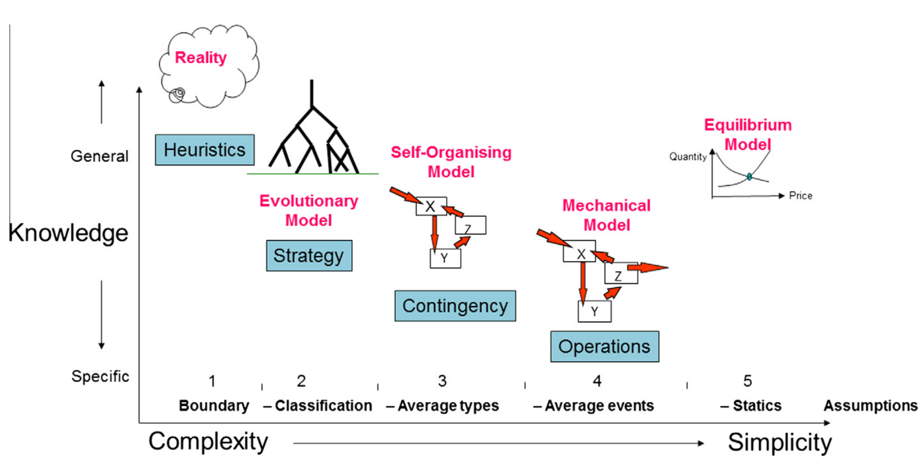

Fig. 1. Increasing assumptions reduce model complexity (adapted from [33]).

potential system pathways; (2) contingently: to find effective strategies that may change systemic outcomes; (3) operationally: to test assumptions about how the system is working. Different contexts demand different models [38].

3.2. Realities of computational modelling

Systems are socio-political, which creates the challenge of independence for the modeller. A model is not fit for purpose if it is developed without sufficient critique of the motives for producing the model.

A model should be capable of producing different results if run using different initial conditions or scenarios. Simulations that show a number of scenario options can be used to explain the complexities of the systems [40].

Interventions, such as those which reflect policy levers or resource constraints, should be user-adjustable and should result in alternative outcomes, provided there is an accurate representation of energy systems.

Finally, in order to represent a system, and its nested systems, we need details of its diversity. Predictive models usually simulate a particular system in detail and so the boundary of the system will contract. Aside from the technology and economic data that is needed in most energy system modelling, models testing hypotheses or probing structural change need reliable input data (or at least a statistically representative sample of heterogeneous agent behaviour such as investor attitude to risk, motivation for technology adoption, decision-making processes) and agent interaction data (e.g. social networks, processes of social learning) in order to provide useful and relevant outputs.

There are two significant barriers with regard to data: availability and uncertainty. These aspects are described in more detail by Keirstead et al. [41]. An example of the need for data about social networks is discussed in more detail by Bale et al. [42]. There is an opportunity to harness open data (and software) [43] for energy-system modelling as it becomes more available, and this is likely to bring benefits for understanding energy systems [44]. In addition, technologies such as smart meters will bring improvements in the quality of energy consumption data (e.g. better temporal and spatial resolution); however, privacy issues do need to be considered. In the meantime, it is essential that data is managed and shared across organisations and research groups [6].

The key types of computational models are discussed in the next section.

3.3. Types of computational model

Models for analysing energy systems change fall into two main types. Equation-based models are also known as 'top–down' and include computable general equilibrium (CGE), macro-econometric optimisation models and systems dynamics models; agent-based models, sometimes correctly referred to as bottom–up models, include behavioural or algorithmic models, agent-based computational economics (ACE) and simulations. Network theory is also relevant for analysis of network topologies which provide insight into the network properties, such as resilience and robustness to attack.

3.3.1. Equation-based models

Most models of energy-systems are equation-based and have a long (over 50-year) record of disciplinary contributions and industrial and policy application. For example, CGE modelling is an established field (see for example Dixon and Jorgenson [45]). CGE offers: (1) established simulation software which is well-documented and has associated data manipulation packages; (2) low skills for use (no need to learn a programming language) and plentiful training; (3) easily communicated model results, making outcomes explainable and understandable by the policy community; 4) incorporation of dynamics, multi-agent and non-standard theories [46]. Examples of optimisation in energy systems include MARKAL, WASP, CGEN [47]. A key feature of such macro models is the ability to integrate outputs; a drawback is their dependence on the non-flexible functional form which is adopted by the modeller, and which influences the modelling results [48]. Equation-based approaches relate system-level observables and use these phenomena to drive the model dynamics [49] or they model uncertainties in parameters to reflect systemic outcomes such as sustainability, uncertainty and dynamics [50].

These equation-based models are sometimes used with 'bottom–up', reductionist approaches which usually break down the system to its technical components, for example, for the purposes of simulation or optimisation [51,52]. Such models make many assumptions about the system and, in particular, assume structural stability and average types. They do not reflect the complex reality of energy systems, and so do not deal with feedback and emergence. They are not complex systems models.

3.3.2. Agent-based models (ABM)

The discipline of agent-based modelling is still maturing. In their review of agent-based modelling practices, Heath and Hill [53] identified improvements that would make ABM a more acceptable analysis tool. A key improvement would be clarity of purpose of the ABM. They proposed a framework which would define the purpose of an ABM and would be linked to the level of understanding of the system being modelled. Three purposes are possible: predictive (linked to high understanding), theory testing or mediation (where understanding is moderate), and hypothesis generation (where understanding is low). These correspond respectively to the operational, contingency and strategic focuses highlighted earlier in the discussion on modelling assumptions. Agent-based predictive models are usually referred to as simulations and seek to represent the system from actual data.

Agent-based models focus on the behaviour of different individuals through which system-level observables emerge but tend not to drive the model dynamics [49]. They incorporate human behavioural rules in innovations [54] and do not assume functional form, which emerges from the bottom–up behaviour and interactions of agents. ABM has much to offer when used with experimental and behavioural economics. Bottom–up models attempt to simulate action. This understanding of actual behaviour is lacking from training and use of CGE, which make assumptions about decision-making and excludes feedback and rebound effects. For this reason, ABM is often focused on specific geographies and research phenomena.

As part of agent-based modelling, particular agents can be removed to detect effects upon the system; this is not available to systems dynamics models [55]. Selective changes in agent behaviour can also be modelled based on exogenous (and endogenous) events, which can show non-linear effects on macro outcomes. An example of this is the government FITS (Feed-in Tariff Scheme) and its withdrawal [56]. Agent-based models can also be used to test hypotheses relating to culturally specific behaviours. Modellers do this by changing the rules of agents (their behaviours) depending on emergent systemic properties, or keeping rules the same and changing scenarios/contexts [76], then comparing results or by using different strategies for agents in uncertain contexts [57]. Hypothesis generation can be structural or relational. Structural changes can be detected in energy supply systems, for example, driven by the uptake of hybrid/electric vehicles and increased use of heat pumps.

The integration of bottom–up complex systems models with top–down models has important advantages for orthodox approaches to make them more realistic [58]. An example is a hybrid climate policy simulation using bottom–up engineering technology detail in a top–down macro-economic framework [59].

However, ABM is not without issues. These include a largely fragmented community which has not made significant inroads into policy debates, the need for economists to learn object-oriented software such as Java, much diversity of development platforms and quality of training materials, and improvement is needed in the reliability and understandability of results [46].

3.3.3. Network theory

Modelling of systems using network theory is a thriving field of investigation. Based initially in graph theory, network theory considers a system as a network of nodes, some of which are connected to each other via edges. Various network typologies have been identified, but the discovery of scale-free networks [60], in which the degree distribution of nodes follows a power law, has helped to explain preferential attachment in which the rich get richer. Network theory has been particularly helpful in supply-chain research in which nodes are the components are of the supply chain. Network theory also helps with the identification of network robustness (ability to avoid disruption) and network resilience (ability to recover after failure) by exploring the direction of connectedness of edges, the strength of network ties and cascading effects of node failure (see, for example, Nair and Vidal [61]). Watts and Strogatz [62] identified 'small-world' networks, where the average path length between nodes depends on the number of nodes in the network. Power grids and many complex systems exhibit the phenomena of 'small-worlds'. Social network models can also be used to examine mutual influences between actors in a system. Real-world networks can be examined under the lens of network theory to explain and predict emergent network phenomena.

4. Developing themes in energy-complexity models

In this section we discuss some examples of recent work where complexity-modelling methods have been applied in the energy domain (however, this is by no means intended to be a complete review of all the literature). In 2009 four projects were funded under the Energy Challenges for Complexity Science call from EPSRC (Engineering and Physical Sciences Research Council, a UK research funding body) [63]. We briefly discuss the research emerging from these projects as a means of highlighting areas where complexity methods have been most commonly applied to date, in the areas of transport, social networks and user behaviour (end-use energy demand) and infrastructure.

4.1. Transport

Transport is an area to which complexity methods lend their advantages as a result of the interplay between physical transport networks and user behaviour. Researchers on the *SCALE: (Small Changes leAd to Large Effects)* project aimed to develop a model which analyses how, at a discrete urban location, information on the change in transport cost diffuses in the urban structure, and instigates urban macro-behaviour that corresponds to actual modifications of the whole urban spatial structure [64].

4.2. Social networks and user behaviour

As we have discussed, complexity modelling can be used to explore complex networks of interacting agents. In the *Future Energy Decision Making for Cities* project a dynamical network model has been developed to investigate the influence of social networks on the adoption of domestic energy technologies. Analytical results show the emergence of unexpected system-level behaviour from the interaction of the households on the network [65]. This work shows how social aspects can be captured alongside techno-economic factors in a quantitative model which can be used as the basis for a decision-making tool when assessing local authority interventions [42,66]. This demonstrates how quantitative and qualitative approaches may be combined to analyse the effects of social context on individual behaviour, in order to support measures to achieve increased adoption.

4.3. Infrastructure

There are two projects which explore aspects of energy infrastructure. The *Complex Adaptive Systems, Cognitive Agents and Distributed Energy* (*CASCADE*) project has developed a framework based on agent-based modelling [67]. Its purpose is to gain policy- and industry-relevant insights into the smart grid concept. Behaviours of different social, economic and technical actors are captured into two scalable agent types, prosumers and aggregators; agent behaviours can adapt through learning. Three separate models are integrated: electricity supply and demand, the electricity market and power flow. Weather data is used to vary the generation of renewable energy, which is a critical issue (due to intermittency) for grid balancing and the profitability of energy suppliers. The CASCADE models have found that an aggregator can achieve stable demand-flattening across groups of domestic households fitted with smart energy control and communication devices. This is in contrast to traditional methods using wholesale price signals, which produce characteristic complex system instability.

Futhermore, the project *Preventing wide-area blackouts through adaptive islanding of transmission networks* has employed graph theory to explore how local behaviour of elements of an electrical grid influences the resilience of the grid as a whole [68].

5. Applying complexity to long-term energy systems change

The above discussion and examples highlight some of the ways in which complexity thinking and modelling can inform analysis of energy systems and system change. This suggests the need to go beyond models in which rational agents adopt the most cost effective technologies, and the evolution of networks can be predicted just by examining their physical characteristics. The need to integrate primarily quantitative physical understanding of energy systems with more qualitative understanding of the social aspects of these systems has been frequently referred to (e.g. Smil [69]). Complex systems thinking and modelling bring a set of approaches and tools that can enable this.

In addition to the types of model of particular energy systems change described above, the need to transition to low-carbon energy systems while maintaining affordability and security requires analysis of long-term, large-scale systems change. Though it is not possible to build a single model that represents change across all scales, high-level qualitative frameworks for analysing systems change may be combined with more quantitative detailed models. This type of approach has been applied by one of the authors and colleagues to exploring alternative pathways for a transition to a low carbon electricity system in the UK [70,71], building on a more qualitative multi-level transition framework [72]. Other approaches have similarly built on this multi-level perspective to develop quantitative models of energy infrastructure transitions using agent-based modelling incorporating increasing levels of complexity [73] or by combining agent-based and system dynamic modelling [74].

More generally, complexity thinking encourages us to consider energy systems change within its broader social, economic and environmental context. There is a clear need for modelling work which does not look at elements of the energy system in isolation, but attempts to apply a whole-systems approach. At the moment modelling tends to focus on sectors, e.g. transport, water, electricity, but these, of course, are all interconnected. Clearly, the development and adoption of new energy supply and energy use technologies is central to energy systems change. However, as we have seen, new technologies have to fit with, and occasionally disrupt, existing systems, which are made up not only of other technologies and infrastructures, but also of institutional rules and norms. As emphasised by Unruh [24], the increasing return to adoption and mutual co-evolution of technologies and institutions has led to the current lock-in of fossil fuel based energy systems. This idea built on the work of Arthur [22] in applying complexity ideas to the competition between adoption of new technologies, which demonstrates path dependency and sensitivity to particular historical events. Further work applied similar ideas to the examination of long-term change in industrial and economic systems, emphasising that firms' strategies also co-evolve with technologies and institutions [71]. Other work, from a more sociological perspective, has examined energy use and argued that this is best understood in terms of evolving practices, such as maintaining comfortable living spaces, laundry and showering, which give rise to demands for energy [75]. From another perspective, ecological economists have long argued that economic systems should be understood in terms of their inputs of energy and material and outputs of waste emissions [76,77]. The influential study of 'Limits to Growth' was built on system dynamics modelling of the evolution of the world economy under resource constraints [78,79]. The application of a broader range of complexity tools and approaches to economic issues, particularly around long-term systems change, has recently been advocated [14–16].

These strands of thinking raise challenges for the development of appropriate frameworks and tools that can address this complexity whilst still remaining tractable. One potential framework for analysing the complexity of a transition to a sustainable low-carbon energy system and economy has been proposed by one of the authors [80], building on the above insights on complexity and coevolutionary interactions and dynamics. The framework focuses on five key coevolving systems: *technologies, institutions, business strategies, user practices and ecosystems* (see Fig. 2). Applied to energy systems, these include:

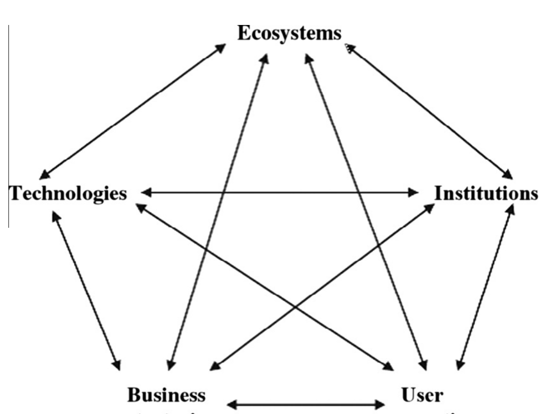

Fig. 2. Coevolutionary framework, from [80].

- ***Technologies*** – e.g. energy conversion, supply and end-use technologies.
- ***Institutions*** – e.g. social rule systems relating to policy, planning, risk, investment.
- ***Business strategies*** – e.g. different business models, such as energy utility or energy service company (ESCo) models.
- ***User practices*** – e.g. social practices relating to heating, cooking, cleaning and appliance use.
- ***Ecosystems*** – e.g. impacts on local air quality, noise and land use, and global carbon emissions.

This framework has been applied to analysing the coevolutionary interactions affecting the adoption of the energy service company (ESCo) business model in the UK [81]. Further work is needed to apply this type of high-level framework to tools and models that can be used to examine and test the likely impacts of particular interventions on these complex, coevolutionary dynamics.

6. Policy challenges – How can complexity approaches help inform energy policy?

One area where complexity methods can add value over other modelling methods is in addressing questions at the technology-policy-behaviour interface by incorporating social and institutional elements. Complexity models can incorporate behaviour that may not be considered rational from an economic perspective by embedding insights from energy behaviour and practice studies into modelling to give quantitative understanding of the complex system.

Most policies aim to intervene in complex systems. Policy-makers can be considered designers in the energy system, and there is therefore a need to translate outputs from complexity modellers to the wider policy community [6]. However, there is a difficulty in taking complexity-science methods directly to policy-makers, not least because of the challenges in language and understanding of complexity, and because of the resources and expertise available in policy and planning departments [82].

Decision-support tools may be more useful to policy-makers than predictive models; agent-based modelling has been proposed as a tool in developing policy in 'deep uncertainty' [83]. However, there is a need for policy-makers and modellers to work more closely together if complexity modelling is to achieve its potential impact. Modellers need to engage with their beneficiaries from the outset so that models are properly scoped and fit for purpose. Policy-makers need to be engaged throughout the process, rather than waiting until models are 'ready'. There is considerable scope for industry/academia/government collaborations in this area, and for funding agencies to support events and schemes that foster these collaborations [40].

In addition, we propose that case studies of examples where complexity science has been used to inform policy be collated and made available, as a means of engendering confidence in the application of complexity methods. However, a cautionary approach needs to be taken to ensure that complexity models are not interpreted as predictive tools and applied in inappropriate ways; explicit communication is needed of the limitations and inherent assumptions.

Complexity models themselves should also been seen as a technology, and in this respect will have to be adapted as policy changes are made, new technologies come online and user behaviours change. Models need to be developed iteratively, much like in system transitions as described by Chappin and Dijkema [73], where the complexity model is a technological component in the system. The use of complexity models that are open to experimentation, such as agent-based models and simulation games, has been proposed as a way of helping decision makers to gain more insight through their own and other people's experience [84].

This suggests that, used appropriately, complex systems modelling can be used in policy advice processes in ways that highlight uncertainty and how outcomes are conditional on the framing assumptions used, rather than applying modelling approaches that may produce over-simplified answers [85].

The application of complexity science to energy challenges calls for deep collaboration across the academic disciplines to embrace the perspectives of maths, engineering, economics and the social sciences as well as engagement with practitioners in the field. There are barriers in academia to working in this interdisciplinary manner [86], but there are also ways forward, such as commitment from funding councils.

The techniques and tools of complexity science, therefore, offer a powerful means of understanding the complex decision-making processes that are needed to promote a transition to a low-carbon, secure and affordable energy system.

7. Conclusions

In this paper we argue that understanding energy system change would benefit from the application of complexity science thinking and modelling. We have shown that the characteristics of complex systems that have been identified in the development of complexity theory, including agents interacting in networks, path dependency of change, emergence of system properties, and resilience and adaptability of systems, can be applied to energy systems. Useful types of complexity modelling approaches, including agent-based models and dynamic network models, are beginning to be applied to energy systems. We have presented examples from research where complexity thinking yielded novel results. Frameworks for thinking about the co-evolution of elements in long-term energy system transitions have been expounded and would benefit from further examination and testing.

We believe that complexity science has useful tools and approaches to offer the energy research and practitioner communities. Complexity theory has started to contribute to our understanding of energy systems, but there is certainly scope, and need, for its advantages to be exploited further in tackling the energy challenges we face.

Acknowledgements

This paper in part draws on some thoughts gathered at the UKERC Energy & Complexity workshop held in Oxford in July 2012; the authors would therefore like to thank UKERC for their support and funding for this event, and also all the participants at the workshop for their insightful comments and discussions. The workshop drew on insights from research conducted in four projects funded under the Engineering and Physical Sciences Research Council (EPSRC) programme *Energy Challenges for Complexity Science*. CSEB and TJF were supported in related work by the EPSRC under *the projects Future Energy Decision-Making for Cities – Can Complexity Science Rise to the Challenge?* (EP/G059780/1) and *iBUILD: Infrastructure BUsiness models, valuation and Innovation for Local Delivery* (Ref.: EP/K012398/1). In addition, CSEB is grateful for an EPSRC Fellowship (EP/K022288/1). EPSRC support under research project *Transforming Utilities' Conversion Points* (EP/J005649/1) and the *International Centre for Infrastructure Future* (EP/K012347/1) is gratefully acknowledged by LV.

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