

Understanding Urban Mobility and Pedestrian Movement

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Abstract

Urban environments continue to expand and mutate, both in terms of size of urban area and number of people commuting daily as well as the number of options for personal mobility. City layouts and infrastructure also change constantly, subject to both short-and long-term imperatives. Transportation networks have attracted particular attention in recent years, due to efforts to incorporate ‘green’ options, enabling positive lifestyle choices such as walking or cycling commutes. In this chapter we explore the pedestrian viewpoint, aids to familiarity with and ease of navigation in the urban environment, and the impact of novel modes of individual transport (as options such as smart urban bicycles and electric scooters increasingly become the norm). We discuss principal factors influencing rapid transit to daily and leisure destinations, such as schools, offices, parks and entertainment venues, but also those which facilitate rapid evacuation and movement of large crowds from these locations, characterised by high occupation density or throughput. The focus of the chapter is on understanding and representing pedestrian behaviour through the Agent-Based Modelling paradigm, allowing both large numbers of individual actions with active awareness of the environment to be simulated and pedestrian group movements to be modelled on real urban networks, together with congestion and evacuation pattern visualisation.

Keywords: Infrastructure, Population Dynamics, Environmental Issues, Agent-Based Modelling, Pedestrian Behaviour

1. Introduction

Currently, the field of urban mobility modelling is experiencing a surge of activity due, in part, to renewed interest in crowd management, (including evacuations due to natural and man-made disasters), but also influenced by increased efforts to reduce CO₂ emissions through optimisation of urban networks for both traffic and pedestrian purposes, [1-2]. Urban sprawl is a recognized phenomenon for growing cities, and tools, such as urban growth models, have proved valuable for planners and decision-makers in identifying challenges and potential environmental impacts, [3]. Expansion of the built environment to meet population demand implies extended daily commutes as well as loss of other land-function, and is recognised as a critical challenge in global change, not only in countries experiencing explosive industrialisation, but world-wide, [4-9]. Growth in population size of many major cities presents complex logistics in meeting demands for increased numbers of daily commuters and alternative transport modalities. In the UK, for example, the eleven most populous cities since 2015 are to be found in Scotland,

(Glasgow and Edinburgh), the conurbations of North-East England, the West Midlands and South and West Yorkshire, (adjacent to the cities of Greater Manchester and Liverpool), Bristol and Cardiff in the South West and, of course, Greater London, [10]. Between mid-2011 and mid-2015, Greater London's population grew by 5.7% to around 8.67 million, compared to that of other city regions (2.3%) and to average growth (2.7%) for the country as a whole.

Under pressures of increased population growth, short-term crises and long-term policies, city layouts and infrastructure constantly adapt to meet need but the many factors involved render solutions for high volume passenger movement far from trivial. Awareness of the consequences of unrestricted urban sprawl has motivated legislation and a global move towards environmental sustainability over several decades, but change is slow, [11]. The performance and modalities of transportation networks have attracted considerable attention, fueled mainly by efforts to reduce road congestion and harmful emissions. For example, Transport for London (TfL) (created in 2000), manages the capital's principal road networks, the underground system and its extension, the Docklands Light Railway and TfLRail, (responsible in conjunction with the Department of Transport for commissioning CrossRail, designed to improve East-West transit). While the TfL budget (~10 billion sterling in recent years), demonstrates major commitment to maintenance and new development, its Business Scorecard also emphasizes the need for a system accessible to all, the 'greening' of the city streets and the health benefits for Londoners 'travelling actively', [12]. Accommodating positive lifestyle choices such as walking or cycling commutes, as well as decreasing the CO₂ burden from road traffic, has served also to shift more attention towards the pedestrian's city experience. In consequence, this chapter also explores the implications for 'travelling actively,' and safely, in London.

From the pedestrian viewpoint, the need for green spaces in city planning has long been recognised, [13], but factors for *active travel* remain complex. Digital street mapping and mobile technology have improved familiarity and navigation within the urban environment but, while novel modes of individual transport (such as smart urban bicycles and electric scooters) reduce the emission burden, road usage is increasingly multi-faceted. Inevitably therefore, strategic emergency management is complicated by the challenge of prompt multimodal evacuation of dense urban areas, [14]. In discussing plausible modelling approaches which capture principal factors influencing rapid transit to daily destinations, (such as schools and offices), as well as leisure trips to parks and entertainment venues, consideration is given not only to throughput, but also efficient evacuation from these high density locations. The focus, specifically, is on the flexibility which Agent-based modelling brings to representing pedestrian behavior. The paradigm permits individual actions, awareness of the environment and pedestrian group movements to be modelled simultaneously on real urban networks.

Pedestrians are distinguished by a number of key features, such as personal choice, variable dynamics and vulnerability. Debatably, they have the least predictable behavior patterns, although it has been shown that crowded venues restrict optimal choice, [15-18]. Specifically, it has long been demonstrated that pedestrians can move freely *only* when pedestrian densities are small, [15]. Designing urban infrastructure in order to increase pedestrian activity, therefore, has to balance often conflicting requirements of personal characteristics, (such as walking speed), against considerations of safety. The problem space is greatly expanded by variation in pedestrian profiles; for example, age, speed, knowledge of the environment,

individual or group transit, entrance and exit point to the network, time of day, occupation density (amongst other factors) all affect efficient transit as well as the logistics of congestion and evacuation. Variable dynamics can be illustrated by examples of walking patterns for an average shopper, which are markedly distinct from pedestrians in a business district. Similarly, an elderly person typically moves differently to a young one, as does a native to a tourist and so on. Even within a particular scene, e.g. a shopping district, logistics are different for the successfully-laden pedestrian and those still browsing, [19].



Figure 1: Aerial views of Singapore (left) and Zurich (right) urban layouts. Both cities consistently rank in the top 10 in the world for urban layout and mobility.[20, 28-29]

As a consequence of this diversity, shaping sustainable city infrastructure relies on understanding pedestrian movement patterns and the environmental and behavioral reasons that guide them, together with provision of suitable public transportation options at key locations. Cities with strong track record in infrastructural design for mobility include Singapore and Zurich, (Fig. 1). While arguably due to large budgets, it has been shown that quality and safety of urban infrastructure does not relate solely to wealth, as good planning practices are vital [20]. Looking ahead, GPS-enabled mobile apps. are likely to shape pedestrian behaviour trends further, with awareness of urban layout, (such as important intersections, walking routes, street signs and transport alternatives), reliant less on physical observation than in-app street map layouts, together with walking time estimates based on the historical consumer mix, [21].

Investing resources in sustainable city planning is not for the faint-hearted. Burgeoning demand for access and choice continues to threaten limits for air quality, noise, energy consumption and biodiversity. The last hundred years has seen urban population growth concentrated on less than 3% of the world's surface but with the corresponding environmental footprint disproportionately impacting climate: currently, 75% of greenhouse gas emissions can be attributed to cities with ecological effects many times larger than the actual urban area occupied [22]. Socio-economic implications, such as health and well-being, are also cause for concern: in France and elsewhere, urban mobility plans are now a required component of the urban planning process for the future, [23], while global city initiatives, such as the 10 Aalborg Commitments [24] attempt to define basic guidelines for sustainable development.

2. Overview of modelling approaches

Within the broader agenda of sustainable urban planning, computer modelling has gained increased popularity as a versatile tool. The ability to explore *in silico* the nature and effect of change can facilitate the planning process, providing insight on the parameters, key dependencies and potential pitfalls, as well as complementing pilot schemes.

Emergency evacuation typically follows natural disasters, terrorist attacks on transport networks or at major events, as well as other causes of injury or where crowd dynamics de-stabilise, [25]. So-called climatic ‘extreme events’ have markedly increased over the last decade, with ever-more severe consequences [26]. Increased frequency of such events, together with increased population density, (mainly concentrated in urban areas and regions experiencing rapid urbanisation, such as Asia), [26], have led to some of the largest losses of infrastructure in recent history. Besides highlighting the need for pre-emptive action and resilient infrastructure, extreme event prediction is widely employed to mitigate the human cost and employ successful evacuation strategies; (as in the very recent example of Cyclone Fani’s landfall in India and Bangladesh (2019) where more than 2.8 million people were evacuated ahead of the storm [27].

Approaches to modelling crowd behavior, pedestrian flows and evacuation methods are varied and range from studies looking at flows of people as a paradigm [30-32] to analysis of individual behaviour patterns, [33-36]. Early work aimed to describe pedestrian motion through physical model types including fluid dynamic and social forces, based on Newtonian mechanics, [37]. Pedestrian motion can be described, for example, using a sum of different force vectors - namely attractive, repulsive, driving and fluctuating. However, the downside of these models is their reliance on sophisticated mathematical expressions that become intractable on expansion for newly discovered parameters and behaviours. Further individual movement is represented as a superposition of pedestrian interactions, not only non-trivial to solve, but often opaque to interpretation [38].

Key features to be incorporated are the agenda of the individual, (purpose of journey), as well as interaction with the built and demographic environment - road traffic, urban layout and crowd size. Two elements present particular difficulty. Pedestrians do not always follow simple logic or ‘stimulus-and-response’-based behavior and, unlike other road users (such as motorized vehicles or bicycles), do not need to, and indeed do not, follow pre-set movement lines. This freedom in choice and execution of movement means that any model must allow for randomness, treating individual behaviour as unique to some extent.

2.1. Pedestrian Movement

Two main model types can be distinguished for pedestrian interactions, namely those for route choice and road crossing behavior respectively. The former category is concerned with optimizing route layouts to achieve shortest travel times between origin and destination under various constraints, such as emergency road closures or congested pathways: investigations of crowd behaviour and evacuation dynamics mainly utilise these scenarios, e.g. [39]. In contrast, road-crossing models focus on pedestrian

decision making and the nature of interactions on road crossings: here key elements include aspects such as crossing gap (gap acceptance theory) and use and location of the crossing itself (utility theory), e.g. [40].

Further categorisation is possible by model scale; usually denoted microscopic or macroscopic. Macroscopic models are often route choice ones, and are underpinned by the mathematics of fluid mechanics and queueing theory. Earlier examples include optimization of pedestrian network topologies [41] based on pedestrian queueing networks; representing crowds as single, flowable entities [42] and resolving bottlenecks by disaggregating upstream and downstream flows around the point of congestion [30]. More recent work includes formulating pedestrian flows as a family of measures and flow maps [43] and vision-based models [44]. Microscopic models currently account for the majority of pedestrian movement studies, [45], with some of the first models in this space based on the Cellular Automata (CA) paradigm, [46]. In CA, the environment and street layouts are represented as matrices of cells with individual pedestrians being able to move from cell to cell by discrete steps in a given model iteration. Update between iterations is performed by applying a matrix of cell state translation rules (the transition matrix) to model successive movements, [Figure 2]. Historically, CA models were used to describe various pedestrian movement scenarios in both route-choice and pedestrian crossing categories, from bi-directional pedestrian flows on footpaths [33] to interactions of pedestrians with the urban layout [47].

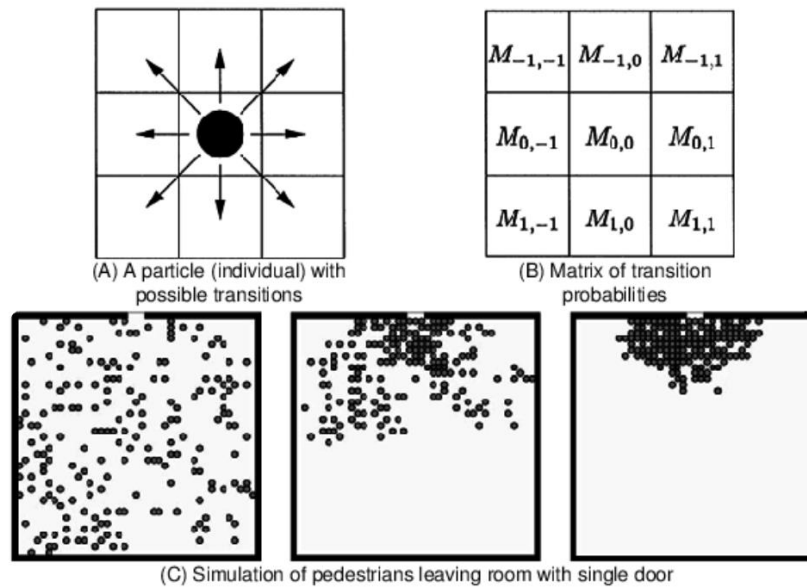


Figure 2: An example of a Cellular Automata model with transition matrix [54]

Increase in computing power over the last decade has seen expansion of the CA paradigm with next generation simulations for pedestrians based on multiple *agents*. These multi-agent or Agent-based Models (ABM) achieve microscopic levels of simulation, based on artificial intelligence concepts, [45]. In agent-based systems, pedestrians are modelled as fully autonomous entities with cognitive and behavioral learning characteristics. Early applications included analysis of global movement patterns [50] and impact of pedestrian space allocation during movement [34]. Recent examples include [48-49] where the former considers interactions of pedestrian agents in counterflow situations and the latter employs ABM to simulate different categories of pedestrian behaviour at congestion points in a large city layout. The ABM approach, combined with the processing power of large computing clusters enables effects of individual

human choice within precise urban geometries to be modelled realistically. The practical potential for the future of city design and provision is considerable; (e.g. Smart City initiatives - such as [51]).

2.2. Evacuation Dynamics

In modelling disaster scenarios, normal pedestrian movement simulation does not apply. Evacuation of metropolitan areas requires rapid crowd dispersion by safe routes to non-hazard zones at short notice. In terms of large-scale natural disasters such as cyclones, circumstances are even more extreme in terms of volume of people movement and area affected; for example, a few million persons might need to be moved to safety from an area of 160 square kilometers, [27], [52]. Evacuation models again, therefore, have a clear division by scale, based on the area impacted: small-scale evacuations may involve isolated locations, such as rooms, buildings, stadia, while large-scale can include anything from sub urban and urban metropolitan areas (with high population density) to tracts of land with different population densities [53].

Microscopic models for building evacuation have been around for some time [54]. A useful categorization is provided by the US National Institute for Standards and Technology (NIST) [55], based on orientation, building type applicability, size of grid, user perspective, type of behavior and type of movement. Of particular interest in the NIST nomenclature is the classification of models into behavioral and movement types. Behavioral models simulate action-taking by pedestrians, depending on the specific emergency circumstances, while movement models concentrate on evacuation flows. Models, which incorporate both individual action and evacuation strategies are classified as mixed.

Further sub-division is possible according to the nature of the behavior exhibited. Thus, implicit behaviour models, conditional behaviour models, models utilising artificial intelligence and probabilistic models have all been proposed, of which the first are the simplest. The behavioral response of individual pedestrians is built into movement patterns or response delays, but is not modeled explicitly as a *conscious choice*, [56]. Conditional approaches follow an 'if-then' rule pattern - evacuee behaviour is modeled as a response to structural characteristics or structural changes in the surrounding environment, [57]. All models simulate individual pedestrians through modeling the human intelligence aspect of their behavior directly, (as opposed to indirectly via movement parameters as for other model types), [58]. Probabilistic models assign behavior probabilities to individual groups permitting random outcomes for each model run, with statistics analysed after repeated runs. Compared with AI models, parameterization can be based on summary data for real disaster events, [49]. Agent-based models (ABM), (combining both AI and probabilistic approaches), thus offer considerable strengths; (discussed in more detail below).

2.3. Model Choice

Choice of the right model does not always involve the more complex or even the most realistic since complexity requires a large set of parameters, for which empirical estimates are often unavailable, (e.g. profiles of people in a given evacuation context), so simplicity can be an advantage. Moreover, the mode of evacuation can be a critical determinant (applicable almost exclusively to macroscopic models). For large-scale evacuations, the majority of research to date has assumed vehicular transport (predominantly car-based) movement, [14]. However, this is sometimes neither practical nor possible and can, on occasion,

lead to further escalation of disaster situations by contributing to congestion, [59]. In other cases, no such transport option is available and/or existing public transport can not be used in the immediate vicinity, [60]. In 2005, for example, hurricane Katrina left 80% of New Orleans in the U.S. state of Mississippi flooded, with some parts under nearly 5m. of water, [61]. In consequence, investigation of exclusively pedestrian-based evacuations in circumstances where utilizing of usual transport modes is not an option (e.g. earthquake disasters or floods), is gaining prominence.

In this context, Fig. 3 illustrates New Orleans (map taken from [62] with vehicular evacuation routes shown in green and population densities in orange). Implications for loss of access to routes for car transport are clear.

Well-established early traffic simulation models such as PARAMICS, VISSIM, CORSIM [63-65], have recently become popular also for emergency evacuation scenarios, using adjusted parameter values, e.g. acceleration of vehicles and reaction time, which differ in disaster situations, [66-67]. However, other transport options, such as the rail system, (arguably an effective evacuation mechanism due to larger capacity), have not been extensively modeled, (although included in existing urban evacuation plans (e.g. for Chicago [68])).

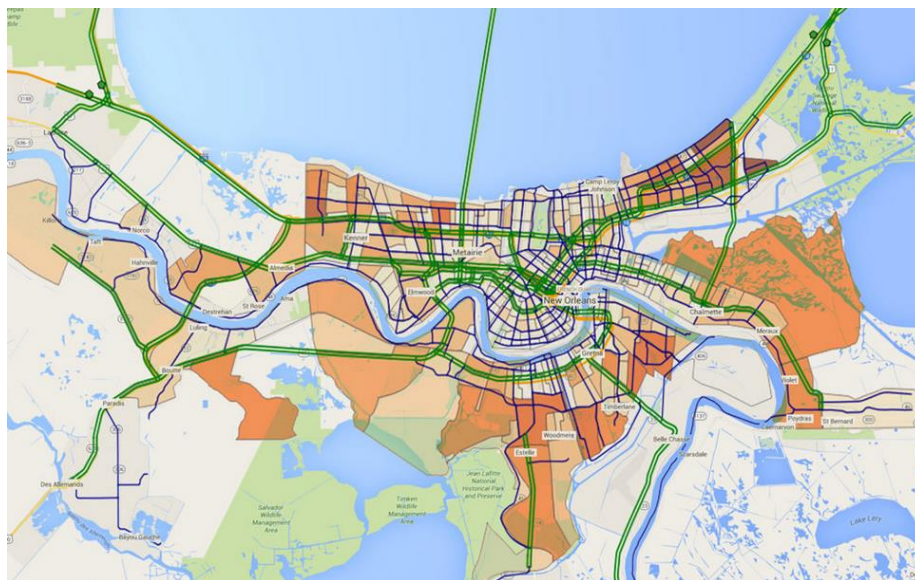


Figure 3: Map of New Orleans showing the sectors of an evacuation plan obtained via optimized modelling. Blue lines indicate secondary roads used in evacuation routes. Green lines indicate roads used as one-way contraflow evacuation routes. The orange shading indicates population density, with darker shading indicating greater density [62]

Clearly, however, major disruption to (or congestion of) available transport networks, combined with the high population density in urban areas, means that evacuation on foot provides a vital mode of escape. Pedestrian evacuation models of this type have only recently begun to feature in the development of city evacuation plans, while adaptation of existing evacuation model tools again necessary to accommodate features involved, [45].

Increasingly important, however, in modelling both urban mobility and evacuation scenarios are new technology tools, such as Volunteered Geographic Information (VGI) systems. VGI systems allow for collection and dissemination of global urban data, based on user-generated content and peer-review, and thus allow creation and curation of geographical datasets that would otherwise be too cost-prohibitive to assemble for individual research purposes. A good example of a VGI system is OpenStreetMap (OSM), an open project with the purpose of creating non-proprietary geographical maps of the world, [69]. Led by the OpenStreetMap Foundation, its stated goal is to encourage the development and distribution of free geospatial data for anyone to use and share. Particularly attractive is its fine-grained coordinate layout and geographic metadata associated with each map element. OSM maps provide a good backdrop on which to develop both CA and AB model types. These can incorporate both quantitative (e.g. street lengths and lane numbers) and qualitative (street types, nearby amenities) map data to accurately simulate grid ‘cells’ (in the CA type) or free-flowing pedestrian environments (for ABM).

3. Pedestrian Behaviour

As urban environments expand, routine travel to work or other destinations typically takes longer and can be increasingly affected by congestion and delays for both public and private transport modes. Alternative lifestyle choices such as walking and cycling can prove both healthy and efficient, but are also subject to constraints of the built environment and demographics. Although pedestrian behaviour has been studied for more than several decades [70], predominantly with respect to self-organization patterns and interaction of pedestrian flows [71], additional parametrization has become possible relatively recently due to expansion in computing power. In consequence, the questions addressed have become more complex and more relevant for both normal movement and for emergency scenarios. Examples cited include use of models to analyze evacuation patterns from enclosed spaces, (such as buildings, underground stations and other public venues) [27], [72-73], to address large-scale problems in morphological urban structure, as well as to understand cognitive behaviour in the context of disasters, (such as hurricanes and terrorist attacks amongst others) [38], [74].

3.1. Groups or Individuals

Addressing self-organization, [15], [32] some studies report that, rather than wholly random or individual movement, interactions inside and between groups lead to formation of typical walking patterns. Distinction exists between travel as a single individual or within a group, however, so that while pedestrian behaviour is diverse, with each individual permitted flexible options for movement through crowds or definition of ‘optimal’ route, such groups or crowd pressure act as limiting factors to free choice, [75]. Equally, knowledge of the built environment and configuration of the urban street network augments visual perception and cognitive understanding of spatial complexity to determine route choice and understanding of the way in which directional change complements distance, [76-77]. Consequently, while motorised (and non-motorized) road-using vehicles are constrained by traffic rules, signalisation and street orientation, pedestrian flows are subject to fewer fixed rules, exhibiting greater randomness at every time point during free movement, [45], but subject to continuous real-time re-assessment and rapid adaptation of route choice under congestion. Figs. 4a and 4b illustrate some of the flexibility of choice available to the pedestrian under his or her perception of advantage to be gained during urban travel.

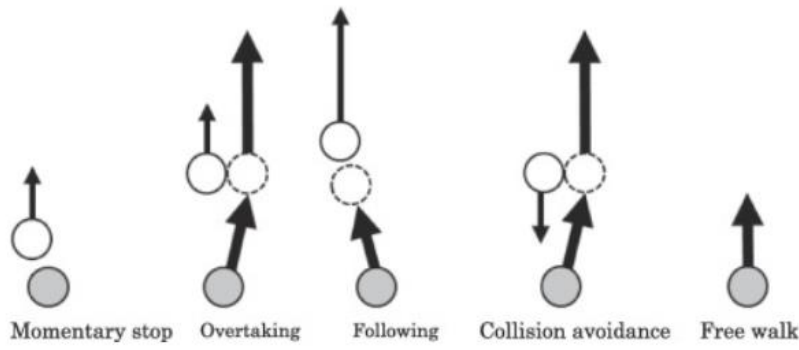


Figure 4a: Examples of different pedestrian behaviour depending on interaction with other pedestrians during street crossing [78].

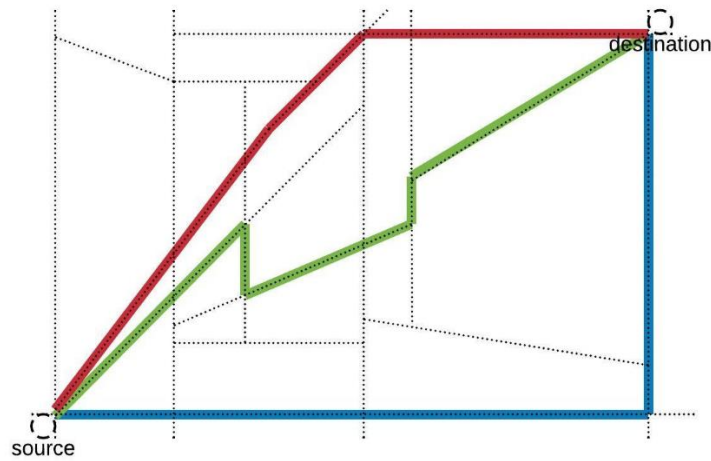


Figure 4b: Examples of different pedestrian behaviour depending on shortest route perception; **green** - shortest distance is the least actual cost path; **red** - least angle change requires pedestrians to course-correct their path towards “most likely” turns; **blue** - least turns puts the highest “cost” of the route into actual turns needed to reach the destination.

The figures serve to highlight those properties which strongly motivate bottom-up modelling of pedestrian movement; the agent basis provides a flexible tool for analysis of complex social behaviour [79], with agents actively aware of their environment (traffic, adjacent pedestrians and the street network).

3.2. Real Urban Networks

Perceptions of the network also depend, however, on how well this can be represented and the importance of VGI, (noted above) has led to considerable model refinement. For example, in [49] the authors introduced a discrete, behaviour-driven space-time framework, allowing pedestrian movement to be modelled on a real urban network. The main focus is on exploring the potential of the approach through example scenarios and investigation of simple hypotheses of pattern evolution. The research considered pedestrian movement originating from three main ‘cognitive features’ [77], [80]: (i) walking strategy, (ii) spatial awareness and (iii) knowledge of the urban grid. Figure 5 shows emergence of flow patterns

originating from such features in a hypothetical peak commute hour scenario for several hotspots in the City of London's financial district.

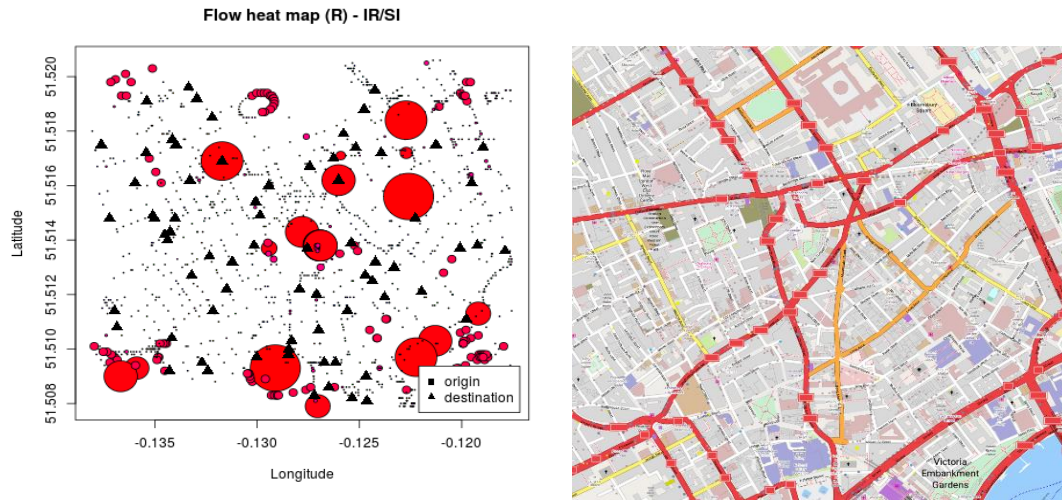


Figure 5: Simulation of pedestrian flow size using commute hotspots in a hypothetical City of London peak hour scenario with agents displaying full knowledge of urban grid; **right** – original OpenStreetMap of the section of City of London district; **left** – hotspot flow rate model (number of pedestrians passing per second) for the map section

Unfortunately, normal cognitive behaviour patterns do not apply in emergencies and route choice during a disaster scenario involves elements that are not present during regular commutes. Amongst others, these include decision-making under pressure, limited visibility, unclear evacuation routes and dependency on others in the same group (and in authority) to indicate optimum or safe direction. Additionally, crowd dynamics can change rapidly. It has been shown that crowd turbulence restricts movement at extreme densities, (a phenomenon observed during recent crowd disasters), [38] and also modelled by [81-82]. Thus self-organizing behaviors, designed to optimize motion on the urban network under normal conditions, break down at high crowd densities and for bottlenecks that occur during large evacuation scenarios [38]. Simple patterns, such as formation of unidirectional pedestrian flows in bidirectional traffic, disappear and are replaced with other collective patterns like long-range collisions and stop-and-go waves that lead to serious participant injuries during mass events. In an attempt to understand the forces and factors involved, recent studies have considered merging behavior of pedestrians under different scenarios as well as models for collision avoidance, [83- 85].

In summarizing model choices and trying to understand pedestrian behaviour, it seems clear that advantage lies in replacing classical physics models with a more cognitive approach, tailored to single-person (agent) granularity. In evacuation scenarios, in particular, behaviour is based on the concept of heuristics, namely quick and simple cognitive processes that tend to pare down visual perception of the world and optimize for speed, (a crucial aspect of emergency decision-making). Agent-based models also permit simulation of well-known ‘grouping’ behavior during such scenes, including cohesive bounds and ‘herding’, where groups of individuals decide to communicate, act and stay together as a group. These fine-grained clustering aspects of behavior are not well-captured by physical approximation, [86].

4. Agent Based Modelling

4.1. Advantages and Scope

Building on earlier discrete methods (such as cellular automata), agent-based modelling (ABM) has gained considerable popularity for representation of individual pedestrian interactions. The approach has several key advantages, the most important being the expressive and intuitive nature of the modelling language, its suitability to high-performance execution environments, adaptability to inclusion of heterogeneous behaviour and incorporation of stochasticity [87-88]. The origins of application of ABM to pedestrian modelling lie in simulations of social behaviour and decision-making, introduced in detail in [89]. From early models, where agents of two distinct types populated a simple grid, [90], use has expanded to representation of complex real-world situations and social behaviour involving millions of entities (e.g. TRANSIMS, [91]).

The modeling strengths of the agent-based approach for pedestrian behaviour are wide-ranging. Characteristics of individual pedestrians can be defined, including estimates of their spatial awareness using cognition precepts, combines with preferential choices determined for different social groups. ABM can be used to investigate behaviour patterns that incorporate rules of movement along pedestrian routes, as well as intermediate decision and conflict points. Dynamic volunteered geographic information system data (such as that from the OpenStreetMap platform) can be utilized, permitting analysis of arbitrary city networks and comparison of the effect of grid structure and amenity distribution. Interaction of multiple social groups can also be investigated, for example those consisting of pedestrians who have 'directed' (e.g. point-to-point) patterns as opposed to those progressing at 'leisure' (with patterns that are more random and less easily graphed). Such features offer the potential for these models to explore urban flows and congestion and the way in which changes in network morphology affect route choice. Equally, characteristics of the urban networks in responding to changing demand can also be modelled as well as disruptions impacting individual agent paths and travel times. ABM also compares well with statistical prediction techniques for pedestrian flows that have gained popularity in recent years, such as Multiple Regression Analysis (MRA), [92]. This type of analysis relies on known parameters such as length of pedestrian routes and visual connectivity between points to estimate e.g. throughput numbers per given unit area [93]. While useful for estimating and understanding aggregate numbers representing pedestrian flow data, difficulties arise in accounting for aspects such as urban network architecture and layout [94]. Although Agent-based models can not access real pedestrian movement data on a large-scale urban level to model flows through individual streets, known information about individual pedestrian behaviour does enable fine-grained implementation to explore different mobility scenarios at individual street level (within the large city model), as well as stochastic approximation for areas with sparse data.

4.2. Visualization of Pedestrian Behaviour on Urban Networks

In simulating crowd and group dynamics, ABM enables exploration of force effects at different crowd densities by using discrete grid cells with assigned *force vectors*, [95], and demonstration of local patterns for random pedestrian walks, utilizing aspects of both micro- and macro-simulations, [96].

In Figure 6, an extract from OpenStreetMap shows a section of central London's financial district for which the agent-based model has been used to simulate different types of progression, i.e. point-to-point or directional walking (that might relate to a commute) vs the more random progression (associated perhaps with tourist sight-seeing). The implications for density and dispersion of occupation are indicated by the colouring. In the first part of the Figure, clear preferred routes are the most congested and are coloured red, the next preferred yellow and so on. Hotspots are clearly identified. In the second part of the figure, clustering occurs at 'sights' rather than along routes, but hotspots often offset in terms of access. Clearly these scenarios represent different challenges in the case of closures or evacuation requirements. Shown specifically here are entrance points to alternative transport modes (black squares and red triangles respectively), such as the underground. In some scenarios these may of course be unavailable or closed down in the immediate emergency zone.

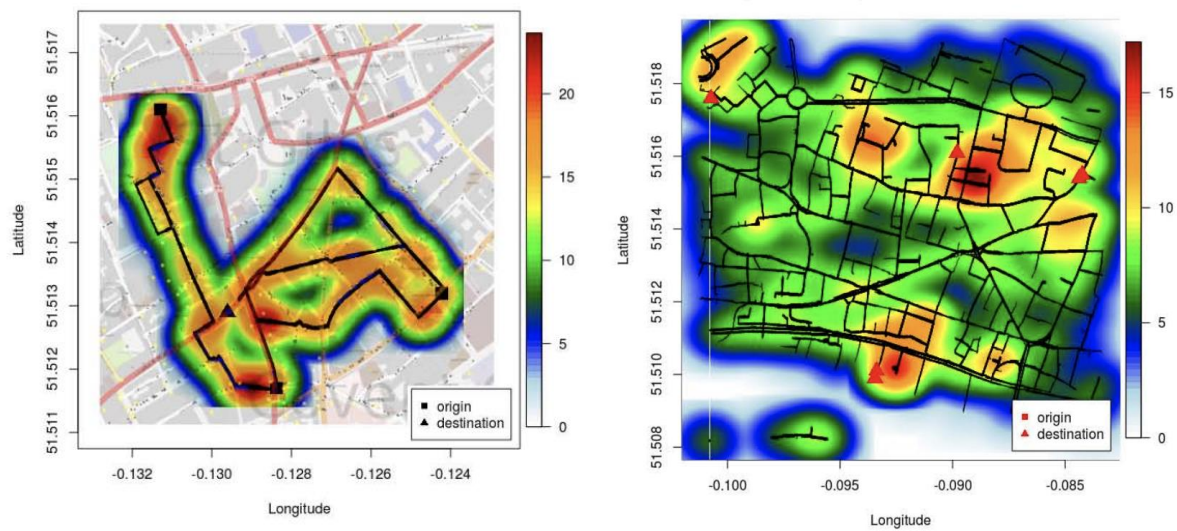


Figure 6: An example of an agent based model simulating the congestion areas of the London financial district for hypothetical pedestrian flows; **left** - point-to-point walking behaviour from a set of local underground stations {denoted by black squares} to place of work; **right** - random behaviour simulating e.g. tourist traffic originating from underground stations and converging at local points of interest. Adapted from [49]

In [49] authors show how a general agent-based model combined with VGI data can be utilized to describe a wide variety of pedestrian behaviors covering both emergency and non-emergency situations. ABMs perform well in modelling individual pedestrian behaviour as *generic state machines*. For every pedestrian we can specify a generic Decision-Transition-Waiting flow. Individual states can then be further broken down to simulate fine-grained psychological or perceptual aspects of individuals. In the example of non-emergency behavior (i.e. daily commute, travel, leisure) we can break down the decision state to distinguish an individual's knowledge of the urban network they are traversing. A person with partial or limited knowledge exhibits a different behavior-set compared to a person with full knowledge who can optimize travel based on this and grid perception. Other factors also contribute to decision-making – e.g. personal walking preference (aggressive, cautious or random), age, pedestrian group size and so on. (As an example, Figure 7 illustrates age and walking preference-based differences in terms of time taken and

distance travelled overall for the financial sector of the City of London grid. In evacuation scenarios, a similar decision state can be used to simulate behavioral aspects under emergency conditions; decision factors can range from group dynamics, placement of safe areas, visual perception under reduced visibility condition and ‘fear’. Transition and waiting states aim to simulate the action part of the behavior, namely execution and re-evaluation as the situation develops. This state transition diagram is illustrated in Figure 8.

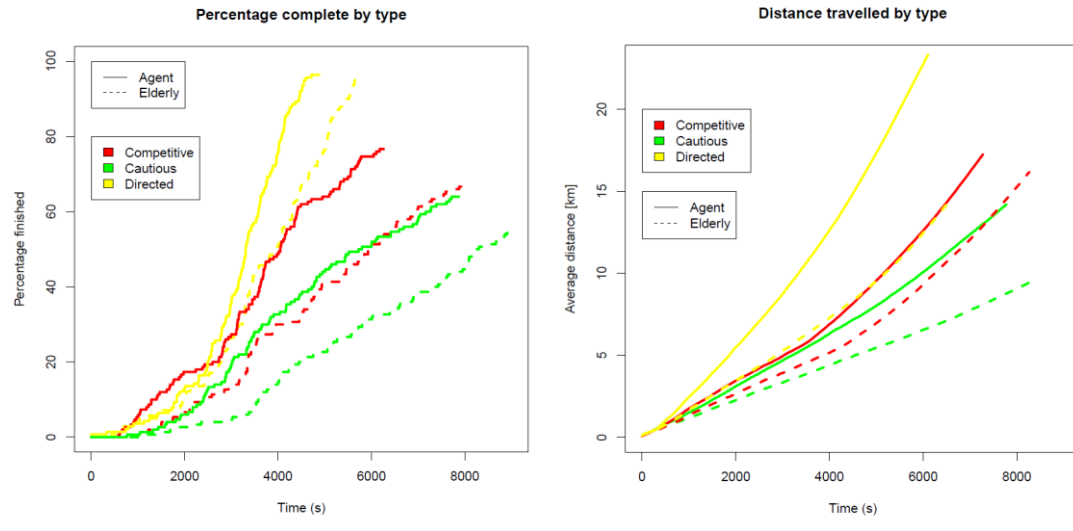


Figure 7: Simulation of age-based agent route performance when traversing an urban network [49], for pedestrians of different behavioral types

This type of model detail facilitates understanding of actual patterns observed in both traffic and pedestrian flows and evacuation scenarios. Similar features can occur for pedestrians to those found in traffic modelling (e.g. lane formation - as agents have to wait for other agents on the same route-choice path to move out of the way). Route-choice preferences (and those with high throughput) are clearly visible. Moreover, as lanes form, the ABM model allows for re-evaluation of routes based on dynamic parameters like congestion, (for example during large crowd events, where destination nodes in the urban or evacuation grid display become jammed, -usually due to too few approaches, or alternative exits become unreachable due to blocking by incomers or slow movers). Congestion avoidance of fellow pedestrians in free movement and in crowds is also readily simulated using the agent-basis. Pedestrians make optimal choices in the context only of perceived *local* grid congestion (as opposed to global knowledge of congestion points). Finally, ABM allow for clear identification of network *inflection points*, when impact of crowd size on travel or evacuation times becomes exponential rather than linear.

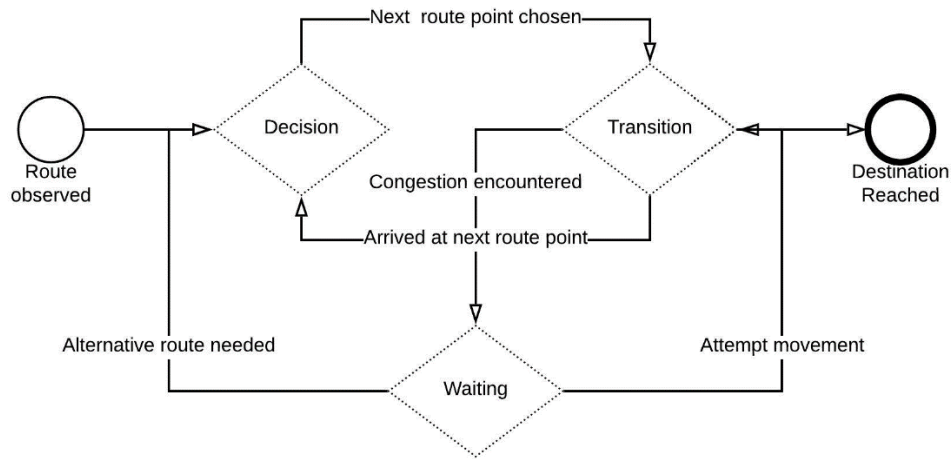


Figure 8: An agent Decision-Transition-Waiting diagram, as implemented by the agent based model in [49]

It should be emphasized again that a critical aspect of ABM performance for these problems is the choice of VGI or GIS platforms used to source the grid information. A platform such as OpenStreetMap permits extraction and visualization of relatively accurate street-level details, not only with respect to street geometry and space, but also in terms of street metadata such as throughput and physical street characteristics –e.g. length, width of sidewalk etc. These data are critical to provision of accurate grid simulations and assessment of pressure points and associated risks. Furthermore, the ability to edit the data to permit experimental analysis of the impact of alternative urban layouts and scenarios is important in building a relevant model, with potential for understanding, anticipating and responding to a range of pedestrian behaviour. Linkage to geographic information systems (GIS), combining spatial and temporal aspects additionally promises an effective geo-simulation tool facilitating interpretation of the urban environment [97]. Nevertheless, models using *both* separate crowdsourced GIS and ABM are relatively rare [98] and further investigation of social behaviour patterns is clearly required.

5. Conclusion

In this chapter, we have discussed factors influencing pedestrian urban mobility, which motivate ongoing research in commute efficiency, together with the wider implications for health and safety. Urban grids with high throughput typically utilize multiple transport modes and require efficient navigation, with non-motorized options increasingly seen as important in terms of reduction of harmful CO₂ emissions and benefits to health. In addition, infrastructure expansion and population growth present increased challenges for city management and emergency-responders. Recently, the ability to visualize urban networks with greater accuracy has received considerable impetus from the emergence of new tools, such as VGI platforms, on which detailed simulations can be built. The use of stochastic agent-based models in these simulations has proved particularly useful in terms of evaluating urban layouts and the diverse patterns of pedestrian movement. Moreover, ABM combined with VGI demonstrates considerable potential in modelling a range of real-world situations, ranging from crowd formation and dispersion to evacuation in the event of natural and man-made disasters.

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