SMARTEES: Deliverable 7.2 (Report)

Simulation model implementing different relevant layers of social innovation, human choice behaviour and habitual structures

Report describing the theoretical principles of the model and justification and clarification of assumptions used

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Author(s)	Patrycja Antosz, Wander Jager, Gary Polhill, Doug Salt, Amparo Alonso-Betanzos, Noelia Sánchez-Maroño, Bertha Guijarro-Berdiñas, Alejandro Rodríguez	
Contributor(s)		
Reviewer(s) (if applicable)	Christian A. Klöckner, NTNU	
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Executive summary

SMARTEES studies how the roles of various stakeholders influence dynamics of social innovation diffusions in ten European cases that have successfully transformed (or are in the process of transforming) communities towards more sustainable practices. The cases range from holistic mobility plans (Groningen, Zürich), transitions towards renewable energy use on island communities (Samsø, El Hierro), district regeneration of housing quality (Stockholm, Malmö), mobility in superblocks where transit traffic is not allowed (Vitoria-Gasteiz, Barçelona), and policies aimed at resolving energy poverty (Aberdeen, Timisoara). An important challenge in learning about the success – and possible risks of failure – of these cases resides in understanding how policy development and community dynamics interacted. To explore this in a systematic way, SMARTEES ABM architecture was designed and described in detail in this deliverable.

1 Introduction

Communities are the natural social structure of humans, often organised around a set of shared resources. In ancient history, human tribes could be found in places with a variety of food and safety conditions. Today, many of us live in urban neighbourhoods providing home, supermarkets, schools and work not too far away. What has not changed throughout the ages, however, is that characteristics of human surroundings still affect life quality and satisfaction of local communities. In modern times, public policies have a significant impact on how these surroundings are shaped.

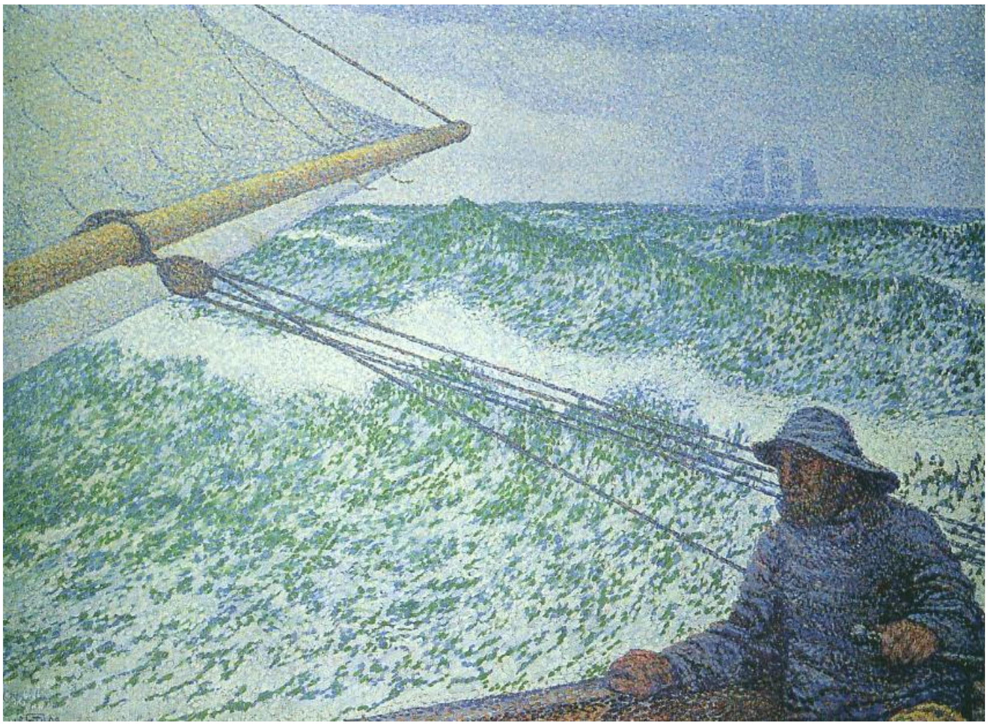
Public policies are becoming ever more community-oriented (Jager, Yamu in press). Whereas in the past municipalities often decided what was best for a neighbourhood, nowadays various forms of participation and co-creation are increasing in popularity. Coherence between top-down policy and bottom-up community dynamics is an important driver for effective collaboration. When "deciding for" successfully changes into "deciding with", the resulting outcomes are often more satisfactory for stakeholders.

The scale and complexity of plans may impact social dynamics, and the collaboration process itself. The wider the array of expected outcomes associated with a plan, or/and the larger the differences between people concerning their expected benefits versus losses, the more likely it is that networks of interest groups and conflicts between them emerge. The question is how a municipality, carrying the formal responsibility for the implementation of local level public policies, can identify the risk of conflicts and mitigate these at an early stage by structuring the planning process. SMARTEES studies how the roles of various stakeholders influence dynamics of social innovation diffusions in ten European cases that successfully transformed communities towards more sustainable practices. The cases range from holistic mobility plans (Groningen, Zürich), transitions towards renewable energy use on island communities (Samsø, El Hierro), district regeneration of housing quality (Stockholm, Malmö), mobility in superblocks where transit traffic is not allowed (Vitoria-Gasteiz, Barçelona), and policies aimed at resolving energy poverty (Aberdeen, Timişoara). An important challenge in learning about the success – and possible risks of failure – of these cases resides in understanding how policy development and community dynamics interacted. To explore this in a systematic way, SMARTEES ABM architecture was designed and described in detail in this deliverable.

The deliverable 7.2 is structured as follows. Section 2 offers an introductory explanation of the approach to prediction in complex systems. Section 3 focuses on presenting all elements of SMARTEES ABM architecture, i.e. representations of local communities and their social networks, energy-related social innovations, policy scenarios, organisations and context. Section 4 outlines interdependencies between SMARTEES work packages and reflects on connecting agent-based models to the Policy Sandbox Tool. Standards for describing ABM code are presented in Section 5. Finally sections 6 and 7 respectively express acknowledgements and cited literature.

2 Prediction in complex systems

Figure 1. Painting by Théo van Rysselberghe: L'homme a la barre, 1892.



Wa't farre wol, moat stoarmen noedzje[1]

A main objective of social scientific research is understanding how social systems work, predicting future developments, and identifying effective policy interventions to change these developments. Often social scientific methods are successful in making accurate predictions of human responses to interventions. In particular within the discipline of marketing, elaborated statistical models have been developed that are capable of predicting how customers respond to price-cuts and advertisements. Having the shopping card data from many customers makes it possible to make accurate predictions in e.g. the relative stable retail domain. However, we have to realise that these successful predictions mainly apply to behaviour in relative stable situations. Acknowledging that most of our daily behaviour is taking place in stable and habitual contexts, it comes as no surprise that the prediction of future states of social systems using statistical methods of linear modelling has become very popular.

2.1 Transitions in society

However, sometimes social systems are transforming and restructuring in more fundamental ways. For example, the rise of the Internet had an enormous impact on communication and purchasing behaviour, and the rise of the private car had a huge impact on where we live and work, and the public space in cities. Such changes, which affect the structure of society, are often called "disruptive innovations". When we identify a situation where a social system is transforming from one stable structural state to another, we deal with transitional dynamics. The transitional period between two stable states is by definition unstable, and if different future states can be envisaged, uncertainty about

[1] Frisian saying. "Who wants to go sailing has to deal with storms" expressing that action comes with uncertainty.

the future will be high. Transitions can be very large, such as the agricultural revolution, the industrialisation and the current information/algorithm/artificial intelligence revolution. Transitions can be violent and have huge impacts on the lives of millions, such as economic and ecological crises, the collapse of political structures, war and mass migrations.

Transitions are often of a smaller scale and have a less profound impact on humanity than in the cases mentioned before; even so, the instability and uncertainty in the transformational period remain. For example, the city of Groningen, a case in our SMARTEES project, started in the 1970s with a radical new way in thinking about traffic in the city. From a social system that was oriented on adapting to and facilitating the use of cars, a new system was propagated stimulating the use of bikes and banning cars – in particular transit traffic – from the city centre. This transition started with segmenting the city centre into four sectors, and obstructing cars' passage from one sector to the other through the centre. This was a revolution, as up until that moment the social system was focussing on facilitating cars. This revolution set the stage for many other developments that promote biking in the city, some successful, but also plans that failed to be realised. The success or failure of certain developments in such transitional conditions can be a close call, as the referendum on closing the Noorderplantsoen park for car traffic demonstrated. After closing the park for cars for a year so people could experience the new situation, a city-wide referendum took place, and 50.9% of the people voted in favour of closure. It is very easy to imagine that one person having a stronger voice in favour of cars could have easily tipped this referendum to keep the park open for cars.

2.2 Complexity and uncertainty

When complex systems are in a more turbulent state, small causes can create large effects. For the weather system this has been identified by Lorenz (1993) and is widely known as the butterfly effect. The roots of this fundamental uncertainty can be linked to the uncertainty principle of Heisenberg (1927). For social and ecological systems that move towards more turbulent system behaviour it is known that predictability using linear models collapses. Ecological science demonstrates that major transitions in ecological systems towards a different regime (transition) are often preceded by increased variances, slower recovery from small perturbations (critical slowing down) and increased return times (Boettiger & Hastings, 2012; Dai, Vorselen et al, 2012; Dakos, Carpenter et al, 2012). The expectation is that also for other complex systems such indicators may signify the approach of a tipping point and a regime shift or transition (Scheffer et al, 2009). A possible thought for further exploration, would be to liken the data to noise: in stable systems, we may expect the noise will be more fractal in nature (pink noise, $1/F$); when approaching a tipping point the noise will become more synchronised and less fractal (e.g. white noise). These ideas, however, are tentative but could be verified with appropriate analysis of simulation data on transitions.

When a linear model is performing badly in predicting system behaviour, the logical response from within this perspective would be adding additional variables to improve predictive power. In a stable system this is a sound strategy, but when a system starts behaving with more turbulence we enter a regime of fundamental unpredictability, and traditional point prediction becomes increasingly short-sighted and ultimately of no practical use. Adding more variables in the linear equation will not contribute to better predictions under such conditions. Instead we would benefit from indicators that inform us that a tipping point is approaching. This can be coined as "predicting unpredictability". When you know a system becomes turbulent, you will have to be more adaptive and responsive to developments as they emerge. A classic example would be the sailor being warned by the meteorologists for thunderstorms. Where and if these thunderstorms emerge remains unclear, but the sailor will keep a close eye to the sky, and will adapt his/her plans when a storm grows. The same holds for policy making in turbulent times. When the social system begins to have more turbulent dynamics, the future becomes uncertain, and policymakers should be very observant and adaptive.

2.3 Self-organisation

Being in a state of turbulence (or chaos), social systems, just like any other organic system, have the capacity to self-organise and stabilise again. Self-organisation is a key to life, and all living species, ranging from bacteria, fungi, plants, insects to the more cognitively endowed species display self-organisational group behaviour emerging from interactions at the local level (e.g., Heylighen, 1997). When people adapt their behaviour to other people's behaviour, the resulting coordination and synchronisation will result in creating a new stable state. This new stable state may be of a higher quality (utopian), but may also imply a worse situation (dystopia). A challenge for the social sciences thus is the identification of processes that lead to more turbulence, and the identification of possible stable future states. An important observation here is that we cannot isolate the human system from natural systems. We have to be aware that the human system is coupled to other natural systems, and that instabilities in other systems may have destabilizing impacts on the human system as well. Examples would be the impacts of climate change and reduced biodiversity on the human condition.

As a metaphoric example, we may think of a flow of water creating a delta. When the water flows and meets an obstruction, it can find different pathways to flow. Such a decisive point (tipping point, or bifurcation) may result in different routes for the water, some bigger, some smaller, as the picture of the Lena river delta shows. Sometimes there will be a simple fork, but also much more elaborate branches of streams may evolve. The wider streams will erode more of the soil, hence will deepen and allow for increasing quantities of water to flow. Self-reinforcing loops may emerge causing some of the streams to become dominant (lock-in).

Figure 2. Delta of the Lena River, Russia.

Using a statistical analysis on an existing river delta we could in principle predict the chances of a water molecule to reach the sea through the larger and smaller branches of the river delta. However, if we want to predict the future of a social system, we deal with the problem of not knowing how the delta of the future looks like, because it still has to form. Moreover, very different delta shapes may emerge, depending on sheer chance and on deliberate actions to control and shape the future.

2.4 Simulating futures

Because the future does not exist yet, we do not have data, but when we have a simulation model we could explore what different futures are more and less likely, and how we effectively can change the course of history. As such, simulation models can produce a landscape like a delta system, identifying more and less plausible developments, splitting streams and whirlpools of attraction. To be more precise about the simile, in our case of modelling the future, the empirical reality that will unfold itself will be like a ball flowing through this landscape. Ultimately, empirical reality will follow a single path, one of the many potential paths. Simulation studies can contribute to the identification of the more and less likely routes. Hence, we face the challenge of growing the potential futures landscape by running a lot of simulations and exploring how different possible futures branch out. Using models that capture the essential causal mechanisms in the social system, and running these models under a variety of starting conditions, we can build a large dataset of simulation runs that, combined, show how different futures may "meander" out.

Here we have to be aware that the metaphor of landscapes is limited, as we do not know how many dimensions actually play a role in these social systems. It will probably be more than in the simple case of meandering rivers.

Such a dataset of potential futures can reveal a number of relevant insights on the transitional dynamics in social systems. First, we may identify more than one "main pathway" that are likely. If we identify a number of these main streams that are most likely to happen, we have identified different "basins of attraction" in the system. Obviously it is of key interest to evaluate these different regions of attractiveness in terms of utopian/dystopian characteristics.

Second, we may identify points in time where different futures branch out. Sometimes these may be in the shape of forks, also called bifurcations in complex systems. These are the situations where the streams split, and can be considered to be the tipping points that determine which pathway is going to be dominant. In the Noorderplantsoen case the referendum typically is such a bifurcation point that determines the future of the park (and developments building upon that). However, we can also imagine situations where multiple branches can sprout of a tipping point. The key is to identify the approach of more turbulent stages in a social system, and having a perspective on the "main pathways" that may emerge from there. This perspective is expected to contribute to a directional adaptive response to developments, blocking negative developments as fast as possible, and supporting processes that grow in a good direction.

Third, we may explore if and how we can identify possibilities to influence the course of the stream at a tipping point. The earlier you detect a stream is likely to go towards a dystopian future, the easier it might be to take measures to prevent that. The longer the stream has taken a dystopian path, the more difficult it will be to "tip" it to the utopian stream. Considering the traffic case, making a city centre car-free in the 1970s was relatively easy because the number of cars were fewer, and many important infrastructural decisions were yet to be made. However, today's situation in many cities will be different, having had decades of ever-increasing numbers of cars and infrastructure to accommodate them. The city has been locked-in a car based transportation system. This makes it more difficult to make a city car-free these days than in the past. When a social system reaches a tipping point it is easier to support the grow in a certain direction, than when you want to stimulate turbulence in the system to create conditions for change. Acknowledging that sometimes social systems are deeply locked in, some authors have reflected on how to stimulate turbulence in society as a precondition for change. One of the key examples is the book by Sharp (1993) that is aimed at supporting revolutions (tipping points), and that has inspired many civil movements to replace dictatorships.

2.5 The value of simulation

Simulation models thus allow for creating a landscape of potential futures, identify possible utopian and dystopian attractors in the landscape, and identify the tipping points where the system becomes turbulent and policy may be very effective in steering towards a benign future. To prevent a dystopia is better than to cure one.

3 SMARTEES ABM Architecture

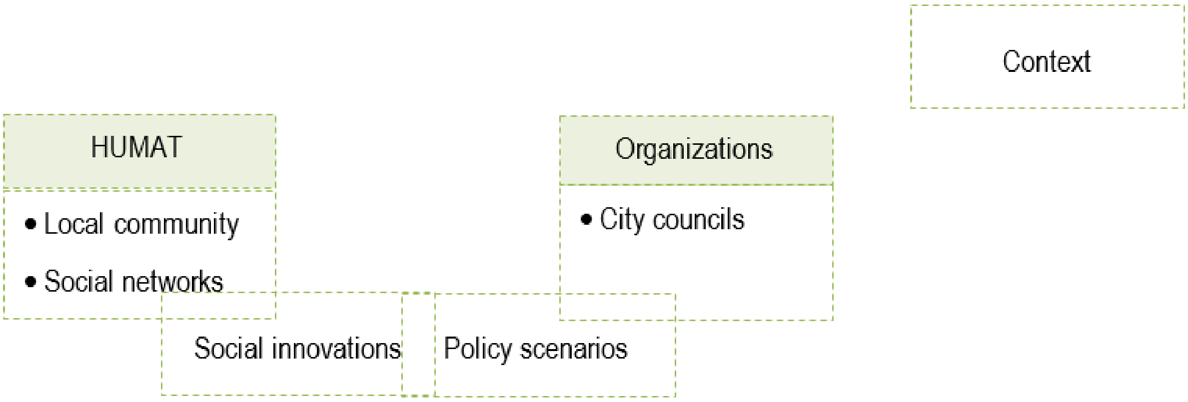
SMARTEES agent-based modelling architecture was designed for the purposes of studying the **diffusion of social innovations in a local community**. The developed approach to modelling will serve two purposes:

- enable systematic comparisons of effects of pre-defined policy scenarios on the diffusion of social innovations, and
- inform the sandbox tool to be developed in the project.

The SMARTEES ABM architecture comprises of standardised model components (i.e. building blocks) representing entities and their characteristics. Five main building blocks (Figure 3) have been identified and standardised for the purpose of agent-based modelling:

- HUMAT - local community and social networks;
- Social innovation and its diffusion in local communities;
- Organizations, including city councils;
- Policy scenarios;
- Context.

Figure 3. Building blocks of the SMARTEES ABM architecture.



Even though each studied case in SMARTEES is different, via the use of ABM architecture the project aims to describe all cases with the use of as many of the same dimensions as possible. Standardising the way dimensions are modelled enables (a) controlling important factors influencing the diffusion of social innovations, (b) comparing agent-based models of different social innovations and (c) possibly introducing these dimensions in the policy sandbox tool. Therefore, whenever possible, the modelling will utilise standardised building blocks for representing case entities. It is emphasised that using the standardised architecture does not necessarily imply all cases will be represented in exactly the same way. On the contrary, the cases should always be represented in the way that resembles the reality to the closest degree convenient for the modelling purpose.

3.1 HUMAT – local communities and social networks

Computer simulations of humans in communities require an architecture that is capable of linking perception, motivations, decision-making, and communication. Hence, it calls for an integrated framework, which combines and causally links theoretical notions of the different relevant elements, and thus can be considered a computational social theory (e.g. Vallacher, Read & Nowak, 2017). Several architectures aimed at integrating cognition with social activity are available, e.g. BayesAct (Schröder, Hoey & Rogers, 2016), dynamical affinity model (Bagnoli et al. 2007; Carletti et. al. 2008), Polias (Brousmiche et al. 2016), Agent_Zero (Epstein, 2014), co-development of beliefs and social networks (Edmonds, 2019).[2] Topics relevant in modelling social dynamics in communities relate to (1) the formation of networks of interest groups in the development of plans, and (2) the processes that drive opinion dynamics and subsequent actions.

Formation of networks of people sharing similar interests is an important social dynamic in community processes, therefore it is crucial to start with identifying how people organise themselves in groups to improve their status quo or to implement changes. The homophily principle, known commonly as "similarity attracts" and "birds of a feather flock together", is a heuristic often used within social simulation models to address group formation, normative pressures and clustering effects (e.g. McPherson, Smith-Lovin, Cook 2001; Jager 2017). Data on how groups sharing particular interest form and grow and on how groups having conflicting interests interact has to be collected, and subsequently implemented in the modelling framework. For example, a plan to reduce car traffic in a neighbourhood may be supported by people living in that neighbourhood for safety or environmental quality reasons, yet shopkeepers may fear a decline of their turnover if the traffic organization changes. Citizens emphasising safety may discuss the issue with parents on a schoolyard, an environmental working group discussing air and noise pollution may be formed, and shopkeepers may voice their concerns through the media. Usually a fixed network with small-world or scale-free properties is used in social simulation models. However, understanding the social dynamics surrounding local planning issues requires letting networks grow on the basis of shared stakeholder interests. Ideally, empirical data reveals what dimensions of similarity play a role in formation of such topical driven networks, and what the emergent properties of resulting networks are. Parents in schoolyards may display a spatially condensed clustered network, whereas a network of shopkeepers may assume a star-like topology, if a strong opinion leader (or formal representative) is present.

The second challenge of modelling social dynamics is capturing communication between actors. Many social simulation models have been developed addressing the conditions under which agents collect social information to make decisions. However, in the communities studied in the SMARTEES cases, communication dynamics are dictated by agents' needs to manage consistency associated with implementing a socially innovative behaviour. That process is realised either by inquiring about information about an (socially innovative) action, or actively signalling their experiences (e.g. people, who are motivated to convince others of their opinion). Psychologically plausible architectures that address agent's motivation to actively communicate particular information to other agents in order to change their behaviour/opinions are not available. Integrating ideas on human motivated cognition and communicative networks led us to develop an agent architecture, that can be used to simulate social dynamics and communication in communities. Outgoing communication often aims to change other peoples' opinions and behaviour, which seeks to improve the outcomes for the sender. These

[2] For a broader review of ABM architectures, see Chin et al. 2014.

effects may relate to (expected) experiential outcomes, the social connectedness and the (core) values a person has. Hence, we propose that the motivation of a simulated agent to communicate to another agent is based on a cognitive dissonance between experienced and expected outcomes related to agent's needs and values.

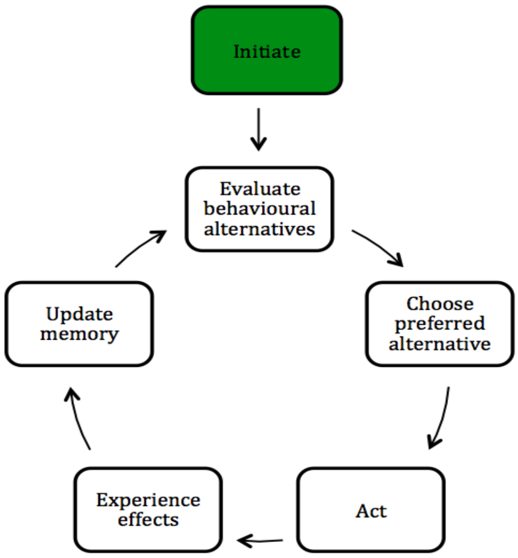
A local community is often heterogeneous with respect to socio-demographic characteristics and attitudes towards socially innovative behaviour. One of the aims of the research of WP6 is to identify stakeholders and subpopulations and their social networks for studied social innovations (task 6.1). Therefore, in agent-based models the local community is represented as heterogeneous agents, who, via sharing similar socio-demographic characteristics, are driven by similar motives to take similar social actions. We will use the concept of typification, present in phenomenology, to construct model assumptions regarding motivated action of individuals in local communities.

3.1.1 Decision-making strategies

HUMAT was developed as a basic architecture for constructing artificial populations, in which agent cognitions, decision-making and social interactions are based on social scientific theory. Real world social dynamics, such as social innovations, opinion dynamics and behavioural transitions (e.g. Nyborg et al. 2016) involve the behaviour and communication of many different individuals connected in social networks, who make decisions on their behaviours on the basis of their interests, share information with others, and are susceptible to norms. They are repeatedly confronted with difficult choices, as trade-offs are often made between short term gratification, social impacts of choices and personal values. Interactions between individuals result in a diffusion of new behaviours, formation of opposite opinion groups, and emergence of tipping points giving dominance to particular norms.

The HUMAT architecture formalises a number of drivers and processes underlying social dynamics. The process of taking action can be divided into several stages depicted in Figure 4.

Figure 4. Taking action in HUMAT.



3.1.1.1 Evaluate behavioural alternatives

The initiation of agent activity starts with the **needs** being satisfied (or not) by different behavioural alternatives. Several theories on needs offer different, yet overlapping taxonomies on what drives human behaviour (Maslow 1954; Max-Neef 1992; Kenrick, Griskevicius, Neuberg & Schaller, 2010). For modelling purposes in HUMAT, we distinguish between three categories of needs: (1) experiential needs (e), which, among others, refer to comfort and costs, (2) social needs (s), referring to belongingness (Baumeister, Leary 1995), relatedness (Deci, Ryan 2000; i.e. to feel close and accepted with important others and with important groups of others), social safety, social status, and (3) values (v), referring to autonomy, biosphere and societal goals. This distinction introduces a possibility of trade-offs between different need groups, which may result in the experience of cognitive dissonances impacting agent's information processing and chosen actions. Moreover, the distinction allows for variance in satisfaction-depletion dynamics of different need categories, which may be relatively fast for experiential needs, and slower for social needs and values.

The overall expected (*p*) (dis)satisfaction from a behavioural alternative *i* for HUMAT *j* at time t_n ($S_{i,j}^{p,t_n}$) is an additive function of the extent of a need satisfaction that the behavioural alternative provides multiplied by the importance of a respective group of needs ($k \in \{e, s, v\}$):

$$S_{i,j}^{p,t_n} = \frac{I_{e,j}^{t_n} S_{i,e,j}^{p,t_n} + I_{s,j}^{t_n} S_{i,s,j}^{p,t_n} + I_{v,j}^{t_n} S_{i,v,j}^{p,t_n}}{3}, \qquad \text{(Eq. 1)}$$

where:

$I_{k,j}^{t_n}$ - importance of *k-th* group of needs for HUMAT *j*,

$S_{i,k,j}^{p,t_n}$- expected satisfaction from behavioural alternative *i* on *k-th* group of needs for HUMAT *j* at time *tn.*

Therefore, evaluation of a behavioural alternative *i* with respect to *k-th* group of needs for HUMAT *j*, i.e.:

$$E_{i,k,j}^{t_n} \;=\; I_{k,j}^{t_n} S_{i,k,j}^{p,t_n}, \qquad \text{(Eq. 2)}$$

can be:

- Dissatisfying (i.e. $-1 \leq I_{k,j}^{t_n} S_{i,k,j}^{p,t_n} < 0$),
- Neutral (i.e. $I_{k,j}^{t_n} S_{i,k,j}^{p,t_n} = 0$),
- Satisfying (i.e. $0 < I_{k,j}^{t_n} S_{i,k,j}^{p,t_n} \leq 1$).

When a behavioural alternative evokes sufficient levels of both satisfaction and dissatisfaction in one (or more) group of needs, a motivational state of cognitive dissonance is experienced, and HUMAT faces a dilemma. Based on the type of trade-off between the need groups, three different types of dilemmas can be identified, i.e. experiential, social and values.

The **experiential dilemma** occurs when a behaviour yields satisfaction on social needs and values and dissatisfaction on experiential needs, or when the experiential needs are satisfied and social needs and values are dissatisfied. For example, when HUMAT is considering insulating its house. The process is costly and disrupts the HUMAT's life (i.e. insulating evokes dissatisfaction on experiential needs), but all neighbours are renovating (satisfaction on social needs) and insulation relates to environmental sustainability (satisfaction on values).

The **social dilemma** occurs when a behaviour yields satisfaction on experiential needs and values and dissatisfaction on social needs, or when the social needs are satisfied and the experiential needs and values are dissatisfied. For example, when HUMAT is considering biking to work. Biking is healthy, fast, and cheap (i.e. it evokes satisfaction on experiential needs) and sustainable (satisfaction on values), but it is the social exception (dissatisfaction on social needs, but for an anti-conformist this would be very satisfying!).

The **values dilemma** occurs when a behaviour yields satisfaction on experiential needs and social needs and values are dissatisfied, or when values are satisfied and experiential and social needs are dissatisfied. For example, when HUMAT considers driving a car to work, which is comfortable (satisfaction on experiential needs), and popular (satisfaction on social needs), but it negatively impacts the environment (dissatisfaction on values).

3.1.1.2 Choose preferred alternative

Once HUMAT assessed the satisfaction level of all the available behavioural alternatives, it chooses the most satisfying one. However, if at least 2 alternatives are about similarly satisfying, HUMAT further explores the similar options with respect to how much cognitive dissonance each will evoke and chooses the alternative that requires least effort to reduce the dissonance.

The amount of dissonance that a behavioural alternative *i* evokes in HUMAT *j* at time *tn* ($D_{i,j}^{t_n}$) is calculated as follows:

$$D_{i,j}^{t_n} = \frac{2d_{ij}}{d_{ij}+c_{ij}}, \qquad \text{(Eq. 3)}$$

where:

d_{ij}- dissonant cognitions, i.e. $\min\ \left(\sum_k satisfying\ E_{i,k,j}, \sum_k \left|dissatisfying\ E_{i,k,j}\right|\right)$,

c_{ij}- consonant cognitions, i.e. $\max\ \left(\sum_k satisfying\ E_{i,k,j}, \sum_k \left|dissatisfying\ E_{i,k,j}\right|\right)$.

If alternatives are also similar with this respect, HUMAT exhibits a preference for the behaviour, which is more satisfactory on experiential needs. Hence HUMAT, when facing a very difficult choice between very similar behaviours, tends to lean towards hedonism. If alternatives remain similar, HUMAT chooses randomly between the competing behavioural options.

Pre-action dissonance reduction strategies. Dissonance between cognitions, in HUMAT pre-defined as given types of dilemmas agents can face, is a motivational force for change in knowledge (Festinger 1987/1999) or behaviour (Harmon-Jones, Harmon-Jones 2002). When dissonance exceeds HUMAT's individual threshold of tolerance (F), behaviour is impeded until the incoherence is resolved (Harmon-Jones, Harmon-Jones 2018, p. 74). At time t_n a behavioural alternative *i* evokes a certain fraction of above-tolerance-threshold non-dissonance in HUMAT *j*:

$$F_{i,j}^{t_n} = 1 - \frac{D_{i,j}^{t_n} - T_j}{1 - T_j}, \qquad \text{(Eq. 4)}$$

If $F_{i,j}^{t_n} > 1$, $F_{i,j}^{t_n} = 1$.

Dissonance reduction can be achieved in various ways (McGrath 2017). Often dissonant cognitions are suppressed or ignored as an effective dissonance reduction strategy. If dissonance from behavioural alternative *i* is below the individual tolerance threshold, it is negligible and distraction or forgetting are sufficient strategies to resolve it. The level of cognitive dissonance is here treated as a motivational state that requires resolution. Following an assumption from motivational intensity theory, the higher the motivation, the more effortful strategies can be implemented in the search of a better alternative

(Brehm et al. 1983; Brehm, Self 1989). Therefore, the HUMAT architecture assumes, that the higher the level of dissonance, the more effortful strategies HUMAT can implement to resolve it. Ex ante-strategies to resolve cognitive dissonance, according to difficulty involve:

1. distraction and forgetting (e.g. forgetting the cold draft of a non-isolated house when insulation is discussed in summer)
2. changing dissonant/consonant cognitions (e.g. reducing the cognition of biking being uncomfortable - decrease the satisfaction of experiential)
3. in cases of social dilemmas – changing ego-network composition (e.g. avoiding discussions with HUMATs, who act differently or have dissimilar views).

Social interactions in HUMAT architecture are dictated by the agent's imperative to manage cognitive dissonance associated with implementing a socially innovative behaviour. On the community level, nodes of the social network denote HUMATs, whereas links denote a communication act, i.e. sharing information about a behavioural alternative. Communication among HUMATs is a result of a motivational state of cognitive dissonance that inspires agents either to inquire about information from a specific part of their ego-networks or to share information with specific members of the ego-network. Changing dissonant and consonant cognitions is realized through actively inquiring about information on a behavioural alternative within an ego-network. Moreover, when social needs are dissatisfied, or when expected satisfaction level from an action is significantly different from actually experienced satisfaction, HUMATs actively signal their experiences (i.e. try to convince others to behave similarly to them, or inform others about disappointment or unexpected gratification the action brought about).

If HUMAT has generative cognitions (i.e. core beliefs related to identity) associated with the modelled decision (core-value HUMAT, hereafter), it will prefer dissonance resolution strategies, which do not involve the adjustment of the core-cognitions. For example, a vegan is not likely to accept meat for a Christmas dinner, and a car aficionado will go to great lengths to persist in using the car for individual transportation. As a rule, HUMAT is very unlikely to compromise its core values, therefore it does not experience all types of possible dilemmas.

It is important to highlight that at the stage of resolving cognitive dissonance before taking action, the decision which action HUMAT will take is already made. Therefore, dissonance resolution strategies are employed only to confirm that decision. All attempts to change dissonant/consonant cognitions via inquiring, especially with respect to choosing the relevant part of ego-network is biased in favour of the chosen behavioural alternative.

HUMAT architecture does not aspire to model all individual cognitions, although is it recommended to gather this information in the study. Therefore, the process of dissonance resolution is mathematically represented by changing the importance of the group of needs, which is involved in causing the dissonance. This implies the depreciation of the not-chosen behaviour, and the appreciation of the chosen behaviour, and relates to post-consumption dissonance reduction (e.g. Cohen, Goldberg 1970). Depreciation of a similar behavioural alternative, which was not chosen as the preferred one, proceeds through the same dissonance resolution strategies, yet in an inverted order, as appreciation of the preferred alternative.

It might be the case, that action has to be taken, even though cognitive dissonance associated with it is not fully resolved. Therefore, a HUMAT can utilise additional resolution strategies post-action.

3.1.1.3 Act and experience effects

If action had to be taken, and dissonance was not resolved to a sufficient level, HUMAT continue inquiring in the ego-network about additional information useful in dissonance reduction or about better behavioural alternatives.

Following action, HUMAT experiences the outcomes of behaviour first hand. When experiencing significant discrepancy between expected and actual satisfaction from a taken action, HUMAT signals its satisfaction or disappointment to other HUMATs in the ego-network. However, knowledge about effects of behaviour can also be acquired by being informed about behavioural outcomes by HUMATs in the ego-network (i.e. when other HUMATs signal), or by observing other HUMATs' behaviours (e.g. observing local community's norms).

3.1.1.4 Update memory

HUMATs are equipped with cognitive representations of past evaluations of possible behavioural alternatives. Memory of a HUMAT is represented by a stack of behavioural alternatives ranked according to their multiple need satisfying capacity. The behaviour on top of the stack is performed and provides the level of need satisfaction experienced by the agent ($S_{i,j}^{p,t_n}$ in Eq. 1). The more positive outcomes and the fewer negative ones, the higher the need satisfying capacity of a behaviour.

The more information an agent has on the (dis)advantages of different behaviours, the more **experiences** the agent has. This does not mean the agent is an expert, as the information may be biased and incorrect. Importantly, having executed a particular behaviour may result in more cognitions, than being informed by other people or observing. For example, experiencing sour buttocks as a newbie cyclist is something people are more likely to feel, rather than to observe or to explicitly be told about by more experienced cyclists that do not have this experience (anymore).

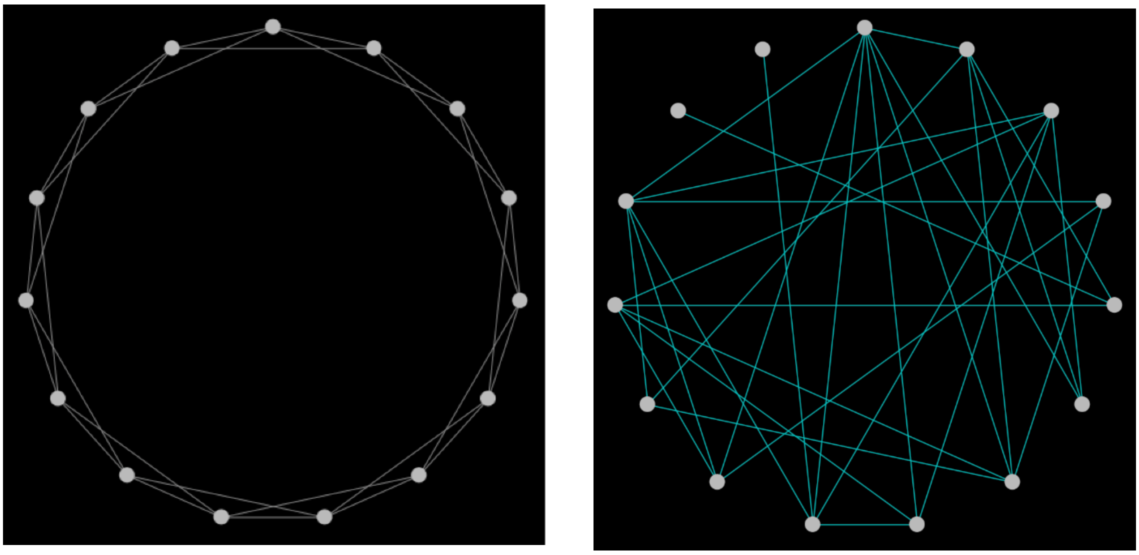
The individual ranking of behavioural alternatives is dynamic. The ordering of the memory stack changes depending on (1) the **actually experienced satisfaction** (e.g. new tarmac makes biking more comfortable), (2) a different weighting of outcomes (e.g. wind and rain make a lack of comfort as **outcome more salient**), (3) adding **new outcomes** (e.g., discovering a new shorter cycling route), (4) the current **need at focus**, (e.g. values are being discussed; observing other HUMATs has a capacity of activating groups of values), etc. Different processes thus impact the composition of the outcomes and the order of the behavioural stack (Cialdini, Reno & Kallgren 1990; Lindenberg, Steg 2007).

3.1.2 Social networks

A critical aspect of the SMARTEES modelling is capturing the basic dynamics of the networks that are activated and developing in the context of a social innovation within a community. In addressing community network dynamics related to a social innovation, we start with the observation that people observe what others are doing, they tend to listen to certain individuals and speak to certain individuals (bidirectionality of interactions). People differ concerning their influence on others. For example, a well-known politician may be convinced about a plan, and is confident the alternative will have negative consequences. The politician with a high expertise/reputation may be motivated to convince others of his/her point of view, and a lot of people may listen to the politician.

Networks have been studied extensively in sociology, and many social simulation models use networks for representing agent interactions. Most often networks in simulation models are depicted as a fixed set of connections between agents. Standard models used are for example the regular lattice or the random network (Figure 5). Links on these standard models range from strictly ordered to completely random (see e.g. Watts & Strogatz, 1998).

Figure 5. Regular network (left) versus random network (right).

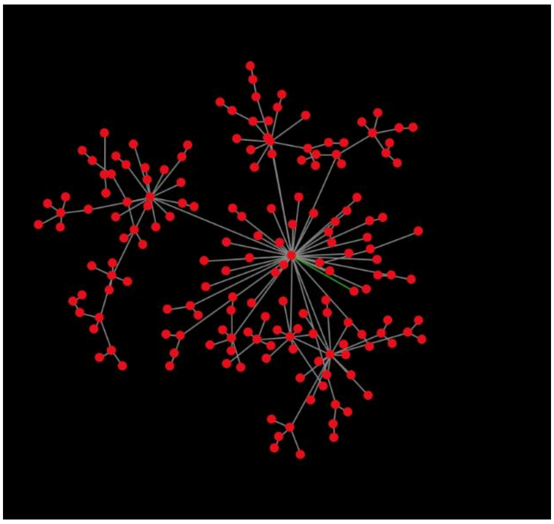


Source: Screenshot of Small Worlds model present in Netlogo's Models Library.

Obviously, in communities some people have more contacts than other. Individuals also often display a preference to connect with persons who already have a lot of connections. Amaral et al (2000) used these ideas to model networks on the basis of preferential attachment. Figure 6 displays a network growing from a preferential attachment algorithm, where it is obvious that a few hubs have many contacts, whereas most agents have fewer connections.

Whereas the preferential attachment approach results in a network structure that reflects more realistically what can be observed in a community, the network structure does not capture that (1) networks are essentially describing who is interacting with whom; something that changes over time, (2) there is a difference between sending and receiving information (bi-directionality of links), and obviously hubs in a network can send messages to many (e.g. media), but will not be capable to listen to everybody, and (3) different contextual (topic related) networks exist simultaneously. In SMARTEES, we are interested in the networks that are related to the interactions relevant to the studied social innovation.

Figure 6. Network based on preferential attachment.



Source: Screenshot of Preferential Attachment model present in Netlogo's Models Library.

Following the ideas of Jager & Amblard (2008), instead of depicting a network as a fixed entity, in HUMAT the network reflects dynamic interactions that take place between different agents. A change in interacting actors implies a change of the network structure. Recording interactions between agents over a simulation run allows for tracking changes in the social structure of the community. For example, clusters of agents may emerge that have different interests and preferences, and that hardly communicate with one another.

In HUMAT, the rules of interaction create the conditions for a network to emerge. Thus, the topology of the network is dynamic. The frequency of communication on a particular issue (in SMARTEES on social innovation) between agents may fluctuate. Agents may also change partners of their interactions. They may bond with new agents they meet, and abandon agents they interacted with in the past. Such rearrangements in links are likely to happen especially when opinions on a topic diverge. In the context of the SMARTEES case studies, this approach to networks helps in the identification of the evolution of communication patterns between the agents. Simulations allow for observing patterns in social innovations, such as clustering around similar opinions, and the influence of hubs (e.g. opinion leaders) on the community dynamics. Table 1 contains an enumeration of features relevant in modelling social networks (based on Will, Groeneveld & Muller 2018). These features will be described in more detail in further sub-sections focused on structure and dynamics of social networks.

Table 1. Features of social networks relevant in modelling.

Element	Feature	Example
Structure of social networks		
Nodes	What constitutes a node?	Identification of stakeholders (individual and collective), including vulnerable groups (focus on gender, different cultural backgrounds, socioeconomic diversity, and vulnerable consumers threatened by energy poverty, etc.)
	Number of agents	
	Level of aggregation	Individual, group (household, interest group, etc.), aggregation over geographical distribution
	Hierarchy	Formal and informal, dependencies between groups
Links	What constitutes a link?	Defining interactions among agents
	Link reciprocity	
	Link strength	If differentiated
Topology	Standardisation of topologies for various agent breeds	Several possible topologies fitted to agent breeds
Dynamics in social networks		
Dynamics of networks	Number of nodes	Population change over the course of simulation
	Number of links	Interaction intensity change over the course of simulation
	Link position	Interaction partner change over the course of simulation
	Link strength	Interaction strength change over the course of simulation
Dynamics on networks	State transitions of nodes	(1) One way/two way discrete transitions, i.e. changing a state (e.g. from being against social innovation to being for social innovation; in one way transition it is not possible to return to a previous state), (2) One way/two way continuous transitions
	Dynamics of link types	(1) No condition on interactions, i.e. if a link exists an interaction takes place, (2) probabilistic interactions, probability constant or dependent on a network property, (3) deterministic or probabilistic threshold for interactions
	Interaction direction	(1) in-directed, (2) out-directed, (3) in- and out-directed links

3.1.2.1 Structure of social network

3.1.2.1.1 Nodes

Nodes in the SMARTEES ABM architecture represent local community (individual actors) and organizations (collective actors). This section focuses on describing individual actors. Collective actors are described in the section 3.4 Organizations (p. 35).

Two types of actors in the local community are distinguished:

1. **Critical nodes** – persons and organizations (key-stakeholders) important in co-creation and diffusion of the social innovation.

2. **Typical nodes** – clusters of typical actors with their typical goals and typical actions.

Critical nodes

Critical nodes are individual and collective actors identified in each social innovation case study. Information to parameterise the simulation models with respect to critical nodes comes from conducted desk research and individual in-depth interviews analyses.

Typical nodes

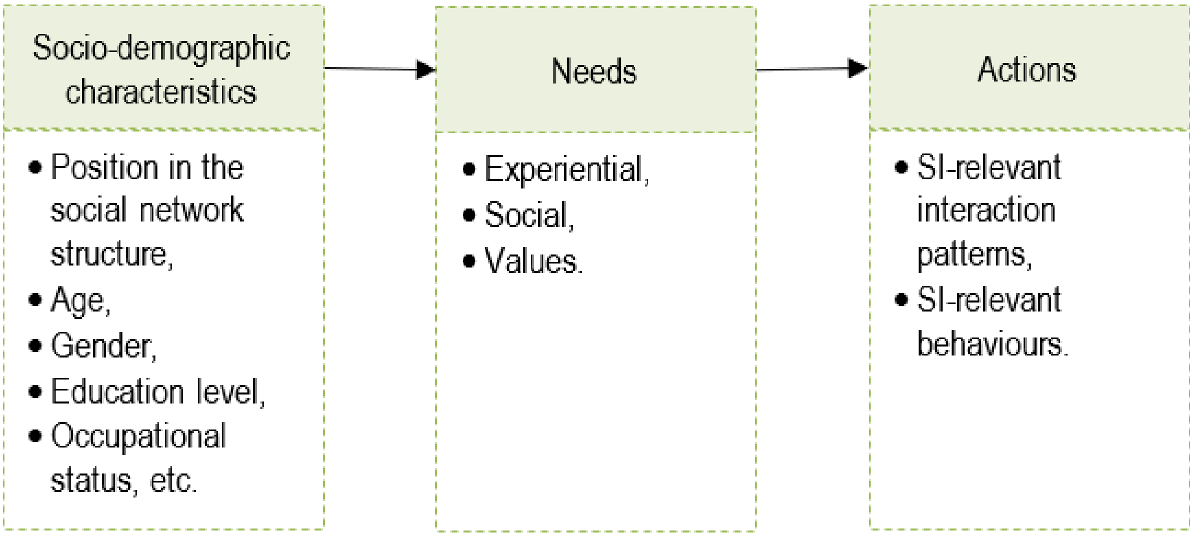
Typification performs a dual function (Kim & Berard, 2009). First, it forms a basis of social interaction. Second, it is a method of social inquiry. As a method, it allows for *the exploration of the general principles according to which man in daily life organizes his experiences, and especially those of the social world* (Schutz 1962, p. 59). In SMARTEES, both functions of typification are utilised in the process of conceptualising social networks. Typification regulates social interactions between agents as described in the next subsection, on links (p. 23). Moreover, is it used in SMARTEES as a method to identify subgroups exhibiting similar behaviours with respect to social innovations, present in the local community. Typification as a scientific method is conducted as follows:

> *How does the social scientist proceed? He observes certain facts and events within social reality which refer to human action and he constructs typical behavior or course-of-action patterns from what he has observed. Thereupon he co-ordinates to these typical course-of-action patterns models of an ideal actor or actors, whom he imagines as being gifted with consciousness. Yet it is a consciousness restricted so as to contain nothing but the elements relevant to the performing of the course-of-action patterns observed. He thus ascribes to this fictitious consciousness a set of typical notions, purposes, goals, which are assumed to be invariant in the specious consciousness of the imaginary actor-model.* (Schutz 1954, p. 271)

Exploratory data analysis techniques (

Figure 7), which find structures in data will be used on SMARTEEES survey data to determine what homogeneous clusters of subpopulations in local communities emerge based on their socio-demographic characteristics, their needs and social innovation-relevant behaviours. The subgroups identified via taxonomy analysis become subgroups represented in agent-based models. Effectively, HUMAT architecture will be parameterised to SMARTEES social innovation case studies, as typical motives (i.e. need structure) leading to typical SI-relevant behavioural patterns in certain socio-demographic subgroups will be present.

Figure 7. Initial dimension of the taxonomy analysis, segmenting local community population into homogenous clusters.



3.1.2.1.2 Links

Nodes in the network denote HUMATs or other types of actors, whereas links denote communication acts, i.e. sharing information about behavioural alternatives (e.g. socially innovative action). Recent studies on communication exchange in communities question the stability of core discussion networks (i.e. set of people to discuss important matters with). McPherson, Smith-Lovin and Brashears (2006) demonstrated that over long periods of time, core discussion networks in the United States of America changed dramatically. More surprisingly, Small, Pamphile and McMahan (2015) fond that short-term dynamics of core discussion networks suggests they are highly contextual support networks, in which people are added and dropped as actors shift from environment to environment. What is deemed as an important matter at a given point in time is dynamic. Therefore, in HUMAT core discussion network related to social innovation is motivated by cognitive dissonances, and its shape is mitigated by opportunities to exchange information and perceived credibility of potential exchange partners.

Similarly to representing clusters of typical nodes, with their typical motives for taking typical actions, the SMARTEES ABM architecture does not aspire to represent social interactions in the local community with one to one correspondence. HUMAT is parameterized to typical SI-relevant interaction patterns occurring in relatively homogenous clusters of typical nodes. Following Schutz's ideas on typification, as two agents interact in HUMAT, they do so through a prism of their typical social roles:

> *Only in the face-to-face relation, however fugitive and superficial it may be, is the Other encountered as a unique individual, with his own biographically determined situation. In all other dimensions of the social world, the Other is experienced and apprehended as "typical," in terms of typical motives, attitudes, and behaviour. Nevertheless, Schutz emphasizes, even in the face-to-face relation of consociates, the partners enter into social action with only a part of their respective personalities; that is, you and I encounter and have to do with one another most often in terms of "social roles." And even this is only half the story: my constructing the Other as a performer of social roles plays its part in my own self-typification. In defining the role of the Other, I myself assume a role; in typifying his behaviour, I typify my own*

> *(becoming, for example, “a passenger,” “a teacher,” “a stranger”). Finally, these typifying constructs are themselves to a considerable extent socially derived and approved, some of them becoming institutionalized in the course of our on-going experience.* (Zaner 1961, p. 88)

Two dimensions seem particularly important for the spread of information over a social network, i.e. **opportunity to exchange information**, defined by egos’ social roles, and **source credibility** (Small 2013). Social roles allow for parameterising SMARTEES agent-based models with respect to the opportunity to exchange SI-relevant information, whether by observation (i.e. normative influence), or by deliberate information exchange (i.e. informative influence; e.g., Cialdini & Goldstein, 2004). The distinction between normative and informative influence is used to address network formation in HUMAT: the normative influence is related to observing alters’ behaviours (i.e. receiving information on observable socially innovative behaviours), and the informative influence requires active communication (i.e. deliberately sending & receiving information) and learning (i.e. updating memory).

Normative influence

Visibility of behaviour is critical for normative influence, and with this respect SMARTEES cases differ, e.g. thermo-modernisation of a house (one off, non-observable behaviour) differs from biking (repeated, easily observable behaviour). Under high satisfaction, normative is the dominating influence, requiring little cognitive effort. The normative network is comprised of all alters, whose behaviour the ego can observe, independent of their social role (e.g. neighbours, work colleagues).

Social roles

For the purpose of parameterizing SMARTEES agent-based architecture, performed social roles inform the frequency of interactions between agents, and therefore provide opportunities for exchange of information about behavioural alternatives, including socially innovative actions. The General Social Survey (GSS, hereafter) study identified typical broad categories of people, who are discussion partners for important matters (Marsden 1987). These categories include:

- Family members,
- Friends,
- Co-workers,
- Neighbours,
- Co-members of organized groups.

In SMARTEES ABM architecture, we use the groups present in GSS and other social surveys researching core discussion networks. However, the category of co-workers is substituted with a broader group of main occupation. Typical roles with regard to main occupation in the population are assumed as follows:

- Economically inactive:
  - Attendants at educational institutions (students),
  - Engaged in family duties and otherwise economically inactive,
  - Retired,
- Employed,
- Unemployed.

These become five dimensions of a node, defining the most important roles that agents typically take. The roles are relative, i.e. an agent is taking the main role in an interaction, depending on the partner of the interaction. For example, when talking to an employee from the same company, the agent assumes a role of an employee. In HUMAT, the relative context of assuming a role is realised through link-breeds. Structurally, depending on a role, stronger homophily/heterophily in the ego-network is assumed (Table 2).

Table 2. Link breeds, homophily and sources of data for parameterisation in HUMAT.

Link breed	Possible homo-/heterophily	Data source
family	Age + gender	Statistical yearbooks
friend	Education level + age	SMARTEES survey
occupation-fellow	Education level	Statistical yearbooks SMARTEES survey
Students	Age + education level	
Engaged in family duties	Age + gender + education level	
Retired	Age	
Employed	Education level	
Unemployed	Education level	
neighbour	Income	Statistical yearbooks
organization-member	Income + Experiential needs + Values	SMARTEES survey

Informative influence

Whereas normative influences require observation of alters' behaviours, informative influence requires an interaction. Specifically, one agent shares information, and another receives it. Hence, to simulate the informative influences spreading through a community addressing motivations to share information is crucial. Likewise is the target's receptivity to information. As described in section 2.1.1 on decision-making strategies, deliberate exchange of information depends on cognitive dissonances of an agent, in particular on the type of dilemma the agent is facing.

Table 3 provides a summary of dilemmas and SI-relevant communication strategies.

Perceived expertise of interacting agents determines the direction of information flow, i.e. the direction and extent to which one agent in the interaction is a voice (gives information) and the other one is an ear (receives information). Within HUMAT, SI expertise is not an absolute concept, but rather a relative perception that may differ between agents. Hence, in HUMAT where one ego may deem an alter an expert on an issue, another ego may not recognise the same alter as being an expert. The bi-directionality of the information flow depends on agent type. For example, highly reputable experts or other critical nodes are heard by many (e.g. through newspapers, social media), whereas these experts hardly ever listen to others.

Table 3. HUMAT dissonance reduction strategies and related SI-relevant informative influence.

Dilemma type	Action	Strategy
Experiential dilemma, Values dilemma	Inquire - seek information in social network to reduce cognitive dissonance via altering ego's knowledge structures	Sequentially target the alters with highest perceived SI expertise
Social dilemma	Signal – share information to reduce cognitive dissonance via altering alters' knowledge structures	For observable behaviours target alters, who act differently to ego For non-observable behaviours target random alter

Social innovation expertise

Source credibility is related perceived SI-expertise of the interlocutor. Individuals seek in their social networks resources that will benefit them in a specific context (Bourdieu 1986, Coleman 1988, Lin 2001). Information seeking strategies are motivated by the perceived utility of the alter, i.e. his/her ability to deliver the pursued resource. Utility of the alter is assessed contextually. *In any given discussion of an important matter, ego would seek the alter most relevant to the topic at hand* (Small 2013, p. 472). As a consequence, the same alter may be perceived by ego as a relevant, knowledgeable expert (and therefore hold high utility) with respect to matter A, and as an irrelevant layman (and therefore hold low utility) with respect to matter B. Such topic-alter dependency (Bearman & Parigi 2004), is implemented in SMARTEES ABM architecture via the level of expertise on behavioural alternatives the ego perceives an alter to have.

The perceived expertise of the alter determines the motivation to receive information from this source. The level of expertise ($0 \leq M \leq 1$) of an alter *l* perceived by ego *j* depends on the similarity of needs structures between the two agents (*N*) and the difference in their socioeconomic status (*O*). In an interaction between two agents, the expertise level of ego *j* is an additive inverse of the expertise level of alter *l*, centred at 0.5.

$$M_{j,l}^{t_n} = N_{j,l}^{t_n} O_{j,l}^{t_n}, \qquad \text{(Eq. 5)}$$

The level of perceived expertise is subsequently used as a weighing factor for received information, therefore the minimum value of perceived expertise, i.e. 0, designates complete scepticism in the alter's knowledge, and the maximum, i.e. 1, denotes complete trust and confidence in their opinion.

The degree, to which two agents *j* and *k* share the same needs ($0 \leq N_{j,l} \leq 1$) indicates belonging to the same interest group, which strengthens knowledge absorption. Previous research showed that certain features of the information source and context might carry informational value, signalling a high probability of the interlocutor belonging to a similar interest group. For example, Furman (1997) showed that the topic of hair loss was discussed by elderly women in the context of a hair salon visit, and Small (2009) described mothers discussing important matters related to their children with other mother in the context of a childcare centre. Suls et al (2002) demonstrated the phenomenon of ''similarity attracts" in particular to the comparison of opinions and beliefs. Moreover, psychological studies show that new information is evaluated against the already possess knowledge (Wyer 1974), and that informational redundancy enhances the acceptance of information by the receiver (Howell & Burnett 1978; Propp 1997). Similarity of the needs structure, indicating similarity of perspectives and interests, serves as a weighing variable for the relative socioeconomic status:

$$N_{j.l}^{t_n} = \frac{3-\left|I_{e,j}^{t_n} - I_{e,l}^{t_n}\right|+\left|I_{s,j}^{t_n} - I_{s,l}^{t_n}\right|+\left|I_{v,j}^{t_n} - I_{v,l}^{t_n}\right|}{3}, \qquad \text{(Eq. 6)}$$

The minimum value, i.e. 0, designates complete opposition of individual needs, and maximum, i.e. 1, stands for complete similarity of interests. Please note that the value of the indicator will be the same for both interacting agents.

Relative socioeconomic status ($O_{j,l} \in < 0; 1 >$) is indicated by differences between ego and alter in education level (G) and income (H):

$$O_{j,l}^{t_n} = \frac{2+ G_j - G_l + H_j - H_l}{4}, \qquad \text{(Eq. 7)}$$[3]

where:

$O_{j,l} \in < 0; 0{,}5)$ - socioeconomic disadvantage

$O_{j,l} = 0{,}5$ socioeconomic equality

$O_{j,l} \in (0{,}5; 1 >$ socioeconomic advantage

Socioeconomic status, as indicated by income and education, was shown as an important social force for upward social comparisons (Festinger 1954). Moreover, socioeconomic status of the source seems to also positively influence receptivity of information in social interactions. For example, Atkinson, Furlong and Poston (1986) found that higher education level and similarity in attitudes and values were the most important factors in choosing counselling.

Proposed conceptualisation of social innovation expertise in HUMAT this translates to a situation, where alters with similar interests and/or alters of a higher social status are perceived to be more expert with respect to social innovations. It also implies that agents having lower education and income consider more alters as having higher degree of expertise. The final implication is that alters with high socioeconomic status are perceived by many other agents as more credible sources of information, and as a consequence will function as hubs in the information spreading network.

[3] Please note, for interpretability the equation uses min-max normalization of relative socioeconomic status, assuming that education and income are both measured on scales between 0 and 1.

3.1.2.2 Dynamics in social networks

Table 4 sums up dynamics in social networks, as implemented in SMARTEES ABM architecture.

Table 4. HUMAT dynamics in social networks.

Dynamics of networks	Number of nodes	Static, parameterised to local community.
	Number of links	Dynamic. Social roles parameterised to information from SMARTEES survey (static, defined as types of links). New links established when ego networks do not allow for cognitive dissonance resolution. New links based on homophily of needs.
	Link position	Static once link is established.
	Link strength	Dynamic perception of social innovation expertise level of the interlocutor, represented as a characteristic of the link (links-own) updated for each interaction with the same alter.
Dynamics on networks	State transitions of nodes	State of the node depicts chosen behavioural alternative. Depending on cognitive dissonance level and effect of implementing dissonance reduction strategies, agents change the most favourable behavioural alternative. Two way transitions possible.
	Dynamics of link types	A Boolean variable represented as a characteristic of a link (links-own) indicates whether normative influence takes place. Probability of observing a behaviour (0 or 1) is defined by social innovation. A Boolean variable represented as a characteristic of a link (links-own) indicates whether informative influence (social interaction) takes place. Probability of interactions is dynamic and depends on the cognitive dissonance of a given agent and on characteristics of alters in an ego network.
	Interaction direction	In- and out-directed links, depending on the perceived SI expertise levels of the interlocutors.

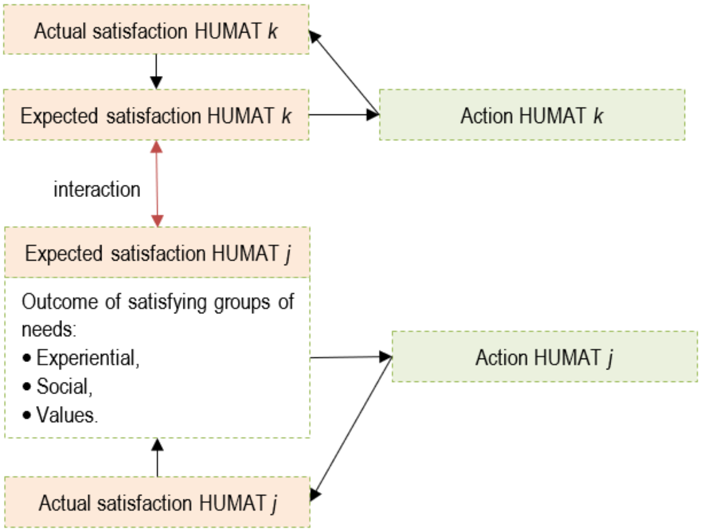
3.2 Energy-related social innovations

A common denominator for all social innovations studied in SMARTEES is the fact, that all are related to a broader process of energy transition. Therefore, the following definition was designed for the purposes of SMARTEES analyses:

> *"Social innovation in energy transition is a process of change in social relationships, interactions, configurations, and/or the sharing of knowledge leading to, or based on, new environmentally sustainable ways of producing, managing, and consuming energy that meet social challenges/problems"* (Caiati, Marta & Quinti 2019).

As highlighted by the definition, studying social innovations requires a processual approach rooted in social network activity. Agent-based modelling and simulation as a scientific method, due to its focus on dynamics and interactions between actors, is particularly suited for investigating the topic. Therefore, agent-based models of SMARTEES social innovations aim to examine the diffusion of social innovations in local communities.

Figure 8. Possible paths for changes in attitudes towards behavioural alternatives in SMARTEES ABM architecture.



Existing theories of social innovations point to two levels, on which social innovations can manifest themselves i.e. cognitive and behavioural. For example, Haxeltine et al. (2016) define social innovations as *changing social relations, involving new ways of doing, organising, framing and knowing*. Such conceptualisations are consistent with assumptions present attitude-behaviour models stating that attitudes towards actions affect behavioural intentions. SMARTEES ABM architecture was designed to represent both dimensions of social innovations, the cognitive (i.e. framing, knowing) and the behavioural (i.e. doing, organising). The cognitive dimension is represented through a HUMAT's episodic memory, which stores attitudes towards socially innovative behavioural alternatives. Attitude towards a behavioural alternative is expressed as expected level satisfaction experienced if the behaviour is realised. On an individual level, perception of a HUMAT is influenced via (a) interactions with other HUMATs and subsequent exchange of information about behavioural alternatives, and (b) via actually experiencing the consequences of the behaviour (Figure 8).

3.3 Policy scenarios

Policy scenarios link closely with the perception of uncertainty and complexity. In the mechanistic era, policymakers had the illusion that with sufficient information and detail, certain effects could be planned in complex environments for prolonged periods of time. Especially when the reality entered turbulent periods, these plans would fail, as they lacked adaptive capacity. Examples of such failures include the problematic 5-year plans in the Soviet era, or the Schlieffen Plan as a detailed blueprint for the invasion of France and Belgium in 1914. These examples made it clear, that being adaptive to changing circumstances is critical in policy making.

Hence developing policy is a complicated balancing trick between developing consistent plans for attaining a certain desired future on the one hand, and, on the other hand, being adaptive to changing circumstances, the task may require adjustment of goals and ambitions. Increasingly, policymakers are becoming aware of the role of complexity and uncertainty in developing and implementing policies (e.g. Jager & Edmonds, 2015). Industries are more and more often making plans in the context of different future world scenarios. For example, Shell works with utopian and dystopian scenarios for the next 50 years to reflect on their strategy.

In SMARTEES, we aim to support municipalities with exploring potential routes to a sustainable future. The "delta of the landscape of possible futures" can be considered as a set of scenarios (Figure 2, p. 8). If there is a scenario identified as preferred policy goal, the key question is how the policy can contribute to increasing the chances that the preferred scenario will be realised. Importance of adaptability in implementing policies, in particular in more turbulent stages in the implementation of a social innovation, was addressed in section 2 describing prediction in complex systems. Yet, policy-making is a balancing act between long-term goals of the policy and short-term adaptation to developments that grow. Referencing the delta landscape, this can be understood as having a policy goal to consistently steering towards one of the attraction basins (preferred scenario), and the identification of possible tipping points (forks, branches), where it is important to steer adaptively towards the desired direction. In terms of policy scenarios, it addresses implementation of consistent policies (e.g. fixed taxation or subsidy schemes) in combination with adaptive policies (e.g. additional information campaigns).

For the adaptability of policies, it is important to explore the possibilities to identify when a tipping point is approached through simulations, because prior to that moment it is easier to stimulate a development of a desired reality. At later stages, a lock-in may have already developed (prevention is better than curing as a key principle). Moreover, planning the representation of policy scenarios in agent-based models entails a close relation to the depiction of organisational decision-making processes. As work on describing policy scenarios in WP5 intensifies, cooperation between modellers and researchers is essential to determine dimensions describing policy scenarios useful in agent-based model representations.

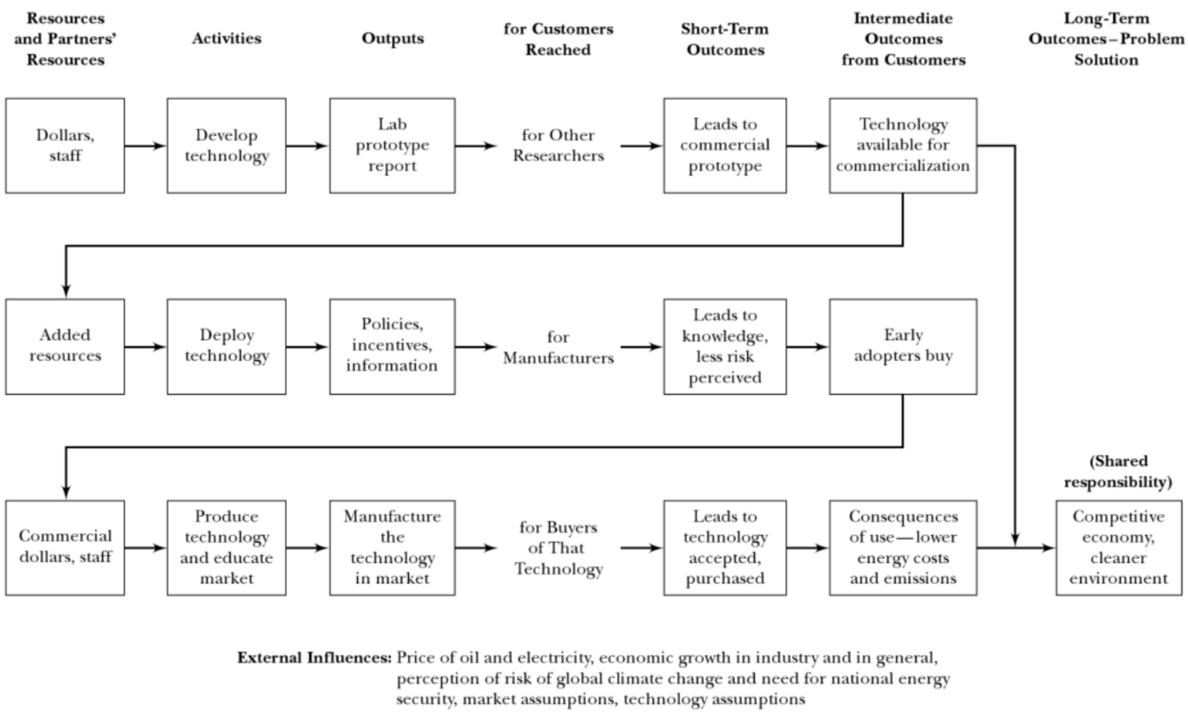
Policy scenarios in SMARTEES are described as specific public intervention implementations. Describing policy scenarios can be performed with a use of programme theory. Recreating a programme theory of a public intervention is a popular approach in evaluation (Rogers 2000). A program theory consists of a set of statements that describe an intervention, explain why, how, and under what conditions (e.g. specify necessary requirements) and via which mechanisms expected effects occur (Sidani & Sechrest 1999).

Figure 9. Elements of a programme theory.

Inputs	Activities	Effects
Necessary requirements	Actions	• Outputs • Outcome • Impact

Specifying inputs, which are necessary to deliver intended results of the public intervention, such as human resources, financial contributions, or equipment. Activities lay out the (implemented) plan, i.e. actions associated with achieving defined goals, and temporal relations between these actions. Three types of results of a public intervention are distinguished, depending on the timing of their delivery. Outputs are direct, immediate results. Implementations' short-term consequences take the form of the numbers of organized meetings or units of purchased equipment. Implementations' outcomes are the medium-term effects related to the goals of the public intervention. Evaluating interventions' outcomes focuses on the effectiveness criterion, i.e. the degree to which the implementation was successful in bringing about a desired result. Impact is formed by an intervention's long-term results. Goal-free approaches (Scriven 1972) that identify all consequences of the intervention, planned and unplanned, for various groups of stakeholders, are often used to determine the impact. Evaluations also use the utility criterion, assessing to what extent actual project results are positive/negative for the stakeholders they affected. Programme theories can be represented with the use of programme logic models (Figure 10).

Figure 10. Example of a programme logic model.



Source: McLaughlin & Jordan (2004), p. 22.

Simulating policy scenarios has been discussed as being one of the main benefits of ABMs (Moss 2002). Even in the early days when agent-based modelling was closely linked with the artificial life community, the idea of "life as it could be" contrasted with "life as we know it" was a central concept (Langton 1989). A considerable body of experience has been built since those halcyon days. Gilbert et al. (2018) reflect on a number of policy modelling experiences, making observations that are worth bearing in mind for SMARTEES. Noting that the (social) process of building and using the model is in some ways more important than the model itself as an artefact, they emphasize the use of agile (Beck et al. 2001) and collaborative approaches to model development and use.

Agile software development is (or perhaps "was", since it was conceived in 2001) arguably a social innovation in the IT industry, involving new ways of working together to build software that delivers value to the customer, motivated by repeated failures of large-scale industrial IT projects. The reasons for the failures were articulated around understandable issues with mutual comprehension between clients and engineers. The clients do not understand what software can do for them, or what is technically feasible; the engineers do not understand the client's context well enough to deliver them useful tools. Agile developed new working practices, roles and organizational structures, central to which are the embedding of the customer in the software development team, and regular, short iterations of development of working code and critical reflection and feedback both on whether the software is delivering what is needed and whether the team is working effectively to do so. For Gilbert et al. (2018, para. 5.18), interpreting agile collaborative development of agent-based models for policy analysis entails *policy makers, analysts, model output users, stakeholders, and peer reviewers should be involved, not just at the problem definition, user needs stage, but throughout to ensure that the modelling approach, model structure and level of abstraction, parameterisation, analysis and interpretation of the results remain fit for purpose and focused on need*.

Besides the matter of the social process by which models of policies are constructed, there is the pragmatic issue of how policy scenarios are implemented as software artefacts in simulations. There are various approaches, outlined below in ascending order of sophistication and complexity. Not all have been attempted yet to our knowledge.

3.3.1.1 Policy as driving variable.

In many ways, this is the simplest way to implement a policy. A predetermined intervention in the system, such as a tax, or an incentive, is specified as a variable of the model, and there are algorithmic processes in the model that use that variable as part of their calculations. (The latter simply ensures that in some way the model has the potential to respond to the policy driving variable.) The variable could be a single number or symbol, or a list of numbers or symbols saying what the intervention is in each time step over which the model will be run. These can be the easiest policy options to elicit from stakeholders and policymakers. Different policy options are compared for their effect on outcome variables of interest. Examples:

a. Ahrweiler et al. (2015) develop an agent-based model simulating the effects of various policies for funding European research in the Horizon 2020 programme. The policies are pre-defined at the start of each simulation, and contain information such as the minimum and maximum numbers of partners, what types of partners are required to be involved in each project, how long projects last, and which calls for proposals will be made. Model runs are compared for the numbers of participants of different kinds (small and large businesses, and research institutions), numbers of proposals submitted, diffusion of knowledge and capabilities, and social network structure.

b. Ge et al. (2018) simulate policy as a switch between various options for trade agreements post-Brexit. These then select among time series of prices for goods, determined in separate work, that then act as drivers for the beef and dairy cattle system simulated. The scenarios are compared for their impacts on the numbers of small, medium, and large-scale farms.
c. Vasiljevska et al. (2017) have three options for simulating policy around smart metering in an agent-based model, each of which is implemented as a set of contract-types that electricity supplier companies may provide. The simulation experiments compare outcomes in terms of savings in electricity and carbon emissions, and changes in welfare and comfort.

3.3.1.2 Policy as an algorithm.

The policy is implemented as a series of rules outlining the conditions under which different options will be undertaken. This builds on the *policy as a driving variable* case in that the policy can respond to conditions in the model. This is more difficult to elicit from stakeholders and policymakers because precise enough specifications of the conditions under which different options are selected (such that they are suitable for implementation as a computer program) can try their patience, even if providing such detail is within their capabilities. In particular, situations can arise in simulations that might be unrealistic (or perceived very unlikely), out-of-scope of the stakeholders' involvement in the project or expertise, or sufficiently extreme that more drastic interventions would have happened at higher levels of governance. An example in FEARLUS (documented in Polhill et al. 2016) is when financial and/or biophysical circumstances reach a point that no farmer can make any money from farming, and every farmer goes bankrupt each time step. The policy-as-an-algorithm approach might be better suited to exploring the *principle* of designing incentives in a particular way, rather than a specific policy implemented in a particular empirical context. The disadvantage with that take on policy-as-an-algorithm, however, is that links with real-world situations can be difficult to evaluate, especially for policymakers and stakeholders needing guidance on their specific concerns. Example:

a. Polhill et al. (2013) coupled FEARLUS with a species biodiversity model to compare the effectiveness of different incentive mechanisms at conserving regional species biodiversity. They compared incentivizing specific activities on the farm with incentivizing by biodiversity outcomes, and also explored 'clustered' incentives, where neighbouring farms received extra money if they all delivered the same outcome or activity. These algorithms all respond to specific behaviours by farmer agents in the model in a predictable way.

3.3.1.3 Policy as an adaptively implemented goal.

Policy can sometimes be expressed as a goal or target, with 'levers' that can be adjusted to achieve the goal. This can be easier to elicit from stakeholders and policymakers, though not necessarily in a formalizable form. Formalization may need intervention of modellers, but essentially would comprise some outcome variables of interest that the model provides values for achieving stated ranges of values, along with the specification of some variables the model responds to being adjusted. The algorithm implemented in the simulation for the policy agent (or agents) then dynamically computes how to adjust the levers to achieve the desired range of the outcome variable, responding to conditions in the model. These algorithms could potentially be quite sophisticated, drawing on Artificial Intelligence (e.g. planning) and Machine Learning (e.g. reinforcement learning neural networks), though they need not necessarily be. The principle risks of such an approach are that the combinations of levers are unrealistic to adjust with the frequency that they are in the model, the goal is unachievable, or the system enters undesirable states before the governance agent has learned out to adjust it. Stakeholders and policymakers may also not understand how the system in the model is governed, particularly if blackbox machine learning algorithms such as neural networks are used. Examples:

a. Adelt et al. (2018) simulate various methods to control congestion and promote more sustainable transport mode choice using a rule-based governance agent. They explicitly represent 'controls' on the system as a data structure combining the outcomes to be controlled, limits on interventions the agents can implement, and a mode of governance (self-organized, soft and strong control). When outcome variables cross thresholds, the governance agent, depending on the mode of governance, can implement measures such as adjusting pricing to make options more or less attractive, or prohibit specific options.
b. Polhill et al. (2010) implemented a control theory (Nise 2008) algorithm in a government agent in FEARLUS-SPOMM (the 'SPOMM' is for the biodiversity part), which adjusted the incentive given to farmer agents in order to achieve a desired level of landscape biodiversity (expressed using an entropy-style formula). Theoretically, such an algorithm could be applied in the real world; however: constant changes to incentives might annoy farmers (especially when they were reduced in financial value), the algorithm failed in the model if it did not find good incentive values in time before local extinctions occurred in the landscape that rendered achievement of the target entropy impossible, and the entropy-style formula would be difficult to justify or explain to the farming community as the basis for the incentive scheme changes. And that is ignoring the politics and ethics of assuming the job of government is to control a social-ecological system such that it achieves the goals of the government.

3.3.1.4 Policy as coevolutionary adaptively implemented goals.

The next level of sophistication is allowing the goals of the policy making agent to adapt in response to macro and micro states. This then requires the elicitation of current and potential goals, and the rules by which goals of the governing organization changes. The points made above about this being a 'black box' are exacerbated here because even the goal of the policy agent is unclear at any one time.

3.3.1.5 Polycentric governance.

Elinor and Vincent Ostrom introduced the concept of polycentric governance to the management of complex social-ecological systems in a number of ground-breaking papers (see Ostrom (2010) for a summary). In terms of how this might be implemented in a simulation model, perhaps the best that can be said is that there is no reason to assume a single agent should be used to represent 'policy' in a model. Policy scenarios, as simulated, could be represented by a number of agents representing organizations (including NGOs, local and regional governments, and community trusts), with each agent implemented using one of the above four options.

3.4 Organizations

The prospect of simulating polycentric governance raises the question of how organizations could be represented as agents in agent-based models. Though many in the agent-based social simulation community are methodological individualists, simulating only individual humans as agents, from a computational perspective, an 'agent' could represent anything, and examples abound of agent-based models representing aggregate social entities using one computational object. Households are a fairly common aggregation, with Gotts and Polhill (2017) using agents to represent households using energy and buying and repairing appliances in their model of domestic energy demand. Similarly, Hailegiorgis et al. (2018) represent pastoral households as agents adapting to climate change in the South Omo Zone region of Ethiopia. Businesses are also represented as agents. Ackland et al. (2019), for example, simulate wholesalers and retailers (as well as individual consumers) in their model of the pharmaceutical supply chain. There are even models where nation-states are agents (Walbert et al. 2018). Parker et al. (2008, p. 797) observe that modelling aggregates is justifiable when so doing does not compromise the purpose for which the model is built, pointing out that though this would ideally be a decision made purely for modelling reasons, it is sometimes also driven by the levels of aggregation at which data are available.

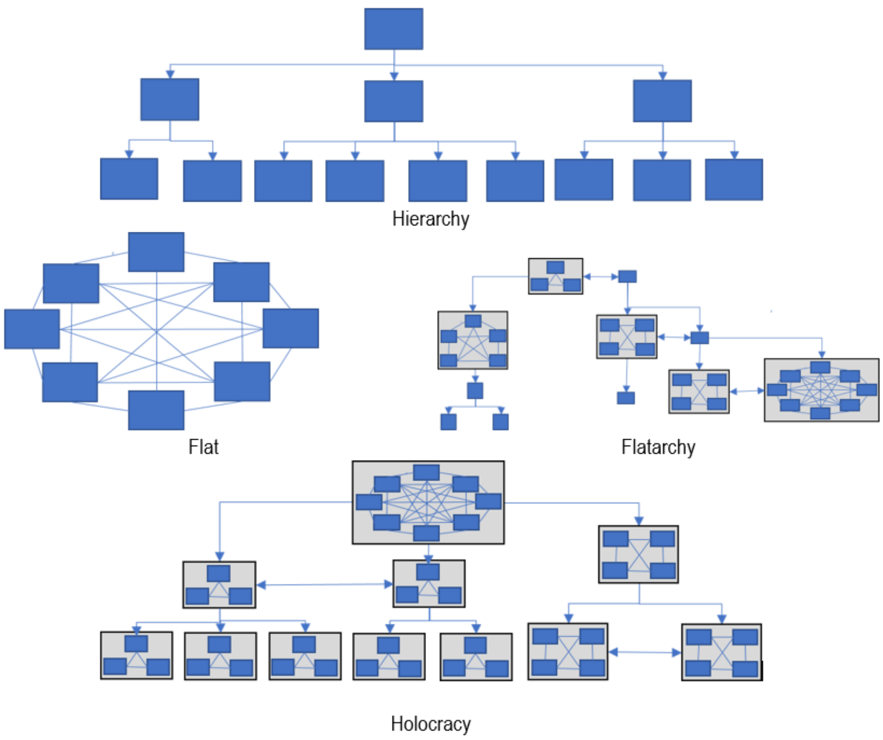
Representation of social aggregates in agent-based models is, in practical terms, not especially different from representation of individual humans. The matter of the representation of decision-making at individual and aggregate levels has been the subject of considerable discussion in the literature. Parker et al. (2008, p. 792) point out that decision-making, though often represented in terms of utility maximization, can also include heuristics, habit, imitation and normative elements. Schlüter et al. (2017), for example, have attempted to make sense of some of the anarchy by developing a meta-model (which they call 'MoHuB') in which to capture the representation of decision-making, and demonstrate how theories including utility maximization, the Theory of Planned Behaviour (Ajzen 1991), and Prospect Theory (Kahneman and Tversky 1979) map on to their framework. Huber et al. (2018), reviewing various agricultural agent-based models, observe that the representation of decision-making depended on the phenomena of interest in the model. They found models used a mixture of approaches, including the use of typologies (e.g. based on cluster analysis of survey data), decision trees, knowledge bases, and utility functions.

In practical terms, therefore, organizations can be represented in agent-based models as aggregates, with little in the way of standards in how this is done in the community. Philosophical objections to the representation of aggregates (methodological individualism) can perhaps be addressed drawing on Dennett's (1971) Intentional Stance, which has been used by the Artificial Intelligence community as a theoretical basis for justifying computers having intentionality. Here, the question of whether or not a system has intentionality is left to an observer of the system who is trying to predict or explain the system's behaviour. The intentional stance is deemed necessary when the observer's attempts to understand the behaviour of the system using the physical and design stances fail. The physical stance would entail the use of dynamical equations to model the behaviour, and indeed the rejection (by some) of such approaches to modelling complex social/ecological systems could possibly be argued, drawing on Dennett, on the basis that the physical stance is ontologically inadequate. The design stance ascribes functions to elements of the system – we do not need to know the underlying physics of how it works, merely that elements of the system have a specific purpose, and by understanding these purposes and their collective functioning, the behaviour of the system as a whole can be understood. The intentional stance is invoked only when the physical and design stances fail to be (adequately) predictive. The observer ascribes beliefs, desires and intentions to the system, assuming it is 'rational' (it believes its beliefs and their logical consequences), predicts its behaviour. Logics based on beliefs, desires and intentions (BDI) date back to the early days of AI (Bratman 1987), and have been implemented in software (Rao and Georgeff 1995). Although the field is far from settled (Herzig et al. 2017), BDI agents are used in some agent-based social simulations (Balke and Gilbert 2014), and so it is a practical option should we choose to take that direction. Though Balke and Gilbert (2014) focus their work on human decision-making, insofar as an organization's behaviour can be understood by the intentional stance (remembering that its beliefs, desires and intentions are *ascribed* not elicited) and not the design stance (bearing in mind that, to some extent, organizations are designed), BDI would be a philosophically defensible, if computationally expensive, approach to the simulation of organizations as social aggregates.

In earlier work for the GLAMURS project (Salt et al. 2017), we simulated the endogenous formation and dissolution of organizations through an implementation of Callon's (1984) theory of translation. The details of the implementation are less relevant than the fact that though each organization, when formed, had an explicit representation, the actions and decision-making in those organization agents were carried out by agents representing individual humans rather than social aggregates. Representation of the organization entailed specifying the organizational structure (as a social networks – Figure 11) and the goal of the organization. The organization structure specified roles that the human agents fulfilled.

As Parker et al. (2008) note, a degree of pragmatism is essential when making model implementation decisions. Consideration of how to represent organizations will be driven by the purpose of the model, availability of data, ability to meaningfully acquire relevant knowledge from stakeholders, transparency in the way the model functions, and computational resource available to carry out the required simulations.

Figure 11. Various organizational decision-making networks implemented in Salt et al.'s (2017) formalization of Callon's (1984) theory of translation.

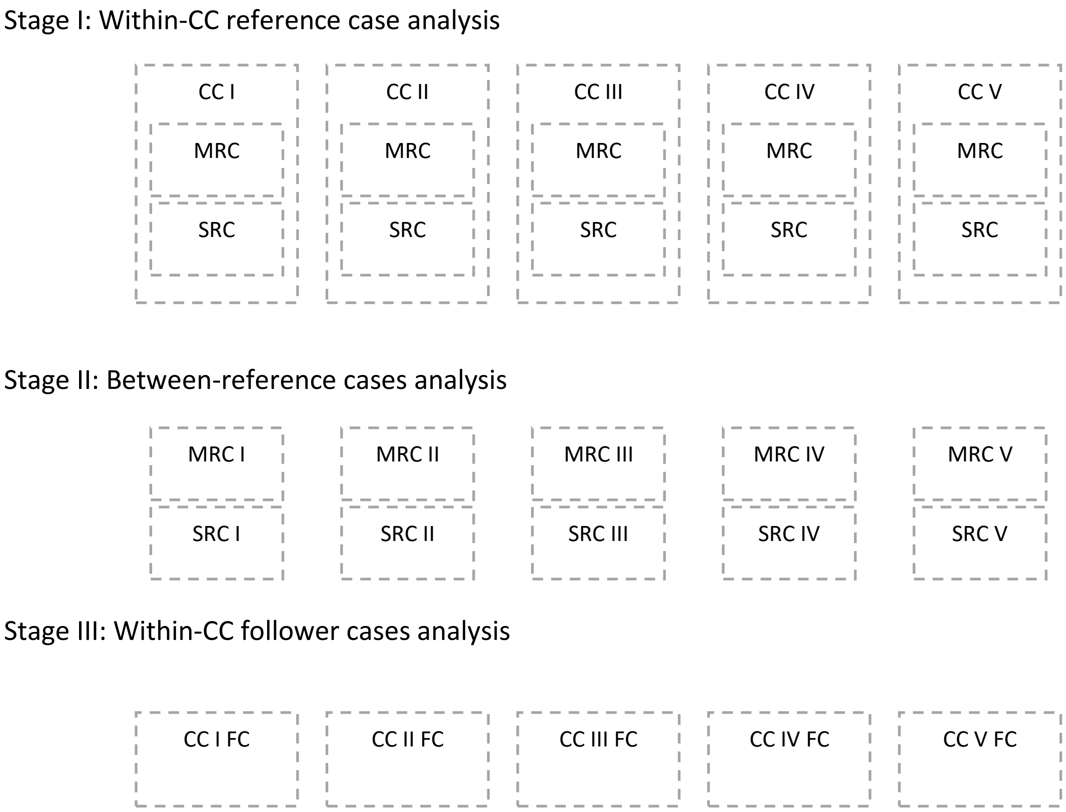


3.5 Contextual drivers

Even though most of the empirical work in SMARTEES is performed in successful reference cases, it is the project's ambition to produce knowledge useful outside of the analysed case studies. Therefore, in WP 3 and in WP 6 efforts are directed at describing success factors and barriers for energy transition related social innovations. It is crucial, that ABMs developed in SMARTEES utilise empirical knowledge about the contexts, in which social innovations have higher probability of success. Implementing such factors in agent-based models contributes to stimulating the discussions on possible implementations of policy scenarios in the project's follower cases.

To increase the comparability between SMARTEES agent-based models, only a limited number of contextual variables can be implemented in the computational stage. Therefore, identification of a broad range of important contextual factors, which determine the success or failure of a policy scenarios, will proceed in a bottom-up manner (Figure 12), starting with within-cluster analyses of similarities and differences between two reference cases. Subsequently, the analysis will proceed to the level of all reference cases, to determine which contextual factors are relevant for the success of energy transition related social innovations. The last stage of the analyses will utilise the expertise present in the follower cases, to prevent the omission of important contextual factors, which might be shared by all reference cases. As the sample, i.e. set of analysed cases, is determined by the project, sampling procedures employed in qualitative comparative analysis (QCA, hereafter; Thomann & Maggetti 2017), by optimising on distributions of factors, will help identify contextual variables implemented in agent-based models. Subsequent use of QCA will enable unravelling combinations of causal conditions, which lead to a success of a policy implementation, instead of focusing on singular causes.

Figure 12. Identification of contextual factors for implementation in agent-based models.



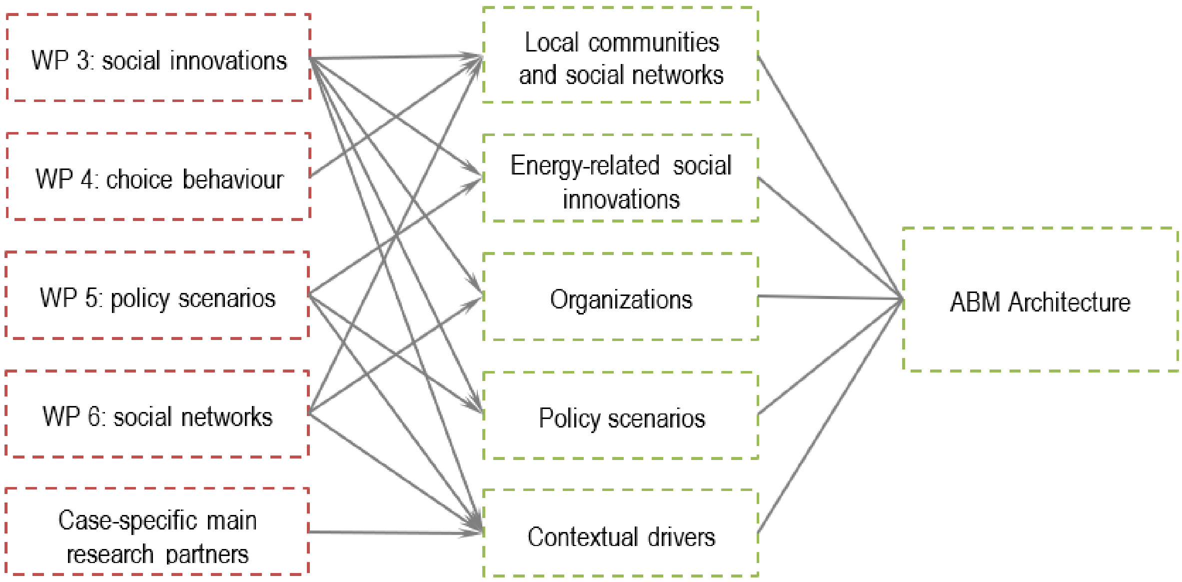
4 Research questions and data sources

4.1 ABM-related interdependencies between WPs

The main purpose of agent-based modelling and simulation in SMARTEES is to study the process of **diffusion of social innovations in local communities**. Computationally replicating the successful cases will allow for simulating alternative counterfactual scenarios to explore to which extent the effects of public policies are dependent on certain contextual and policy characteristics. Moreover, re-implementing the same policy scenarios in follower cities can shed light on possible effects in different contexts.

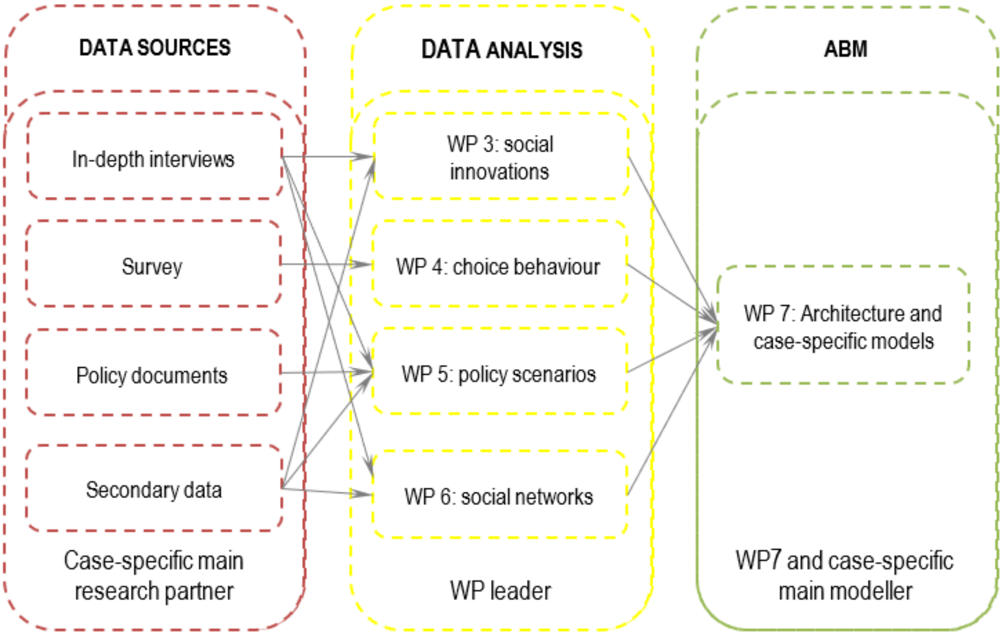
Even though agent-based models are not able to make point predictions of certain indicators, simulations can be used to explore relative changes of indicators under different, well-defined scenarios. To increase confidence in agent-based models designed in SMARTEES, the utmost attention is devoted to verifying assumptions present in the models. Therefore, the developed SMARTEES ABM architecture draws on scientific theories and previous studies. Moreover, empirical analyses of primary and secondary data are performed in the SMARTEES work packages. Figure 13 presents the structure of the WPs, as they provide parameterisation information for specific elements of SMARTEES ABM architecture.

Figure 13. Interdependencies between ABM architecture elements and WPs.



SMARTEES as a research project is characterised by a high degree of complexity, as multiple WPs inform numerous elements of the ABM architecture, and various data sources are analysed in SMARTEES WPs (Figure 14).

Figure 14. Interdependencies between data sources, WPs and ABM.



The aim of this section of D7.2 is to explicitly show the interdependencies between SMARTEES WPs from the perspective of agent-based modelling and simulation efforts. Next subsections are devoted to project WPs, identifying ABM-critical work tasks for the upcoming period (until M24 of the project), defining the research goals from the perspective of agent-based modelling and simulation, and, where appropriate, presenting research questions and research tools allowing for eliciting answers.

4.1.1 WP3: Clusters of case studies of social innovation

Table 5. ABM-critical tasks in WP3.

Task#	Task name	Timescale
Task 3.2	Profiles of the different types of social innovation	M3 → M10
Task 3.3	Overall analysis of social innovation in energy transition "in action"	M5 → M13
Task 3.4	Models of social innovation - conclusions and inputs for the following WPs	M6 → M14

Based on analysing available secondary data and conducted individual in-depth interviews, efforts undertakes in WP 3 resulted in re-constructing models of social innovation, described in D3.4 Report on "Five models of social innovation". Moreover, from the perspective of WP 7, critical aims of the qualitative research performed in WP 3 include:

- Identification of actors, factors and dynamics, which enhance collective engagement, empowerment of citizens in energy transitions and contribute to the strengthening of social innovations (e.g. social norms, collective identity, collective efficacy, etc.).
- Identification of tipping points in the evolution of each case study – from emergence to designing and implementation – (e.g. entrance of new actors, barriers to sort out, public reactions: contestation, conflict and resistance) as well as insights/learnings drawn from these (e.g. how to gain public acceptability; how to engage citizenship in energy transitions, warnings and recommendations for the "follower cases").

To reach these aims, sections of the IDI presented in Table 6 are of particular relevance to WP 7.

Table 6. Research questions, and related IDI questions

Research question	IDI operationalisation
Who were/are the main actors involved in the promotion and development of the social innovation?	• *Who were the promoters of the initiative?* • *How the initiative was generated? Are there some specific ideas that inspired the initiative?* • *What other actors were actively involved in the project? (How and why were they involved?)*
What were/are the motivations for people to engage in the (particular) social innovation? (i.e. values, goals and motivations that foster social innovations as well as the fulfilment of personal needs and goals that sustain motivation).	• *How did you become involved in this project (name of the project/initiative/)? Under what circumstances? At what stage of the project did you become involved? What motivates you to engage? (Ask for values, environmental awareness, perception of collective efficacy, sense of impact, other goals?)* • *What aspects would you highlight as the more satisfying ones in your experience in this (name of social innovation)?*
How have conflict and resistance been overcome?	• *Did you have to deal with any instance of contestation or resistance? How did you overcome this?* • *What strategies were the most effective in engaging social groups/beneficiaries?* • *What are the main lessons/learning you draw from the experience?*

4.1.2 WP4: Choice behaviour and energy usage: knowledge co-production

Table 7. ABM-critical tasks in WP4.

Task#	Task name	Timescale
Task 4.4	Development of interview protocols	M7 → M9
Task 4.5	Development of the questionnaire framework for the surveys	M7 → M9
Task 4.6	Adaptation of questionnaire framework for each case cluster	M8 → M11
Task 4.8	Data analysis workshop	M16 → M17
Task 4.9	Preliminary data analysis	M18 → M24

Data collection efforts undertaken in WP 4 are crucial for parameterising agent-based models to studied cases. Whenever necessary and appropriate, representative surveys will be conducted on the sample of local community. It is important to implement a design scheme that is consistent with the conceptualisation of the case specific agent-based models. As the population studied with the use of survey will be represented in agent-based models as individual agents who adopt energy-related social innovation, the definition of that population, and hence primary sampling unit, data collection technique and sampling technique, will reflect the specificity of each case and may vary between the cases. The SMARTEES ABM architecture in general, and HUMAT architecture in particular, is designed to represent individuals. However, for the social innovations that are behaviours implemented on an aggregate level, e.g. household level, the architecture can be sufficiently modified to represent aggregate units. Depending on primary sampling units and availability of sampling frames, Table 8, outlines possible data collection and sampling techniques.

Table 8. Possible data collection and sampling technique depending on a primary sampling unit and availability of a given types of sampling frames.

Primary sampling unit	Sampling frame	Data collection technique	Sampling technique
Individual	Register of email addresses of individuals	CAWI	Exhaustive sampling2
	Register of telephone numbers of individuals	CATI	Stratified sampling (given availability of information on individual's belonging to a relevant stratum), or simple random sampling.
	Register of addresses of individuals	PAPI1/CAPI	Stratified sampling (given availability of information on individual's belonging to a relevant stratum), or simple random sampling. Both sampling techniques combined with clustering with respect to geographical location.
	Lack of a satisfactory individual level register	PAPI/CAPI	Two stage sampling. Sampling households in the first stage, and using Kish grid to sample individuals in the second stage.
Household	Register of household addresses	PAPI/CAPI	Stratified sampling (given availability of information on individual's belonging to a relevant stratum), or simple random sampling.
	Lack of a satisfactory household level register	PAPI/CAPI	Random route

[1] filled out PAPI (pen and paper interview) questionnaires can be distributed and collected via available post service.
[2] Available registers of email addresses of individuals (e.g. available city panels) might have been created with a use of a sampling technique. Nonetheless, invitation to participate in the study will be sent to all members of the sampling frame.

Subsequent data weighing will reflect the implemented sampling technique, realised response rates (non-response weights) and, if relevant, post-stratification weights.

4.1.3 WP5: Policy scenarios

Table 9. ABM-critical tasks in WP5.

Task#	Task name	Timescale
Task 5.2	Building a common framework for the development of local-embedded future policy scenarios	M14 → M18

Task 5.3	Definition of future policy scenarios	M18 → M24

One of the goals of WP5 is to develop locally-embedded policy scenarios in the process of co-creation with stakeholders from SMARTEES case studies. Subsequently, the parameterized and calibrated agent-based models will be used to experiment with the developed policy scenarios. As described in section **Error! Reference source not found.** on policy scenarios will be described and implemented in agent-based models as specific public intervention implementations. To minimise the risk of incompatibility of the policy scenarios with modelling efforts, all agent-based modelling teams will be engaged in specifying how the policy scenarios will be implemented in ABM architecture, and co-designing the workshop with critical stakeholders. The aim of early engagement and close cooperation between research partners is to create an architecture that is able to account for variability between policy scenarios defined in SMARTEES cases, and, to the greatest possible extent, will allow for implementing standardised dimensions of policy scenarios in both versions of the sandbox tool.

4.1.4 WP6: Equality and the Energy Union: Data and knowledge analysis

Table 10. ABM-critical tasks in WP6.

Task#	Task name	Timescale
Task 6.1	Identifying stakeholders and subpopulations and their social networks	M2→ M12
Task 6.2	Identifying drivers of and barriers towards social innovation	M11 → M18
Task 6.3	Analysing decision-making mechanisms of actors	M12 → M19

From the perspective of WP 7, critical aims of the qualitative research performed in WP 3 include:

- Identifying stakeholders and subpopulations: Analysing the selected cases of social innovation to identify the relevant stakeholders, agents and subpopulations and their social networks with a focus on gender, different cultural backgrounds, socioeconomic diversity, and vulnerable consumers threatened by energy poverty,
- Identifying drivers of and barriers towards social innovation; analysing decision-making mechanisms of actors: Analysing primary and secondary data to identify drivers of and barriers to social innovation diffusion, including the decision-making mechanisms of the relevant agents,
- Integrating data and preparation of data for use in the ABM: Synthesis of the existing and new datasets, harmonizing them and preparing them to be used for parameterizing the ABMs,
- Scrutinizing the results of the simulations for theory development, and
- Identifying drivers and barriers for social innovations – contextual variables, later to be discussed with reference to future policy scenarios.

Table 11 presents a tool used in SMARTEES to collect ABM-relevant data on stakeholders and subpopulations.

Table 11. Information about actors collected in WP6 for the purpose of agent-based modelling.

	Actor	*e.g. local community member, city council, newspaper, energy company, etc.*	
	Number of actors of this type in the case	*please write here an exact number (if known) or estimation or choose a category from the drop-down list*	*choose*
Characteristics	Important characteristics of the actor /*state variables*/	*what are the important attributes the characterize the actor with respect to decision-making or acting? if more than one actor of this type - with respect to what characteristic do the actors differ? do the important characteristics of the actor change over time? - please indicate by choosing static or dynamic from the drop-down list*	
		characteristic #1	*choose*
		characteristic #2	*choose*
Decisions and actions	Decisions and/or actions	*with respect to the social innovation, what important decisions or actions does the actor take (e.g. vote for or against something, implement new heating type, participate in a payment scheme, etc.)*	
	Goals of the decisions and/or actions /*objectives*/	*is the actor trying to achieve any specific goal (e.g. make the most money)? if yes, what is being maximized?*	
	Factors influencing decisions and/or actions /*sensing & prediction*/	*what factors (internal or external) does the actor take into account when making a decision/taking action? does the actor take into account future consequences of the decision/action in the time of decision-making?*	
	Adaptation capabilities /*adaptation*/	*does the actor change decision-making or actions in response to changes in themselves or the environment? if yes, how?*	
	Learning capabilities /*learning*/	*does the actor learn over time? If so, what does it learn, is that process solitary or does it learn from other actors?*	
Collectives & structure	Groups /*collectives*/	*is the actor a part of any group that is important for the context? e.g. association (e.g. of shopkeepers)? if so, please indicate here and describe the group as a separate entity*	
	Organizational structure	*if actor type is an organization, are organizational levels (e.g. the fact the city council is divided into departments with different objectives) important for the case? If so, what are they and why are they important? e.g. departments in the city council, who have contradicting goals*	
Interactions	Interactions /*interactions*/	*what other entities does the actor interact with and how? please note that the indicated interactions should be reflected in created diagrams*	
		entity #1 - interaction description	
		entity #2 - interaction description	

4.2 Agent-Based Modelling and the Policy Sandbox Tool

As will be clear from having read the section of policy modelling earlier in this document, experience of conducting policy modelling work with agent-based models has led to the conclusion that modelling is more part of a process than an artefact in its own right that can be consulted for predictions on the outcomes of policies (Gilbert et al. 2018). As has been discussed in SMARTEES meetings, this insight has important implications for what the project's Policy Sandbox Tool might be, with the project agreeing the following:

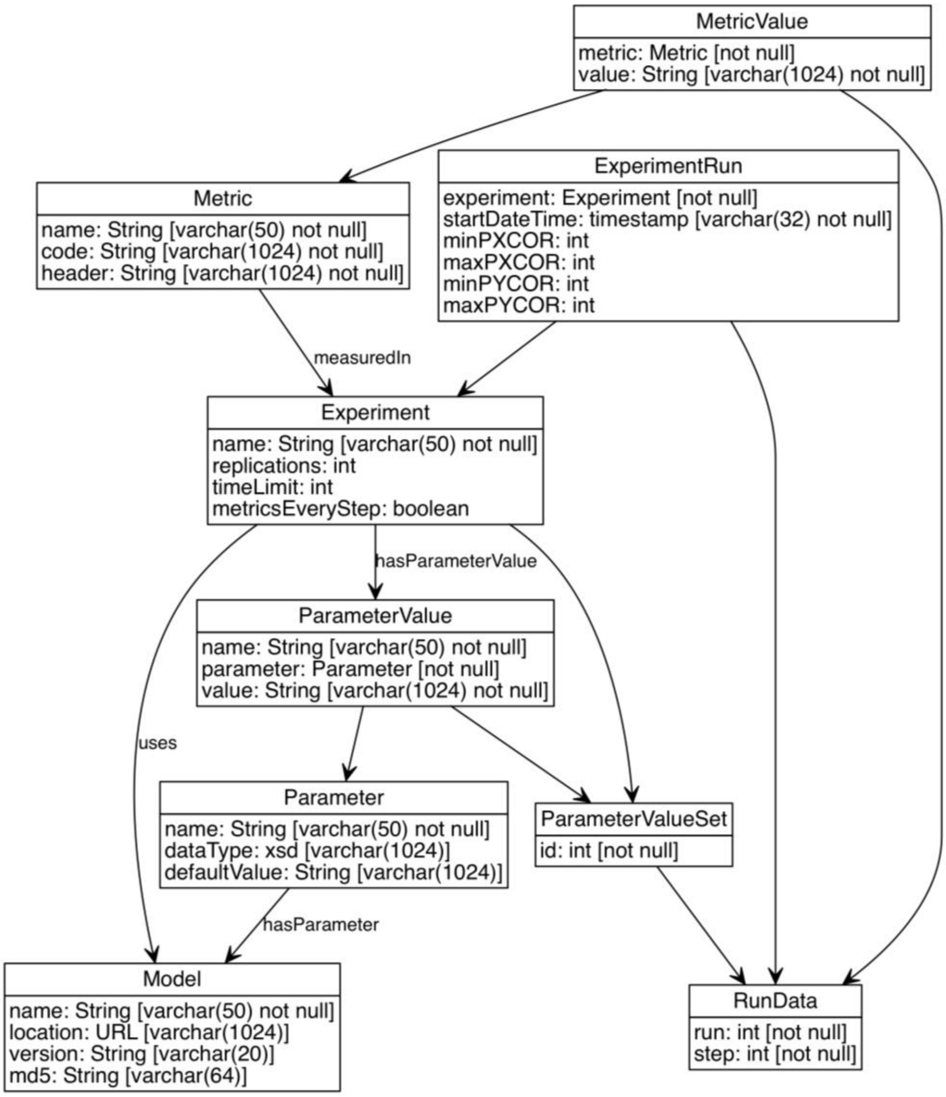
- We will use runs of the agent-based models of the ten main and supporting reference case studies to create a database of run results that can be interacted with on-line. Effectively, this 'shows what we can do', but does not promise to deliver policy analysis for situations the models were not designed to simulate (nor indeed could they reasonably do so).
- The 'full' policy sandbox tool is effectively a combination of workshops, modelling and data collection and analysis that can be used to explore specific policy options where funding is available to support it. For the five premium follower case studies, effectively this minimally entails evaluating the web interface developed for the other case studies and giving us feedback on whether they think such an approach might be useful to them. If funding and time allow, and particularly if much of an existing model can be reused for the purpose and data are readily available, there could be scope to proceed with modelling work too.

The implications of this strategy for the design of the models are twofold. First, we need to ensure the models output data of interest and use for the web version of the policy sandbox tool. Second, we need to keep an eye on the potential requirements of the premium follower case studies and ensure that in the ten reference case studies we avoid as far as possible the use of data that could not easily be obtained in other cases. The latter is more challenging than the former for two reasons, one technical, the other practical. The technical reason is that NetLogo doesn't naturally support what is known as 'modularity'. In the ideal world, code to achieve a particular piece of functionality would only be written once. This is easier to maintain: if there is a habit of copying and pasting code, then it can be hard to keep track of everywhere code has been copied and ensure it is kept up-to-date with code fixes. A possible workaround would be to write as much code as possible using NetLogo extensions. These are Java or Scala code libraries defining new commands that can be used in a NetLogo model importing the extension. Extensions for reading GIS data and CSV files are already available, for example, and the Hutton team has written extensions for case-based reasoning, working with bitstrings, saving ontologies, working with encrypted personal data files and using look-up table data structures. The practical reason is that specialist data requirements are fairly typical in agent-based modelling contexts, though this can to some extent be ameliorated by thinking about 'backup' or 'alternative' sources when data collected by SMARTEES are not available. The discussion of data sources for SMARTEES models is covered elsewhere in this deliverable.

Fortunately, saving data from NetLogo models is relatively trivial, especially if NetLogo's 'BehaviorSpace' utility can be used to get the data needed. BehaviorSpace is a utility embedded into the NetLogo GUI and also available when run in 'headless' mode (i.e. from the command line, without user interaction). Parameter settings, stopping conditions, metrics to gather on each run, and number of replications of each setting, can all be specified. BehaviorSpace can collect data at the end of a run, or every time step, and records results in CSV files that can easily be converted to SQL for storage in a database. After a header containing some metadata about the experiment, the rows of the CSV file will be one per run (or step) with columns for each parameter varied and each metric requested.

The simplest solution would be to prepare a script that converted BehaviorSpace output to SQL suitable for storage and query in a database accessed through the Policy Sandbox Tool's web front-end. Such a script is in preparation at the time of writing, as agreed at the A Coruña SMARTEES consortium meeting. The following data model could be used to store the model results database, and should be reasonably generic to any NetLogo model. The ExperimentRun, MetricValue, ParameterValueSet and RunData tables can be populated from reading BehaviorSpace output CSV files. The other tables would either need to be populated manually, or by reading NetLogo model source code files.

Figure 15. A UML class diagram providing a data model for storing data from BehaviorSpace output.



In Figure 15, the 'Model' table stores information about each model. Though it is intended to focus somewhat ruthlessly on model output only, augmenting the design of the above with a Case Study table would be relatively trivial, and probably a good idea. Models have Parameters, Parameters have ParameterValues, and ParameterValues can be grouped together into ParameterValueSets. An Experiment combines one or more ParameterValueSets, and records Metrics. Metrics are model output that, effectively, will be used to derive information about the outcome of a policy scenario. Linking Metrics to Policy Scenarios is a further potential augmentation of the above data model that could be beneficial. When an Experiment is run, an entry is made in the ExperimentRun table, populated by parsing the BehaviorSpace output header. With each run of an Experiment, and possibly each step of that run, a RunData entry is created from the BehaviorSpace output data, which links the ExperimentRun with a ParameterValueSet and one or more MetricValues.

NetLogo models can output several different kinds of data beyond those merely produced by BehaviorSpace, as well as the possibility to write bespoke data output. Where BehaviorSpace cannot be used to provide the data needed for exploring scenarios with the Policy Sandbox Tool, alternative provision will be needed. Data output from NetLogo (and agent-based models generally) includes the following:

- Time series data. Plots on the NetLogo GUI can be exported to CSV files; this can also be done in ‘headless’ mode using the export-plot command.
- Patch data. NetLogo provides the export-view command, which saves an image of the current ‘environment’ to a named file. This is saved as a PNG format file, which is not especially useful. Patch data for use in R is perhaps better saved using a CSV file with one row per patch.
- Agent data. No provision in NetLogo is made for saving the state of an agent, which may be useful, but writing code to produce a CSV file containing certain state variables of each agent is trivial.
- Link data. As per agent data, code is needed to save link data. CSV format files could be used, either saving the full link matrix (one row and one column per agent), or (more efficiently for sparse matrixes), using one line in the CSV file for each link. The latter option also allows more than one datum per link to be saved.
- Global data. Monitors and global variables may also contain useful data about a run that could be saved.
- export-world. NetLogo does provide the export-world command to save the full state of a model run at the time the command is called. This would allow all the data above to be captured, and can even be read in later using the import-world command. Scripts could be written that parse these data to extract desired information, which would save reimplementing code in several different models and provide more opportunities for efficient code sharing. However, the output file should probably be discarded as it will otherwise use a lot of disk space. If seeds are kept, then the data can be regenerated by rerunning the model.

5 Coding conventions

```
; General Advice
; ==============

; All variable names, procedure and reporter names should be in
; lower-  and kebab- case, e.g. a-variable-labelled-with-kebab-case.

; All procedures, reporters, agents, link and variable names must be meaningful. Do not
; be scared to use longish variable names - you will be grateful that you did, later.

; A list of the assumptions that the model makes that you are aware of, should be listed either
here, or
; in the INFO tab.

; e.g. A household of disparate individuals can act a single agent with consistent and predictable
response.

; The INFO tab must be completed.

globals [
  a-global-variable; PURPOSE: some purpose
                   ; SOURCE: URL or some explanation.
                   ; (optionally) MIN; minimum value
                   ; (optionally) MAX; maximum value
                   ; (optionally) INC: If there is an incrementor
                   ; (optionally) VALUES: If this is a list of values,
                   ;   then a list of the valid values.

]

breed [some-agents some-agent]

some-agents-own [
  an-agent-property; PURPOSE: some purpose
                   ; SOURCE: URL or some explanation.
                   ; (optionally) MIN; minimum value
                   ; (optionally) MAX; maximum value
                   ; (optionally) INC: If there is a incrementor
                   ; (optionally) VALUES: If this is a list of values,
                   ;   then a list of the valid values.
]

directed-link-breed [parents parent]

undirected-link-breed [siblings sibling]

; Breeds, agents and links must have a plural, so try and choose your names that have plurals.
; However you will also run into defective nouns, such as "glasses". I tend to use the plural
; form "all-glasses" to get around this. For irregular plurals, you can add an "s" to the end,
; e.g. "fish" and "fishs"

; All procedures and reporters must be commented with

; {agent_1|agent_2} procedure_name

; where {...} contains a single agent type or a list of agent types separated by '|' on which
; the procedure or reported may legally act. Ad-hoc means can be instantiated by a button in
; the interface.

; Optionally a note can be added describing the purpose of the reporter or procedure.


; {observer|adhoc} setup

; Explanation Procedure to set up the initial state of the model

to setup
```

```
  clear-all
  create-some-agents n-some-agents [
    set xcor random-xcor        ; Why this value has been set to this initial value with
                                ; ideally a URL explaining why
    set ycor random-ycor        ; Why this value has been set to this initial value with
                                ; ideally a URL explaining why
  ]
  set a-global-variable 10      ; Why this value has been set to this initial value
                                ; with ideally a URL explaining why
                                ; (Preferably, load in settings like this from a file rather
                                ; than hard-coding them as 'magic numbers'
  reset-ticks
end

; {observer|adhoc} go

; Procedure to run a single iteration of the model

to go
  ask some-agents [
    if even-agent? [
      do-some-stuff-with-an-agent a-global-variable
    ]
  ]
  tick
end

; { some-agent } smoe-some-stuff-with-an-agent

; silly procedure to demonstrate conventions.

to do-some-stuff-with-an-agent [some-global-value]

  ; I indicate any variable that is set in context by the use of the prefix "this-". Similarly
  ; for any variable that is passed as an argument, I use the prefix "some-". This means I can
  ; tell at a glance the origin of the variable, but this is just a suggestion. However if you
  ; do adopt such a convention, be sure to note it down at the top of the program and use it
  ; consistently.

  let this-agent self
  set an-agent-property some-global-value
end

; {some-agent} even-agent?

; This is a reporter that returns true or false. By convention we append a "?" to any variable
; that returns or contains a boolean value.

to-report even-agent?
  if xcor mod 2 = 0 and ycor mod 2 = 0 [
    report true
  ]
  report false
end
```

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7 References

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