Complexity and Urban Simulation: Towards a Computational Laboratory

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The urban environment is a complex system. The evolution of cities is path-dependent, involving massive interactions at a microscopic scale. New urban structures and forms emerge from ill-defined, non-linear, and interactive processes. The complexity justifies computer-based simulation because simulation is often the only practical way to study a complex system. However, it is the complexity that raises a series of methodological issues that need to be scrutinized. Urban (social) systems differ from natural systems in that the microscopic rule of the former is complex. Recently, bottom-up models such as cell-based spatially explicit models, cellular automata (CA), microsimulation and multiagent simulation (MAS) have emerged. This paper addresses some important issues of the new generation of urban simulation and advocates the use of simulation as a computational laboratory.

Keywords: Urban simulation, cellular automata, land use modelling complexity, dynamics, GIS-based simulation.

Urban simulation is a general label given to a highly diversified field (Maguire, 1989), which refers to a range of methods from quantitative urban modelling (Batty, 1976) and operational models (Wegener, 1994), qualitative system dynamics (Forrester, 1969), microsimulation (Orcutt et al., 1961) and spatial diffusion (Hägerstrand, 1965), to mathematical spatial models based on a catastrophe and bifurcation theory (Wilson, 1981; Allen, 1997). Simulation was at a low ebb in the late 1970s when disillusionment with large-scale models became apparent. The advance in computation technology has led to the development of geographical information systems (GIS), and then renaissance of geocompuation in the tail of quantitative geography (Macmillan, 1997). A new generation of urban simulation models emerged, highlighted by a special issue of *Environment and Planning B* on computer-based cellular simulations (Batty et al., 1997). Under the umbrella of cellular automata (CA), microsimulation or multiagent simulation (MAS), these models are quite diversified except that they are spatially-explicit and disaggregate, and temporally dynamic.

The new generation of urban models is spatially explicit in the sense that the basic units of simulation have an explicit relationship with each other, whereas in spatially

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aggregated models regions can be denoted by an index or subscript that can suffi-
ciently represent the spatial relationship through mathematical formulae. Because the
number of basic units in an aggregated model is limited, a matrix of distance between
the origin and destination can be set up. After this transformation, spatial presenta-
tion becomes irrelevant. The new generation of urban simulation, however, has a
massive number of basic units (which are called cells in CA or agents in MAS). As the
state of a cell or an agent is dependent upon its environment, the spatial relationship
has to be maintained during simulation. MAS develops an extremely explicit spatial
relationship because an agent can move from place to place. Thus, agents interact
with each other and then produce a constantly changing spatial relationship. The
simulation of urban movement in a network through spatial syntax (Hillier, 1996),
for example, requires a detailed knowledge of spatial configuration.

The emergence of the new generation urban simulation model is related to the
notion that the urban system is a complex system (Batty and Xie, 1994). Langton,
for example, characterizes the phase transition of the system that consists of mas-
sive microscopic components as two separate regimes–the periodic and chaotic one.
Between the two is a transition regime that displays complex behavior. As commonly
noted, the complex system is poising on the 'edge of chaos' (Langton, 1992). The
transition regime demonstrates a complicated structure. According to Langton, the
phase transition is a 'second-order, or *critical*, transition'. "Crossing this critical
transition region gives rise to 'complex dynamics'" (Langton, 1992:76). This fea-
ture is observed in so-called Boolean NK networks (Kauffman, 1991). The Boolean
network consists of N elements linked by K inputs per elements. In biology, this
model can be thought as an abstraction of N genes connected by K links. Kauffman
noted that "phase changes between 'solid' and 'gaseous' states can occur in self-reg-
ulating NK networks, depending on their local characteristics" (Kauffman, 1991:
68). While the previous state can be described by conventional and usually linear
systems and the latter can be approached through statistical methods, the complex
system has to be simulated in order to understand its behavior. Casti (1996) listed
three 'fingerprints' of a complex system: (a) there are a medium number of agents,
(b) these agents are intelligent and adaptive, and (c) their behavior follows local in-
formation. The first 'fingerprint' means that the number of the agents is too large
for intuition and hand calculation. These agents make decisions and take actions
according to local information. The constraint of local information field is in fact
a property of severe 'non-linearity', which makes the use of deduction extremely
difficult. Obviously, the urban environment shows these fingerprints of the complex
system and therefore we cannot use deduction to study the urban environment. This
further suggests that we should use a computer model approach. Following this ra-
tionale, Nagel and Barrett (1997) developed a whole transport system of the city of
Albuquerque, New Mexico in the computer.

The bottom-up models such as cell-based spatially explicit models, cellular au-
tomata (CA), microsimulation and multiagent simulation (MAS) are based on local
rules to generate forms and patterns at the macro levels. These models are dynamic

in the sense that the system-time proceeds irreversibly. The state of each component changes along with the system-time in a discrete step. The system evolves with iterations and exhibits the path or trajectory of growth. In this property it differs from the Garin-Lowry model wherein the iteration is used as an 'algorithm' to calculate the static state of convergence (Lowry, 1964). In a sense, time does not really matters in the latter but it is absolutely essential to the former.

The advance in computation capacity has led to the blurring of distinction between science and social science. The use of simulation is not limited to geography and planning. The word 'artificial societies' has been coined to reflect the existence of societies in the media of computer. These artificial societies are astonishingly similar to human societies (Gilbert and Doran, 1994; Gilbert and Conte, 1995). By studying the artificial societies, insights can be gained to the change of our own society. Simulating social phenomena thus became a new bottom-up paradigm for social science (Conte et al., 1997; Epstein and Axtell, 1996). The key feature of this paradigm is 'computational'. Computation has been applied to explore theories of human behavior such as competition and collaboration (Axelrod, 1997) and the principle of economics (Tesfatsion, 1997) and to find solutions for practical problems such as traffic congestion (Casti, 1996; Resnick, 1994). A surge of computer-based models, particularly driven by GIS, not only calls for 'a more computationally minded scientific' approach (Openshaw, 1998), but also requires a careful examination of the strength and weakness of simulation as an essentially heuristic method.

The emergence of bottom-up models raised the need for rethinking simulation as a general method (Whickeer and Sigelman, 1991). This paper is not intended to provide a comprehensive review of the literature of urban simulation. The principles for urban model development and implementation have been addressed by Couclelis (1997). Batty (1997a) discussed the application of CA in urban planning. Rather, this paper will focus on the complexity inherent in urban simulation.

SIMULATION—AN EPISTEMOLOGICAL STANDPOINT

Simulation as a Tool for Studying Complex Systems

The notion of complexity imposes a serious challenge to our epistemological capacity to understand the built environment. Complexity justifies the adoption of a simulation approach. Traditionally, researchers had to simplify urban systems in order to use a deduction or statistical approach. In fact, because of the difficulty in applying a deduction approach to complex systems, simulation is often the only practical way to study the dynamics of complex systems.

The complexity of the built environment is not confined to the self-organization, irreversible and chaotic features of urban systems (Allen, 1997). The urban system

is a complex system because it consists of a large number of actors that interact with each other at a microscopic level. Because the components involve nonlinear interaction, such a system often denies deductive reasoning, i.e., developing new propositions through manipulating an axiomatic system.

For a complex system, there are two traditional ways to approximate its property. Both reduce the system of complexity to a system of simplicity. First, to simplify it to such an extent that deduction is manageable by human brains and second, to use a statistical method to filter out the noise and extract 'regular' part of behavior. To take industrial location as an example, the Weberian industrial location theory belongs to the former; and the discrete choice theory is a typical example of the latter. The industrial location theory developed by Weber (1929) simplified the problem of location choice as the trade-off between access to the locations of materials, labors, and markets. The discrete choice theory decomposes the utility of choosing a place into a deterministic part and random part (Ben-Akiva and Lerman, 1985). The purpose of the discrete choice model is to extract the deterministic part of behavior.

However, there are problems of using these approaches. First, it is difficult to encapsulate a complex system without losing crucial details. While it is widely accepted that a model is simplification of reality, reducing the complexity might lead to a model with behaviors qualitatively different from the reality. Macmillan pointed out that "...the reason why they cannot be anything but simple is, of course, the computing technology; the technology allows the problem to be solved but constrains its conceptualization" (Macmillan, 1997:9). Second, related to the first problem is that the urban system is of organized complexity (Dibble, 1996). The property of an aggregated population is not a simple collection of all behaviors of its components. As shown in the study of complexity urban models, the stochastic disturbance often paves the way for system evolution (Allen and Sanglier, 1981; Allen, 1997). As a result, the reductionism approach may be problematic.

Computer-based simulation allows a more flexible representation of the real world. For a complex system like a boat or an aircraft, it has been difficult to imagine the design without actually building a model (Hill, 1996). Despite a simplification of the real world, a computer model can maintain useful details to such an extent that it reproduces the fundamental behavior of the real system. Simulation therefore can reveal the hidden dynamics, which is difficult to spot without running the model. Conte et al. (1997) argue that simulation can provide an alternative means to study social phenomena that are so complicated that observation cannot find a clear interrelationship.

Schelling's model of residential segregation is perhaps the best to illustrate that local interactions can produce global structure (Schelling, 1978). The model begins with a cellular space and two different races. Each household occupies a cell. Assume that each household has a certain degree of racial tolerance towards the neighborhood. That is, a household is satisfied with a mixed neighborhood as long as the neighborhood is not occupied by too many households from a different race. As

each household does not insist on living with the same race, it would be expected that there should not be a phenomenon of residential segregation. However, if the model is actually run either on a chessboard or in the media of computer, a pattern of segregation begins to emerge. This is intuitively unbelievable. However, it occurs because a slight change in one neighborhood may cause the proportion of opposite race to exceed the threshold of tolerance. Consequently, this drives away the resident, which in turn leads to the changes in the racial composition of the neighborhood. Thus, a chain of movements starts. Eventually the city is split into two homogenous residential areas. This means that the divided residential areas are the result of many individual location choices. No single cause is responsible yet every movement contributes to residential segregation. The result of the simulation is therefore counter-intuitive, which can shed light on the formation of social areas.

Complexity research shows that the complex behavior of a system is not necessarily resulted from complicated rules. The wellknown 'Game of Life' is an example. The rules of the Game are quite simple and can be clearly defined (Gardner, 1970). A cell will remain alive if it is surrounded by either 2 or 3 alive cells in the neighborhood; it will change from the dead to alive if it is surrounded by exactly 3 alive cells in the neighborhood; and for all other situations it will become dead. When applying the rules to a large number of cells, a complicated pattern will emerge as if the cellular automata has a life (Gardner, 1970).

Simulation as an Alternative Reality

The epistemological stance of simulation varies from positivism to interpretative one (Séror, 1994). The positivist believes the reality is fully observable, measurable and objective, while the interpretative stance regards reality as a social construction, embedded in context. Classical urban models belong to the former. Because there is a fully observable law governing changes, simulation is simply used as an extrapolation method to apply this law to the future. That is, simulation is calibrated from observations. The result of simulation is then compared with observations to assess its recursive goodness-of-fit.

The positivist view of urban simulation is now under attack. Besides the wellknown 'flip of a butterfly' effect, i.e., a tiny local change at a bifurcation point can lead to a whole different trajectory of system evolution and thus unpredictability of self-organizing systems (Allen, 1997), a postmodernist believes that there is no such a law of the human society that is external to social existence. There are alternative realities that are not yet materialized. As the rules of the game do not exist independently from the society and human interactions, it is irrelevant whether simulation can replicate a *real phenomenon*. Instead, simulation is thought as the only way forward to explore the possible form of a *different* reality. According to this interpretative stance, simulation therefore is an artificial process to 'grow' or create phenomena that are not yet known.

This postmodernism view has echoed in bottom-up simulation modes. Langton (1989) suggested that simulating life systems as 'life-as-we-know-it' should be different from 'life-as-it-could-be'. Emmeche (1994) emphasized that the emergence of virtual reality blurs the real with the hypothetical and that simulation is seen as a postmodern science. Epstein and Axtell (1996) questioned what constituted an explanation of an observed social phenomenon and suggested that the question 'can you explain it' will be interpreted as 'can you grow it' in the future. According to their view, the explanation provided by simulation is to find initial micro-specifications that are sufficient to generate the macro-structure of interest. Therefore, they proposed a *generative* view for the social sciences and believe that the artificial simulation should be a principal scientific instrument.

URBAN COMPLEXITY AND THE RULES OF THE GAME

Complexity can be created by simple behavior (i.e., the behavior that can be defined by a set of simple state transition rules) or by complex behavior (Table 1). CA seems to be tackling the first type of complexity quite successfully. By assuming that the state of a cell changes according to universal and local laws, CA applies the laws to every cell. Through the iteration of rules, we can observe how local changes create global structures. For example, the spread of forest fire and disease, the formation of local drain direction on a terrain (Burrough, 1998), the movement of pedestrians and traffic flows in a transport system are relatively well defined. The change of the states is subject to the law of physics or, slightly complicated in the case of pedestrian movement, the plausible rule of behavior, for example, 'comfort walking' (Helbing et al., 1997). An active walker in the comfort-walking algorithm decides the movement and orientation by considering the feedback with the surrounding environment. In the case of vehicle movement, a traffic regulation is applied without exception to the whole transport network. The performance of a vehicle such as the time of accelerating and the braking distance can be observed through experiments.

In dealing with the first type of complexity, i.e., complexity developed from simple rules but repeatedly applied to a large amount of simulation units (cells), bottom-up models are obviously appealing. In fact, in many circumstances, the behavior can only be defined properly at the most disaggregated, i.e., individual level. The rule

Table 1: The complexity of physical (natural) and urban (social) systems.

	Physical or natural systems (consisting of non-linear interactions)	*Urban or social systems* (consisting of more complicated interaction)
Microscopic behavior	Simple	Complex
Macroscopic property	Complex	Complex

of simulation is axiomatic, which is near to a common sense or at least can be veri-fied by observation. But because a large amount of simulation units are involved, it is impossible to deduce the aggregated effect. The task is ideal for the computer because the algorithm basically consists of iteration loops.

Unfortunately, urban systems have the second kind of complexity, because the rule-space, i.e., the set of all possible rules, is extremely complex. The process of urban development is ill-defined and thus it comes to the rationale of a spatial decision support system (Longley and Batty, 1996). The rules themselves are evolutionary and can be redefined according to the interaction between the components (or agents). In other words, the rules are not independent from agents and thus cannot be predefined. The interaction at a local level cannot be specified into a set of simple rules. There are two reasons. First, when impossible to describe the behavior at the individual level, the rules are generalized from the description of a collection of individuals. For example, the economic system in a classical Lowry model consists of residential and industrial sectors. The interaction is defined between the two sectors rather than individual households and firms. The same is Allen and Sanglier's (1981) self-organization model of the urban system. Second, the individual behavior itself is complicated. The rules may be evolutionary, as agents can learn from the history. For example, cognition and adaptation can occur in a life-like system as shown in generic algorithm (Holland, 1998) and the game theory (Axelrod, 1997).

A simulation model in essence is an analogy to the real system. To what extent the model simplifies the behavior of the real system is a critical issue. Certainly, here exists a dilemma between recognizing the complexity of rules and understanding behavior of the system. If the complexity of rules is reduced to such an extent that the model cannot capture the property of the real system, simulation actually produces the property of the simplified rules (in most cases manifested in a set of mathematical equations) rather than the property of reality. However, if the complexity of rules is maintained, the rule space is so complicated that it is impossible to understand the property of the model, as the values of parameters can be combined in an astronomically large number of ways.

To deal with the complexity of the rule space, we can adopt two different simula-tion approaches. The first approach is developing an analogy model. In this analogy model, the complexity is substituted by simple but plausible rules. The property of the simplified rules is then fully investigated, which may *indirectly* shed light on the dynamics of complex urban systems. This approach is useful because of its power of conceptualization. Just like conceptualization through natural languages, the concept constructed is not claimed to be identical to the reality. Moreover, just as there are many ways to describe the reality in a narrative way, the rules of a generic model can be generalized in different ways. The model is therefore evaluated according to its plausibility rather than accuracy. The purpose of simulation is to explore or build theories, that is, to provide an explanation for the system. The appropriate-ness of the explanation can only be contextualized in the view that it explains the

salient feature of the system. This means that its explanatory power cannot even be judged in an ultimate sense and by the accuracy of data fit. For example, we may be interested in understanding whether or not the urban spatial structure can evolve into a polycentric one and under what conditions (Wu, 1998). Such a model can only approve/disapprove the possibility of polycentric development but cannot predict the change in a real city, largely because the model is only a plausible analogy of reality.

The second approach is developing a 'calibrated' model. The complexity is fully taken into account. Because the system is extremely complex, the purpose of simulation is not to develop a theory independent from the complexity of context. In this case, conceptualization is not thought to be useful. The approach is an *a posteriori* simulation because the behavior of the real system can be measured (the distinction between *a posteriori* and *a priori* simulations will be discussed in detail in the next section). The property found from the model is specific to *that* complex system and is not claimed to be the property of *other* complex systems. For example, expansion of urban land is dependent on the configuration of land uses of a city, which is specific to the city to be modelled. The same land use policy applied to a different context may produce a totally different result. To maintain complexity of the rule space, a complicated set of rules are adopted to follow land use conversions *specific* to the city under concern. Since the simulation model is specific to the context, it is unnecessary to examine the full range of parameter values as parameters can only take specific values. In fact, the values of the parameters should be measured or observed. Thus, it is necessary to adopt a procedure of calibration to justify the model.

The complexity of rule space can be better tackled by heuristic simulation, as simulation is a flexible method. Resorting to computation, simulation can maintain an appropriate level of rule generalization. Simulation can be more accurate than narrative as the former can develop a testable hypothesis. On the other hand, simulation can include more complicated rules than a mathematical model. The latter is often not manageable (deducible) in a complicated situation. Cautions must be taken, however, not to add 'artificial' complexity to simulation. The artificial complexity is referred here to the complexity due to model specification rather than the complexity existing in the real world. To translate a model into a computer program, it is often necessary to specify parameters and make detailed assumptions. The parameter values and assumptions should be transparent in the sense that their effects on the model should be understood.

## SIMULATION AS AN *A POSTERIORI* AND AN *A PRIORI* PROCESS

The discussion of the epistemology stance of simulation and complexity of urban systems suggests that simulation can be used for different purposes. Simulation can be used as *a posteriori* if the rule of the real system is well-understood and can be

clearly defined. What we do not know is the future state of the system according to the set of the rules. In many ways, the simulation of a natural system can fit into this category. For example, we clearly understand that the flow of water is subject to the law of gravity. What we do not know is how water flows over a complicated surface. The purpose of simulation is to 'extrapolate' the known state (t) to an unknown future state (t+1) from a set of well-defined behavior rules (Figure 1). The key issue of this type of simulation is to extract the rules of transition from observed data. Simulation tries to mimic the rules of the real system without substantial modification. Parameter values are 'calibrated' and thus justified.

As the real system is usually large, it will be too expensive to replicate it in order to simulate its change. The model therefore is a simplified version, which still preserves a similar structure. However, the effect of simplification must be understood so that parameter values are adjusted properly. A critical step is to understand how rules work through the process of 'calibration'—i.e., we will use the observation from the reality to establish a relationship between input and output of the model. A 'static' calibration procedure includes observation of the system at its current state and the use of existing rules to simulate its future state. The success of simulation is thus dependent on the extent to which the model correctly captures the fundamental mechanism of the real system. The ultimate test of the model is the degree of agreement between the result of simulation and observation. A 'dynamic' calibration procedure is to observe the history of the system in at least two time periods (t-1 and t). The model first simulates the change from state t-1 to t and compares the result with the observation. If the mode can successfully reproduce state t from t-1, then it can be regarded as a reliable one to predict an unknown state t+1. This is in fact a multi-temporal analysis, because the rules observed in the first phase (from t-1 to t) are used as the dynamics of the systems to predict the second phase (from t to t+1).

The existence of urban complexity, however, suggests that it is difficult to 'extract' the rules that govern the urban system. A set of plausible rules are 'proposed' in the belief that they can capture some important feature of the system. Because the real

Figure 1: An *a posteriori* simulation.
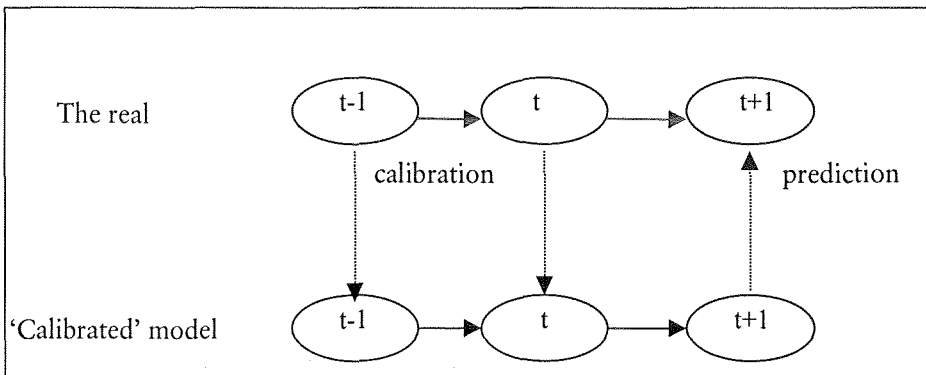
system is not well-understood, simulation as *a priori* is to develop an analogy model to speculate the system change, which might shed light on the issue under concern. The classic urban gravity model is an example. Although the model describes spatial interactions fairly well, it is in essence an *analogy* and the model cannot be justified by the existence of 'gravity' between cities. So-called 'calibration' is in fact *specification*, which is based on plausibility.

The significance of an *a priori* simulation does not lie in the empirical findings *per se* but rather in the fact that it helps to develop a better understanding of the system. Because the model is developed as an analogy, which is not based on the 'mechanism' of the system, model validation, i.e., justification of the analogy, becomes an important issue. Even when developed from empirical data, the model is useful only in a sense similar to regression. The latter describes how the dependent variable changes with independent variables. But it by no means suggests an underlying cause.

Figure 2 shows that an *a priori* simulation in fact develops an analogy, a virtual reality, to the real world. The rules of the virtual reality are specified according to our proposed virtual micro-configuration. Then, the property of this virtual reality is examined thoroughly through computation so as to understand the properties of macro-patterns. The parameters of this model therefore do not need to conform to any observation, because the parameters of the real system may not take the same values. The simulation however can suggest an alternative reality—what if the parameter takes a proposed value.

The complexity of the urban system, however, imposes a challenge for model validation. It is widely recognized that all simulation faces the difficulty of validation, especially when a complicated computational procedure and a wide range of parameters are involved. But to an *a priori* simulation as a method of theory building, validation is particularly important. It is critical to separate behavior under concern (such as the level of segregation in a residential location model) from other factors (such as the procedure of implementation and parameter values). An ultimate test

Figure 2: An *a priori* simulation.
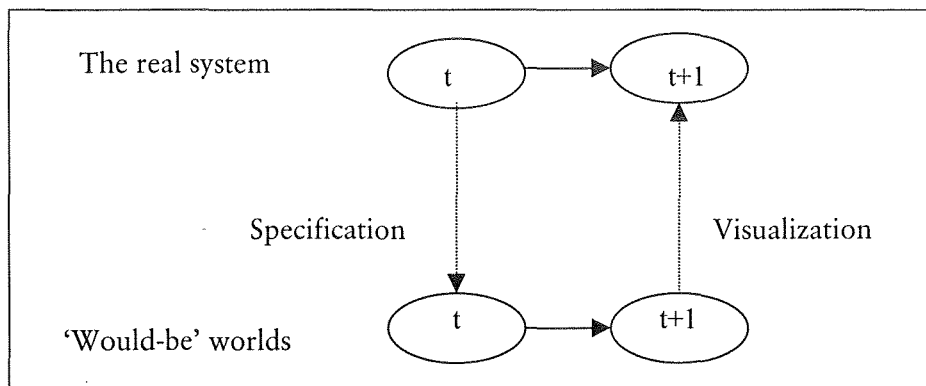
is whether the model behavior can be controlled towards a desired direction. If the answer is positive, then we may have sufficient knowledge of the system and thus can prescribe a better solution for the development of a system.

The co-existence of micro and macro complexity means that it is extremely difficult to validate the model to such an extent that its rule space can be thoroughly examined. To validate a certain relationship requires running the model repeatedly with different parameters and their combinations in order to isolate the effect of a particular parameter. As social systems present a high level of interdependence, a theory developed through simulation is dependent upon the context. Validation is therefore related to the purpose of model building. As Macmillan (1997) pointed out, it is true but unhelpful to say that models involve simplifications of reality. Any description involves simplification. But we evaluate descriptions according to whether they serve their purposes. Similarly, the model complexity is a reflection of the purpose of their authors and users. The advantage of building a computer-based simulation model is that the simplification of the model can be made in terms of the purpose rather than computing constraints. The validation of the model thus should take the purpose into account. This understanding helps to constrain the task of model validation to a reasonable and manageable one.

In sum, an *a posteriori* simulation is used to test a model that can be specified against the real mechanism and calibrated on the basis of real data. While the behavior of the system may not be well-understood (like an economic system), its rule is relatively well-understood, or at least is regarded so (such as the profit motivation, utility maximization, and market clearing). Sometimes even when the real mechanism is more complicated (involving real man, for example), we can tolerate some simplified basic assumption to some certain extent (for example, an economic man). An *a priori* simulation aims at exploration and development of theory, or explanation. Clearly the line between the two is fuzzy.

URBAN SIMULATION AND THE ARTIFICIAL CITY (A-CITY)

The interpretative view of simulation is that simulation is essentially an analogy. This understanding opens a new opportunity to build artificial worlds. The construction of artifacts in the media of computer is of no surprise because the computer is recognized as a universal computation machine (von Neumann, 1966). The idea of automata and artificial life can be implemented in the computer. The study of artificial life (A-Life), defined by Langton (1989; 1992), is a field of studying devoted to understanding life by attempting to abstract the fundamental dynamics in computer media and making them accessible to experiment manipulation and test. The A-Life research has led to similar artifacts developed in social simulation, such as artificial societies (Gilbert and Doran, 1994; Gilbert and Conte, 1995; Conte et al., 1997) and agent-based economic systems (Arthur, 1991; Tesfatsion, 1997). Similar ideas have been proposed in the study of urban systems but with a more

visualization-oriented purpose, for example the computable city (Batty, 1997b; Batty and Jiang, 1999).

The artificial city (A-City) is a virtual object that exhibits the characteristic of real cities. The strength of A-City lies in its realism of dynamics, i.e., the behavior of transition, instead of representation and visualization. The A-City research is significant because of the need for integration of theoretical urban dynamics with operational models. The simulation of A-City can reveal latent and causal effects that are difficult to examine through deduction in urban dynamics

In urban CA studies, the rules of transition have been specified in a variety of ways (e.g., White and Engelen, 1993; Batty and Xie, 1994; Portugali and Benenson, 1995; Wu and Webster, 1998a). In a sense, the cellular automatic city is an artificial city in which the complex urban dynamics is characterized by transitional rules. The study of A-City is to reveal a general knowledge of how our environment works or to provide the experience of managing our cities (Portugali and Benenson, 1995; Macmillan, 1996). Managing the city is a complex task. This can be learnt from a game-like process in *SimCity* (a popular computer game, Macmillian, 1996)). Macmillian (1996) suggested that urban modelling should produce rigorous simulation games, which he called 'serious toys', to provide the learning process about the way the city works.

The usefulness of an analogy model is demonstrated in the self-organized criticality (SOC) model, or canonically known as a sand pile model, developed by Per Bak and his colleagues (Bak et al., 1988; Bak, 1996). The model explains the tendency of large systems with many components to 'evolve into a poised, 'critical' state, way out of balance, where minor disturbances may lead to events, called avalanches, of all sizes' (Bak, 1996:1). To examine the property of avalanches, a sand pile can be developed. If sand grains are poured slowly onto a flat surface, a sand pile is being built up. Now and then, when the slope of a sand pile becomes too steep, the sand grains slide down, causing a small avalanche. As the sand pile becomes bigger, the average size of the avalanches increases. The pile stops growing when the amount of sand falls off the edge equals the amount of sand added. At this point, the sand pile reaches a critical state. The slope of the sand pile remains constant through avalanches. At the critical state, a grain of sand added to the pile can start an avalanche of any size. The size of the avalanches conforms to the power law, that is, the frequency of avalanche can be described by a power relationship with its size.

The sand pile model, though simple, analogously suggests the fundamental nature of some phenomena like earthquakes. Explanation typically relates earthquakes to specific faults or fault segments. But it does not provide any insight into their properties of size distribution (Bak, 1996). Just as in the sand pile model, a slide of sand grains can be explained by the history of the toppling of sand grain A leading to the toppling of a sand grain B and then C, and so on and so forth, one can report what happened after an earthquake in some detail. But in fact a large avalanche is triggered exactly by the same reason as a small avalanche. The sand pile experience

suggests that even if 'we can explain with utmost precision what has happened does not mean that we are able to predict what will happen' (Bak, 1996:87).

In urban transport research, model construction is a common practice. But the first attempt to build an electronic version of the whole urban transport system was made in 1991 by so-called TRANSIM (TRansportation ANalysis and SIMulation System) (Casti, 1996; Nagel et al., 1999). The model has been built by the Los Alamos National Laboratory. The initial model was based on the city of Albuquerque, New Mexico and now is developed into a full working model of Dallas (Nagel and Barrett, 1997). Some basic features of TRANSIM include disaggregation of demographic data, individual activity plans, micro-simulation and scenario testing (Nagel et al., 1999). The use of the simulation approach to an artificial world can generate insights relevant to the real urban world. For example, in real estate development, fluctuation and the burst of property price have been widely observed. However, until recently we did not know the source of fluctuation. Simulation models can suggest how a small disturbance may or may not create a chain of reaction which then sweeps across the whole urban space (Wu, 2002).

The advance in virtual reality (VR) technology opens up new opportunities to develop the artificial city to its fullest visualization realism. In an application of simulating the movement of museum visitors of the Tate Gallery in London, Batty et al. (1998a) predict the impact of room configurations. The virtual Tate has been built on three different presentations: the space syntax model, CA, and agent-based networked virtual world. In the first virtual Tate, the configuration of space and how they are connected largely determine the movement in a complex building. The second model is developed according to the CA principles using StarLogo. The third model is a more elaborate multi-user virtual Tate based on the ActiveWorlds software. Users from remote sites over the Internet can enter the Gallery and appear as avatars and walk in the virtual world. These worlds constitute a virtual laboratory for testing the factors that determine the movement of museum visitors.

More interestingly, the artificial city can be built through multiple users in different places thanks to the VR and Internet technology. In a sense, the process of model construction itself is distributed. Doyle et al. (1998) discussed the five stages of development of virtual worlds, from a simple HTML web page to full avatar-based 3D real-time interactivity. The largest virtual worlds developed by ActiveWorlds is so-called 'AlphaWorld'. Users can 'cut and paste' building objects into the AlphaWorld (Doyle et al., 1998). Over 10 million building objects were placed on the digital plain in a period of 15 months (Damer, 1998).

The AlphaWorld grows as real cities and exhibits morphological features. It has a clustered central area in a similar form to the Central Business District (CBD) (Batty et al., 1998b). A raster image can be thought as a 'satellite' image of this artificial world to show the full history of land use changes in AlphaWorld. At the web site of AlphaWorld (http://www.activeworlds.com/satellite.html), three images of land uses at December 1996, February 1998 and August 1999 have been produced, using a special program to scan through the database and assign a land use to a

pixel of the image. This provides a rich source for understanding the morphological development of the virtual world. The study of AlphaWorld *per se* would unlikely yield insight into questions about the real cities (Batty et al., 1998b). However, if a decision-making process is known in a controlled experiment environment, again in the form of the digital city, the analysis of the morphology can generate useful understandings (Batty et al., 1998b).

The purpose of building A-City varies from a participatory planning and design experience, visualization with the fullest realism, to a simple yet theoretical representation of urban dynamics. A remarkable strength of the A-City lies in its controlled environment in which it is possible to find the determinants of a specific morphology. For example, to understand the impact of property rights on urban land use mix and urban performance, we can build two theoretical A-City models, respectively representing a 'free-market' and 'regulated' regime (Wu and Webster, 1998b, Webster and Wu, 1999a, b). In the free-market regime, property rights are controlled by developers, whereas in the 'regulated' regime property rights are in the hands of communities. The development process is proposed in such a way to capture the competition between developers' profit-seeking behavior and communities' welfare-seeking behavior. The two cities generated different land use mix scenarios and produced different urban performance. The approach can be extended to test some hypotheses derived from economic theories in an explicit spatial form (Webster and Wu, 2001).

CONCLUSION: SIMULATION TOWARDS A COMPUTATIONAL LABORATORY

The new generation of bottom-up simulation models, ranging from CA, micro-simulation to MAS, offers a chance to explore the dynamics of the built environment in its fullest sense of complexity. With the advance in computation power, model construction is redirected from solvability to computability. The complexity means that it is easier to characterize the urban development process at a microscopic than at an aggregated level. Spatial details can be incorporated into the model.

CA, microsimulation and MAS are different in the ways to characterize urban dynamics. CA emphasizes the switch of a cell state under the influence of the cell's neighborhood. More complex CA can have an ability to modify the way a cell reacts to the changes of its environment. Naturally the change of CA state is akin to that of land use and urban structures. Microsimulation emphasizes the disaggregation of behaviors according to individual choice and decision-making. Individuals in microsimulation have life styles and sophisticated preferences such as travel demand (Wegener and Spiekermann, 1996; Wegener et al., 1999). The advanced application of microsimulation in urban models is travel modelling (Wegener et al., 1999). MAS is a formalism of distributed systems in which entities or objects interact with each other. The entities can be movable objects like 'agents' or spatially fixed objects like

a patch of the environment in which agents act. Agents can be divided into 'reactive' and 'cognitive' ones with respect to whether the agents simply react to the change of the environment or can behave according to their own plans (Batty and Jiang, 1999). In a sense, MAS is a generalization of bottom-up model as CA can be seen as a reduced version in which agents are immobile and microsimulation is more application-oriented. In short, the simulation approach, especially implemented in a GIS environment, can provide a new tool for understanding spatial and temporal processes (Wu, 1999, 2000). These models could be either related to some real world phenomena such as the expansion of urban areas and creation of multiple subcenters (Wu, 1998) and the burst of real estate markets (Wu, 2002) or more theoretical query of mixed land use (Wu and Webster, 2000) and urban efficiency (Webster and Wu, 2001).

In terms of implementation, both models are evolving towards the object-oriented technique, through which agents (as well as the environment) are represented as objects. The generic object-oriented toolkit SWARM developed at the Santa Fe Institute (http://www.santafe.edu/projects/swarm/) helps to implement both CA and MAS. A variety of tools are available to develop bottom-up urban models. Schelhorn et al. (1999) developed a MAS model called 'STREETS' using SWARM, while Batty and Jiang (1999) used StarLogo to simulate pedestrian movement over a road network. The request for integrating simulation models with GIS has been known for some time (Wagner, 1997; Batty and Jiang, 1999) and discussed in a geoprocessing formalism (Takeyama and Couclelis, 1997). But a fully integrated platform that can resort to GIS functions as well as object-oriented agent characterization is yet to be developed.

The real obstacle to future bottom-up modelling does not lie in the technique of model implementation. Understanding the complexity of the real world and thus dealing with it appropriately are important. Among many remaining issues is how to incorporate plausible behavior into urban simulation with respect to the fact that the rule space itself is enough complex. Surely a model is built according to its purpose and so is its performance assessed. The recognition of complexity raises an acute need to use simulation as a computational laboratory, in which complex urban form and function can be explored. Urban modelling is not alone in the development of computational approaches towards understanding complexity. Simulation has come into the arena of social sciences (Arthur, 1991; Emmeche, 1994; Epstein and Axtell, 1996).

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