Mass Gatherings Health 4

Crowd and environmental management during mass gatherings

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Crowds are a feature of large cities, occurring not only at mass gatherings but also at routine events such as the journey to work. To address extreme crowding, various computer models for crowd movement have been developed in the past decade, and we review these and show how they can be used to identify health and safety issues. State-of-the-art models that simulate the spread of epidemics operate on a population level, but the collection of fine-scale data might enable the development of models for epidemics that operate on a microscopic scale, similar to models for crowd movement. We provide an example of such simulations, showing how an individual-based crowd model can mirror aggregate susceptible–infected–recovered models that have been the main models for epidemics so far.

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Introduction

More than 50% of the world's population were living in cities in 2008.[1] By the end of this century, most of the population will be living in some type of city, although some of the population might still be living in rural areas mostly for agrarian purposes. This increasing urbanisation has been accompanied by a rise in larger cities with increasing population densities because the large-scale economies generated by urban agglomeration lead to increased prosperity. Big cities generate wealth by attracting skilled migrants.

Besides the strain on urban living and infrastructure, as the planet becomes increasingly crowded, cities in particular are becoming places of frequent and large mass gatherings (MGs). At the local and regional scales, large movements of populations during commutes from home to work and other routine travel are resulting in massive congestion on road systems and public transport. Local entertainment events generate extreme crowding in small spaces such as sports arenas, festivals, and other popular entertainment sites. This extreme crowding is particularly difficult during emergency evacuations.[2]

Bringing people together has many positive social and economic benefits, but also several negative outcomes. When the density of people becomes too high, crime, incidence of injury and illness, severe traffic delays, and pollution also increase, often more than proportionately through the interaction of populations.[3,4] Densely populated areas are also ideal for the development and spread of some respiratory epidemics. Frequent interactions between people whose physical contact increases non-linearly with the density of individuals in any particular place results in transmission of contagious diseases to a large population in the shortest time.

During any MG, environmental and public health planning includes protecting the health and wellbeing of participants, staff, and spectators from infections, other illnesses, and injuries related to improper management of food, water, waste, land, and traffic. Health authorities need to consider basic human needs, including potable water, sufficient public toilets, adequate refrigeration for perishable foodstuffs, recognised and approved suppliers of bulk foodstuffs to the food providers at the site, sufficient capabilities for the disposal of liquid and solid waste, appropriate storage and removal of liquid waste, and control of rodents and insects that affect health.

Some environments for MGs are so crowded that the risk of a disaster is ever present.[5,6] An example of such a crowded environment is the Hajj, the Muslim pilgrimage to Mecca,[7,8] which is an annual event that takes place in the sacred areas of Mecca, Mina, Muzdaliffah, and Arafat, in Saudi Arabia (figure 1). At the Hajj, accommodation ranges from the most basic to the most sophisticated, but most pilgrims have to share public facilities and live in semipermanent tents. Inadequate storage, cooking, or transportation, lack of refrigeration, and lack of proper food handling can contribute to the pilgrim's risk of disease. The Hajj attracts about 3 million pilgrims during 1 week. It is very crowded, with millions of pilgrims undertaking their religious duties within strict constraints in terms of space and time; this rigour and strictness have led to a series of large crowd disasters over several years,[9] thus putting pressure on the authorities. In the past few years, efforts have increased to solve this difficulty by scientific means, use of crowd simulation models,[9,10–12] assessment of the best ways of grouping and scheduling pilgrims,[13] crowd management and control,[14] luggage management, video monitoring,[5,10,15] and changes in the construction of the transport system for the event.[16]

The range of logistical challenges for MGs is large and includes the management of solid waste. During the Hajj in 2010, 25 612 tonnes of solid waste had to be gathered, transported, and placed underground by 6446 cleaning staff, 424 inspectors, and 630 drivers. Density of pilgrims can prohibit the use of refuse removal vehicles. Use of covered refuse containers is essential for food waste, particularly for outdoor settings in summer. As a result, some method of emptying containers to prevent overflow must be considered—possibly a central, properly

Figure 1: **The Hajj**
(A) Pilgrim crowds at the Jamarat bridge. (B) Overcrowding preventing the access of an ambulance.

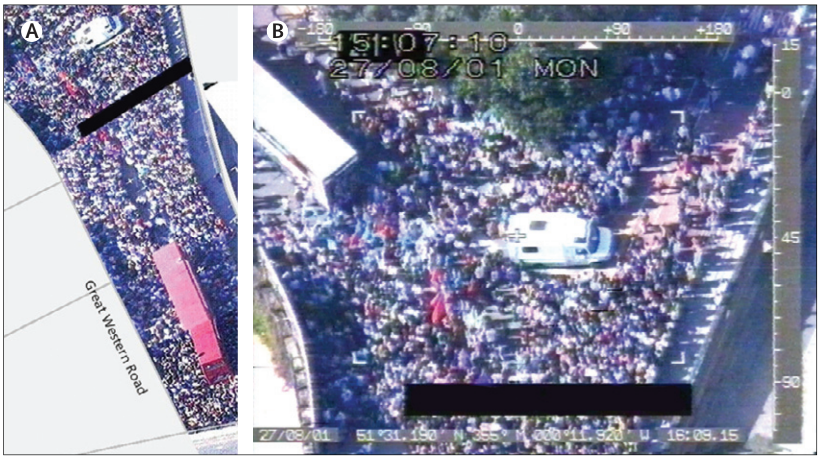

Figure 2: **Notting Hill Carnival**
(A) Float passing though crowds in the parade. (B) An ambulance passing through the parade and crowds.

prepared holding area, until bulk removal after the event. Another consideration during the Hajj was waste from the slaughterhouse that provided animals for religious ritual sacrifices (700 000 goats per Hajj season).

A different and contained event based on a different form of passion is the Notting Hill Carnival, held every year in central London, UK, that consists of a parade and a series of related musical entertainments (figure 2). The carnival first began as an informal street procession between 1959 and 1964 as a way of bringing the local community together after a series of race riots in the area in the late 1950s. Notting Hill then was the first area in the UK to have such riots in modern times and the predominantly West Indian community at the time decided to celebrate their culture, diversity, and potential to integrate through the carnival. The carnival now attracts more than 1 million visitors over the 2 days of public holiday in late summer compared with tens of thousands in its early days, and is now a major event for crowd control and public order, involving the use of important resources including health care and street management. The event is not marred by the scale of disaster associated with the Hajj, but crowding leads to increasing numbers of accidents, severe delays in treatment, and many public order offences every year. The carnival has been under much scrutiny by the authorities since it was marred by two murders in 2000. Proposals for its rerouting were subsequently generated with various scientific simulations that focused on the way crowds interacted and dispersed under different conditions of movement and congestion.[17–19]

Helbing and colleagues[20] catalogued key disasters relating to crowds during the previous century until 2003. The results of their report show the need for detailed study of crowd behaviour not only under normal circumstances, but also in situations in which fire or related hazards sweep through small spaces, particularly in enclosures such as nightclubs and stadiums where exits and entrances are obstructed. We will explain how various models of crowding are developed and how these can be adapted to deal with other features of MGs in cities, particularly the transmission of infectious diseases that might lead to epidemics.

Crowd modelling

Crowd research has been going on since at least the 1890s when Gustave Le Bon[21] studied the psychology of crowds by observing how they formed. Crowd behaviour is generic and Isaac Newton generalised its dynamics when referring to the “madness of crowds” during the financial crisis of the South Sea Bubble in the early 18th century.[22] However, about 40 years ago, quantitative methods started to be used for crowd research, based on experiments under controlled conditions, to measure the effect of architectural configurations in buildings and streets on the flow of people,[23] and study the video recordings of crowds.[24] However during the past 20 years, more advanced quantitative techniques have become increasingly popular because of advances and reduced costs of computation. New methods for data capture implement fine spatial scales such as those used in global positioning system (GPS) technologies. These techniques include the simulation of pedestrian flows,[18,20] automated computer vision,[25] and new methods for modelling navigation and route finding.[26] Many methods for modelling and simulating pedestrian crowds were proposed, such as agent-based,[27,28] social force,[20,29] cellular automata,[30–32] fluid dynamic,[33–35] and queuing models,[36,37] and those based on least effort[38] and simple heuristics.[39]

Studies of pedestrian crowd dynamics have focused on different scales—from the microscopic, dealing with individual pedestrians, to the macroscopic, dealing with the characteristics of the crowd. These methods have shown several self-organising principles about the patterns of crowd phenomena; corresponding patterns have been noted in real crowds.[5,40,41] These included macroscopic crowd patterns that result from local interactions of multitudes of pedestrians at the microscopic level. Examples of such phenomena are presented in panel 1.

In attempts to manage crowded places, different, sometimes conflicting, objectives come into play—eg, the general idea behind a MG is to bring people together, but the aim of crowd managers is to keep people separated (both in space and time). This fundamental paradox in crowd management is one that needs to be resolved in a way in which optimum flows are maintained and the crowds react appropriately to the constraints imposed on their location and movement.

Agent-based models, a new class of simulation models, have been developed and encode various principles of flow and movement and key features of pedestrian dynamics (panel 1). Different principles of flocking and dispersion can be built into the algorithms according to which pedestrians move in confined spaces, whereas various issues such as congestion can be embedded into agent-based models. In particular, the idea of a default model of movement based on the random walk is often the starting point.[17] Various methods have been widely used that enable entities or people to swarm in the process of learning about their local environments.[42]

The complexity of these kinds of agent-based models means that they require good visualisation. For example, in the Notting Hill model,[18] the swarm behaviour of people enables them to learn about the street pattern and find the shortest routes, which are crucial for entrance and exit (figure 3).

These kinds of simulations are also supported by other forms of visual analyses relating to crowding and movement that can be used to identify points of congestion and overcrowding and are thus key diagnostic factors in the use of the models to proactively simulate crowd management policies.

Much of the data to validate these models now come from various types of remote sensing. Aerial and oblique photography, as shown in figure 1 and figure 2, is still important, but detailed video recording like that used at the Hajj and remote capture of movements from fixed-laser scanning devices, closed circuit television, and fixed GPS monitors are increasingly being used. Increasingly, records of local movements from personal devices are providing datasets that can be used as samples of movement. This method is fraught with difficulties because of privacy issues. However, great progress is being made in the capture of such data remotely either through GPS or from websites that provide automatic archiving, when movements are based on vehicular traffic.

Panel 1: Self-organising principles in crowds

- Lane formation:[40] bidirectional pedestrian movement in corridors, resulting in a separation of walking directions into lanes as a result of the simple interaction heuristic—ie, step aside if you are approaching someone walking towards you, otherwise continue walking in the current direction
- Oscillations at bottlenecks:[40] bidirectional pedestrian flow within a narrow bottleneck, such as a doorway in the middle, results in oscillations of groups passing through the bottleneck in opposite directions
- Intermittency:[41] unidirectional pedestrian flow through a narrow bottleneck is not smooth, but rather intermittent, with periods of total blockage and bursts in the outflow of small groups of people through the bottleneck
- Stop-and-go waves:[5] when the crowd density is high, smooth unidirectional flow breaks down into dynamic stop-and-go waves
- Crowd turbulence:[5] for very high crowd densities, pedestrians are involuntarily moved around by the crowd in unpredictable directions and with varying force

Many of these methods are directly useful for crowd management. In both the Notting Hill and Hajj models,[5,15,18] direct use of the simulations have been used to improve surveillance of critical congestion points and suggest proposals for physical changes to the routes of the walkers and the actual transport infrastructure by which visitors travel to and around these festivals. For example, for the Notting Hill Carnival, an agent-based pedestrian model was used to simulate and assess some alternative routes, and one of the simulated routes was chosen as the actual route for the carnival.[18] Also for the Hajj, several important improvements have been implemented, informed by the results from studies of crowds.[5,9–16] A multidirectional street system was replaced by a one-way system in 2007, giving higher throughput and smoother flow than for any previous Hajj.[5,13] Further, groups of pilgrims are spread out in time and space by use of optimised schedules[13] and the compliance with these schedules is monitored in real time with video analyses of real crowd movement.[10,15]

Spread of diseases

In crowded places, fear of being crushed is not the only concern. Another worry is the transmission of disease.[43,44] Even though epidemiological processes are closely related to pedestrian crowding and modes of transport, the timescales are typically longer and the spatial extents are larger. For these reasons, epidemiological models typically operate on a population (macroscopic) level rather than on an individual (microscopic) level. The advantage of working at a macroscopic level is that the scale of the problem does not become a restricting factor. Disadvantages are that the interventions that can prevent the spread of disease—eg, immunisation, screening, quarantine, and travel restrictions for infected individuals—typically operate on a microscopic level.

Moreover, macroscopic models are typically based on the assumption that populations are in equilibrium, homogeneous, and well mixed, which is not true for real populations. Mobility and interaction patterns in real populations, shown in the way that cities are organised, tend to be highly skewed in terms of distribution, similar to power laws rather than normal Gaussian distribution. This skewing typically means that distributions of the population contain many clusters, some large and many very small clusters. Diseases will spread faster in the largest clusters but are restricted by the cluster size, which has important effects on the spread of an epidemic.[45,46] For example, Simões[47] in modelling the spread of mumps in Portugal during the 1997–98 epidemic showed how network clusters (strongly interconnected parts of the network) of populations at all scales were important in determining the spread of disease.

On the basis of all these reasons, we propose a shift in epidemiological modelling from the more top–down macroscopic level to a microscopic bottom–up level. Some attempts have been made to move epidemiological models to a microscopic level, by running computer simulations of the spread of computer viruses in scale-free networks such as the internet,[48] or by use of the international airline transportation network with census population data to simulate the spread of disease.[49–51] We propose to delve further at the microscopic level and make use of actual trajectories of individuals obtained through techniques such as GPS or mobile-phone tracking,[52] and begin tracking how individuals in confined spaces enable the spread of disease through their proximity.

Many different models for the spread of epidemics exist, but one of the simplest and most well known is susceptible–infected–recovered, first proposed by Kermack and McKendrick,[53] which divides the population into three groups—people who are susceptible to the disease (S), those who are then infected (I), and people who have recovered (R), and, in proportional terms, we have $S+I+R=1$. The rate of transition from state S to I is determined by $\beta=0{\cdot}15$, and the rate of transition from state I to R is determined by $\gamma=0{\cdot}0032$, giving us the system of ordinary differential equations, where dS/dt, dI/dt, and dR/dt are time derivatives of S, I, and R, respectively,

$$\left.\begin{aligned}\frac{dS}{dt}&=-\beta I(t)S(t)\\ \frac{dI}{dt}&=\beta I(t)S(t)-\gamma I(t)\\ \frac{dR}{dt}&=\gamma I(t)\end{aligned}\right\}$$

Rather than modelling a perfectly mixed homogeneous population with these differential equations, we now construct the same type of disease-spreading model from a microscopic perspective. In this microscopic model, N individuals can be in one of the three states S, I, or R, but individuals now have a spatial location that is changing with time.[54] The recovery rate is still modelled with parameter γ, but the rate of passing on the infection is now related to the proximity between two individuals. If an individual in state I is within a 10 m radius of another individual in state S, the probability of passing on the infection is β. The final components in such a model are space of interaction and mobility patterns. To test this model for an entirely hypothetical epidemic, we chose the centre of London, and the movement trajectories of individuals in the model have been obtained from couriers moving in central London who were tracked with GPS devices (figure 4; webvideo).[55] By measuring the proportion of individuals in states S, I, and R as functions of the simulated time, we obtained a result similar to that obtained with the Kermack and McKendrick model, indicating that our microscopic approach has dynamics that are similar to those of the original model. Such a microscopic model can be used to study how different interventions on the individual level exert their effects at the macroscopic level. For example, the system-level difference in immunisation of 10% of the population can be compared randomly with immunisation of 10% of the population travelling the longest distances. We might also immunise those whose travel behaviour places them in the largest clusters in terms of home, workplace, or even shopping centres that they visit, thus tailoring the intervention policy to produce the most efficient and cost-effective immunisation possible. Such strategies for inoculation of children and other susceptible groups against mumps are assessed in a similar model by Simões.[47]

See Online for webvideo

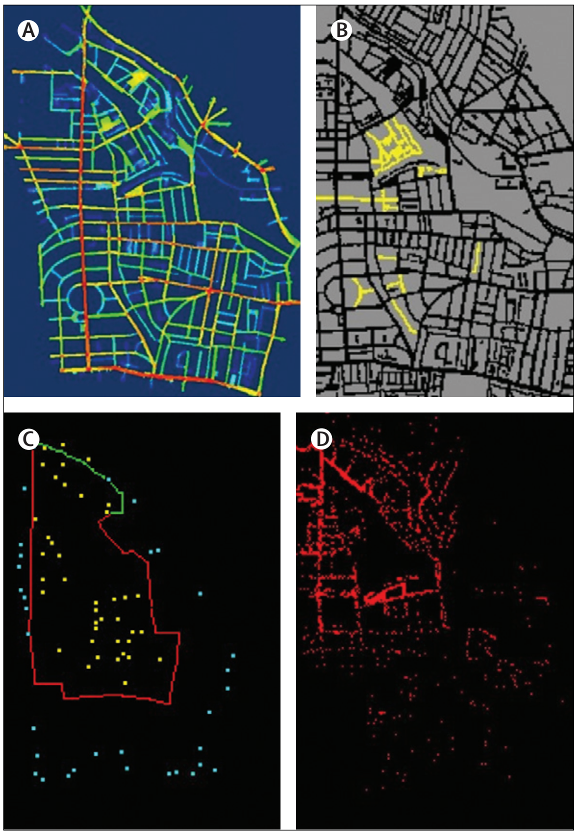

Figure 3: **Visual agent-based modelling of crowds at the Notting Hill Carnival**
(A) Flow density of the crowds along the streets (red [most dense], yellow, green, blue [least dense]). (B) Streets (yellow) closed by the police. (C) Carnival route (red and green [section closed ahead]), entry points (blue), and music events (yellow), with spectators along and within the parade route (red and green). (D) Movement of walkers.

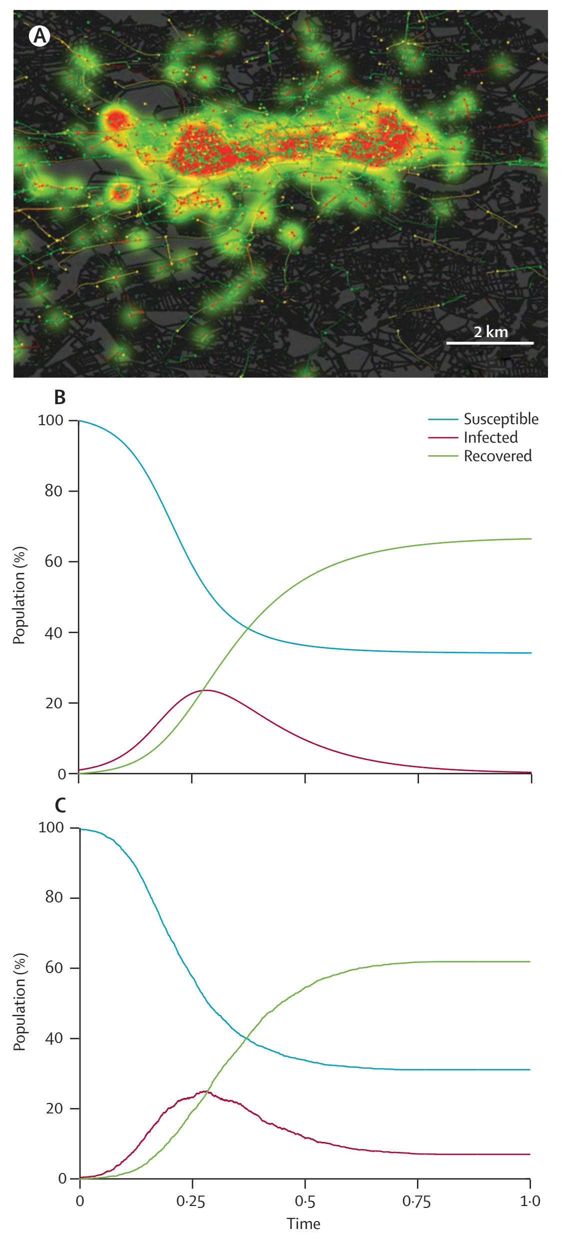

***Figure 4:* An individual-based susceptible–infected–recovered epidemics model for a hypothetical disease**

(A) Snapshot of central London, UK, showing the results of running this microscopic model in terms of the spread of infection, susceptibility, and degree to which the populations have recovered. The heat map colours correspond to the density of people being infected with disease. (B) Results from a macroscopic (Kermack and McKendrick[53]) model. (C) Results from a microscopic epidemic-spreading model run by use of global positioning system trajectories in central London.

Panel 2: Characteristics of human mobility patterns and interaction

- Human mobility is not random, but is characterised by temporal and spatial correlations.[52,56]
- On a small scale, pedestrian crowds do not spread out uniformly and fill the available floor space. Rather, for an average crowd density D (people per m^2) within a large area, local measurements of crowd density can be approximated with a Gaussian distribution with the standard deviation,[57]

  $$\sigma=\sqrt{D/3}$$

  Therefore, the critical proximity distance for passing on an infection arises at lower average crowd densities than would be expected.
- Group sizes follow a zero-truncated Poisson distribution.[58]
- Walking speed decreased with increasing crowd density and as a result the flow of people follows an inverse parabola-like function of crowd density. Therefore, the maximum flow possible (capacity) occurs at an intermediate crowd density and a high throughput of people is difficult to maintain. In addition to density, greater time spent by people around an infectious individual will affect subsequent numbers of infected and ill contacts.

Search strategy and selection criteria

We searched Google Scholar and Medline for references for this review using the search terms “crowd”, “mass gathering”, “environmental”, “disease”, and “Hajj”. Priority was given to articles that addressed more than one of the subtopics discussed in this review. We included articles published in English and German from 1890 until July, 2011.

Conclusions

In addition to the advantages of a microscopic epidemic-spreading model, the disadvantages include the large computational burden for city-level or wider spatial applications, and fragility of a complex model that has many variables. Calibration of such a model with empirical data is more difficult because the level of detail and quantity of available empirical data vary from area to area. Although detailed GPS trajectories of individuals can be obtained, detailed information about where, when, and whom individuals interact with throughout the day is much more difficult to obtain.

For these reasons, we propose a mesoscopic level, as an intermediate step, in the development of epidemic modelling. This model would essentially run on a macroscopic level, but still have all the known characteristics and scaling laws (usually expressed as law of sizes in the form of a frequency distribution of those sizes) in human mobility patterns and interaction (panel 2).

Simões[47] model for the spread of mumps in Portugal is also built on a modified susceptible–infected–recovered base (in which a latent stage is introduced for individuals who are infected but not yet infectious). This model blends microscopic and macroscopic elements, in particular taking account of the social networks that are important for the spread of diseases, and which, like in the models for pedestrian crowding, represent local distances and proximity. We believe that this method is the way forward in the development of epidemic models that represent local circumstances but have macroscopic effects. Such models would allow us to test various interventions on a virtual population with a computer and measure their success rates before testing them on real populations, possibly saving both resources and life.

Contributors

All authors participated in writing the review and did the literature review. AJ provided figure 1B and figure 4, and MB provided figure 2 and figure 3.

Conflicts of interest

We declare that we have no conflicts of interest.

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