

A general framework for analyzing techno-behavioural dynamics on networks



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ABSTRACT

A general framework for assessing future impacts of technology on society and environment is presented. The dynamics between human activity and technological systems impact upon many processes in society and nature. This involves non-linear dynamics requiring an understanding of how technology and human behaviour influence each other and co-evolve. Conventionally, technological and behavioural systems are analyzed as separate entities. We develop an integrated theoretical and methodological approach termed techno-behavioural dynamics focussing on networked interactions between technology and behaviour across multiple system states. We find that positive feedback between technology learning, evolving preferences and network effects can lead to tipping points in complex sociotechnical systems. We also demonstrate how mean-field and agent-based models are complimentary for capturing a hierarchy of analytical resolutions in a common problem domain. Assessing and predicting co-evolutionary dynamics between technology and human behaviour can help avoid systems lock-in and inform a range of adaptive responses to environmental and societal risk.

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1. Introduction

Understanding the future impacts of technology on society and environment is of fundamental importance. For instance, low carbon technologies play a central role for climate mitigation (IPCC, 2011), and the rapid adoption of information and communication technology (ICT) is altering economic and environmental systems (Hilty et al., 2006; Basole and Rouse, 2008). Emerging technologies will become increasingly ubiquitous and non-invasive across society and environment (Bohn et al., 2004). Synergistic advances in emerging technologies including energy, nano, bio, and ICTs coupled with the rise in genetic engineering and cognitive sciences will influence the quality of human life and societal outcomes (Roco, 2004). Therefore, understanding how technology impacts upon human decision-making and behaviour has implications for responding and adapting to future risk and uncertainty. Yet the feedbacks between technological performance and human decision-making are not well understood. Technology and behaviour are typically assessed as discrete non-interacting

phenomenon, whether it is technological change modelled by differential equations (Bass, 1969) or decision theoretic models based on representative rationale decision-makers (McFadden, 1974). But there is inherent uncertainty and feedback between social, technological and physical processes not well captured by conventional approaches. Part of the challenge in modelling complex dynamical systems involves a hierarchy problem where model output resolution, and therefore understanding of a system across multiple states diverges between mean-field and agent-based approaches. Responding to those challenges, advancements have been made in systems modelling using optimization (Brede and de Vries, 2013) and multi-agent methods for assessing complex human–environmental interactions (van Oel et al., 2010; de Almeida et al., 2010; Smajgl et al., 2011; Filatova et al., 2013). Disaggregated approaches have also been used to model behaviour and networks showing the importance of assessing multiple scales of interaction (Caillault et al., 2013; Gerst et al., 2013; Schreinemachers and Berger, 2011). But there is further need for new analytical frameworks that focus on coupled dynamic interactions between technology and behaviour, better able to capture real world phenomenon (Barabási, 2005, 2009; Vespignani, 2009).

From a theoretical perspective there is scope to integrate techniques from decision theory, networks and dynamical systems to

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further our understanding of a broad range of complex socio-technical systems, characterised by heterogeneous technology and behavioural interactions across multiple system states. Here we develop a general theoretical and methodological approach termed techno-behavioural dynamics focussing on the networked interactions between technological systems and agent behaviour. We provide a case study of emergent technology to assess feedback between state dynamics, and argue for the advantages of applying both mean-field and agent-based methods within a flexible modular framework, enabling complimentary analytical resolutions. The paper proceeds with 1) methods and materials, 2) model outputs and discussion, and 3) conclusions.

2. Methods and materials

2.1. Techno-behavioural dynamic approach

Environmental and sustainability analyses are often informed by computational modelling and framed in scenarios to assess impacts and alternative strategies. Alternative strategies typically depend on technological interventions to mitigate future impacts. More recently there has been recognition of the importance of behaviour, lifestyle and other demand-side factors for mitigation and adaptation. This has led to a divergence in supply and demand side approaches in sustainability analyses. We propose an integrated theoretical and methodological approach to address some of those challenges. Scenarios are often used as a complimentary measure to mathematical modelling and simulation to ensure internal logic and consistency for model parameterization. The overarching goal of scenario analysis is to account for inherent unpredictability in various future trends. Scenarios are not predictions but exploratory visioning exercises to consider future pathways that break from current trends (Schwartz, 1998). Fig. 1 shows scenario archetypes typically used in sustainability modelling including: 1) status quo, 2) technological optimism, and 3) behavioural change. We integrate key elements from 2 to 3 to develop a new framework termed 4) techno-behavioural dynamics.

Status quo – reflects a baseline scenario typically used as the starting point in a scenario building exercise and used to compare against the assumptions and simulation results for other scenarios. It usually relies on extrapolating historical and current macro level trends. It is typically assumed that there is not a strong policy or industry initiative to induce significant change on either the supply

(technological innovation) or demand (end-use) side, hence the continuation of current trends (IEA, 2008).

Technological optimism – characterizes scenarios that generally focus on advanced technological solutions to societal and environmental challenges. There is often an assumption that rapid technological deployment will be supported by a strong emphasis on supply-side industry investment and radical policy support (IEA, 2010). These scenarios typically do not explicitly account for heterogeneous agent behaviour. There is often an assumption that the future reduction in cost of technology, extrapolated from historical technology learning rates is the central mechanism for widespread adoption. While technological learning rates are more appropriate for supply-side technologies that have little interaction with human behaviour, it does not account for demand-side technologies more dependent on behavioural factors that influence adoption and end-use. Nevertheless, these scenarios were the first to take a problem solving approach and show the technical potential in mitigating environmental impacts (IEA, 2008, 2010; Skea et al., 2011).

Behavioural change – is a response to the conventional focus on technological solutions without social context. This approach is characterised by a focus on demand-side behaviour such as the reduction in energy end-use or vehicle kilometres travelled (Anable et al., 2012; Hickman and Banister, 2007). Those reductions are often based on the premise of dramatically changing normative behaviour through policy or other economic interventions i.e. price signals. There is often an assertion that end-use behaviour will have to radically change to meet sustainability objectives, but no mechanism is given as to how that change might arise, particularly at the individual level. The approach is more focused on overall lifestyles, consumption patterns, and normative practices (Anable et al., 2012; Eyre et al., 2010). Nevertheless, these types of scenarios highlighted the important role of end-use behaviour, recognizing that technology is an important, but insufficient means to achieve sustainability. Although the importance of behavioural change has been well argued, the approach typically lacks a mechanism for change, and has not accessed well developed analytical tools for decision-making and strategic behaviour found across social and biological disciplines (Jackson and Yariv, 2010; Nowak and May, 1992; von Neumann and Morgenstern, 1944).

Techno-behavioural dynamics – integrates key elements of technological optimism and behavioural change, but is embedded in dynamical systems, network and decision theory. This approach implies a simultaneous emphasis on both supply and demand-side factors i.e. technological performance, and end-use demand patterns. Specifically it focuses on individual level decision-making and how heterogeneous micro-level behaviour can scale up to influence systems performance. This approach views technology and behaviour as a coupled dynamical system co-evolving over time. With the rise of ubiquitous emerging technologies, these co-evolutionary processes will become increasingly prevalent throughout society (Barabási, 2005; Roco, 2004; Vespignani, 2009, 2012; Watts, 2007). This approach seeks to understand how individual behaviour and technologies interact, and influence each other over space and time. Importantly, the approach considers how technological performance feeds back on end-use behaviour, which in turn can positively influence continued use and technological change, leading to a co-evolutionary process. This departs from current approaches that view technology and behaviour as discrete non-interacting systems. Moreover, it is different from the literature on behavioural change that does not propose underlying mechanisms for changing individual behaviour, and also departs from the transitions literature (Rip and Kemp, 1998; Smith et al., 2005), which takes a far broader view of sociotechnical systems incorporating firms and institutions, while our focus is on

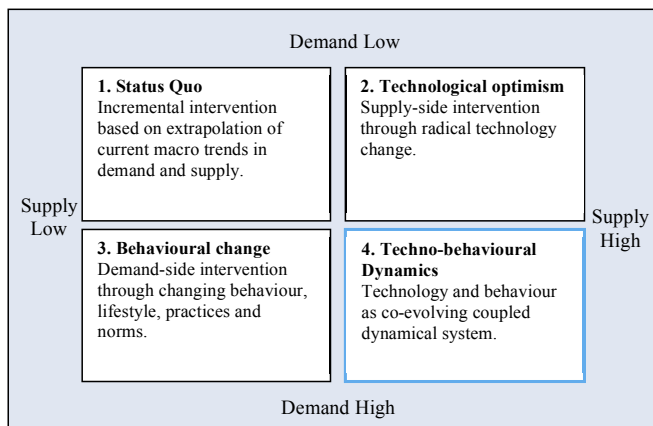


Fig. 1. Techno-behavioural dynamic framework informed by scenario archetypes. The different levels of demand and supply indicate the conceptual focus typical for each scenario. During scenario development this translates into assumptions on what key interventions will influence the trajectory and composition of the system.

individual decision-making and technical performance.

2.2. General theoretical framework

We propose a flexible module based modelling framework to assess techno-behavioural dynamics on networks (Fig. 2). The framework captures multiple system states where agents and processes interact within, and across states including: 1) the Microstate captures stochastic individual-level behaviour, 2) the Mesostate focuses on assemblages of decision-makers, technologies and network structures, and 3) the Macrostate includes macro-level phenomenon that can emerge from, or constrain lower state behaviour. The dashed boundaries of the system states depict feedback which could be thermal, material or information flows over varying spatial and temporal scales, where non-linear dynamical interactions between system states can result in emergent phenomenon (Prigogine, 1997). From an analytical and computational perspective, the different states frame the analysis and help specify appropriate implementation models e.g. deterministic vs. stochastic. The modelling framework is composed of a series of interconnected computational modules that share input/ outputs shown by two way directed arrows. Each module encodes state behaviour at time t_0 and computes state change at $t > t_0$. The following summarises the theoretical background that informs the general modelling framework specification, and implementation models (Section 2.3).

2.2.1. Systems behaviour

Macro-level phenomenon can be modelled by dynamical systems theory, which includes a phase space M whose elements x represent possible states of the system, and an evolution rule ϕ^t determines the state at time t . The state at time t_0 often allows determination of the state at any subsequent time $t > t_0$. Analysis of the system is based on continuous $dx/dt = \dot{X} = f(x)$, or discrete $x_{t+1} = f(x_t)$ time variables, which determines how the state $x \in M$ of the system evolves. We use discrete dynamical systems to generalise our modelling framework. The Systems Module S captures

emergent behaviour at the macrostate that can arise from substate interactions. The behaviour of the system can include changes in physical and information stocks, or other phenomenon to be specified.

2.2.2. Technology behaviour

Change in technological systems have long been modelled by variants of the logistic function, which has non-deterministic chaotic properties in its difference form $X_{t+1} = rX_t(1 - X_t)$ where X_t is a number between zero and one representing the ratio of an existing population to the maximum possible population in year t , and r is a positive number representing the combined rate for growth and decay of a population. When $1 < r < 4$ non-trivial dynamical behaviour occurs, which has been used to approximate many real world processes because it captures the negative feedback found in natural systems (May, 1976). The logistic function informs our Technology Module T capturing the behaviour of technological assemblages, which can be composed of same class variants (e.g. petrol, electric vehicles) or different technology classes (e.g. photovoltaics, smart meters).

2.2.3. Network behaviour

Network structure and dynamics are formalised as a mathematical graph $G = \{P, E\}$ where P is a set of N nodes ($P_1, P_2 \dots P_N$) and E is a set of edges that connect two elements of P . In theoretical random networks all pairs of N nodes are connected with probability p resulting in $\sim pN(N - 1)/2$ edges distributed randomly, with most nodes assigned the same number of edges following a Poisson distribution (Erdős and Rényi, 1961). However, in real world networks non-random structure and dynamics occur. Structural change is captured by 'small world effects' measured by a clustering coefficient $C_i = 2E_i/k_i(k_i - 1)$ where node i having k_i edges connecting to k_i nodes results in $k_i(k_i - 1)/2$ edges between the original node i and its nearest neighbours forming a clique of personal contacts; E_i is the actual number of edges between the neighbors of i . Empirical networks typically have larger clustering coefficients than random networks (Watts and Strogatz, 1998). A second

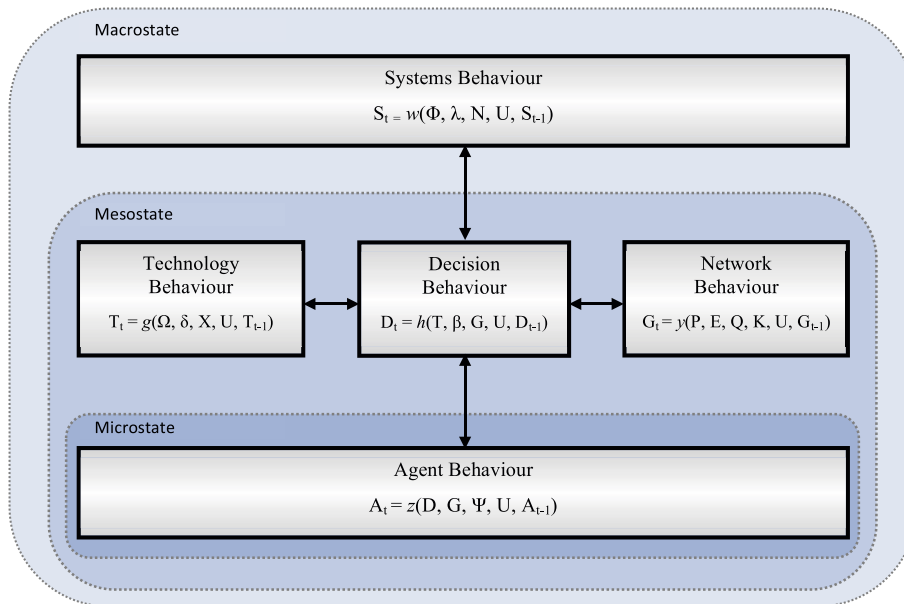


Fig. 2. Techno-behavioural dynamic general modelling framework. Solid boxes represent computational modules composed of state and process variables; Solid arrows indicate two way flows of input/output values, common variables, functions or algorithms; Dashed background boxes depict state levels: Microstate – stochastic individual behaviour, Mesostate – assemblages of technologies, decision-makers and networks, Macrostate – macro-level phenomenon and emergent behaviour. All model variables are explained in Framework Definitions and specified under Implementation models (Section 2.3).

fundamental property is network connectivity measured by a degree distribution function $P(k)$, which is the probability that a randomly selected node i has k edges. Empirical work has shown that the number of edges k connected to a node often follows a power law distribution of the form $P(k) \sim k^{-\gamma}$ providing a mechanism for network evolution (Barabási and Albert, 1999). Those properties inform our Network Module **G**.

2.2.4. Decision behaviour

Decision theoretic models can capture human interaction with technology and the built environment. For example, choice models can link individual preferences with technology performance, and evaluate decision-making based on observed and unobserved parameters. An important class of decision theoretic models are discrete choice models based on random utility theory (RUM), which can take the general form $P_{ij}(\theta) = \int_{-\infty}^{+\infty} L_{ij}(\beta) \mathcal{Z}(\beta | \theta) d(\beta)$, $L_{ij}(\beta) = \exp(\beta' x_{ij}) / \sum_j \exp(\beta' x_{ij})$ where P_{ij} is the probability that agent i chooses alternative j . The vector x_{ij} are observed variables for agent i and alternative j , β are parameters randomly drawn from a density function $\mathcal{Z}(\cdot)$ and θ is a vector of underlying moment parameters characterizing $\mathcal{Z}(\cdot)$. The probability $P_{ij}(\theta)$ is numerically integrated using Monte Carlo simulations, which allow for general patterns of heterogeneity across individuals in their sensitivity to exogenous variables (McFadden, 1974; Train, 2009). This model flexibility is well suited for simulating interactions between technology and decision making capturing general patterns of demand. The Decision Module **D** computes a human activity to be specified. Here we assume human activity is generally characterised by a series of discrete choices made over time.

2.2.5. Agent behaviour

The behaviour of individual agents can be computed using agent based models (ABM). While mean-field models have been widely successful at predicting average systems behaviour, ABMs are designed to capture stochastic heterogeneity in agents (Fibich and Gibori, 2010). ABMs evolved from cellular automaton (CA) defined over a two-dimensional grid Z^2 where each grid point (i, j) is a site or node. Each site has a state $x_{i,j}(t)$ often a binary at time step t . The neighbourhood NB is the collection of sites that influence the future state $t + n$ of a given site. Based on the current states $x_{i,j}(t)$ and N a function $J_{i,j}$ computes the next state $x_{i,j}(t + 1)$ of the site (i, j) following $x_{i,j}(t + 1) = J_{i,j}(\bar{x}_{i,j}(t))$ where $\bar{x}_{i,j}(t)$ denotes the tuple consisting of all states $x_{i',j'}(t)$ with $(i',j') \in N$. The flexibility of CA's and related ABMs can relax many of the assumptions implicit in mean-field models. A general ABM approach empirically tested demonstrating predictive behaviour is $Prob(t) = 1 - (1 - p) * (1 - q) \wedge k(t)$ where $Prob(t)$ is a binomial choice to be specified such as willingness to adopt at time t and $k(t)$ are previous adopters in a social network, while p and q are internal and external influences respectively (Bass, 1969; Goldenberg et al., 2001; Garber et al., 2004; Goldenberg et al., 2009). Those properties inform our Agent Module **A**.

2.2.6. Framework definitions

Systems behaviour is encoded by a general function $S_t = w(\Phi, \lambda, N, U, S_{t-1})$, where the state of system S_t at time t evolves as a function $w(\cdot)$ of macro-level growth processes Φ e.g. natural resources, GDP, population, etc.; decay λ captures deterioration e.g. average life span of a physical stock, or other negative growth processes to be specified; N is a normalisation algorithm that encodes information feedback between system states to impose limiting constraints across state behaviour e.g. cumulative adoption (microstate) does not exceed total market demand (macrostate); U is the evolution rule, and S_{t-1} is previous state behaviour. We

therefore generalise systems behaviour S_t as a function of growth, decay and information feedback to substate behaviour.

Technology behaviour is encoded by $T_t = g(\Omega, \delta, X, U, T_{t-1})$ where the state of technology T_t at time t evolves as a function $g(\cdot)$ of growth Ω , such as industry investment or policy incentives for innovation and adoption; decay δ captures technology specific negative growth processes such as operational life or targeted decommissioning policies; X is a vector of physical attributes that characterise the performance of a technology e.g. cost, efficiency, information, etc.; U is the evolution rule, and T_{t-1} is previous state behaviour. We therefore generalise technology behaviour T_t as a function of growth, decay and technical performance.

Network behaviour is encoded by $G_t = y(P, E, Q, K, U, G_{t-1})$ where the state of network G_t at time t evolves as a function $y(\cdot)$ of network size P , connectivity E , and what we specify as global Q and local K information feedback signals that influences how the clustering coefficient C_i and degree distribution $P(k)$ changes over time t . For example, Q can specify how agent behaviour is indirectly influenced through exposure to a larger population (global signal), and K specifies direct influence through exposure to personal contacts (local signal); U is the evolution rule, and G_{t-1} is previous state behaviour. We therefore generalise network behaviour G_t as a function of structure, connectivity, and information feedback that influences network evolution.

Decision behaviour is encoded by $D_t = h(T, \beta, G, U, D_{t-1})$ where the state of decision-making D_t at time t evolves as a function $h(\cdot)$ of technology behaviour T e.g. changing performance of incumbent technology, emergent new technology, etc.; personal preferences β for a given technology, which captures various socioeconomic or lifestyle factors; network behaviour G can specify physical, virtual or social networks that influence decision behaviour e.g. supply chains, peer group influence, information transmission, etc.; U is the evolution rule, and D_{t-1} is previous state behaviour. We therefore generalise decision behaviour D_t as a function of individual preferences, technology performance and network influence. In this module, decision behaviour is characterised by a mean-field representation of more than one agent, and interactions with technological assemblages, as opposed to agent behaviour which captures stochastic microstate processes described next.

Agent behaviour is encoded as $A_t = z(D, G, \Psi, U, A_{t-1})$ where the state of agent behaviour A_t at time t evolves as a function $z(\cdot)$ of decision behaviour D , network influence G , and an algorithm Ψ that captures stochastic processes to be specified e.g. asymmetrical information, non-utility maximizing behaviour, bounded rationality, etc.; U is the evolution rule, and A_{t-1} is previous state behaviour. We therefore generalise agent behaviour A_t as a function of decision-making, network influence, and inherent randomness.

2.3. Implementation models, data and calibration

The modelling framework is demonstrated by assessing emerging alternative technology, which involve technological and behavioural interactions across multiple system states. The UK transport system is used to calibrate the model, where systems behaviour S_t is total passenger vehicle stock; technology behaviour T_t disaggregates total stock into vehicle technology classes; decision D_t and agent A_t behaviour compute adoption probabilities at different states, where the former is mean-field average behaviour at longer time scales, and the latter is stochastic individual behaviour at shorter time scales; and network behaviour G_t is specified as social influence on adoption. In the implementation model, systems behaviour is specified as

$$S_t = S_{t-1} * \Phi_t + S_{t-1} - \lambda_t \quad (1)$$

where S_t is change in total technology stock in year t , the growth rate Φ_t of the total stock represents aggregate market demand calibrated to macroeconomic forecasts of demand growth in the UK. The decay parameter λ_t is stock scrappage calibrated to vehicle licencing statistics where a low fraction (~5%) of new vehicles (<3yrs) compared to a high fraction (~70%) of older vehicles (>13yrs) are scrapped (DfT, 2012). The total stock S_t is then disaggregated into vehicle technologies T_{jt} of class j that compete for market share at time t implemented as

$$T_{jt} = (\hat{T}_{jt-1} * \Omega_{jt} + \hat{T}_{jt-1} - \delta_{jt}) * D_{jt} \quad (2)$$

where Ω_{jt} is the growth rate of technology j at time t representing investment, and calibrated to the proportion of technology j to the total stock S_t between 2000 and 2010; δ_{jt} is the scrappage rate of technology j ; \hat{T} is the normalized technology stock specified in equation (5); and D_{jt} is the probability that technology j is adopted at time t . D_{jt} is implemented as

$$D_{jt} = \frac{1}{R} * \sum_{r=1}^R L_{jt}(\beta^r), \quad L_{jt} = \frac{e^{\beta^r X_j^r}}{\sum_{j=1}^R e^{\beta^r X_j^r}} \quad (3)$$

where L_{jt} is the conditional probability to adopt, X_j^r are the observed performance parameters of technology j which can change over time denoted by $(^r)$ capturing technology learning effects, and β 's are random coefficients that capture individual preferences for technology j which also change over time $(^r)$. R is a random draw of β 's from a density function $Z(\beta|\theta)$ where $(\beta_n) \sim Z(\beta_n|\theta)$ as the number of draws R increases variance σ decreases resulting in \sim model convergence. To simulate heterogeneous behaviour different density functions $Z(\cdot)$ can be used, but the normal and lognormal distributions are the most general (Bhat, 2001) and also ensure the model is not over parameterised. A lognormal distribution is used where a β coefficient is the same sign (+/-) for every agent. This allows specification of expected global behaviour, such as negative preferences for high technology costs. To implement feedback constraints between the System **S**, Technology **T** and Decision **D** modules and ensure the growth of individual technologies j does not exceed growth of total vehicle stock S_t specified by aggregate demand Φ_t we implement a normalisation algorithm N where,

$$N_t = S_t / \sum_{j=1} T_{jt} \quad (4)$$

$$\hat{T}_{jt} = T_{jt} * N_t \quad (5)$$

resulting in $S_t = \sum T_{jt}$. The total technology stock S_t therefore places an upper bound on the growth of individual technologies at each time step t . This simulates multiple sigmoidal growth curves with different inflection points, some of which can be negative trajectories due to interaction with decision behaviour D_{jt} where some technologies j are phased out over time t due to low probabilities of adoption due to competing personal preferences β for different technology performance attributes X . The above implementation models S_t , T_t , D_t evaluate long-term (50 yrs) mean-field behaviour at the macro and mesostate. Table 1 summarises technology performance parameters X used as model input values for S_t , T_t , D_t and the Agent Based Model A_t discussed below.

Here we assess stochastic agent behaviour, the Agent Module **A**

assesses shorter term (20 yrs) stochastic individual behaviour specified as the probability to adopt A_{jt} technology j at time t implemented by,

$$A_{jt} = 1 - (1 - P_{jt}) * (1 - Q_{jt}) \wedge K_{jt}, \quad A_t(\Psi) \quad (6)$$

where P_{jt} are personal preferences for technology j which is computed by D_{jt} where $P_{jt} \equiv D_{jt}$ when a low number of random draws R are computed to calculate the conditional probability L_{jt} therefore not converging the model, which otherwise simulates average mean-field behaviour of a population. Recall that a low number of random draws R increases variance σ thereby introducing higher stochasticity, which is interpreted as reflecting more individual randomised behaviour. Network effects enter the model as Q_{jt} which is indirect influence to adopt technology j at time t which is a function of previous adopters n_k out of a population n that an agent is exposed to defined as global exposure $E_Q = Q_{jt} = n_k/n$; Direct network influence is specified as K_{jt} which is a function of previous adopters w_k within a personal network of contacts w where local exposure is $E_K = K_{jt} = w_k/w$. The decision algorithm Ψ is implemented at each time step t specifying that in initial condition $t(0)$ no individual has adopted; in time step $t + 1$ a probability function $A(t)$ is applied to each agent and stochasticity is introduced to capture random behaviour where a random number \bar{Q} is drawn from a uniform distribution $[0, 1]$. If $A(t) > \bar{Q}$ than adoption occurs and agent i is assigned a value (1). By summing values over period $t + n$ cumulative adoption is determined (Goldenberg and Shapira, 2009). We therefore build on the original binomial form of Equation (6), which has been tested empirically showing predictive ability (Garber et al., 2004; Goldenberg et al., 2009, 2010).

For this implementation, ABM simulations take preference P values from the Decision Module **D** as input values $P = 0.20, 0.16, 0.10, 0.25$ combined with random network influence from a synthetic population arbitrarily set at $Q = 0.3, K = 0.1$. For sensitivity analysis, the network is then rewired to simulate different combinations of information feedback including personal preferences $P = 0.1, 0.9$ and global $Q = 0.1, 0.9$ and local $K = 0.1, 0.9$ network influence. Thus stochastic agent behaviour A_t is based on multiple information signals where personal preferences P_{ijt} are weighed against global E_Q and local E_K network influence. Also, while macro and mesostate variables are direct inputs into the microstate agent module **A** there is no explicit feedback from the microstate back to the other state modules. Here the objective is to use the agent module to provide higher resolution analysis for which the results can be used to compare and compliment other model outputs. However, other situations may call for an explicit feedback from the agent based module back to the other state modules for example, where a stochastic agent i determines decision-making behaviour, which could be computed with the agent module **A** providing input for the decision module **D** where $D_{ijt} \equiv A_{ijt}$.

3. Results and discussion

We first implement the Decision Module **D** to calculate adoption probabilities D_{ijt} using 4 simulations shown in Fig. 3 that depict A) a reference case mass market with preferences for low cost, B) early adopter with preferences for environmental performance, C) balanced with combined mass and early adopter preferences, and D) external effects with preferences for increasing support infrastructure e.g. electric vehicle charging. The mass market simulation gives expected results where the incumbent technology T_p is dominant. The balanced and external effects simulations give mixed signals with no clear winner. But the early adopter simulation gives a clear signal showing the highest adoption of T_h over time. The simulations indicate that at discrete time steps there is a

Table 1
Normalised technology T performance parameters X as example model input values.

Technologies	$X_{\text{Purchase Price}}$	$X_{\text{Running Cost}}$	$X_{\text{Fuel Efficiency}}$	$X_{\text{Acceleration}}$	X_{Range}	$X_{\text{Emissions}}$	$X_{\text{Refuelling Availability}}$
T_{Petrol}	1	1	1	1	1	1	1
T_{Diesel}	1.21	0.88	0.85	1.34	1.26	0.95	1
T_{HEV}	1.57	0.59	0.58	1.54	1.52	0.86	1
T_{PHEV}	2.42	0.33	0.56	1.85	1.35	0.67	0.50
T_{BEV}	1.97	0.32	0.29	1.69	0.21	0.47	0.01
T_{FC}	6.00	0.14	0.48	1.85	0.68	0.45	0.01

Notes: Vector X can specify any number of performance parameters for any technology T . Here new technologies compete against incumbent technology T_{Petrol} therefore performance values X are normalised and indexed against T_{Petrol} for model inputs. The full set of technologies include: petrol, diesel, hybrid-electric (HEV), plug-in hybrid electric (PHEV), pure battery electric (BEV), and hydrogen fuel cell (FC). See Tran (2012) for full data description and sources.

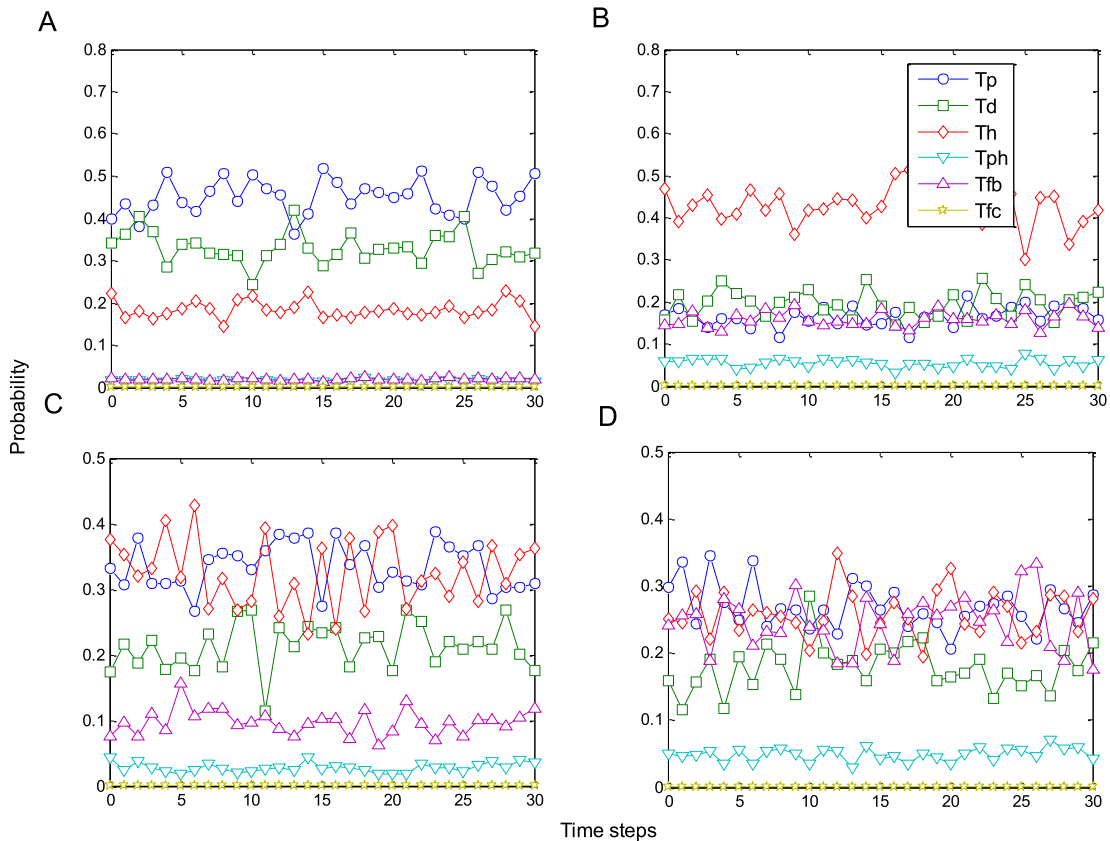


Fig. 3. Mean-field adoption probabilities (D_{jit}) based on agent preferences β for technologies T over time: A) Mass market, preferences for purchase price and reliability, B) Early adopter, preferences for fuel economy and CO_2 emissions, C) Balanced between mass and early adopter preferences, D) External, preferences for support infrastructure; T_p = petrol, T_d = diesel, T_h = hybrid, T_{ph} = plugin hybrid, T_{fb} = full battery electric, T_{fc} = fuel cell.

high level of variation but over time a general trend in decision making emerges. The simulations also allows us to focus in on a particular state behaviour (high adoption of T_h) and assess additional factors, such as change in technology performance X or effects on longer-term system behaviour S_t . In doing so, the Decision Module **D** probability outputs are used as input values for the Technology Module **T**, which then feeds into the Systems Module **S**.

The Technology implementation model T_{jt} is calibrated to the UK passenger vehicle stock (1999–2010) and used to forecast a reference scenario where change in the performance X of incumbent and new technologies are equal. We then show the changes in System Behaviour i.e. total technology stock, when accounting for changing adoption probabilities from increasing technology performance X over time. Fig. 4 A and B shows the reference adoption probabilities and technology growth forecast. Fig. 4C shows how adoption behaviour D_{jt} responds to changes in technology

behaviour T_{jt} when performance attributes X (fuel efficiency, fuel cost, carbon emissions) for alternative technologies improve at twice the rate as the incumbent system. Fig. 4D shows how these co-evolutionary dynamics between technology and decision behaviour can lead to a tipping point in systems behaviour S_t where around 2040 the incumbent technology system is displaced by emergent technology. The simulations show how individual preferences for how a technology improves over time at the unit level can accelerate deployment and influence systems level behaviour, where incremental changes in techno-behavioural dynamics can build up overcoming systems inertia resulting in new technology overtaking the incumbent system. This suggests that an underlying mechanism to trigger tipping points in sociotechnical systems is the positive feedback effect between evolving individual preferences and technology learning.

Although integrating the decision and technology models has

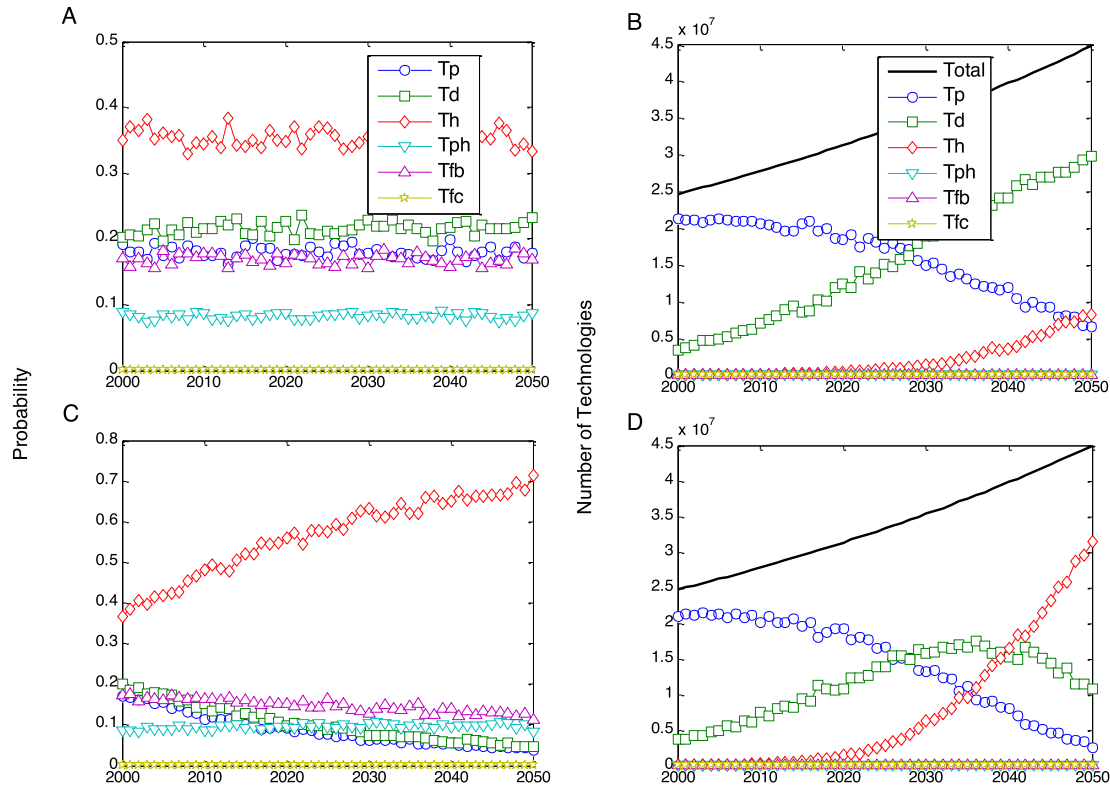


Fig. 4. System behaviour impacts from interaction between technology and decision dynamics: A) Early adopter probabilities (D_{jit}) and resulting B) Technology growth (T_{jt}) i.e. calibrated to UK passenger vehicle stock (S_t) from 1999 to 2010, $R^2 = 0.9702$ at 95% confidence bounds and forecasted to 2050; C) Adoption probabilities when technology performance X (fuel efficiency) of alternative technologies ($T_h, T_{ph}, T_{fb}, T_{fc}$) exceed incumbent (T_p, T_d) by factor 2, resulting in decreasing fuel costs, and CO₂ emissions, and the resulting D) Technology growth.

given some insight into systems behaviour, some resolution has been lost. For example, when the decision model D_{jit} was parameterised to account for increasing technology performance X Fig. 4C shows the resulting high adoption probabilities for T_h . Consequently, all other adoption probabilities are suppressed, but interestingly one alternative T_{fb} was impacted the least, as opposed to previously more dominant preferences for technologies T_p and T_d . But this signal is not picked up in the mean-field technology growth outputs in Fig. 4D because the resolution is too coarse to assess what happens to T_{fb} since the total stock of the incumbent system is orders of magnitude greater. But the signal, however slight, may contain interesting insights, for example why certain behaviour is more or less resistant to change from internal or external effects. The modelling framework now has the flexibility to deploy an agent based approach to evaluate the problem domain at higher resolutions capturing micro-behaviour at shorter time scales.

Feedback between meso and microstate modules $P_{jt} \cong D_{jt}$ allows adoption probabilities D_{jt} for T_{jb} to be specified as individual preferences P and used as input values for the Agent model A_{jt} . Fig. 5A–D show stochastic adoption probabilities based on individual preferences P and global Q and local K network influence held constant to first assess the impacts from variable preferences P . When accounting for these combined micro-level factors a high degree of variability is shown in the short-term, which is more realistic than stylized logistic curves. This is shown by comparing simulation results against empirical data shown in Fig. 5E–H. In general, accounting for high variation could inform a range of adaptive responses rather than depending on single response mechanisms. However, this variability is not picked up in the mean-field technology growth model T_{jt} . Moreover, the simulation results

can be used to establish a baseline by determining the best match to empirical data, which appears to be 5B with parameters $P = 0.16$, $Q = 0.30$, $K = 0.10$ since 5F is data for electric vehicles (T_{fb}). Fig. 6 shows further simulations to assess network clustering where the greatest influences on behaviour are individual preferences P and combined network effects $Q + K$ revealing a potential mechanism to understand and influence decision-making.

4. Conclusions

Complex systems have critical thresholds also called tipping points, where a system abruptly shifts from one state to another. In ecological and financial systems, tipping points generally indicate increasing vulnerability, abrupt change, and loss of resilience (Scheffer et al., 2009; Scheffer, 2010). However, in the context of sustainability, tipping points can also be beneficial where climate policy for example seeks to displace the incumbent fossil based energy system with new clean and efficient technologies (Westley et al., 2011). Our modelling results suggest that an underlying mechanism that can trigger a tipping point in a sociotechnical system is the positive feedback effects between evolving individual preferences, technology learning, and network influence. These combined feedback effects can result in systems level change where an incumbent technology is overtaken by a new innovation. Those feedbacks would not be detected without an integrated approach across multiple system states.

This paper also addresses a common hierarchy problem in computational systems modelling where there is often divergence between mean-field and agent-based approaches. This divergence can dictate the types of questions asked depending on the implementation model chosen. We demonstrate the advantages of

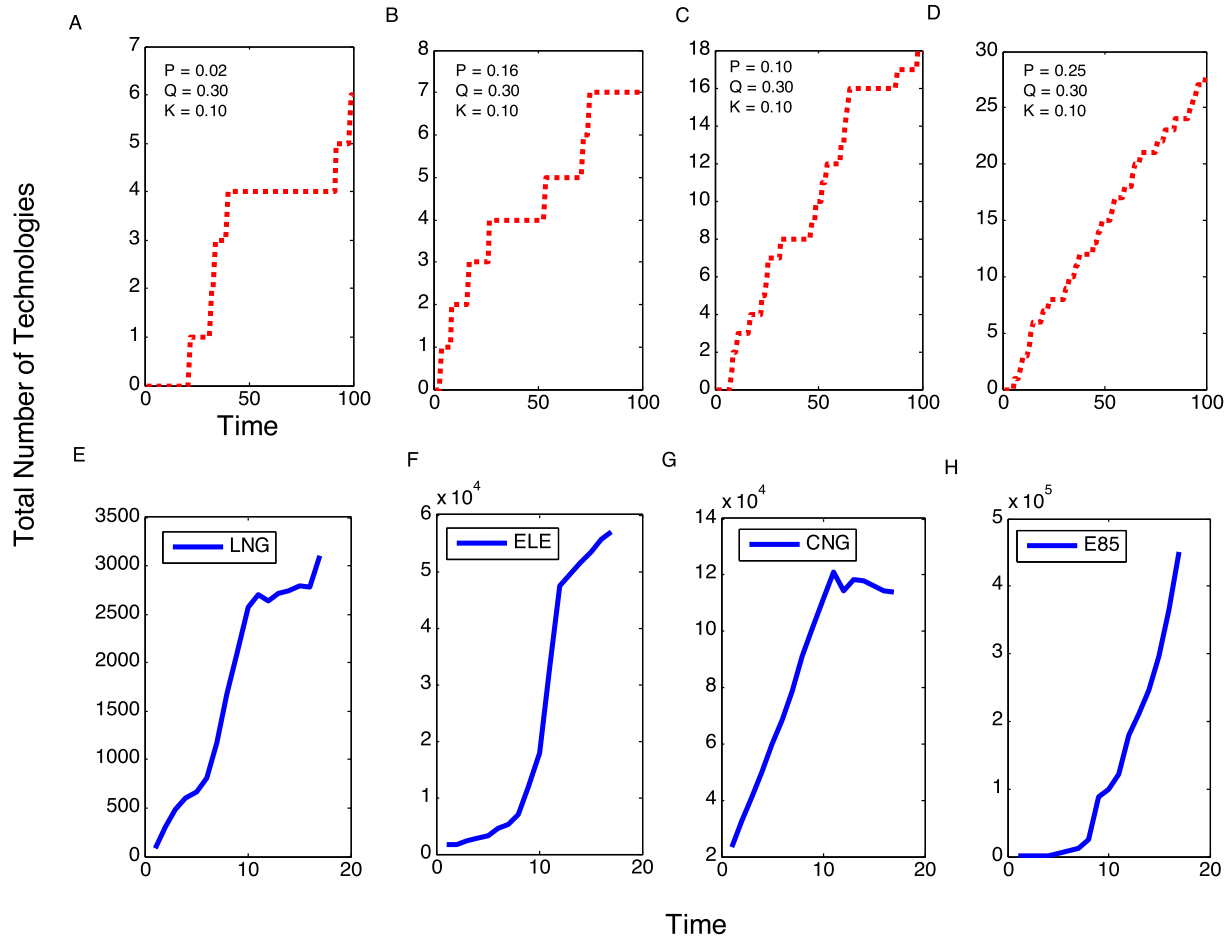


Fig. 5. Total number of technologies at each time step computed by stochastic adoption probabilities (A_{jt}) based on individual preferences P and global Q and local K network effects held constant. Panels A–D are simulations showing high variability in adoption trends reflecting E – H empirical data over 20 years: E) Liquid Natural Gas, F) Full battery electric, G) Compressed Natural Gas, H) Ethanol 85 (EIA, 2013).

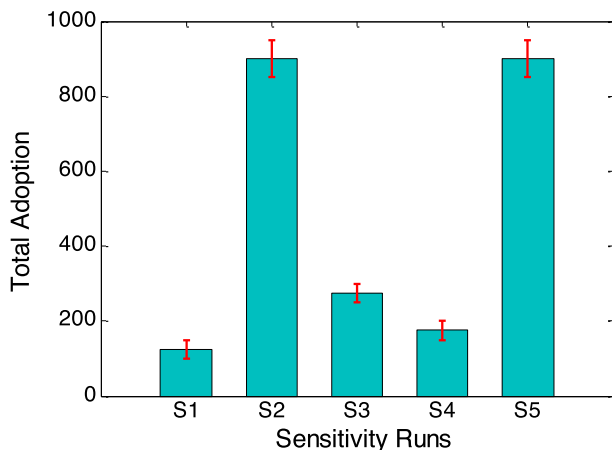


Fig. 6. Sensitivity analysis on model parameters P , Q , K showing highest total adoption based on $\sum A_{jt}$ for individual preferences S2 and combined network influence S5. Solid bar is total average, error bar is range. S1-5 have different parameter settings with 10 model runs each over time step $t = 1000$. Parameter settings: S1 reference case ($P = 0.1, Q = 0.1, K = 0.1$), S2 high individual preferences ($P = 0.9, Q = 0.1, K = 0.1$), S3 high indirect network influence ($P = 0.1, Q = 0.9, K = 0.1$), S4 high direct network influence ($P = 0.1, Q = 0.1, K = 0.9$), S5 high combined network influence ($P = 0.1, Q = 0.9, K = 0.9$).

enables different spatial and temporal resolutions across multiple system states. This allows computational flexibility, which can help to address a common problem domain from different analytical perspectives depending on what question is being asked. This approach is also effective because insights from one set of model results may lead to other questions that require another set of modular tools. This is demonstrated by assessing the emergence of alternative technology across multiple system states, and showing how analytical and computational flexibility can provide insight at different but complimentary scales.

We need to improve our understanding of how behavioural patterns can co-evolve with technological change. Our techno-behavioural dynamic framework provides tools for assessing a wide class of emerging ubiquitous technologies (nano, bio, ICT) that will directly interact and respond to human behaviour, and have to compete against incumbent technological systems and normative risk. We argue for the need to move away from the arbitrary separation between supply and demand-side factors and view technology and behaviour as a coupled dynamical system. This is important for understanding how new technology influences human activity, and more generally for assessing the risks and benefits of emerging technologies on society and environment.

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