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On the engineering of agent-based simulations of social activities with social networks

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ABSTRACT

Context: Models of how people move around cities play a role in making decisions about urban and land-use planning. Previous models have been based on space and time, and have neglected the social aspect of travel. Recent work on agent-based modelling shows promise as a new approach, especially for models with both social and spatial elements.
Objective: This paper demonstrates the design and implementation of an agent-based model of social activity generation and scheduling for experimental purposes to explore the effects of social space in addition to physical space. As a side-effect, the paper discusses the need for and requirements on structured design of agent-based models and simulations.
Method: Model design was based on the MASQ meta-model and implemented in Python. The model was then tested against several hypotheses with several initial networks.
Results: The model allowed us to investigate the effects of social networks. We found that the model was most sensitive to the pair attributes of the network, rather than the global or personal attributes.
Conclusion: As demonstrated, a structured approach to model development is important in order to be able to understand and apply the results, and for the model to be extensible in the future. Agent-based modelling approaches allow for inclusion of social elements. For models incorporating social networks, testing the sensitivity to the initial network is important to ensure the model performs as expected.

1. Introduction

Travel is derived from the activities in which people participate, such as work, school, shopping, sport, leisure, and social events. Non-discretionary activities such as work and school can be partly explained by the traveller's sociodemographic characteristics and generalised travel costs [1], as well as by long-term decisions such as a decision to move to a particular town. Participation in, and scheduling of, other activities is not as easily predicted. Social and leisure activities are the reported purpose for a large number of trips, ranging from 25% to 40% for various countries [2].

Activity-travel simulations are used by transport and urban planners to evaluate the travel effects of different scenarios. In these simulations, activities involving one or more people are predicted for a sample population. As this field moves towards more dynamic environments, agent-based simulation is being used more frequently to represent the decisions made by people and therefore negotiation is a natural solution for activities where two or more people have differing needs.

In order to model joint activities, the transport modelling field is experiencing a shift from understanding "where are people going" and "what activity are they doing" towards "who are they interacting with" (e.g., [1,2]). We believe that the generation and scheduling of social activities depends not only on the structure of the spatial network, which is covered by "where" and "what", but requires that social networks, which means "who", need to be incorporated as well.

Given this interest in dynamics and interactions, multi-agent simulation is becoming increasingly important in travel simulation, travel analysis, and travel forecasting, in particular due to its possibilities to model explicitly the individuals' decision making processes. In fact, all travel is a result of individual decisions, as people try to manage their life in a satisfying way. As such, travel can be seen as result of individual goals (e.g., go to work to earn money, visit friends for pleasure) [3].

Social networks are a graph representation of individuals and their relationships. Our overall hypothesis is that understanding the social network that lies on top of the spatial network (as seen in Fig. 1) should lead to better predictions of social activity schedules and forecasts of travel patterns and demand for urban facilities, in particular those relating to social and leisure activities.

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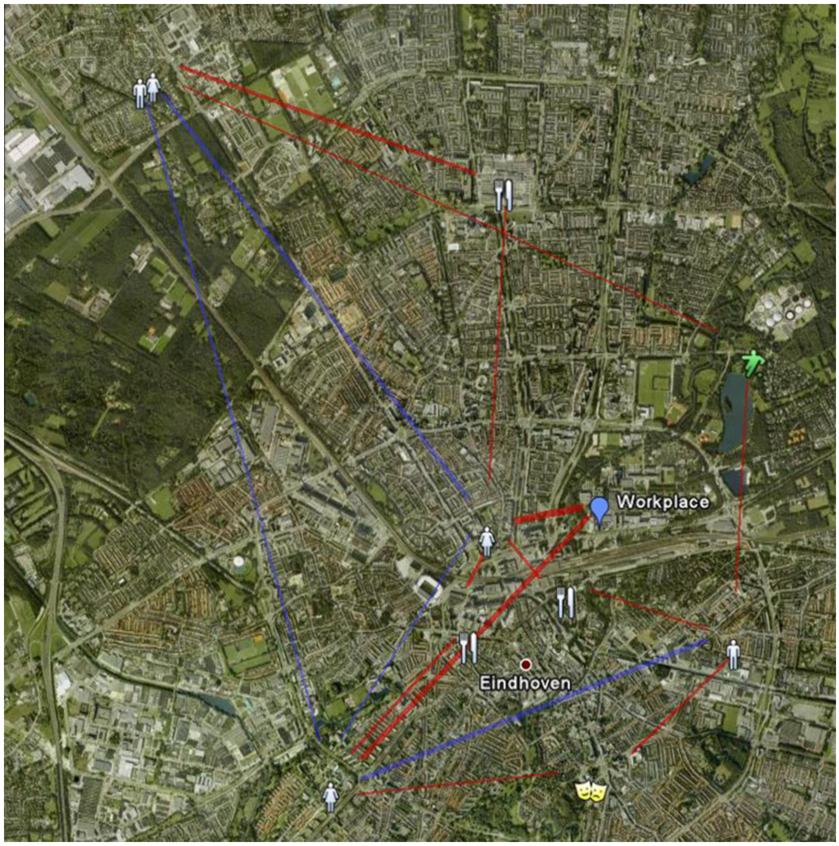

Fig. 1. A social network (blue) and an activity network (red), overlaid onto a spatial network. The thicker the blue lines, the stronger the relationship between the two people. The thicker the red lines, the more often the person visits that location (which could be, for example, a cafe, park or theatre). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

This understanding could also influence the urban design of residential areas and public spaces, in order to encourage participation in social/leisure activities in local communities.

However, a literature search did not reveal any agent-based urban models that consider joint decision making for joint activity-travel choice of individuals. Existing work focus on the conceptual or early implementation phases and concentrates on one or two aspects of selection, influence, and activity generation, which are the concepts we have identified as being key to this domain [4]. The domain contains extra complexity as space, time, and social aspects of the system need to be considered. There are few guidelines available for the development of agent-based models that consider these concepts. One issue amongst others discussed by Klügl [5] is that the "general intuitiveness of the modelling leads to a tendency of ad hoc development", which leads to difficulties when the model is scaled or applied to the real world.

This paper demonstrates the design and implementation of an agent-based model of social activity generation and scheduling for experimental purposes to explore the effects of social space in addition to physical space. Firstly, we present a review of related models. We then follow with a demonstration of using the MASQ metamodel to design a model, in particular focusing on the interaction design. An illustration of the model, based on utility agents, is shown in which the input social network is altered as an example of model testing. The performance of the model with respect to the number of activities generated for individuals, pairs of individuals and for the entire population is analysed. We conclude with recommendations for other applications and future work.

2. Background

2.1. From spatial to social

Activities are generated due to "physiological, psychological and economical needs" [6]. A distinction is commonly made between subsistence (work-related), maintenance (keeping the household running), and leisure. Leisure activities are difficult to define: for example, what may be considered maintenance for one person could be leisure for another [7].

A more detailed description of an activity is that it is "a continuous interaction with the physical environment, a service or person, within the same socio-spatial environment, which is of importance to the person" [8]. Activities have a spatial element, a temporal element, and also a social element. In the context of transport research, the connection between "social networks, locational choices and travel" has not been investigated in detail [2]; the focus has been on space and time.

Spatial models also have a long history, and are mainly concerned with tracing and predicting changes in the environment. Transport models, or models of individual movement, are also considered to be spatial. The early models used an aggregate mathematical approach, measuring the flows between small areas or zones. This later developed into modelling individual trips, followed by chains of trips (tours), and more recently activities, however the focus was still on individual decisions about travel and activities. (A review of activity-based modelling, including the disadvantages of earlier models and also future directions, can be found in [9].)

Activity-based travel demand modelling has centered around individual plans and scheduling, however the presence of joint activities can influence individual plans [10]. As a result of this, research into joint scheduling within households has grown in importance. Activity-travel schedules need to be synchronised in time and space. This is a more complicated task than it may seem. As recognised in [10], sometimes household members may stay longer or arrive earlier at a particular location.

In addition to these analytical studies, several models of joint activity participation have been developed over the years [11,12]. These studies took into account the heads of households only. Obviously, the problem of joint activity-participation involving members of a social network is equally important for improving transport demand models. Buliung and Kanaroglou [13] state that some researchers are already looking beyond households to the influence of social networks.

One of the first urban models was Schelling's model of segregation, in which individuals were modelled in a cellular automata environment and changed their location in order to satisfy their needs for living among similar people. There is both a spatial and social component to this model. Edmonds [14] extended this model to include a social network, and individuals tried to align themselves with their friends. This leans more towards social simulation, which is an experimental method for testing theories in social sciences. These models revolve around the interactions between social entities. In a larger scale model, Eubank et al. [15] present a method for generating the network for determining the spread of disease. They use TRIPS to generate people's travel activity for a day. From that data, a bipartite graph linking people and locations is created and an indication of colocations and possibilities for spread is found.

Social networks are a representation of individuals (known as nodes) and the relationships between them (known as links or ties). From our point of view, the nodes are people, located in space, who are connected to other people. Both the nodes and links can have attributes. For example, a person node could contain age, gender, and other sociodemographic information, while the relationship between two individuals can be defined in a number of ways, for example how similar they are, how they are related to each other, whether they interact or how often they interact, or how information flows between them [16].

Networks can be represented in two ways: complete or personal. A complete network contains all of the relationships for all the individuals in the network, for example, all the friendship links between students in a class. Personal networks contain the relationships for a particular individual (known as the ego), however the attributes of the people they name (known as alters) are provided by the ego rather than the alter themselves. It is not guaranteed that the personal networks of egos in the sample will intersect. For transport applications, however, it is not possible to survey an entire town and find out who knows who in order to create a complete network. As a result, egocentric or personal networks are more useful for open systems. These focus on a single person (an ego) and their links to other people (known as alters) [17]. The individuals can be sampled from a larger population and links between alters can also be investigated.

As Newman [18] recognised, research has been slow in understanding the actual workings of networked systems and the focus has been on structural form and analysis. As a result, there are many methods for generating (e.g., the small world model [19] and the scale-free network [20]) and measurements for comparing static, complete (and not necessarily social) networks (e.g., [21]). However, it has been recognised that social networks have certain properties, in particular with respect to the similarity between people, their spatial proximity, the overall clustering coefficient (i.e., how tightly-knit the network is) and the variation in size of personal networks (e.g., how many friends do people have; also known as the degree). Progress has been made with incorporating spatial considerations into network generation [22–24]. These models claim to model social networks more accurately than previously proposed models that do not consider distance between network nodes. Hamill and Gilbert [23] presented a model known as social circles, where two people are connected depending on the distance between them. This distance could be social (e.g., based on whether two people are similar in terms of age, gender, occupation, religion, or shared values, etc.) or spatial.

2.2. Existing work

In current state-of-the-art activity-travel models, social activities, if at all scheduled, are assigned to random locations and times [25] and do not take into account the constraints or preferences of friends. These activities, however, place constraints on other non-social activities, which signals their importance in activity scheduling.

Hackney and Marchal [26], building on previous work, developed a microsimulation which incorporated a social network on top of a daily activity scheduler. The individuals in the system exchange information with each other, either about locations or about friends. Currently their system does not include collaborative scheduling. However, the bulk of the research on the effects of social networks on activities is at the data analysis stage. Individuals are surveyed about their social network and asked to complete an activity diary for several days, listing who they interacted with and the nature of the activity.

As part of the Connected Lives study, Carrasco [27] collected data on individuals' personal networks and interactions, then used multi-level modelling to look for influences on frequencies of activities. The results showed that the number of components (i.e., subgroups), density (i.e., clustering), and degree of the personal network influences the frequency of social interactions, and are a better indication of frequency than the size of the network or isolates. At an individual level, younger people tend to have a higher frequency of activities, as do friends of similar ages at a pair level.

The latter is an example of homophily, which is based on the idea that individuals interact with others who are similar to them [28]. Homophilies can be separated into two groups: those based on status, both ascribed (e.g., age, gender, etc.) and acquired (e.g., occupation, religion, etc.), and those based on values, such as attitudes and beliefs.

Given the data collected for activity-travel modelling purposes, at least two network generation algorithms have been developed. Illenberger et al. [29] presented a model based on spatial distance, while Arentze and Timmermans [30] developed an algorithm based on spatial and social distance. The latter can also be extended to include the influence of common friends, following the theory that if person 1 is friends with person 2 and person 3, then persons 2 and 3 have a good chance of also being friends.

A theory currently being explored for generating discretionary activities is based on needs. Activities both satisfy and generate needs and needs grow over time [31]. Maslow's hierarchy of needs has been proposed as a starting point [32], however it is difficult to collect data for model validation. A separate set of needs was proposed by Arentze and Timmermans [31] which could be identified through empirical research.

2.3. Agent-based modelling

There is recent interest in exploring social and leisure activities, which requires different model functionality from existing models which are individual-based. It appears that combining the interactive nature of social simulation with spatial models is a suitable approach for our proposed model.

Agent-based modelling and simulation is based on modelling individual units (or agents) and the interactions between them. The focus is on the individual actions and reactions to other agents and the environment. As a result, it is frequently used for applications where the behaviour and intentions of heterogeneous individuals and interaction between individuals is required. Both Bonabeau [33] and Macal and North [34] present lists of system attributes that are ideal for selecting agent-based modelling for that system, including amongst others: agents have dynamic relationships with other agents; relationships form and dissolve; agents have a spatial component to their behaviours and interactions; and the topology of the interactions is heterogeneous and complex.

According to Edmonds [14], "agent-based simulation seems to be the only tool presently available that can adequately model and explore the consequences of the interaction of social and physical space."

Exploiting agent-based models in urban planning and geographic applications is a relatively new notion [35,36]. Most such simulations are based on cellular automata (CA) techniques. However, CA techniques have several limitations when it comes to model individual decision and the human-like behaviours of urban components. This lead to an increasing number of studies using agent-based modelling for urban simulation, including the simulation of residential dynamics in the city (e.g., [37]); the application of agent-based models in studying the dynamics of pedestrian behaviour in streets (e.g., [38]) and modelling the discrete dynamics of spatial events for mobility in carnivals and street parades (e.g., [39]). Nevertheless, most of these studies have approached modelling from a domain perspective, and provide few insights on the structured application of agent concepts to urban simulation.

The real-life system that we want to create a model of consists of different people, their relationships and interactions with each other, and their activities in and possible movement around the environment. The topology is not homogeneous and clusters may form. Therefore agent-based modelling appears to be appropriate for our model, due to the complex relationships and interactions between individuals and the individuals' situatedness in an urban environment. These models also have the benefit of being more behaviourally rich than statistical models, and should therefore be more sensitive to the types of policy and environmental changes that planners are interested in.

However, currently, agent-based modelling (ABM) is basically a bottom-up approach from generative science, through which the whole society can be formed and evolved from the individual agents and their interactions [40]. That means that in current modelling practices social structures are not explicitly considered but, at most, are merely taken as properties of individual agents. To reflect reality, social structures must be explicitly specified and implemented independently of individual agents. This requires theories to link micro and macro behaviour that are able to reconcile intentionality, deliberation, and autonomous planning with playing social functions and contributing to the social order. According to [41], a systemic framework is needed to help us create a manageable snapshot of reality and define our models in a sound, understandable and reproducible manner. In Section 4, we discuss existing agent-oriented software methodologies and propose the MASQ metamodel as a way to define agent-based models.

3. Case study

Our focus in this paper is on social face-to-face activities. People frequently interact face-to-face with each other. This could fulfill several needs: to gather information, to share an experience, to help one another, or for relaxation. Face-to-face or in-person interaction is sometimes also crucial for relationships to continue. Urry [42] notes that "[e]specially in order to sustain particular relationships with a friend or family or colleague that are 'in the mind', that person has intermittently to be seen, sensed, through physical copresence". Following Arentze and Timmermans, we define social activities to be those activities that involve commitments to meet other persons at certain locations and times. Furthermore, these commitments may impose constraints upon the times and locations of other activities [43].

The individuals in our model will interact and negotiate with others to schedule social activities, in particular negotiating about participants, time, and location. After participating in an activity, individuals update their state depending on their satisfaction with the activity. Individuals will also meet new people as a result of activity participation, so just as their activities are influenced by their social network, their network is influenced by their activity participation.

This model will be an experimental tool that can be used by planners to explore the effects of different parameters on travel associated with social and leisure activities. Our spatial area of interest is interactions of residents within a particular city, including day-trips to neighbouring cities.

In this project, we are interested in ascertaining the influence of social network typology (at global, dyad or pair-wise, and individual levels) on the number, frequency and type of social activities between network nodes. This is necessary because incorporating social networks into existing activity-travel models will add a lot of complexity and require more intensive data collections. Testing the sensitivity of potential models of activity behaviour to different networks is an important step in evaluating the usefulness of their incorporation.

4. Model design

4.1. Process

Several design methodologies have been developed for agent-oriented applications. However, most methodologies are developed for the engineering of "physical", problem-solving or decision-making, applications, which are characterised by open dynamic environments, heterogenous participants and common goals. An example is the control of a manufacturing system, where a software agent could replace a human controlling a machine, or an open auction system, where agents make offers on behalf of a human.

In such applications, it is possible for agents to be treated as part of one, distributed system. Design starts therefore from the analysis of the overall system, while the resulting software consists mainly (if not exclusively) of the agents. The main concepts that are used in these methodologies centre around goals, plans and interaction protocols. However, these methodologies pay no attention to models of the environment in which the MAS should function. Specifying the environment is important for transport and urban planning models, where the modellers are interested in the effects on and of the environment. Well-known examples of methodologies for MAS are Gaia [44], Prometheus [45], Roadmap [46] and Tropos [47]. Some of these methodologies provide a graphical design tool for MAS models (e.g., PDT for Prometheus [48]) and support semi-automatic generation of agent code (e.g., the PDT can generate JACK code).

Wooldridge et al. [44] describe their Gaia methodology which is divided into analysis (roles, interactions) and design (agents, services, acquaintances). This was noted to be insufficient for open systems, and was soon extended by Juan et al. [46] (as ROADMAP) for this purpose. One of the shortcomings of Gaia for modelling purposes is the lack of separate environment model: this information can be found in the role definitions [46]. ROADMAP kept the analysis and design phases of Gaia, but added more models to the analysis phase, which now consists of use-case, environment, knowledge, role, protocol and interaction models.

Gaia purposely did not include a requirements phase, assuming it was independent of the analysis and design. However, ROADMAP does include specific requirements models. Another methodology, Prometheus [45], which was developed for a particular architecture of agents, provides some useful generic requirements models, such as system goals and scenarios.

Another type of agent-based design methodologies centres on the idea of organisation as first class concept. In these methodologies, roles are seen as positions in an organisational structure that can be fulfilled by autonomous and independently developed agents. Of importance is the balance between the organisational goal and the goals of the agents (or global, system goal vs. local goals). The fact that agents are seen as separate from the roles they fulfil leads to the fact that social concepts like norms are explicitly modelled. Examples of methodologies for this type of systems are OperA [49] and MOISE+ [50]. Because the resulting systems are seen as "open", in the sense that agents can enter and leave the system, the methodologies for agent organisations rely on other methodologies for the design of the agents themselves. The previous methodologies impose some form of process. Another methodology, INGENIAS [51], does not, however provides views of the world, including models of agents, interactions, tasks/goals, organisations, and the environment.

An effort has been made to create a compilation of several metamodels currently in use that can be used as a reference point to achieve some form of standardisation and maturity [52]. The common models were found to be agent, role, tasks, and communication. Other important elements were environment, organisation and social structure, cooperation, mental attitudes, and services.

Klügl [5] notes that agent-based simulation differs to agent-based software engineering (AOSE), but some of the concepts from AOSE can still be used, especially in the absence of a fully-usable meta-model for agent-based simulation. This was seconded by Heath et al. [41], who state that methods must be adapted or developed specifically for ABM for the approach to reach some sort of maturity. Drogoul et al. [53] presented a description of a methodology, but focussed more on the people involved in the design of a model rather than the detailed steps.

Methodologies for agent-based modelling and simulation should follow the standard development cycle, including analysis, conceptual design, detailed design, implementation and testing, and maintenance, but should specifically support the design of an (agent-based) model of an (existing or fictional) real system, and contain the guidelines to conduct experiments with this model for the purpose of understanding the behaviour of the system and/or evaluating various strategies for the operation of the system. In particular, comprehensive methodologies for the conceptualisation and implementation of agent-based (social) simulations, should enable analysis of and represent the concepts that exist in a real-world domain or society, such as ways to provide a detailed definition of individuals and the social and physical environments which constraint or facilitate their behaviour and interactions. Furthermore, the dynamic context which the individuals perform actions in also requires intricate definition.

Some of the traditional AOSE methodologies have properties that make them more suitable for MABS, for example, an emphasis on cooperation and emergence. Bernon et al. [54] describe ADELFE, which was developed for adaptive multi-agent systems. The agents are considered to be cooperative, and the emphasis is on how local interactions lead to a global system. However, these methodologies still lack or have limited components for culture, social-cognitive reasoning, values and norms, which are required for fully-fledged MABS.

4.2. MASQ metamodel

As discussed in the previous subsection, methodologies directed specifically to agent-based modelling and simulation are so for mostly non-existent. Development of a standard methodology, as a defined, repeatable series of steps to address a particular type of problem, requires knowledge acquired from a large number of simulation projects in different application domains, which are not yet available in the area of agent-based modelling and simulation. Nevertheless, in a effort to provide methodological foundations to our work, we have taken meta-modelling as a starting point for the development of our model. Recently, the MASQ meta-model has been proposed with the aim of describing a multi-agent system (MAS) in all its aspects (actors, environment, interaction, organisations and institutions) [55,56]. Such a meta-model is a principled approach to describes how and with what the architecture will be described in a structured way. MASQ is applicable both for the engineering of multi-agent systems as for the design of agent-based simulation [57]. MASQ is based on a 4-quadrant framework [58], where the analysis and design of a system is performed along two axes: an interior/exterior axis, and an individual/collective axis. In this section, we introduce the main concepts of the MASQ meta-model.

Distinguishing between exterior and interior perspective means distinguishing facts (objectivity) and opinions (subjectivity). From the exterior perspective we consider what is observable in the environment (e.g., a behaviour exhibited by an agent, a property of an object), whereas from the interior perspective we consider the mental representations about the environment, the decision-making processes, and more generally anything which is a matter of interpretation.

The individual/collective distinction is commonly used to analyse complex systems. From an individual point of view, each atomic component of the system is described by itself, where as from a collective point of view the system is described in terms of the relations which link together all its components and the interactions that occur between them.

A 4-quadrant framework consists of the combination of these two axes – interior *vs.* exterior, and individual *vs.* collective. This is shown in Fig. 2.

4.2.1. MASQ components

MASQ provides four basic constructs – *Mind*, *Object/Body*, *Space*, *Culture* – to describe a complex social system, each of them capturing one of the four quadrants.

Mind. (Interior-Individual) A *mind* is the internal architecture of an agent, i.e., its decision-making component. The mind is responsible for the behaviour selection of the agent (what it intends to do), but not for the behaviour execution (what it can do and what it actually does in the environment). This behaviour selection takes as input the perceptions delivered by the environment.

Object/Body. (Exterior-Individual) *Objects* and *bodies* are individual entities that compose the environment. They are characterised by a static state which describes their properties (e.g., the dimension of a ball), and a dynamic state which describes their individual activity (e.g., a ball which is rolling). Unlike minds, objects and bodies are neither proactive, nor autonomous. Their evolution is entirely determined by the laws of the environment and the different activities that occur in it.

Bodies are special objects that are connected to a mind. A body allows its mind to act on its environment, perceive it and be perceived by other minds. It is the manifestation of an agent in its

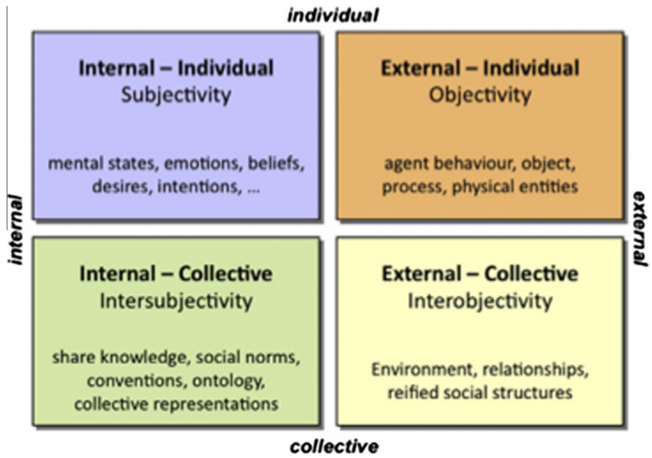

Fig. 2. The four quadrants of the MASQ meta-model.

environment; it allows its very existence in it. A mind does not have an absolute control over its body but may influence it. A body then reacts to the received influences according to the laws of the environment. Thus, the body allows for the definition of the action capabilities of an agent within the environment.

Space. (Exterior-Collective) The overall environment is described through several *spaces*. A space describes roles, relationships and forms a boundary between its objects and the rest of the environment (an object belongs to one space). Each space establishes the structure which interconnects its objects (e.g., a spatial topology, a network, ...), handles the interferences that result from the combination of the individual activities (e.g., a collision between two rolling balls) and defines its own dynamics (e.g., gravity).

Agents interact in a space through the enactment of roles, which describe the agent's body in that space. That role represents a specific context for their activities and interactions with the other entities of the space. One agent has a unique mind but may have several bodies (i.e., enact several roles) in different spaces. Therefore different types of activity can be modelled separately by different spaces, each of them defining a specific structure and dynamics. Moreover, the concept of space can be used to model both physical and social environments. A social space models specific and deterministic social structures of interaction and contains social bodies, a social body being the manifestation of an agent playing a role.

Culture. (Interior-Collective) The environment, which is described by spaces and objects, is factual: things are as they are. It constitutes the *brute reality* in the sense given by Searle [59]. A *culture* provides means for a group of individuals to build cultural (or institutional) interpretations of the environment. The interpretation mechanisms provided by a culture are not proper to a single individual, but are shared by a group of individuals; they are based on the notions of *constitutive* and *regulative* rules defined by Searle in [59]. In MASQ, culture enables the representation of institutional or organisational facts, such as dependencies, norms and values.

4.2.2. MASQ for modelling social activities

We have based the design of our model on MASQ, focusing on agents goals, the environment, acquaintances, roles, and services. The interaction model is explained in more detail in Section 5.

Minds enable the description of the internal part of the agents (the people being modelled). It includes the definition of their specific *goals* and the specification of their *decision-making strategies* Minds also define what are the *internal costs* related to the social activities such as the cognitive costs induced by information processing deciding on a joint activity, but also the actual travel costs (time, distance, price). Finally, each mind may contain functions to evaluate its *performance satisfaction*. Performance satisfaction is defined in [60] as the degree in which an activity or transaction meets the expectation of the actor. Performance satisfaction allows to measure the value of specific social activities for each actor.

The goals of the agents in our system are derived from the social needs of humans. These include interacting with, and gaining the respect and esteem of others. Minds therefore have the following goals:

- Making and maintaining (longterm) relationships with other people.
- Sharing experiences with other people, in the form of joint activity participation, possibly within a group/club setting.
- Sharing (giving and gaining) information with other people.
- Learning individually about their local environment.

Levels of achievement are measured individually, e.g., everyone will have some level of satisfaction. If they are not satisfied with their current situation, then they will try to change it. The same applies to how involved people will be in the community – it depends on their needs.

In order to meet its goals an individual will initiate and participate in discussions about activities, as well as participating in the activity itself. Utility maximisation is used to determine the preferred activity choices. Furthermore, the agents in our model each have an agenda consisting of activities they have already scheduled.

Spaces describe the various interaction structures. The *physical space* has a link-based representation, derived from the actual road network. The links contain the actual distance, as well as some idea of the travel time for different modes. The nodes exist at a point in space, and most (if not all) nodes contain a location, which is a facility where (joint) activities can be undertaken. Note that, each individual will have their own representation of this environment to account for limited knowledge and information.

Another space is the acquaintance space, or *social network*. Each person has a set of acquaintances, where each link defines the type of relationship (e.g., family, work, friend) and also how long it has been since they last saw each other. Each pair of agents has a similarity measure, which follows from the notion of homophily. Links are undirected, meaning that friendships are mutual. The social structure of our model is similar to the CASE model proposed by Zhang et al. [61], however a difference is that our neighbourhood is static.

As for the physical space, each agent will have its internal representation of the acquaintance space. Using the ideas presented in Section 2, our friend selection model is based on the similarity between two people, the geographic distance between them, and their friends in common. When considering proposing or participating in an activity, the agent's time availability, the opportunity costs, the time since they last saw the other agent, the social credit balance between the two agents, and their satisfaction from their last encounter are also taken into account.

Bodies describe the external part of actors which includes their external properties (the attributes that can be perceived within the environment), their action and perception capabilities and their resources available to perform these actions.

Bodies are associated with the different spaces. The Social body enables agents to interact and negotiate with others to schedule social activities, in particular negotiating about participants, time, and location. After participating in an activity, individuals update their state depending on their satisfaction with the activity.

Individuals will also meet new people as a result of activity participation, and another task is the maintenance of a personal network. Just as their activities are influenced by their social network, their network is influenced by their activity participation.

As agents participate in or discuss activities, they may visit or learn about new locations. This is an activity associated with their body in the physical space. The individuals will also keep track of the locations they are familiar with. They may share them with others, which is a form of influence.

Aside from bodies, we use objects to model the passive elements such as the characteristics of specific locations (type, activities possible, etc.). There are several different types of location, and each type has a set of attributes. The major distinction is between a private residence and a public location. As an example, the latter will have opening hours. Categories of public locations include restaurants/cafés, cultural locations (e.g., museums, theatres), green space, and sport centres/gyms.

The **Culture** quadrant describes the rules of interaction and the social expectations of the agents. An example of such rule is reciprocity, i.e., agents are expected to return visits to others in their network. Culture also determines the likelihood of meeting at someone's home or in a public place, and the frequency and type of social interactions.

5. Detailed design

Interactions between agents are an important component of agent-based applications. The individuals in our model each have an agenda, and interact and negotiate with others to schedule social activities, in particular negotiating about the nature of the activity, participants, time, and location.

This means that current methods of modelling decision processes in an individual manner will need to be revised to take into account that many decisions are made jointly. In some cases, joint activity decision making within households has been investigated, however existing models do not capture the actual mechanisms behind the decision making. Moreover, these models focus on interactions within households and have not considered personal social networks at large.

However, there are two triggers for beginning an interaction:

> "When one goes to a ball game with friends, is the activity social, or entertainment? The answer probably affects the activity choice process, including the choice set of perceived alternatives: if the primary motivation is social, one may first decide to get together with friends, and then choose an activity around which to organise the gathering, whereas if the primary motivation is entertainment, one may first decide to attend the ball game and then see who else is able to join." [7]

Therefore, both activities and acquaintances need to be evaluated to see whether there is a need to be satisfied.

Agent interactions have several components: the negotiation set (the possible proposals), a protocol, strategies, and a rule to determine that the interaction is complete [62]. For the negotiation set, we have developed a list of activity patterns, including the activity purpose and location, as well as an indication of which acquaintances are likely to be involved and when (e.g., interacting socially with work colleagues is likely to be during the week, whereas visiting family is mostly a weekend activity).

The protocols we use are based on those developed by Wainer et al. [63] for agreeing on a meeting time. As these protocols are concerned with only one issue (time), elements from multi-issue negotiation need to be incorporated. Fatima et al. [64] explains three methods for dealing with issues in multi-issue negotiation: all issues are discussed together (package deal), issues are discussed separately and independently of each other (simultaneous), or issues are discussed one after the other (sequential). Although it has been shown that proposing complete deals at each step is computationally more complex, it has advantages such as Pareto optimality [64]. In our model, it is too difficult to decide issues independently (for example, the activity may determine the time and location or vice versa) and also determine in which order they should be discussed (should we decide on the activity first? or who we want to see? or when we are free?), therefore we use the package deal method.

5.1. System architecture

The model consists of six modules: *input*, *simulation*, *environment*, *population*, *schedule*, and *output*. Within population, a communication module is located. The overall system architecture showing the package structure and the flow of control is depicted in Fig. 3, which are described below in more detail.

5.1.1. Input

Several input files are required for the model to run. This module reads in the details of the environment, the details of the individuals in the population, and the values of parameters.

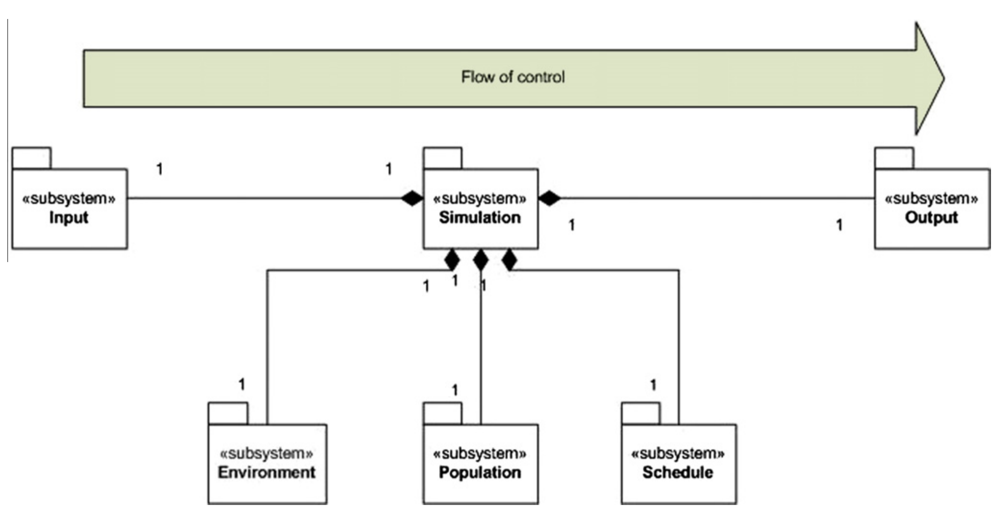

Fig. 3. Overview of system architecture.

5.1.2. Simulation

The simulation runs as follows:

1. `Initialise:`
   (a) `Read parameters from file`
   (b) `Initialise environment`
   (c) `Initialise population`
2. `For each day:`
   (a) `Shuffle individuals`
   (b) `For each person:`
      i. `Determine if they want to start an interaction on that day`
      ii. `If so, start interaction`
      iii. `If interaction completes successfully, possibly schedule activity`
   (c) `For each time of day:`
      i. `Find activities to execute`
      ii. `For each activity:`
         • `Each participant updates self: visited location today, undertaken activity today, travel`
         • `Each pair updates self: last seen today, travel`
3. `Print outputs`

5.1.3. Environment

The global (city) network is stored as a network, with location details for some of the nodes.

5.1.4. Population

The population module stores the agents, the social network and the communication module.

5.1.5. Schedule

The schedule stores the activities for each person, as well as all the activities in the system. Each day is divided into four parts: morning, afternoon, evening and night. No activities take place at night. Dividing the day into hours is too detailed. Note that the model described in this paper ignores time of day for simplification.

5.1.6. Output

In this version, five outputs files are produced: personal, pair, conversation, schedule, and activity. These are further discussed in Section 8.

5.2. Agents and utility

The model consists of agents located in a spatial environment, where they have a home location. This environment is represented by a network of locations. Each agent has a list of other agents he/she is friends with and a list of locations that he/she knows. Each agent has sociodemographic attributes (e.g., age, gender, car ownership, work status, etc.) and a schedule with a certain number of time periods. Each agent can undertake maximally one activity per time period. Fig. 4 shows the agent architecture.

In this paper we focus on the second goal of joint activity participation. Utility-based agents are used as this allows the agents to evaluate the outcomes of participating in different activities. This has advantages and disadvantages: utility functions are difficult to develop and tend to oversimplify the real-world processes [62], however as the aim is to create a model of a sample population for a city, i.e., thousands of agents, the agent model needs to be simple in order to be scalable. Utility functions are commonly used in transport models for evaluating alternatives and making decisions [65].

A utility function (Eq. (1)) has been developed to take into account the required issues – type (a) and purpose (p) of the activity, location (l), day (d), the other person involved (j), essentially, what, where when and who. This is based on the needs-based theory discussed in Section 2.2.

$$U_i(a,p,l,d,j) = V_i^{ap} + V_i^{l} + V_i^{j} + \epsilon \quad (1)$$

$$V_i^{ap} = f_t(\alpha_i^{ap}, d - t_{ap}) \quad (2)$$

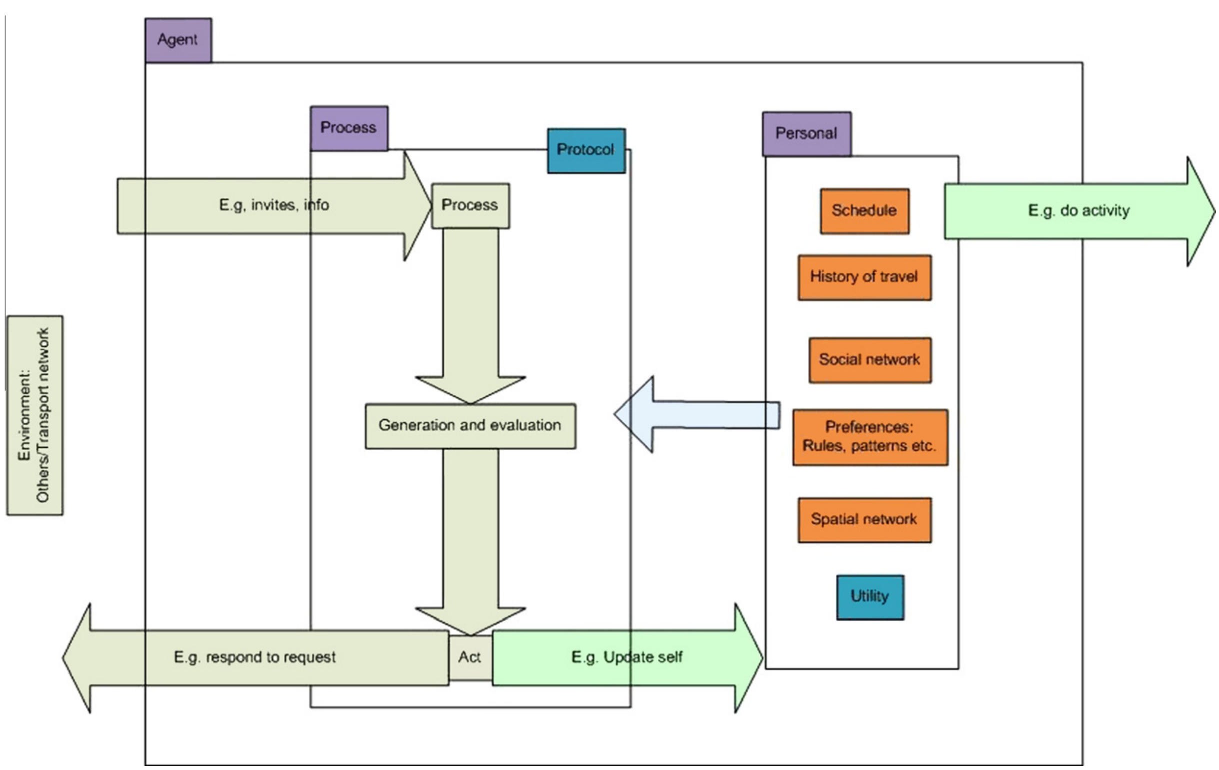

Fig. 4. The agents' architecture.

$$V_i^l = f_t(1 - d_{il}, d - t_l) \quad (3)$$

$$V_i^j = f_t(s_{ij}, d - t_j) \quad (4)$$

$$f_t(x, t) = \left(\frac{2}{1 + e^{-xt}}\right) - 1 \quad (5)$$

$$s_{ij} = Q_g + Q_a \quad (6)$$

Activities can have a purpose, chosen from sharing experiences, sharing information, informal chatting, and support. The different purposes can be used to determine who is suitable for a given activity. Activities can also have a type, such as shopping, eating out, or sporting activities, which determines the location of the activity. In future, this will be also used to determine the duration of the activity.

The components of the utility function U_i consider when an individual last undertook an activity (Eq. (2)), visited a location (Eq. (3)), or saw someone (Eq. (4)). These values (t_l, t_{ap}, t_j) are combined with the date of the proposed activity d to find the last time the particular event happened. The utility increases over time (Eq. (5)), so that an activity/location/person that an individual has not seen/visited for a while is more attractive than one seen/visited the previous day. This is based on the needs-based theory presented by Arentze et al. [31].

The preferences for an activity with a particular purpose and type (α_i^{ap}) is also an input to the model. In this instance of the model, we consider preferences to be unidimensional as a simplification. It could be that preferences are dependent on the composition of the group, for example, in terms of gender, cultural background, size of the group etc.

The distance to the location (d_{il}) is also taken into account, based on the individual perception of the environment and travel time. For each pair of individuals i and j, a similarity measure was calculated (Eq. (6)), taking into account age (a) and gender (g). The values of d_{ij} and s_{ij} are scaled to [0, 1].

5.3. Interaction protocol

The decision to start an interaction depends on whether the utility of meeting a particular person (or group of people) or undertaking a particular activity exceeds a threshold. This is calculated using the relevant components of Eq. (1). The individual who begins an interaction is known as the host, and the other participants are respondents.

We further assume that interactions and activities are undertaken between two agents, who are connected to each other in the social network. This means that the social and location networks do not change (as new connections are not being made), therefore the centrality calculations do not change.

Agent i, the host, makes a decision to start an interaction using an altered utility function, where the initial location l is set to the other agent's (j; the participant) house:

$$U_s(a, p, l, d, j) = V_i^{ap} + V_i^j + V_i^{jl} \quad (7)$$

$$V_i^{jl} = f_t(1 - d_{il}, t_j) \quad (8)$$

If U_s exceeds i's threshold, the host and participant exchange ideas for days and locations.

1. Host proposes an activity as a starting point.
2. The respondent then creates a list of the possible day/time combinations (taking into account the host's time window) and sends them to the host.
3. The host collates the day/times and creates a list of the *intersection* of the suggestions.
4. The respondent determines what type of locations are appropriate from the patterns provided. They then look up which locations they know of that match those location types.
5. The host collates the locations and creates a list of the *union* of the suggestions.
6. The host then creates a list of possible activities, taking into account when agents are available and the locations they have suggested. The list is returned to the respondent.
7. The respondent evaluates this list using a utility function and returns the list with their preferences.
8. Using the Borda ranking method, the host determines the chosen option and notifies the respondent, who adds the activity to their schedule. The host also adds the activity to its schedule.

Negotiations can be unsuccessful if neither individual is available on the same day, neither can suggest any suitable locations, or one individual finds that the utility of all proposed activities does not exceed their threshold.

The protocol satisfies a number of basic properties, such as termination, liveness, and safety. The protocol contains no loops and is completed in a constant number of rounds. All messages are sent from one role to another (either from host to respondent or vice versa) and the messages are unambiguous regarding the next step. Both roles proceed towards termination states, either when an activity has been scheduled, when a respondent cannot suggest any suitable days or does not approve of the activities suggested, or all parties cannot agree on options to negotiate about.

6. Network inputs

For all input networks, the agent population was constant, with the same personal properties (age, gender), thresholds and parameters, and home location. One hundred agents were present in each network. The average degree was kept roughly the same (~10), which is in line with analysis of friendship/social interaction networks [30].

Four different networks were generated. The first was a random graph based on Erdos–Renyi random graph [66], randomly generated by the NetworkX package for Python [67]. This network is shown in Fig. 5.

The other networks were based on the social circles algorithm [23]. All individuals used the same distance size for simplicity,

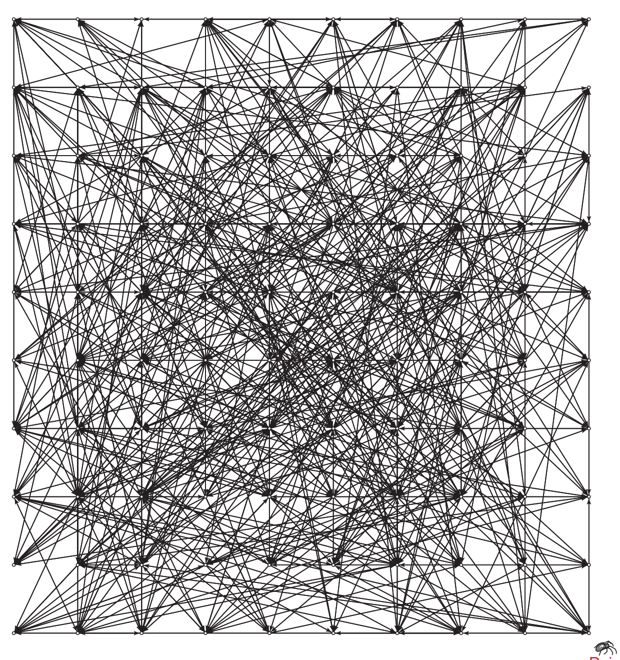

Fig. 5. The random network.

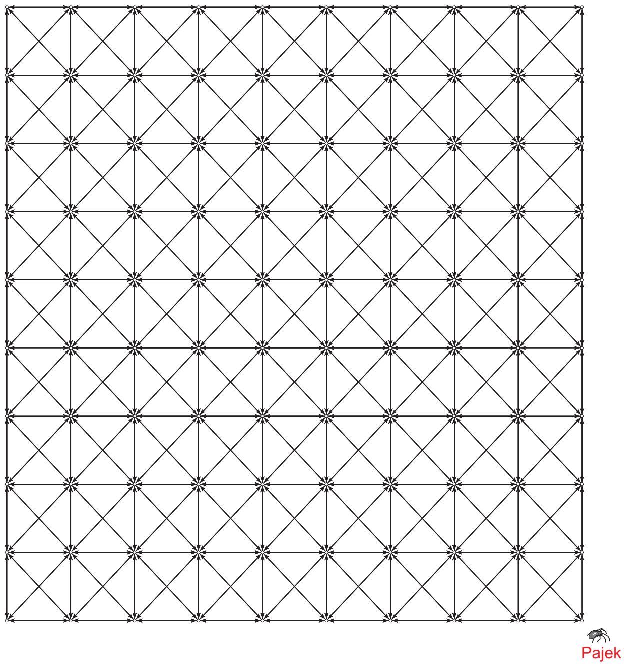

Fig. 6. The social circles network taking into account spatial distance.

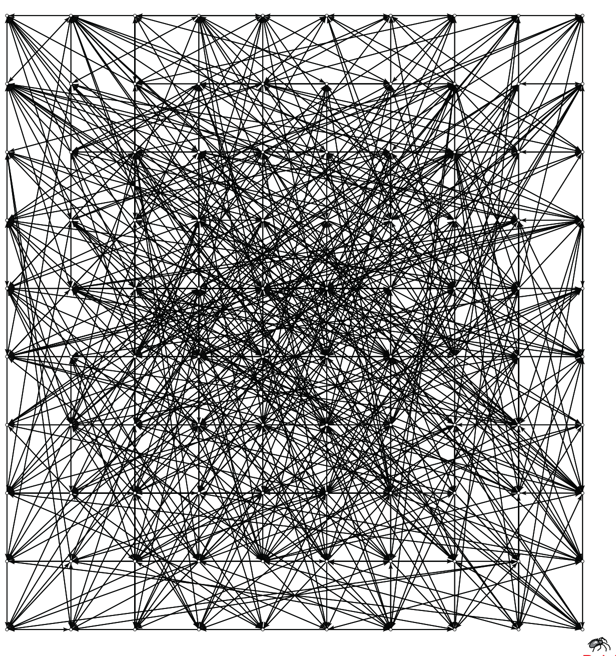

Fig. 7. The social circles network taking into account social distance.

however this varied per network in order to meet the average degree requirement. The social distance was based on Eq. (6).

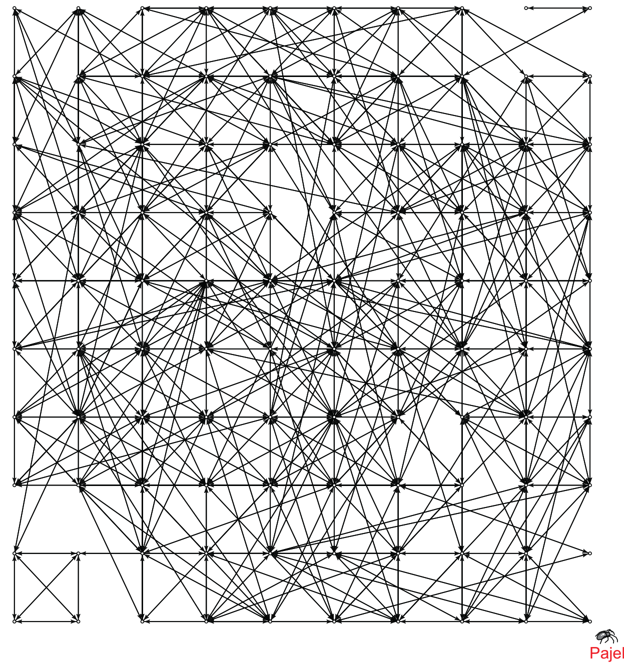

Fig. 8. The social circles network taking into account spatial and social distance.

The second network used only spatial distance as the distance measurement (Fig. 6).

The third used only social distance as the distance measurement (Fig. 7).

The fourth used both spatial and social distance as the distance measurement (Fig. 8).

The different social networks have differing clustering coefficients and assortativity on degree (i.e., nodes are connected to other nodes with similar number of nodes [18]) and on node attributes such as age, gender, and activity threshold. A value of 1 for assortativity indicates a perfect correlation on the attribute for pairs in that network, while a value of −1 indicates a negative correlation.

These properties are shown in Table 1.

7. An illustrative scenario

In this scenario, the only locations present are home locations. This means, that for an activity between two agents, only two locations are possible. Activities were also scheduled for the current time period, however the protocol does allow for looking ahead. For the one activity type and purpose, $\alpha_{home,social}$ was set to 0.5. Each agent has an activity threshold randomly chosen from [0.5, 1, 1.5, 2.0].

The agents all use the same utility function and negotiation protocol. Each agent also has an age level in the range [1–4], which is consistent with the aggregation used in activity-travel surveys (e.g., [30]). The gender similarity is $Q_g = 1$ if two agents have the same gender, and $Q_g = 0$ otherwise. For age, following [30],

Table 1
The properties of the different social networks.

Type	Degree	Cluster	Assort (degree)	Assort (threshold)	Assort (age)	Assort (gender)
Random	10.141	0.105	0.036	0.017	−0.021	−0.040
Spatial	10.141	0.509	0.531	0.009	0.069	−0.052
Social	12.040	1	1	0.0112	1	1
Soc/spa	10.505	0.491	0.264	0	0.862	0.565

$Q_a = 4 - n$, where n is the difference between the two age classes. The overall similarity or social distance s_{ij} is scaled to [0, 1].

The error term takes into account the location ($N(0, 0.2)$), each participant ($N(0, 0.1)$), and a personal short- (i.e., drawn every timestep, $N(0, 0.5)$) and long-term (i.e., drawn at the start of the simulation, $N(0, 0.2)$) error.

The model was run for 28 time periods as a warmup, and then for a further 28 time periods to collect data. As a multi-period model, this is a departure from previous transport models that attempt to optimise one period (usually a day) only.

The aim of the experiment is to validate the following hypotheses:

H1. The network structure will affect the number of activities.
H2. The network properties will affect the number of activities.
H3. At the node level, the distribution of activities will be different for different input networks and the node attributes (degree, clustering) will affect the number of activities.
H4. At the relationship level, the distribution of activities will be different for different input networks and the dyad attributes (similarity, distance) will affect the number of activities.
H5. The interaction protocol will be sensitive to different input networks in terms of the number of successfully and unsuccessfully negotiated activities.

8. Results and discussion

All analysis was done in *R*, a statistical analysis package. ANOVA tests were used to measure the difference in means of output variables for different input networks, while Kolmogorov–Smirnov tests can indicate whether two distributions are similar. The p indicates the significance of each test and r denotes the correlation coefficient. If p is less than 0.05, then this indicates that the result is statistically significant.

8.1. Hypothesis 1: The overall network structure

The effect of the overall network structure on the number of activities was measured using an ANOVA test. The result suggested a significant difference between the input network types ($p < 0.001$).

This means that Hypothesis 1 can be accepted, as the network structure affects the number of activities.

8.2. Hypothesis 2: The network properties

The correlation between each network property (clustering coefficient, assortativity on degree) and the number of activities was not significant. This indicates that these aggregate measurements are not a good indication of the outcomes of the processes in the system and therefore Hypothesis 2 cannot be accepted.

8.3. Hypothesis 3: At the node level

By averaging the number of activities across the ten runs for each person, the distribution of the activities can be measured. Using a Kolmogorov–Smirnov test can indicate whether the distributions are similar or not.

The distributions at the node level are not significantly dissimilar, as shown in Figs. 9–12.

The correlation of the number of activities per person and their centrality or degree is significant ($p < 0.001$, $r = 0.216$). This could be because those with more friends have more opportunity to engage in activities. The threshold for activities is also significant ($p < 0.001$, $r = -0.328$), meaning that those with lower thresholds are participating in more activities as expected. The individual clustering coefficient is not significant, as activities are limited to only two agents. We would expect this to become significant if larger group sizes are modelled.

Although some individual properties are significant, as the overall distribution of activities is not dissimilar, Hypothesis 3 cannot be accepted.

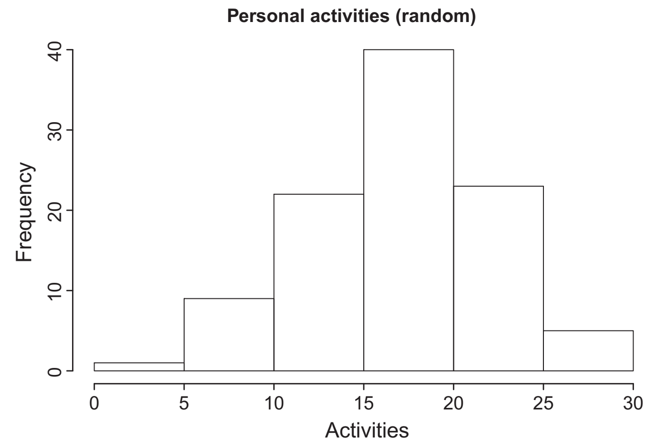

Fig. 9. The distribution of activities for the random network.

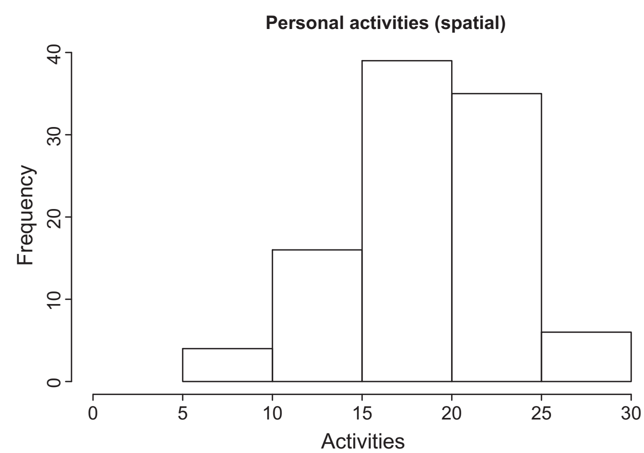

Fig. 10. The distribution of activities for the spatial network.

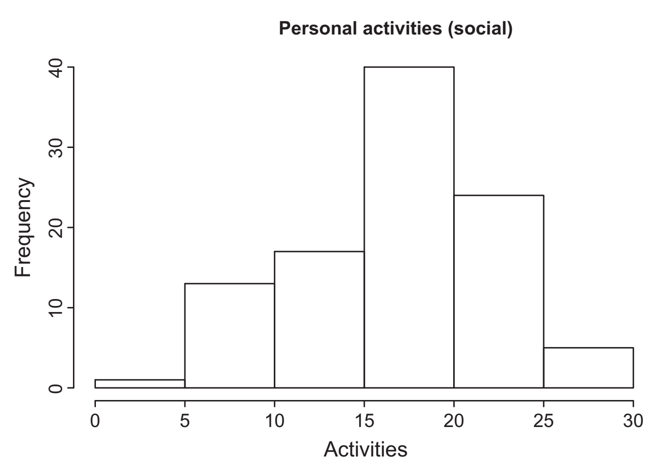

Fig. 11. The distribution of activities for the social network.

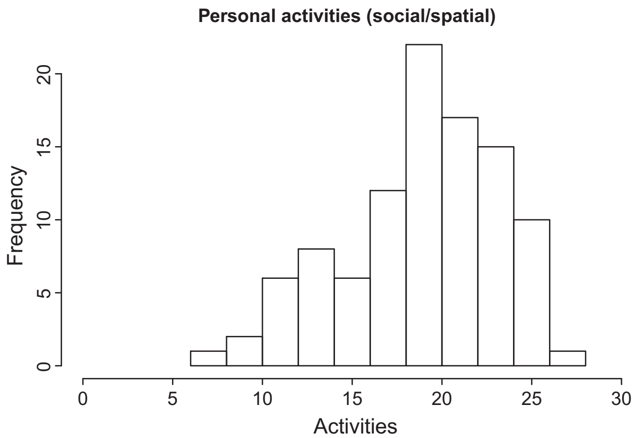

Fig. 12. The distribution of activities for the social/spatial network.

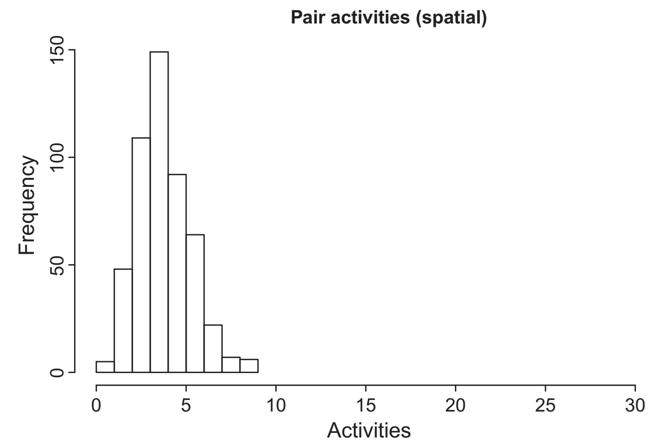

Fig. 14. The distribution of activities per pair for the spatial network.

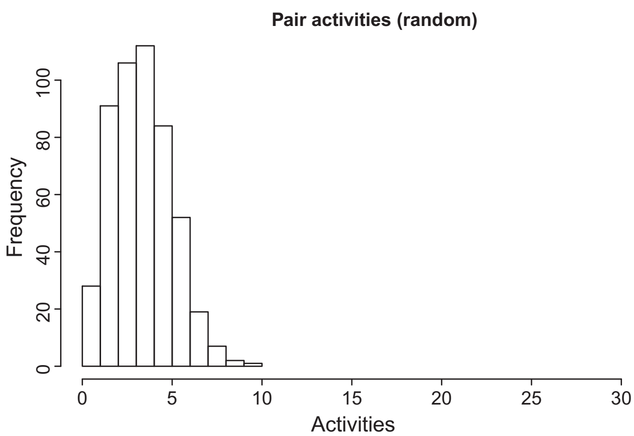

Fig. 13. The distribution of activities per pair for the random network.

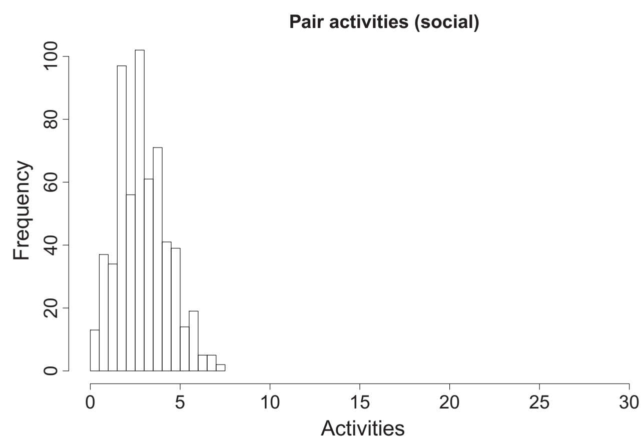

Fig. 15. The distribution of activities per pair for the social network.

8.4. Hypothesis 4: At the relationship level

As with the personal level, the activities across runs for each pair were averaged. The distributions at pair level were significant (all $p < 0.01$), with the exception of the random network and the social/spatial distance network ($p = 0.70$). The distributions can be seen in Figs. 13–16.

There was a very weak correlation between the similarity of pairs and activities ($p < 0.05$, $r = 0.041$).

The correlation between distance between pairs and the number of activities was stronger ($p < 0.001$, $r = -0.347$), which shows that pairs who live closer to each other are engaging in more activities together.

These results indicate that the relationship level attributes of the network are more significant than the overall or the node attributes and therefore Hypothesis 4 can be accepted.

8.5. Hypothesis 5: Performance of the protocol

We expect that the negotiation protocol is sensitive to the network. The protocol can fail at two points: if agents are not available at the same time, or there is no overlap in the preferred activities (e.g., both agents want to do completely different activities, or one does not like any of the options).

We have already shown that the successful activities differs for each network. The unsuccessful activities due to time ($p < 0.1$) and due to activity disagreement ($p < 0.01$) also differs for each network. Table 2 shows the average for each type.

The networks with some sort of spatial component performed better; with these networks as a base, agents are less likely to decline an activity based on distance.

From these results, Hypothesis 5 can be accepted.

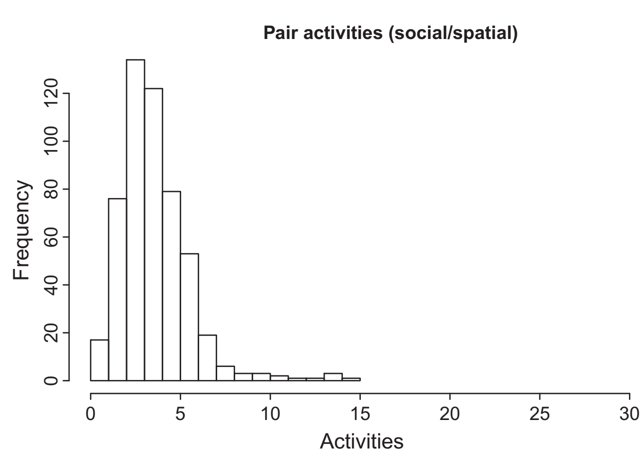

Fig. 16. The distribution of activities per pair for the social/spatial network.

Table 2
The number of successful and unsuccessful negotiations.

Network	Successful	Unsuccessful (time)	Unsuccessful (activity)
Random	868.2	834.2	437.5
Spatial	967.5	876.5	178.7
Social	882.7	834.4	405.5
Soc/spa	951.3	868.8	200.7

8.6. Summary

The experiment shows that overall, the key factor is not the overall structure of the network, but the nature of the links between agents.

Whether spatial or social distance is given more weight in the utility function will also influence the outcomes. In this experiment, they were treated equally.

9. Discussion and conclusions

This paper describes the design and implementation of an agent-based model of social activity generation and scheduling for experimental purposes to explore the effects of social space in addition to physical space. Due to the current interest in predicting social activities and the changing nature of social activities due to our use of information and communication technologies, this type of model is relevant for planners who need to be able to predict social activities and travel.

Multi-agent simulation is a useful method for modelling the decision-making processes undertaken by individuals, in this case, regarding whether they participate in a social activity with other people or not. However, even though many AOSE methodologies have been developed, none are specifically for agent-based simulation. We have used the MASQ meta-model as a basis for the modelling process and combined features of several methodologies to demonstrate a design.

Current research assumes that social networks influence social activities [31], therefore testing the sensitivity of potential decision-making models to different networks is an important step in evaluating the usefulness of incorporating social networks in activity-travel models. This step could also important for other domains where the social network is influential, e.g., social support networks or exchange networks [68].

We have described an agent-based simulation of social activities and discussed the results of experimentation with several input networks, differing in structure and properties. We show that the relationship properties within the network are more significant than individual or overall network properties for this type of model. However, as the model is developed further, some personal or network properties could become important. For example, people can only maintain a certain number of friends, so the degree becomes important.

We also describe joint decision processes for scheduling social activities with many participants. The use of interaction protocols for inter-agent communication is not radical from the point of view of the agent community, however it is novel for activity scheduling and is not often seen in social simulation. The different interactions we describe permit a more decentralised and collaborative approach to joint activity scheduling, that is better aligned with both the principles of agent-based modelling and decision making in reality than determining schedules individually or within a household. Unlike other activity-based models, activities are jointly scheduled outside households. Although other models (e.g., [26]) have included the effects of social influence, they have not modelled the scheduling process.

The model was simplified to one activity type/purpose and no network dynamics, so that the effects of the input network could be seen. Future work involves extending the model to include further details about activities (including different locations, activities with more than two participants, and taking into account time pressures/value of time), experimenting with agents using different utility functions and/or negotiation protocols, and exploring the effects of social distance/homophily in closer detail, in particular in the context of cultural characteristics. The use of the MASQ metamodel, which contains a Culture quadrant, means cultural extensions can be easily incorporated. As interactions and negotiations differ across cultures [69], the interaction protocols could be refined further to take culture more into account.

The results of the model can be used by city planners to evaluate the effects on social activities and travel of both changes in population and their characteristics (e.g., increasing elderly population, an increase/decrease in car ownership) and changes in infrastructure (e.g., public transport routes, locations of new shopping facilities).

As research into the effects of social networks on travel behaviour is in its early stages, there are little data available and as a result most models are in early stages of development. Research into how these models can be validated is in progress [70]. However, this work can be seen as a step forward in the requirements for sensitivity testing of such models.

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