Bringing agents into the spatial microsimulation

B. M. Wu[1], M. H.Birkin[1] and P. H. Rees[1]

[1] School of Geography
University of Leeds
UK LS2 9JT
Telephone: +44 (0 in UK)113 34 36838
Fax:+44 (0 in UK)113 34 33308
Email:B.Wu@Leeds.ac.uk

1. Introduction

Computer simulations/models have now become more important in modelling complex systems including the social systems. Modern policy problems often require disaggregate information with great details. IBM (Individual Based Model) models the system at the individual level to assist decision making, in contrast to the traditional models where individual characteristics are often blurred or even disappeared. MSM (Microsimulation Model) and ABM (Agent Based Model) are the two important approaches in IBM.

MSM has been extensively applied and well tested in social modelling. Especially in the public policy domains, its application has ranged from tax-benefit, pension, health to transport policies (Redmond *et al*. 1998; Sutherland, 2001; Curry, 1996; Morrison, 2003; PTV AG, 2000). Geography has an important impact on individual behaviours and plays an indispensable role in effecting social progress and welfare (Birkin *et al.*, 1996b; Clarke, 1996; Wu and Hine, 2003). Spatial MSM simulates virtual populations in given geographical areas so that local contexts can be taken into account (Ballas et al, 2005).

However MSM have been criticised of being less strong in behaviour modelling and most MSM only models one-direction interactions: the impact of the policy on the individuals, but overlooks the impact of individuals on the policy (Krupp, 1986; Williamson, 1999; Citro and Hanushek, 1991; O'Donoghue, 2001; Gilbert and Troitzsch, 2005). MoSeS (Modelling and Simulation of e-Social Science) attempts to provide a better individual based simulation for UK population with a spatial MSM, where individual behaviours are modelled with ABM insights.

2. Spatial MSM and ABM

2.1 Spatial MSM

MSM have come a long way since Orcutt (1957), one of the founders of the micro-analytical research methodology, first conceptualised and developed a new way to predict distributions of individual decision-making units. This kind of model has advantages in handling nonlinear relationships over the traditional aggregate representations. Spatial MSM is a special type of MSM that simulate virtual populations in given geographical areas (Ballas et al, 2005). In a spatial MSM, local contexts can be taken into account when studying the characteristics of these populations. Such MSMs are concerned with the creation of large-scale datasets estimating the attributes of individuals within the study area and are used to analyse policy impacts on these microunits (Birkin and Clarke, 1995; Clarke, 1996). Spatial MSM models therefore have advantages in exploration of spatial relationships and analysis of the spatial implications of policy scenarios.

Spatial MSM was first studied by Hägerstrand (1985) since the 1950s by first introducing the spatial and temporal dimensions into social studies. Wilson (1967), Clarke (1996) and Birkin and Clarke (1995) extended the theoretical framework over the years. Such MSM allows data from various sources to be linked and patterns to be explored at different spatial scale with re-aggregation or disaggregation of the data. Furthermore they allow updating and projecting, which is of particular importance in forecasting future patterns (Clarke, 1996; Ballas and Clarke, 2001).

However, unlike the data and computing limitations, two criticises against MSM remain to be addressed: MSM are less strong in behaviour modelling and most MSM only models one-direction interactions: the impact of the policy on the individuals, but overlooks the impact of individuals on the policy (Krupp, 1986; Williamson, 1999; Citro and Hanushek, 1991; O'Donoghue, 2001; Gilbert and Troitzsch, 2005).

2.2 ABM

ABM on the other hand can strengthen the criticised two points of the spatial MSM. It can provide insight into the structure and effects of policies and assist in understanding and modifying behaviour and interaction patterns (Luck et al., 2003). The behaviours of agents within an ABM are governed by different rules, depending on their goals, preferences and decisions etc. Agents can interact with each other and the environment that they live in. Hence the individual behaviour is affected by and will have an impact on the environment.

However, generally speaking, the research on the Agent and ABM is still at an early stage and many important questions are still being studied or need further study. Therefore, despite the usefulness of the ABM as described in previous discussion, being a relatively new technology, sometimes it is felt that it can benefit from more refined and well-established theories and concepts of other approaches (Gilbert and Troitzsch, 1999; Conte *et al.*, 1998). Such features of MSM and ABM make them naturally complementary to each other (Caldwell, 1998; Rephann, 1999; Boman and Holm, 2004).

3. Bringing Agents in the spatial MSM

In the MoSeS model, UK population is annually projected at the ward level by gender and single year of age. The model projects each component of population change (births, deaths, marriage, health change and migration) separately, but each component of change affects the others, eg., in process of the marriage, it can lead to changes to migration(Figure 1).

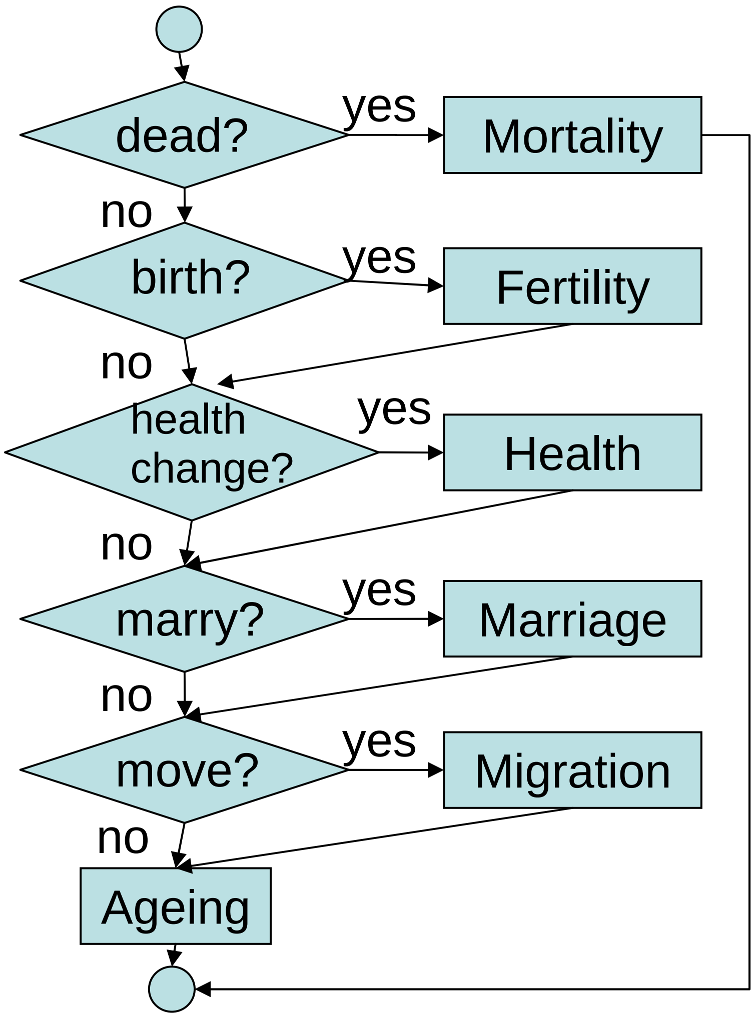

Figure 1 Process of the population simulation

The MSM is driven by probabilities of different demographic processes. However, some processes such as Marriage and Migration are of a more complicated nature and they will require numerous probability calculations and assumptions, if using a pure MSM approach. This is not only arbitrary and cumbersome, but also very inflexible to accommodate behaviour modelling.

Using agents, on the other hand, allows individual behaviour be modelled through different built in rules. For example, during the process of migration, agents (people) can choose to move in moving parties or alone; move to different locations not only by distance distribution probabilities, but also according to individual preferences and decisions. This makes the distribution consistent with the distance distribution patterns at the global level, while allows individual variance at the local level (eg. students population may move in and out of university areas within a city at one stage, but the whole city's migration pattern will still reflect the distribution pattern at the UK level). Such movements are subjected to the environment limitation, eg. housing price and availability. During the process, interactions between the individuals and their environment are also modelled, which is very important in such processes. Such migration process will be modelled on different spatial and temporal scales (eg: annual local impact vs. ten years global impact) and there is potential to integrate observable and postulated behaviour while preserving achievability of endogenous emergence.

4. Conclusion

Spatial MSM has been proved to be an effective approach in modelling social systems with a geographical context and therefore is very useful for strategic planning and policy making support. However, although the data collection and computing have advanced and reduced most critics for MSM, two points remains to be addressed: MSM is less strong in terms of behaviour modelling and normally only capture the one-direction impact of policy on the people.

Bringing agents in the spatial MSM provides MoSeS the capacity to tackle such issues and this hybrid approach also gives MoSeS a new angle to classical modelling problems where we need to:

1. achieve consistency with the world outside a defined core system boundary;
2. simultaneously represent processes on different spatial and temporal scales;
3. enable agents to concurrently obey internal and external rules, and
4. integrate observable and postulated behaviour while preserving achievability of endogenous emergence.

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