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Research Article

The discrete dynamics of small-scale spatial events: agent-based models of mobility in carnivals and street parades

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Abstract. Small-scale spatial events are situations in which elements or objects vary in such a way that temporal dynamics are intrinsic to their representation and explanation. Some of the clearest examples involve local movement, from conventional traffic modeling to disaster evacuation where congestion, crowding, panic, and related safety issues are key features. We propose that such events can be simulated using new variants of pedestrian model, which embody ideas about how behavior emerges from the accumulated interactions between small-scale objects. We present a model in which the event space is first explored by agents using 'swarm intelligence'. Armed with information about the space, agents then move in unobstructed fashion to the event. Congestion and problems over safety are then resolved through introducing controls in an iterative fashion, rerunning the model until a 'safe solution' is reached. The model has been developed to simulate the effect of changing the route of the Notting Hill Carnival, an annual event held in west central London over 2 days in August each year. One of the key issues in using such simulation is how the process of modeling interacts with those who manage and control the event. As such, this changes the nature of the modeling problem from one where control and optimization is external to the model to one where it is intrinsic to the simulation.

1. Introduction: small-scale spatial events

Analysis at ever finer geographical scales changes the emphasis from a concern for understanding the structural arrangement of objects to ways in which those

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objects move to position themselves in time and space. This change in perspective is occasioned by several factors. At finer scales, we increasingly become part of the scene as observers, identifying more closely with elements nearer to our everyday experiences. This, in turn, changes the need to abstract and generalize. The law of large numbers also breaks down when the phenomena cannot be classified into categories from which general relationships can be inferred. But more importantly, spaces observed at the finest scales cannot be viewed as being predominantly static. What comes into focus is routine movement which keeps systems energized, alive if you like, and as observers within the scene, our own actions are enough to change the focus from statics to dynamics. The implications of this are important for geographic information science. As we approach the human scale, relationships begin to be articulated between objects rather than aggregates. Interactions between objects suggest that 'mobility' as well as location becomes important. More routine processes on finer time scales are introduced and the focus changes to one where many system elements can be directly observed in real-time.

Progress in developing science at this fine scale has been immensely slow for human systems. Systematic data has been absent while ways of defining and manipulating such objects mathematically have only emerged recently with the advent of object-orientated representation and agent-based modeling. There has thus been very little work on examining changes in, for example, urban form at these scales, despite some extremely promising work on the fine-grained socio-economic structure of cities half a century or more ago (Rannells 1956). Perhaps the most obvious problems at the local scale comprise one-off spatial events which involve the movement of large numbers of people over short periods of time. These largely fall within the sphere of entertainment although some of them relate to work, but all involve issues of mobility and interaction between objects or agents which generate non-trivial problems of planning, management, and control. Classic examples are football matches, rock concerts, street parades, some kinds of shopping, the entry and exit of large numbers of people from high capacity buildings and vehicles such as airports, stations, subway trains, and high buildings. Recently disaster scenes involving evacuation have become more significant, especially following 9/11, where methods for dispersing large concentrations of people are being explored. These types of events, however, have tended to resist scientific inquiry, never being thought of as particularly significant in terms of their impact on spatial structure.

Much of this is now changing. A new momentum to develop geographical information science at much smaller scales is coming from at least three directions. First there are changes in data availability where ever smaller scales are being observed, measured, and represented digitally. Sensing technology for detecting fine-scale geometries and textures as well as geodemographic data capture through electronic transactions are driving acquisition and measurement at the small-scale. The second source revolves around a sea change in the way systems are being conceptualized. There is increasing recognition that systems must be understood from the bottom-up as many systems function and maintain their structure in this manner. The way local actions generate emergent structures with order at higher levels is important to many functioning spatial systems such as traffic in networks, the development of edge cities, and residential segregation (Johnson 2001). The third source is a consequence of our growing abilities to interact more globally than hitherto. The movement of large numbers of people over short periods of time is an ever growing feature of our cities, and the spatial problems that these movements generate are increasingly important.

We first discuss dynamics of small-scale events and ways in which these might be observed and measured. Because such events are subject to considerable control, we propose a two-stage structure in which control is gradually introduced into the simulation. In the first stage, we explore the effect of geometry on movement and develop an algorithm based on 'swarm intelligence'. This generates hierarchies of shortest path and surfaces of attraction relating the location of events to points at which agents enter the event. In the second stage, agents—visitors/walkers/pedestrians—are launched from the entry points and climb the attraction surface to reach the event. An initial assessment of crowding is then made and, if necessary, controls introduced manually to reduce congestion. The model is re-run through this second stage and this process continues until a 'safe solution' is reached.

We then discuss model calibration. This model, like many, only touches our knowledge of the event in terms of the limited data available. Data requirements are enormous, always less than optimal, quite unlike aggregate modeling where parsimony is key. We use the model to simulate the effect of changing the route of the parade in the Notting Hill Carnival, an annual event held over two days in August each year in a 3.5 km^2 area of west central London. This event attracts over 1 million visitors and is widely regarded as posing a major problem of public safety. Our simulations continually reference problems of safety and we finally indicate how the model can be used to change routes and introduce controls which reduce crowding to acceptable levels. Our focus is not however on applications *per se* but on introducing a generic class of models that might be generalized to a variety of small-scale spatial events based on dynamics which involve local movement.

2. Observing and understanding local dynamics

Spatial models at any scale imply interactions based on movements of people, goods, ideas, between two or more locations which are usually classified as origins and/or destinations. These movements cover processes operating over different time scales at different speeds, from slow (in years) to fast (in minutes and seconds). At the human scale, interactions occur over different sized areas, each implying a different dynamics, purpose, and goal. Where interactions take place in very small spaces of the order of tens of square metres, the dynamics of movement are dominated by density considerations such as crowding, whereas over wider areas of hundreds of square metres or even tens of square kilometres, movement is more likely to be characterized by cost and purpose. What complicates the dynamics of the small-scale are events based on different individual movements which switch from one purpose and/or scale to another. In our example, we will deal with movements in confined spaces such as subway stations, along streets where density and crowding are less important, and at fixed attractions where density once again becomes important.

Although the events we will simulate exist from fixed origins to destinations like the journey to work, they are quite unlike such work trips in being much more protracted in duration, with greater freedom of movement in time and space. While attractions are assumed to be the main foci for such movement, multiple other purposes can intervene and compete, such as shopping, eating, and so on. There is also the somewhat mystical property of large crowds being formed with their own momentum which binds them together and drives their movement. Such characteristics are hard to identify and model although such herding instincts due to identity of purpose—'crowd fever' so-to-speak—are important. The morphology of such events has barely been examined to date. There is little descriptive material on which good models of these dynamics might be built, and the interpretations that do exist are not found within mainstream geographical, urban, or architectural analysis. There is a useful classification from Canetti (1962) while there is a persistent line of research in psychology from LeBon (1905). Much of this, however, relates to what Isaac Newton once described as the 'madness of crowds', dealing as much with speculation and gambling as with physical concentrations.

Canetti (1962) describes such events as being highly focused on single points of attraction which are spatially associated with agglomerations of individuals. The crowds we deal with here form slowly with minimal diversions, but because of competing attractions, there is continual circulation within the highest density places as individuals move to experience adjacent attractions. It is possible, too, that crowds can grow to sizes and densities which are out of control. Fear and panic can set in as crowds attempt to disperse if densities become too high and safety is compromised. Crowds form at points of ingress and egress where they are channeled into and out of high-capacity containers like buses, subway trains, and buildings. In short, there is an implicit morphology of crowds which likens them to organically growing and changing phenomena but there are few attempts at describing the dynamics and the transformations that take place as crowds form and dissipate. In this context, our events are considerably calmer than crowds at football matches or in Japanese subway trains. Canetti (1962) describes the kind of crowd that we are dealing with here when he says: 'There is a … type of slow crowd which can better be compared with a network of streams. It starts with small rivulets gradually running together. Into the stream thus formed other steams flow, and these, if enough land lies ahead, will in time become a river whose goal is the sea. The pilgrimage to Mecca is perhaps the most impressive example of this slow crowd' (page 40).

We shall see that this picture is close to the way the crowds form in our applications here. It is directly reflected in the dynamics captured within the model but depends on the way we define the objects that make up the event. It is worth thinking of these as mobile agents which move within a geometric landscape, streets in the urban case. Most models of pedestrian movement are now being developed in this way but here our agents are not simply the walkers who are visitors at the event. The attractions themselves may be treated as 'agents', some fixed such as concert venues but others mobile like parades. The geometry of the landscape, the streets, as well as barriers, police who control access, and the whole range of emergency services can be modeled as 'mobile agents'. This suggests that many different types of interaction such as that between the physical landscape and users of that landscape, can be represented as agent interaction where the cells that actually define the landscape geometry may themselves be considered as agents (Box 2001). Such characterization is similar to that used in particle physics where the concept of the 'active walker'—a particle (agent) that both changes and is changed by its environment (landscape)—has become popular (Schweitzer 1997).

A critical issue involves the difficulties in observing this kind of system in sufficient detail. Strictly speaking, with models composed of individuals, there should be data on the decision-making events associated with each individual throughout the time periods and across the space associated with each decision event. What is usually possible is good data on the density of crowds but not on paths taken by individuals. Good path data from closed circuit TV or even from laser scanning is fundamentally limited (at present) due to privacy considerations. The best data that have been collected to date are for the most confined spaces where crowding at sports events and in subway stations is under scrutiny. Over wider areas, this has always been problematic and the fact that the best examples are not contemporary indicates a recurrent and lasting dilemma posed by the observation problem (Pushkarev and Zupan 1975). This lack of path and interaction data actually influences the kind of models that can be built. Similar problems exist in eliciting preferences which cannot be observed but only inferred through actions. Agent-based models must therefore be designed to account for such omissions.

3. The control of spatial events

Simulation usually follows the conventional cycle of mathematical modeling: data assembly, representation, and analysis is prior to model specification and testing, and prediction is usually only attempted when a good enough fit of the model to reality has been achieved. The final stage of the cycle involves using the model for optimization where model outputs are managed or designed to achieve certain targets or goals. This process works well where models are aggregate and parsimonious, where data is adequate and where it is assumed that plans or designs required to control/manage the future system are absent from the way the system has evolved in the past. With small-scale spatial events, these assumptions are no longer tenable for many of the events of interest cannot be separated from explicit controls. Often these controls are passive, being part of the wider environment, but some are active in a way that makes them critical to simulation and calibration. For example, as crowds at sporting events get bigger and denser, safety standards come into force through police control of crowd behavior. In the case of crowds which are not policed directly, constraints on the design of physical infrastructure act in a passive way to control behavior.

In short, we cannot build models of spatial events where we assume that data is collected first, the model calibrated, and then if appropriate, used for prediction, thence design and control. What this implies is that our model must integrate all these stages from data assembly to prescription and control and that the process of calibration is contingent on the entire sequence. It is easiest to illustrate this with the example used. We have some data on where people originate and where they are destined for but we do not have data on their spatial preferences or on the paths that they actually take, connecting up their origins to destinations. Thus the first stage of the model is to generate paths that are consistent with normal walking behavior. The problem is one of simulating the missing data but in such a way that the most likely behavioral pattern emerges. However, the event we will be modeling is also highly controlled by the police who channel crowds by closing streets and erecting barriers as well as positioning attractions. These controls are known, so we could model the actual situation with these in place. However, as the purpose of this model is to 'redesign' these controls, then what we actually do is begin our simulation with no controls at all. We assess the situation first in the absence of control, then gradually introduce controls to a level which meets the goals of safety associated with local movement. This means that the calibration must thus be structured around the whole cycle. When it comes to testing different controls, the entire cycle must be run again, for new controls imply different data patterns.

There is a further twist to this circularity. The controls themselves cannot be divorced from the event itself, indeed they define the event, and these are also generated from the bottom-up. Moreover, these controls cannot be easily modeled without the interventions of those who design them. The most appropriate way to design and operate this kind of model is to provide an interface to those who actually control the real event and to use their expertise in running the model through its various stages. In the first stage in which data is being assembled, such stakeholder involvement is not required but in the second stage where 'virtual agents' are simulated under different controlled conditions, the way these controls are introduced is best accomplished by the 'real agents'—the police and related authorities—who design these in the first place. As the process of calibration loops around this entire sequence, this breaks the model into stages where different kinds of expertise are required, further complicating the way it needs to be executed.

Before we explain the class of agent-based models that we consider suited to these types of problem, it is worth briefly noting alternative and complementary approaches. In fact there is a disjunction in the field of pedestrian or walker modeling between models which emphasize density and crowding and those that focus on the way walkers move from origins to destinations. These approaches are not mutually exclusive, they may be complementary but they do not deal with the same kinds of walking phenomena. The former apply to confined spaces while the latter to much larger areas; the former are designed for issues of safety and evacuation which involve channel capacity for movement while the latter are for predicting aggregate volumes where locational capacity is more significant. Yet all these models incorporate self-organization through push-pull effects which occur when individuals form crowds through herding, and when individuals seek to escape from crowds due to panic.

Helbing (1991) and his colleagues have developed a whole series of models which are built around social forces, which relate variously to ideas from fluid flow, particle systems, and flocking (Helbing *et al.* 1997). Similar approaches have been developed by Still (2001), and Hoogendoorn *et al.* (2001). Several reviews exist (Helbing 2001). In contrast there are models being developed by Blue and Adler (2001) for more constrained route systems using cellular automata akin to those developed by Nagel and Schreckenberg (1992) for vehicular traffic. These models are also being applied at slightly larger scales by Dijkstra *et al.* (2002) and Burstedde *et al.* (2001). At smaller scales for more ordered flow schedules, queuing models have been adapted but with limited success (Lovas 1994) while for building and urban spaces where preferences associated with different locations are key, event-based simulation has been attempted (Baer 1974). At larger scales where movement on malls and even entire neighborhoods is the focus, spatial choice and interaction models have been applied (Borgers and Timmermans 1986).

There have never been enough applications to generalize this field into distinct types, for there are elements of each approach in every other. For example, agent-based models are now becoming popular at small scales ranging from town centers (Haklay *et al.* 2001) to buildings but there is also the implication that such approaches can be applied at much larger scales (Schweitzer 1998, Batty 2001). Our model reflects different aspects of all these approaches which we will pick up in its formal development in the following sections. But as the field develops from this somewhat rudimentary level, models might be better classified according to the events that they simulate rather than the formal mathematics that they employ.

4. Movement dynamics: a formal model

Our generic approach is best illustrated through the example of the Notting Hill Carnival. This event is represented by several groups of agents which move at different speeds—fast, slow, and immobile. We define: *walkers* (W)—visitors who interact with each other and the Carnival events in real time; *paraders* (P) who move in more routine fashion along the parade route, again in real time; *bands* (B) which form the fixed sound systems, are immobile but emit noise which decays exponentially from source, thus attracting walkers; and physical objects which are *streets* (S), reflecting building layout and street geometry which act as obstacles to movement but are 'movable' in themselves. In fact, the parade and paraders, the bands, and the street objects can all be 'moved' occasionally but infrequently, and it is these that provide controls which can be manipulated to meet standards of public safety.

In table 1 we show these agents in terms of their mobility characteristics and data requirements, while in figure 1 we graph their potential interactions. From these interactions, it is very clear that the focus is on the walkers. These interact with each other, forming crowds by flocking, and then dispersing if congestion is too high. They are directly affected by paraders, street geometry, and sound systems. The paraders and bands interact with themselves in a relatively passive way but not with each other while the street geometry simply affects the walkers. These interactions

Table 1. Varieties and characteristics of agent in the Notting Hill model.

Agent group	Agent type	Mobility level	Movability	Data sources
Walkers (W)	Visiting parade Visiting bands Visiting bands and parades	Fast in real time Fast in real time Fast in real time	Completely flexible Completely flexible Completely flexible	Origins and destinations of observed walkers, Paths not known
Paraders (P)	Moving vehicles	Fast but fixed route	Movable in long term	Observed
Bands (B)	Fixed sound systems	Fixed	Movable in long term	Observed
Streets (S)	Physical objects/ barriers	Fixed	Movable in medium term	Observed and managed

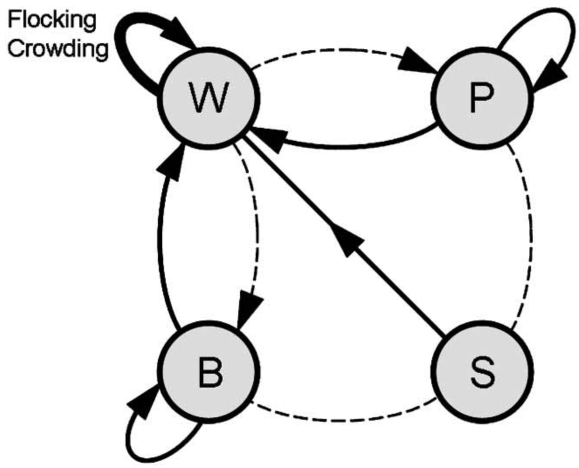


Figure 1. Interactions between agents. Also see http://www.casa.ucl.ac.uk/ijgis/figure1.htm

exist in real time but there are longer-term interactions between all agent types: first through changes to the street geometry affecting parades and bands (the broken arcs with no arrows in figure 1), and second in the much longer term when the parade route and the band locations are themselves changed (the broken arcs with arrows). Table 1 also makes clear that at least three kinds of walkers exist in the system: those who interact solely with the bands, those who visit simply to see the parade, and those who visit to engage with both. Although preference schedules are not explicitly incorporated, these three walker types involve implicit behavioral differences with respect to their attraction to the events that comprise the Carnival.

The spatial simulation is extremely straightforward. Walkers enter the Carnival area and move through the street system to the various attractions. They interact with each other, the parade, and the sound systems, and these interactions can cause crowding which can violate safety limits. The paths they take from the points at which they enter are defined by the noise that they hear, and by feedback from other walkers which leads to 'flocking'. When large crowds form at the various attractions, they disperse if congestion exceeds certain thresholds. If they cannot disperse sufficiently quickly, panic can set in and accidents occur. In terms of the simulation, the paths that walkers take are unknown and must be generated and thus the first stage of the model involves generating this 'missing data'. The hierarchies of shortest routes and related accessibility surfaces which emerge are used in the second stage to effect the simulation of walkers from which patterns of crowding and public safety levels can be evaluated. Controls designed to raise levels of safety are then systematically introduced, the two-stage model being reiterated until acceptable limits are reached.

To generate the shortest routes, we can either begin with walkers at known origins, the entry points, or with walkers at known destinations, attractions, searching either for destinations from origins or vice versa. We will use an algorithm in which walkers begin to search for the relevant locations randomly but as these are discovered, others learn by watching where the successful walkers are moving to. This kind of algorithm is based on a class of behaviors called 'swarm intelligence' (Kennedy *et al.* 2001), based on intelligence amongst insects which is determined in a bottom-up fashion through such learning. These techniques are finding wide applicability in all kinds of routing problems from telecommunications to robot manipulation (Bonabeau *et al.* 1999). In this application, we search for origins from fixed destinations, walkers moving out randomly from their starting points (their ultimate destinations). Those closest to entry points (origins) will discover these first and once this occurs, they head back to the starting points which they remember. However, to remind themselves of the path between their entry point and starting point, they lay a trail. In analogy to the way ants react to the discovery of food sources, they drop 'pheromone'. (Camazine *et al.* 2001). Other agents who have not yet discovered any destination points see these trails, sensing the scent, leading them more and more quickly to the various entry points. Once an agent has returned to the destination after such a discovery, it begins again but this time reacting to the pheromone surface where it exists. In this way, the hierarchy of routes is reinforced with the shortest being the most heavily trafficked. This first stage is illustrated as part of figure 2 opposite.

In the second stage, we use the information discovered at the first to construct appropriate accessibility surfaces for each class of walker. Essentially these surfaces link origins (entry points) to destinations (Carnival events), walkers being launched

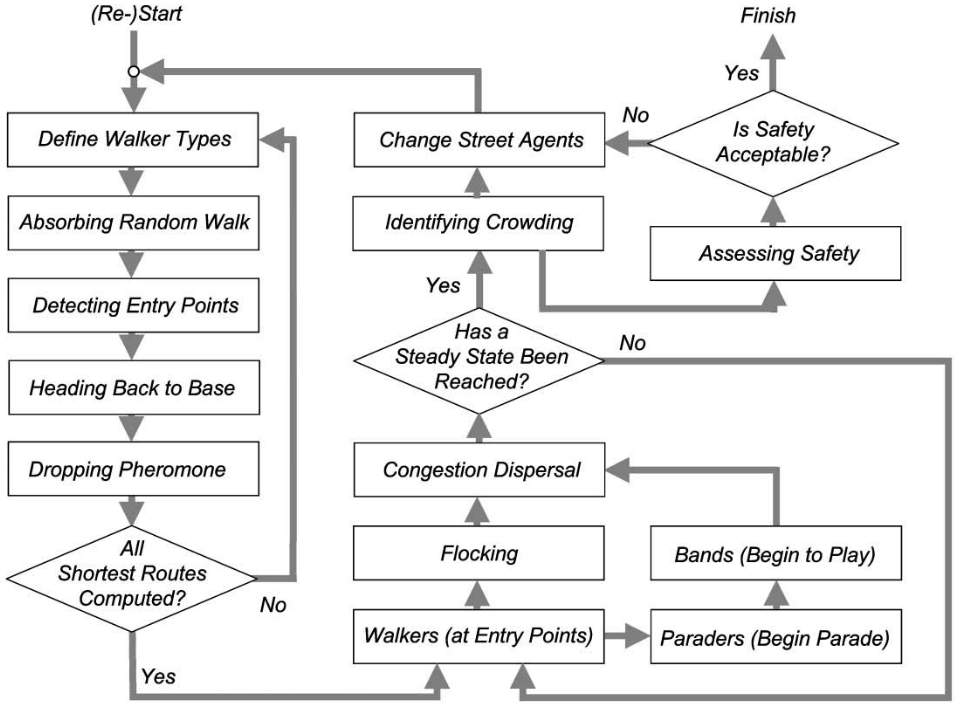


Figure 2. An outline of the two-stage model. The first stage which is the 'swarm' algorithm, is the initial left-hand sequence, while the second stage simulation of crowding is the right-hand sequence. Note how controls ('Change Street Agents') are gradually introduced through reiterating both stages of the entire sequence. Also see http://www.casa.ucl.ac.uk/ijgis/figure2.htm

from entry points and 'climbing' these surfaces to reach the attractions. The walkers interact with each other through watching where others walk, thus 'following the crowd.' Walkers flock to the parade routes and to the fixed sound systems and in doing so generate congestion which is resolved by dispersal. Flocking is positive feedback and dispersal is negative. The interaction with the parade can lead to conflict other than congestion, for as walkers try to cross the parade route, accidents can occur. However, the greatest source of potential safety problems occurs when crowds build up and are unable to disperse. Dispersal takes time and meanwhile flocking continues, especially in areas where the street geometry is highly constrained.

Only when average distances travelled in each time period converge, are we able to make a clear assessment of crowding. In short, we simulate the steady state at the peak period during the Carnival, and to reach this point in time, we do not simulate all walkers throughout the two-day period but build up the relevant number from scratch just prior to the peak. Various measures are used to assess whether public safety requirements have been breached, and if so, controls are introduced, first on the street system consisting of street closures and movable barriers which constrain movement and densities. This is the point at which those stakeholders who know the problem need to be involved with the model. Once we make such changes, however, the shortest routes and related accessibility surfaces also change and these must be recomputed so the entire sequence based on these two stages needs to be reiterated. Its essential logic is illustrated in figure 2 with the various loops terminating when an overall steady state has emerged. Along the way, we may have ascertained that safety levels are too tight and that looser ones are possible or that safety measures are too slack and new ones required. In the latter, we can initiate changes to the location of the parade and sound systems, thus beginning to use the model in traditional 'what if' fashion as a means of testing alternative configurations of the Carnival.

5. The mathematics of the simulation

All actions and interactions in the model take place in an event space composed of N cells (square pixels) indexed $i, j = 1, 2, \ldots, N$. The agent groups, walkers (W), paraders (P), bands (B), and street objects (S) are always located with respect to these cells at time $t = 1, 2, \ldots, T$ with W_{it} the number of walkers, P_{it} the number of paraders, B_{it} the number of bands, and S_{it} the number of street objects, in each cell i at time t. In the case of bands and street objects, these are fixed in space and time and only a single agent is associated with each cell. For bands, $B_{it} = 1$ or 0, that is a band exists in a cell or does not, and the total number of bands is thus $B = \Sigma_i B_{it}$, $\forall t$. For streets, if $S_{it} = 1$, this means that the street agent is signaling that a cell is available for a walker to move to, that there are no obstacles to movement; if $S_{it} =$ 0, obstacles such as barriers, buildings or street closures exist, and the cell is off-limits to movement. The total number of cells available is $S = \Sigma_i S_{it}$, $\forall t$, and thus there are $\bar{N} = N - S$ cells which act as barriers or obstacles. The bands and street objects are entirely passive and do not change within a single run of the model. Street objects are however changed when control is being manipulated to meet safety measures through the outer loop in figure 2. Band and parade locations are only changed when different routing scenarios are evaluated.

The three types of walker are composed of those whose motive is to visit the parade (W^1), those who primarily visit the bands (W^2), and those who visit both (W^3) with the total $W = W^1 + W^2 + W^3 = \Sigma_{z=1}^{3} W^z$. Each individual walker is defined by the binary variable W_{it}^k, set to 1 if a walker of type z is in cell i at time t, or 0 otherwise. A series of accounting relations defines densities in cells and totals in the system at any one time, and the total number of walkers in each group W^z is fixed over all time periods. Then the total number of walkers of type z in i is $W_{it}^z = \Sigma_{k_z} W_{it}^{k_z}$, the total in cell i $W_{it} = \Sigma_z W_{it}^z = \Sigma_z \Sigma_{k_z} W_{it}^{k_z}$, and the total of type z in the system $W_{\mathrm{t}}^z = \Sigma_i \Sigma_z \Sigma_{k_z} W_{it}^{k_z}$, $\forall t$. The same kinds of relations pertain to paraders except that there is only one type defined as P_{it}^k, $k = 1, 2, \ldots, P$ which is equal to 1 or 0 depending upon whether or not a parader occupies cell i at time t. The total paraders in cell i is $P_{it} = \Sigma_k P_{it}^k$ and the global total $P_t = \Sigma_k \Sigma_k P_{it}^k = P$, $\forall t$.

The first stage of the simulation is based on the swarm algorithm which is solely based on walkers and does not involve paraders and bands other than their being sources for random exploration of the street system. The walkers are launched from these sources D at time $t = 1$ where $W_{D1} = \Sigma_z W_{D1}^z = \Sigma_z \Sigma_{k_z} W_{D1}^{k_z}$. Walkers of each type z can move from cell i to an adjacent cell j in each time period $[t \rightarrow t+1]$ where $j \in \Omega_i$ and Ω_i is the eight cell (Moore) neighborhood around i. In general, some of these cells will not be accessible because of obstacles but if the street agent signals an empty cell, that is $S_{jt} = 1$, the agent is able to make a move. We will now call the street agent S_j, dropping t which does not change during the two-stage simulation, and only changes when the entire cycle is reiterated if routes are changed. Movement from i to j in search of an origin O is then determined by the relevant probability for type z as

$$p^z_{ijt+1} = \frac{\tau^z_{it} S_j}{\sum_{l \in \Omega_i} \tau^z_{lt} S_l} \tag{1}$$

τ^z_{jt} is the route accessibility to origins for agent type z, and this depends on the destinations which act as the sources of each walker type. A move from i to j is determined randomly according to the schedule of probabilities in (1). We also compute a composite accessibility surface for all the walkers η_{jt+1} which in principle could be walker type specific, but in practice is more useful as an index combining the influences of all walkers. This is in contrast to τ^z_{jt} which, as we will see, is more like a density of movement associated with the use of routes. Then if $W^{k_z}_{it} = 1$ and $W^{k_z}_{jt+1} = 1$, the accessibility surface to destinations is updated as

$$\eta_{jt+1} = \eta_{jt} + \sum_z \sum_{k_z} (d^{k_z}_{Djt+1})^{-\beta} \tag{2}$$

where $d^{k_z}_{Djt+1}$ is the distance of walker k_z from D to cell j, and β is a tunable parameter reflecting the friction of distance. In fact, this is also a 'sound surface' as the distance decay through the power law implied in (2) can be considered as a proxy for the decay of sounds from the attractor destinations. As we have implied earlier, in small spaces, walkers are attracted to sounds and this is one way in which this feature can enter the model, at least implicitly. The analogy should not be taken too far as we have not attempted any analysis of sound decay with distance but this surface is used to incorporate system-wide effects on all walkers. Sound is one such effect. Finally at this point, the density of walkers at j can be computed as $W_{jt+1} = \Sigma_z \Sigma_{k_z} W^{k_z}_{jt+1}$, or in terms of walker types, as $W^z_{jt+1} = \Sigma_{k_z} W^{k_z}_{jt+1}$.

The process implied by (1) and (2) continues until a walker discovers an origin O. For each walker $W^{k_z}_{jt+1}$, if $j \in \Omega_O$, the walker switches from exploratory to discovery mode $\bar{W}^{k_z}_{jt+1}$ and returns to the destination D with knowledge of the discovery. The probability of returning is thus

$$q^{k_z}_{ijt+1} = \frac{\pi^{k_z}_{jt} S_j}{\sum_{l \in \Omega_i} \pi^{k_z}_{lt} S_l} \tag{3}$$

where $\pi^{k_z}_{jt}$ is based on the difference between the heading in the direction from i to j, $\theta^{k_z}_{ij}$, and that from i to the position defined by $W^{k_z}_{D1}$, $\theta^{k_z}_{iD}$, which are combined as $[1 + |\theta^{k_z}_{ij} - \theta^{k_z}_{iD}|]^{-1}$. This move is also chosen randomly and when $\bar{W}^{k_z}_{it}$ moves to $\bar{W}^{k_z}_{jt+1}$, the walker marks the move by updating τ^z_{jt} as

$$\tau^z_{jt+1} = \tau^z_{jt} + \sum_{k_z} \bar{W}^{k_z}_{jt+1} \tag{4}$$

This process is akin to the walker laying a pheromone trail when a discovery has been made: τ^z_{jt+1} measures the density which ultimately reflects a hierarchy, the highest of which form the shortest routes. When the walker comes within the neighborhood of its destination $j \in \Omega_D$, it switches back to exploration mode and the search begins again. Note that unlike traditional spatial interaction theory which uses index i for an origin and j for a destination, no such convention is adopted here.

It takes some time before agents discover an origin. Before this, the search is a random walk with the route accessibility surface set as a uniform distribution, that is $\tau^z_{jt} = 1$ until a time t is reached when the first entry point is found. If a walker crosses the edge of the event space, it is absorbed, regenerates at its source destination, and begins its search again. In its early stages, this is a random walk with absorbing barriers with a standardized variance of distance traveled proportional to $t^{0.4}$, a little less than the value for an unconstrained random walk where $\sigma = t^{1/2}$ (Sornette 2000). As the process continues, more and more origins are discovered while during exploration, walkers 'learn' to direct their search at routes to origins already discovered. Those origins closest to destinations are discovered first and the hierarchy of 'shortest routes' is thus built up, continually reinforced by this positive feedback. The algorithm is a variant of that observed in trail formation and collective foraging behavior amongst animal populations such as ants (Helbing *et al.* 1997, Camazine *et al.* 2001). The swarms created are extremely efficient in predicting shortest routes in geometrically constrained systems (Bonabeau *et al.* 1999). Here we do not let the pheromone trail τ^z_{jt} decay, while the accessibility surface η_{jt} gives the relative attraction of destinations to different street locations in terms of distance and its proxy as noise. The exploratory stage finishes at time T when differences in densities $\tau^z_{t+1} = \Sigma_j |\tau^z_{jt+1} - \tau^z_{jt}|$ and $\tau_{t+1} = \Sigma_z \Sigma_j |\tau^z_{jt+1} - \tau^z_{jt}|$ fall below various predetermined thresholds which we fix through experimentation.

In the second stage, we launch the walkers from their entry points, and these walkers move towards the event using the surfaces τ^z_{jT} and η_{jT} as indicators of accessibility. We suppress T, normalize these as τ^z_j and η_j and combine them as $(\tau^z_j)^\alpha \eta_j^{1-\alpha}$. The basic probability of movement for each walker type z is now defined as

$$q^{k_z}_{ijt+1} = \frac{(\tau^z_i)^\alpha \eta_i^{1-\alpha} S_j}{\sum\limits_{l \in \Omega_i} (\tau^z_l)^\alpha \eta_l^{1-\alpha} S_l} \tag{5}$$

where α is a tunable parameter which plays a role similar to an homogenous production function of degree 1 such as the Cobb-Douglas, widely used in microeconomics for its scaling properties (Henderson and Quandt 1980). We use (5) to select directions of movement from i to j where we use each probability q^k_{ijt} in the neighborhood Ω_i to determine the direction j in which the walker moves. This is done randomly with new headings in the direction j computed as $\bar{\theta}^{k_z}_{it+1}$ and then used to update the existing heading as $\hat{\theta}^{k_z}_{it+1} = \lambda \bar{\theta}^{k_z}_{it+1} + (1-\lambda)\theta^{k_z}_{it}$ where λ reflects a lag in response.

There are two effects that complicate this movement. The first is herding or flocking (Reynolds 1987, Vicsek *et al.* 1995). This directs movement as an average of all movement in the immediate neighborhood reflected in the headings where $\theta^{k_z}_{it+1} = \Sigma_z \Sigma_{l_z \in j} \Sigma_{j \in \Omega_i} \hat{\theta}^{l_z}_{jt+1} W^{l_z}_{jt} / \Sigma_z \Sigma_{l_z \in j} \Sigma_{j \in \Omega_i} W^{l_z}_{jt}$. However a move by walker $W^{k_z}_{it}$ to $W^{k_z}_{jt+1}$ only takes place if the density of walkers in cell j is less than some threshold $\Psi \leqslant \Sigma_z \Sigma_{k_z} W^{k_z}_{jt} = 2$ based on the accepted standard of 2 persons per meter squared (ppm^2) (Fruin 1971, Still 2001). If this is exceeded, the walker evaluates the next best direction and if no movement is possible, remains stationary until the algorithm frees up space on subsequent iterations. These rules are ordered to ensure reasonable walking behavior. There are many variants that can be tried but those adopted seem to be plausible from *ad hoc* observation and from the literature.

The paraders P^k_{it} move in a much more structured manner, around a parade loop defined by a linear sequence of cells $\{i\}$ forming the set $i \in \Pi$ which are ordered so that there is only one direction of movement from $[i \to j]$ in time $[t \to t+1]$. Headings and probabilities of movement do not have to be calculated for the paraders although movement is determined with some random input. Although the floats normally travel to adjacent cells in the given direction with the flow controlled to give reasonable moving behavior, this smoothness does incorporate a degree of intermittency. At any time t, the total number of paraders in each cell i, $P_{it}=\Sigma_k P_{it}^k$, $i \in \Pi$, is distributed approximately uniformly amongst the total number of cells used for the parade $(\Sigma_{i \in \Pi} 1)$. A parader will progress to an adjacent cell in a time period according to a random function which ensures that most paraders make such transitions, but a few do not and stay in the cell that they are currently in. For any parader P_{it}^k, if $\text{rand}(1) < \Theta$, then $P_{jt+1}^k = P_{it}^k$ otherwise $P_{it+1}^k = P_{it}^k$. If the threshold Θ is set a little less than 1, then most paraders will move smoothly to the next cell. The parameter is set experimentally to introduce a level of intermittency in the flow of the parade that is observed in practice and which, for the most part, avoids major incidents.

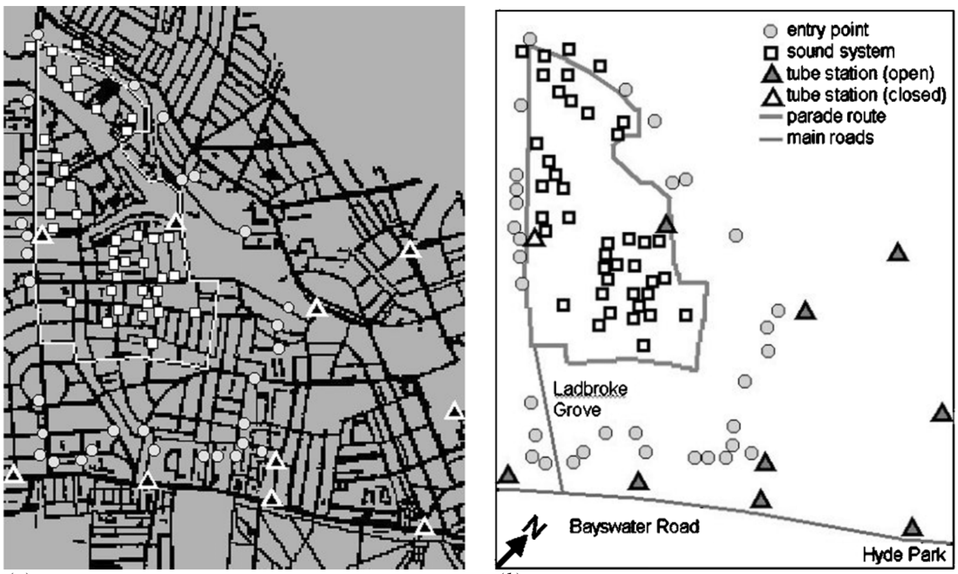
There are, of course, potential conflicts between paraders and walkers when they come into contact. We define cells in these neighborhoods as $j \in \Phi_i^P$ where we compute the density of walkers in these cells. Note that walkers cannot occupy cells which define the parade route. Then if $\Sigma_{j \in \Phi_i^P} \Sigma_z \Sigma_{k_z} W_{jt}^{k_z} \geqslant \Lambda$, where Λ is the critical density in cells adjacent to the parade, then walkers disperse in the same way they do when they interact with each other and breach critical density limits. We keep a trace $A_i^P(t) = \Sigma_{t'=1}^{t} \Sigma_{j \in \Phi_i^P} \Sigma_z \Sigma_{k_z} W_{jt'}^{k_z}$ which provides us with a record of potential accident hot spots along the parade. The same logic is used in relation to crowding around the fixed sound systems where the bands are playing. In analogous fashion, we define cells in neighborhoods around each band i as $j \in \Phi_i^B$, an equivalent test for dispersion as $\Sigma_{j \in \Phi_i^B} \Sigma_z \Sigma_{k_z} W_{jt}^{k_z} \geqslant \Xi$, and the trace of potential accidents as $A_i^B(t) = \Sigma_{t'=1}^{t} \Sigma_{j \in \Phi_i^B} \Sigma_z \Sigma_{k_z} W_{jt'}^{k_z}$. This second stage is terminated when the density of walkers enters a steady state which implies that all walkers are moving in the area of the Carnival and that movement between attractions is beginning to repeat itself. We can test for this using various criteria such as the statistics which we present below. A generic test is based on $\xi_z^{T-t'} = \{\Sigma_i \Sigma_{t=1}^{t'} \Sigma_{k_z} [W_{iT-t}^{k_z} - W_{iT-t-1}^{k_z}]\} / \{T - t' - 1\}$, a lagged density difference defined for each type of walker z (or for all walkers) where the summation over time is from the point where the simulation enters the steady state t' to the point where the simulation ends T. This formula handles the case where periodicity is feature of the simulation.

We can now assess how good the model is at predicting the observed distribution of crowds. We do not define any statistics for the individual groups z for two reasons. First, we do not have good data on these differences and second, as those visitors whose prime concern is to visit either bands or the parade but not both are likely to visit each of these, our observations do not directly tie in with motivations. Thus we will only work with aggregate quantities. We compare the predicted density of all walker types W_{it} and $\tilde{W}_{it} = \Sigma_z \Sigma_{k_z \in j} \Sigma_{j \in \Omega_i} W_{jt}^k / \Sigma_{j \in \Omega_i} S_j$, the average neighborhood density in cells where observed densities are available. We then relate these to the number of occupied cells $\Sigma_i n_i = M$ (where $n_i = 1$ if $W_{it}^{k_z} > 0$, otherwise $n_i = 0$) and the number of available cells $\Sigma_i S_i = S$, defining averages as $\rho(t) = \Sigma_i W_{it} / \Sigma_i n_i$, $\sigma(t) = \Sigma_i \tilde{W}_{it} / \Sigma_i n_i$ and $\vartheta(t) = \Sigma_i n_i / \Sigma_i S_i$. For different threshold values Ψ, if $W_{it} > \Psi$, then $c_{it}(\Psi) = W_{it}$ otherwise $c_{it}(\Psi) = 0$, and the proportion of the population at risk is thus $Z_t(\Psi) = \Sigma_i c_{it}(\Psi)/M$. Average distance travelled in each time period $[t \to t+1]$ is $U_{t+1} = \Sigma_z \Sigma_{ijk_z} d_{ijt+1}^{k_z} / M$ with the percent actually moving $V_{t+1} = \Sigma_z \Sigma_{ijk} W_{it}^{k_z} W_{jt+1}^{k_z} / M$.

These two stages define the complete model with subsequent stages being generated through reiteration of the entire sequence. These additional stages are activated if the statistics generated at the end of the second stage suggest that public safety is compromised. It consists of examining the statistics from the second stage, and gradually making changes to reduce the population at risk by introducing barriers, capacitating entry points, and closing streets. This is achieved by changing the number of street objects—switching street agents off or on to signal how much space for movement is available. The set of agents $\{S_j\}$ is updated to $\{S_j'\}$ where the prime indicates that this is the next iteration in the sequence with the model beginning again and the original time t being indexed back at $t=1$. As the repercussions of these changes are not immediately obvious, we make these changes one by one forming $S_j', S_j'', S_j''', \ldots$, rerunning the model each time until an acceptable solution emerges. These reiterations assume that the shortest routes surface needs to be updated and this involves rerunning the entire two-stage procedure shown in figure 2.

6. Dimensioning the problem and calibrating the model

The main feature of the Carnival is the parade which involves 89 floats and 64 support vehicles that continuously move around a closed loop of 4.9 km from noon until dusk on each of the two days of the event. Within the loop, there are 42 static sound systems—bands—and across the entire area, some 240 licensed street stalls with well-resourced health and comfort points for visitors and paraders alike. Most visitors to the event use public transport to reach the 38 entry points which define the traffic exclusion zone managed by the police, some 40% using the tube and 22% using buses. Many others walk from central London or neighboring areas and only a small number ($<10\%$) travel to the Carnival by car or taxi. The street system, and the entry, parade, static sound, and tube stations, are shown in figures 3(*a*) and (*b*), respectively.



(*a*) (*b*)

Figure 3. Geometric and locational features of the carnival. The scale of these and all subsequent similar maps is 2.4kms in the east-west horizontal direction. Also see http://www.casa.ucl.ac.uk/ijgis/figure3.htm

The number of visitors grew dramatically in the 1990s, reaching 1.2 million (over the two day period) in 1999 but dropping to something like 700 000 in 2001. Informed speculation suggests that this is possibly due to the negative publicity associated with high levels of crime at the event which have dominated policing in recent years. Problems of crowding have become significant with accidents due to congestion rising dramatically and problems of emergency vehicle access being compounded by the conflict between the parade and visitors entering the inner core of the area to visit the sound systems. In 2001, there were 500 accidents (100 requiring hospital treatment with 30 percent related to wounding) and 430 crimes with 130 arrests. Two fatalities occurred in 2000 from violent crime. This and the need to review resources allocated to manage the event—3500 police and stewards were required each day—was the trigger that led to the review that initiated this technical work (CRG 2001).

Attendance is more than twice as large on the second day with the peak level between 4 pm and 6 pm when around 260 000 visitors are in the Carnival area. During the event, there is considerable movement between the various attractions and although precise movements are not known, the rate of 'churn' which is the ratio of those entering and leaving the area to those within, is around 40%. In terms of the volume of movement from entry points to attractions, four streets located at E–W–N–S of the area account for over 50%. Crowd densities are high at about 0.25 persons per m^2 of which 0.47 ppm^2 line the parade route and 0.83 ppm^2 lie inside. Critical densities up to 1 ppm^2 exist in the central section where many of the bands are clustered while around the judging point in the south west area of the parade, route densities rise to 1.3 ppm^2 which are critical.

The data we have available were collected at the Carnival in 2001 specifically for this analysis. Essentially origin and destination data are available, the origins from a cordon count at all 38 entry points throughout the 2-day period, while destination data along the parade and at some static sound locations were derived from video footage taken from police helicopters during the late afternoon of the second day (IPS 2002). From this footage, 1022 images have been extracted from which densities have been manually computed and averaged to cells, as indicated in figure 4. Additional data on entry and exit volumes at the subway station from surveys by London Underground Ltd., and bus volumes at setting down locations have been integrated into the density database.

To set up the simulation using this data, we need to decide on the level of resolution of the space within which the Carnival is to be modeled. This is largely dictated by software considerations in that the software used has upper limits on the number of agents and cells that can be handled. No more than 16 000 agents can be simulated on no more than 52 500 cells. Thus the area of the space was set as 207 pixels $\times$ 251 pixels and 13 000 agents were defined, divided into those whose intention is to visit the bands (3000), those visiting the parade (5000), and those visiting both (5000). This must be interpreted as a 5% sample of the 260 000 visitors in the peak period that is being modeled and thus all quantities must be scaled and adjusted accordingly. This is less than satisfactory because we consider that a fully-fledged model should be able to handle not a sample but the full population of agents. This however would require considerable programming that was simply not possible within the project at this time but it remains a longer-term aim of this research. The cell structure is implied by the pixelation shown in figure 3(*a*). Key locational features of the problem—entry points and Carnival destinations (parade

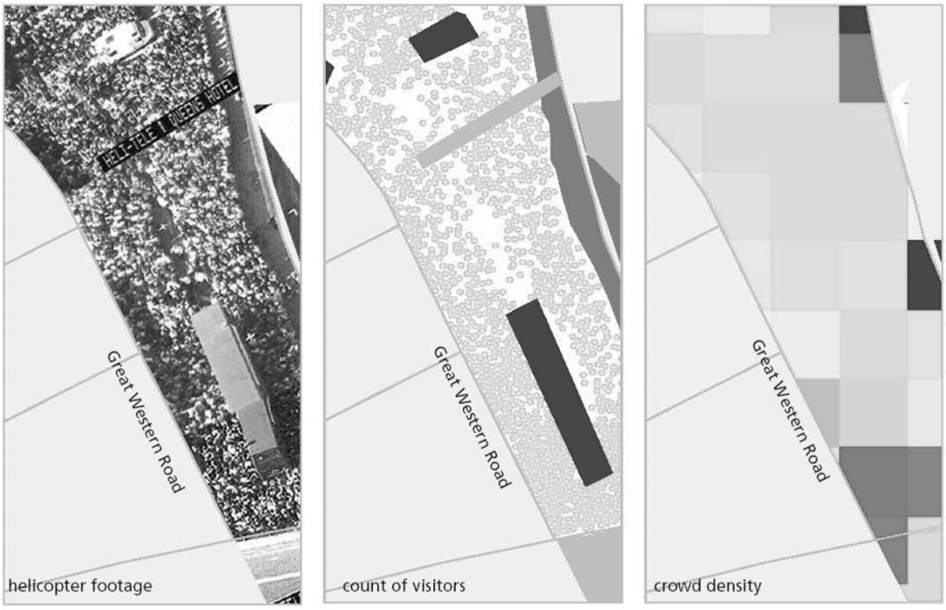
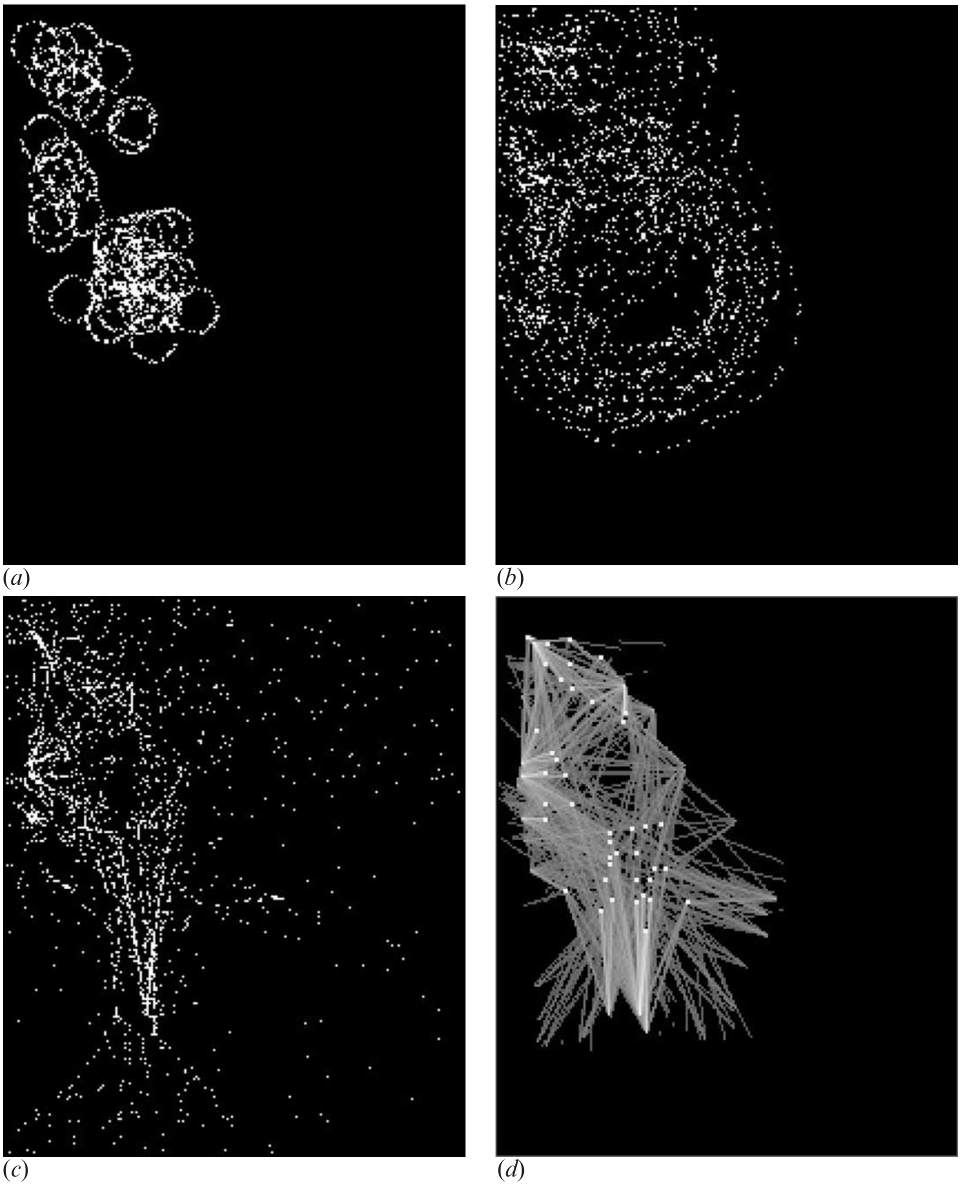


Figure 4. Translating video footage of walkers to cell densities. Also see http://www.casa.ucl.ac.uk/ijgis/figure4.htm

and bands) shown in figure 3(*b*)—represent the sources for the swarm algorithm which generates the paths in the first stage of the model and thus the starting (entry) points for the visitors in the second stage.

Like all calibrations, the purpose is to define values for the model parameters so that the predictions of the model are as close as possible to the observed data. In terms of equations (1) to (5), we have fixed several parameters relating to lags and crowding at what we consider reasonable values. This enables us to reduce the search problem to a phase space defined by only two parameters—the friction of distance β and the accessibility weighting parameter α. The density thresholds for walkers with respect to each other Ψ, to paraders Λ, and to bands Ξ have all been set at 2 ppm^2 as suggested in official advice (Fruin 1971, ISP 2002). In the second stage of the simulation, once paths and accessibilities have been defined, the lag in updating the heading from the previous value is set at $\lambda=0.4$ while the intermittency threshold for moving the elements in the parade forward is set at $\Theta=0.9$. The calibration thus consists of running the model through its two stages (together with any subsequent control) over samples of parameter values α, β until a combination is found which optimizes the model's predictions based on the fit of observed to predicted densities.

The simulation starts with the three types of walker W^z_{D1} located at the Carnival event locations *D*. They begin their random walk through the streets in search of entry points where they will actually start their walk to the Carnival in the second stage. Purely to illustrate the power of the swarm algorithm, we show the paths that are generated for walkers ($z=2$) starting from the sound systems (W^2_{D1}) and finding the entry points but in the absence of any geometric constraints posed by the streets. In short, we set the streets $S_j=1$, $\forall_j$, and in this way the walkers find the entry points directly. They move out in concentric rings from the static sound locations, the symmetry of this concentricity being broken when entry points are first discovered. In figures 5(*a*) and (*b*), we show the location of the walkers at times $t = 10$ and $t = 50$. By $t = 500$, the pattern is dominated by the paths between sound systems and entry points as shown in figure 5(*c*), and this is confirmed by the straight line traces based on the densities τ_{jT}^{2} reproduced in figure 5(*d*). All the results in this section are based on simulations with the best combination $\beta = 0.65$, and $\alpha = 0.35$. With the streets in place, the three shortest route hierarchies τ_{jT}^{z}, $z = 1, 2, 3$ are shown in figures 6(*a*)–(*c*) together with the overall accessibility surface η_{jT} in figure 6(*d*). These show the hierarchy of routes which are then combined into a composite accessibility



(*a*) (*b*) (*c*) (*d*)

Figure 5. Swarming in search of entry points without any street geometry. Also see http://www.casa.ucl.ac.uk/ijgis/figure5.htm

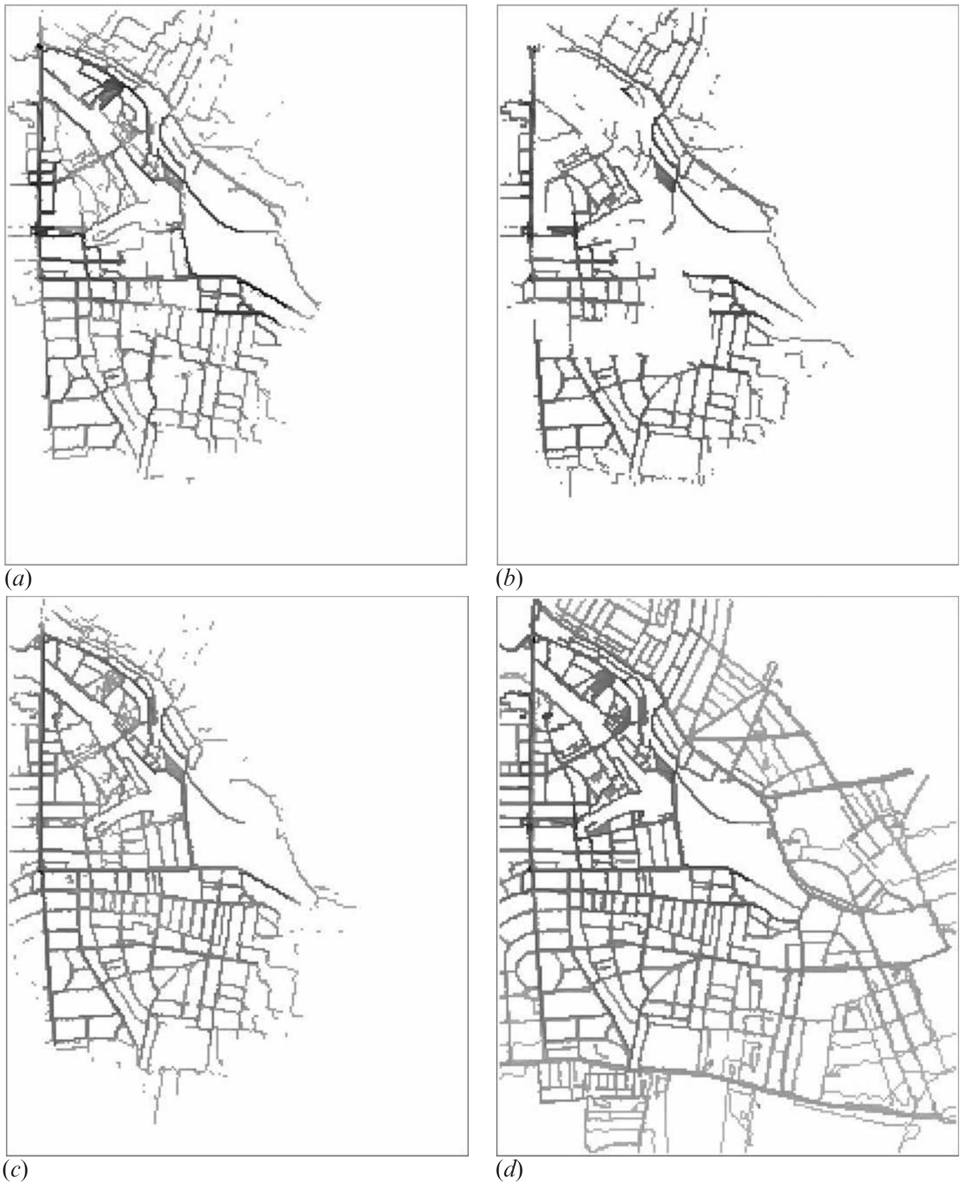


Figure 6. Hierarchies of shortest routes and associated accessibility. Also see http://www.casa.ucl.ac.uk/ijgis/figure6.htm

surface used to initiate the actual walks to the Carnival in the second stage of the model.

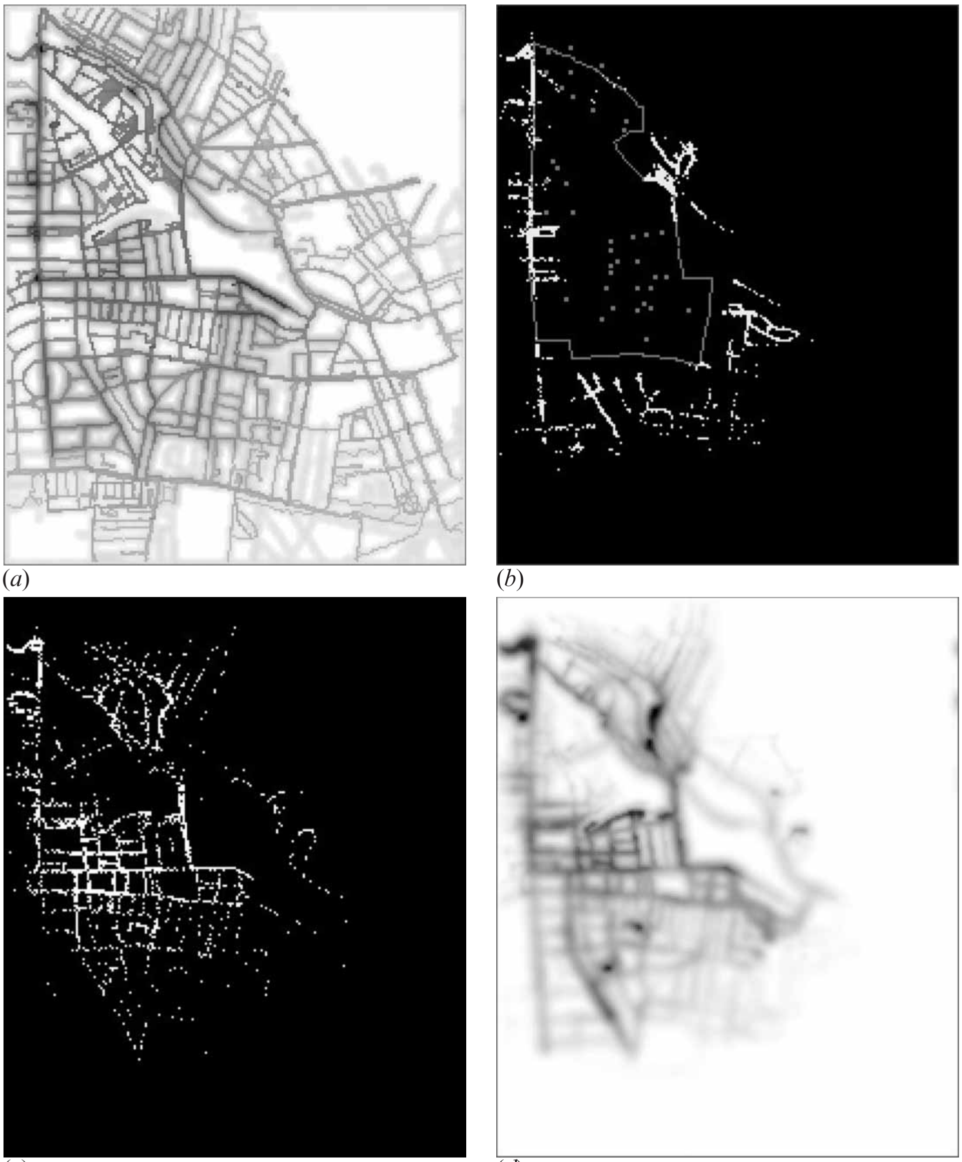
We will examine the various statistics associated with these simulations after we have examined the second and subsequent stages where safety levels determine how control is developed as part of the modeling process. Using the accessibility surface shown in figure 6(*d*), we locate all walkers at the points where they are observed to enter the Carnival area (at the entry points in figure 3(*b*)) and we then launch these using the access surface to guide the directions that they walk. Flocking and congestion dispersal are an integral part of this second stage, as are the interactions between walkers and paraders, and walkers and bands. We have not included emergency vehicles as separate agents for we consider the scale of the simulation (at a relatively crude level of cell resolution) makes the interactions between walkers, paraders, bands, and emergency vehicles somewhat arbitrary. Accidents caused by congestion can be further exacerbated by the difficulties of getting emergency vehicles to attend to injured walkers and paraders but explicit consideration of these effects must await the detailed model that we are currently constructing with more appropriate software. In figure 7(*a*), we show the composite access surface for just one walker type—those who visit the parade and the bands ($z=3$)—as $(\tau_i^3)^{0.35}\eta_i^{0.65}$ where we use $\alpha=0.35$, this best value determined through running the entire model through different combinations of its parameter values within its phase space. We show the movement of all three walker types at $t=100$ and then in the steady state at $t=500$ in figure 7(*b*) and (*c*).

In the steady state, we have also computed the hotspot trace indices $A_i^P(t)$, $A_i^B(t)$ defined earlier as well as those for walkers not in the parade or band locations $A_i^W(t)=\Sigma_{t=1}^{t'}\Sigma_{j\in\Omega_i}\Sigma_z\Sigma_{k_z}W_{jt}^{k_z'}$. We have added and smoothed these surfaces as shown in figure 7(*d*) and this gives a good indication of the accident and crowding hotspots at the end of the second stage. It is this picture that is essential in determining where safety controls are to be introduced. In fact the simulation reveals a mismatch between actual hotspots and those produced by the simulation. Congestion along the parade itself in the south-west corner is not as problematic as actually observed in 2001, while there are more serious problems in the northern part of the route. The model does tend to give greater weight to the northern area and this is a systematic error that needs to be addressed in the new simulation.

At the end of the second stage, we assess safety levels. To illustrate how we proceed, we have introduced the various barriers that are associated with the actual Carnival in 2001. The core area in the center of the parade route is reserved for police and emergency management in case a serious disaster occurs and other roads are closed for resident access and due to constrictions in streets unsuited to large crowds. The areas are shown in figure 8(*a*) where we also produce a summary of density levels which provides some idea of how the crowding problems might be resolved. These are shown in figure 8(*b*) where it is clear that the north-east leg of the parade is problematic in terms of crowding as is the center area of the Carnival where many static sound systems are clustered. In fact, the existing crowd control through barriers and street closures does go some way to reduce problems although it is best to consider the map of hotspots in figure 8(*b*) as a diagnostic for future action.

7. Safety, policy, and scenario testing

Before we examine safety issues and provide some sense of how the model is being used in evaluating different routes for the parade, the performance of the existing model must be examined. At each stage of the simulation, we compare existing densities of walkers in their steady state with observed densities at 120 locations which we have extracted as being significant from the density database. In the first stage, however, the swarm algorithm predicts the numbers of walkers who 'find' each entry point, and from the cordon survey (ISP 2002), we are able to account for 64% of this variance based on the numbers observed entering the Carnival area during the peak period from 4 pm to 6 pm on the second day. The second stage, which involves locating the observed walkers at these entry points and



(*a*) (*b*) (*c*) (*d*)

Figure 7. The second stage of the simulation. Also see http://www.casa.ucl.ac.uk/ijgis/figure7.htm

'walking' them to the Carnival attractions generates 72% of the variance of observed densities in the 120 locations. These predictions not only relate to the sound systems but to selected points on the parade route for which density data are available. At the third stage, when the model is rerun with the official street closures and barriers imposed, the variance explained increases to 78%, but not all the points of extreme crowding have been removed, as already shown in figure 8(*b*).

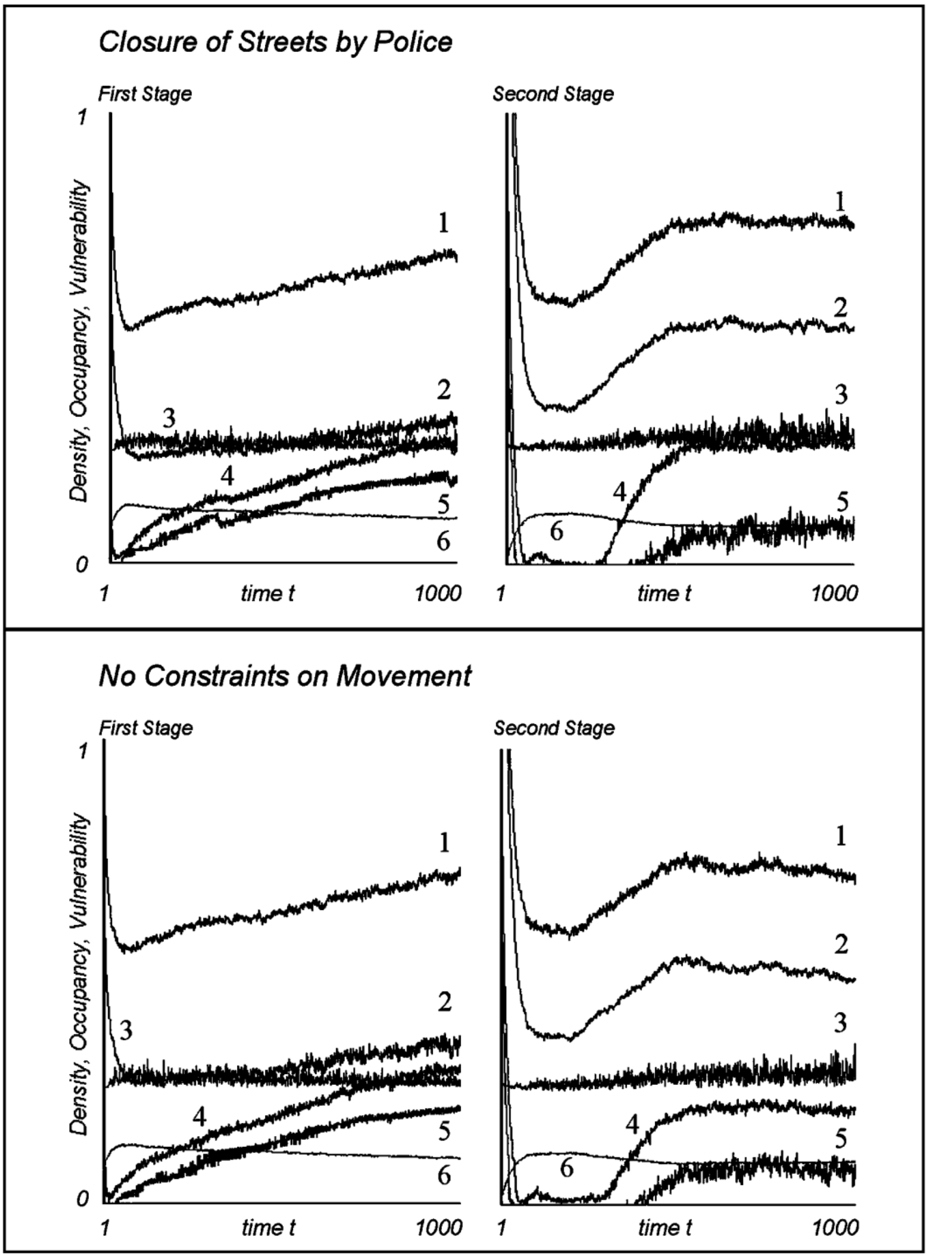
We graph the key indicators in figure 9. These statistics are averages and totals and to understand their impact locally, reference to the densities and hotspots in

(*a*) (*b*)

Figure 8. Control of crowds after the second stage simulation. Also see http://www.casa.ucl.ac.uk/ijgis/figure8.htm

figures 6, 7 and 8 must be made. Nevertheless, besides showing how the simulation works, the trajectories give some sense of how these densities change. There is a critical distinction between the densities and occupancies associated with the first and second stages of the model—between the swarm and climbing algorithms. The swarm algorithm begins with all walkers at destination attractions and as these spread out in the search for entry points, densities drop dramatically as illustrated in the upper and lower left-hand graphs in figure 9. As the algorithm converges on the most favoured shortest routes, the percentage of the walkers who breach the critical thresholds of 0.5 and 1 ppm^2 continuously increases. Although there is some sense of convergence to stable values, these percentages continue to rise as more and more walkers are attracted to the shortest routes. The percentage who occupy the streets is fairly stable as is the average distance travelled in each time period. In all cases, there is continual volatility in these trajectories as local geometric factors perturb the movement of walkers. Nowhere is there a smooth flow of walkers, and this seems characteristic of what actually happens as walkers move between events at the Carnival itself.

In contrast, the second stage of the model displays quite different behavior. Walkers move from their entry points by climbing the accessibility surface towards the attractions. Again walkers begin at very high densities which fall off as they spread out from their origins. These densities then rise slowly, peaking as walkers enter the Carnival area and move between attractions. The graphs of average point and neighborhood densities, and critical threshold values converge to quite stable levels which mark the steady state shown by the graphs on the right-hand side of figure 9. The average distance travelled slightly increases as walkers enter the steady state and the volatility of walkers gets greater as they crowd together around the Carnival attractions. A key issue of course is the difference between the simulation without any controls on street closures and that which develops when routes are



1: Average walker density ρ(t)3; **2**: Average neighborhood walker density σ(t)/3; **3**: Average distance just traveled $U_{t+1}/4$; **4**: Percent vulnerable >0.5 ppm$^2 Z_t(\Psi)>0.5$; **5**: Percent vulnerable >1 ppm^2 $Z_t(\Psi)>1$; **6**: Percent occupancy ϑ(t)

Figure 9. Walker densities and safety levels in the two-stage simulations. Also see http://www.casa.ucl.ac.uk/ijgis/figure6.htm

closed as in figure 8(*a*). The results are encouraging: density levels at each point and in each neighborhood are reduced by around 12% with the percentage vulnerable to crowding at 0.5 ppm^2 and 1 ppm^2 down to about 14%. This must be attributed solely to the effect of closures, suggesting that existing controls are effective but with considerable room for further improvement. As figure 9 shows, existing controls reveal that 20% breach the $Z_t(\Psi) > 0.5$ and 8% the $Z_t(\Psi) > 1$ thresholds.

For reasons of confidentiality, we are not able to present the detailed results of using the model to assess the impact of alternative parade routes. However it is worth presenting some general comment on the way the model has been used. The process of developing six different alternative routes was based on a series of meetings organized by the Greater London Authority's Carnival Review Group (CRG 2001) and from this process, six somewhat different routes emerged for testing. These routes essentially broke the circularity of the existing route. The simplest was based on an L-shaped procession along the existing north–south route (Ladbroke Grove) and then west-east along the Bayswater Road finishing in Hyde Park (see figure 3(*a*)). The other five routes were variations either on this or on the existing route. The key issue in running the model, however, is in determining visitor volumes at entry points with the location of the sound systems unchanged. In fact a series of related models was built to predict these volumes based on linear regression of observed volumes against key route factors such as visibility, accessibility, and various distance measures to related facilities (ISP 2002). Thus for any location in the area, it is possible to predict visitor volumes which, when normalized to total visitor numbers, give the numbers entering the Carnival area associated with any new parade route.

There was considerable variation in average densities, occupancies and vulnerabilities associated with the six new routes although in every case there was improvement. In general, the new routes which were longer in distance traveled and simpler in configuration spread the visitors over a wider area, thus lowering the maximum and average densities of walkers. For example, for the L-shaped route, the maximum density is 60% lower, the average neighborhood density is 45% lower and the average density is 36% lower than for the existing route. The interim solution adopted in 2002 essentially breaks the circuit by cutting the start from the end of the parade on the northern loop, reducing crowding by 37%, 21% and 9% across these same measures.

8. Conclusions: future research

Our current model is limited in its ability to simulate behavior across spatial scales and within different time periods due to software constraints on the number of agents handled and the level of cell resolution. We are unable to simulate a complete range of behaviors, which include panic situations where we need to represent the full agent population at very fine scales. As we move to full populations, we also require finer scales and finer time intervals to represent speed and acceleration which are features of many pedestrian models (Helbing *et al.* 2000, Still 2001). Only when we are able to represent all agents would we be able to resolve the scaling problem and include behavioral protocols in the form of schedules governing movement. All these additions require us to reprogram the model in a more powerful language. This is work in progress. An important issue, however, is the need to develop software in which we can quickly visualize inputs and outputs from the model at different scales and through time. Some geographical information systems software can be extended in this way and we are already at work on using such software to handle visibility fields. It is unlikely, however, that in our new model there will be anything other than a loose coupling to such software (Batty and Xie 1994).

We also need much better data for such models. Path data are probably of lesser importance than attitudinal and related behavioral data that can only come through direct questionnaire. Our model depends on knowing the distribution of different types of agent and this in turn is reflected not only in their behaviors at the Carnival but also in their demographic profiles. In short, following the law of requisite variety, we need to ensure that the richness of our models is matched by sufficiently rich data. Finally the model structure developed here provides a rather different perspective on the nature of control, design and planning. In many small-scale spatial event situations such as the movement of people into and out of high-capacity buildings and vehicles, there are already major controls on what is possible, established by various legislative and local mandates. These must be built into the models directly and if they are to be altered in any way, then the experts and stakeholders who know most about these situations and what is possible must be intimately involved. This in turn requires the models to be accessible in a way that is not usually the case. We need to establish environments in which a variety of stakeholders can be involved in the science and can provide essential inputs not only in the interpretation of results from the models but also the design of the models themselves. This presents a new frontier for geographic information science which the models developed here are just beginning to address.

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