Artificial intelligence and ‘waves of complexity’ for urban dynamics

NING WU and ELISABETE A.SILVA
Department of Land Economy
The University of Cambridge
Cambridgeshire, UK
wn214@cam.ac.uk  es424@cam.ac.uk

Urban land use change is a complex and dynamic process. It is important to understand the complexity and dynamics in the change process of urban land (and choose correct data models) by analyzing the driving forces and its associated dynamics, in order to predict changes in the speed, intensity or trajectory (the process known as bifurcations or phase-transitions). For this purpose, this paper firstly demonstrates how artificial intelligence (AI) approaches provide solutions to aid urban land dynamics modelling. Then, we try to build the relationship among the three dimensions of urban land dynamics, planning support and AI infrastructure. Furthermore, we clarify the different solutions space provided by AI approaches with the waves of complexity in urban systems in order to understand how to choose the best data model to represent different phenomena in urban systems through the analysis of bifurcations and phase-transitions.

Key-Words: Artificial intelligence, urban and land dynamics, complexity, bifurcations and phase-transitions

1 Introduction
The speed and intensity of urbanization has created pressure to the change in land use pattern. Therefore, it has become of utmost importance to study the driving forces of land use change in order to understand what the change process is and also to predict substantial changes in the speed, intensity or trajectory (the process known as bifurcations or phase-transitions) of land change in urban regions.

The great strides of computer techniques, and in particular, with the complex analysis and artificial intelligence coming into the field of spatial analysis during the 1970s [1], fundamentally changed the traditional methodologies and are providing deeper theoretical insight into the dynamics of land use change. At the same time, some new challenges are arising, for example, how AI approaches efficiently aid to analyze the complexity in urban land dynamics and how to choose correct data models to represent specific phenomena in urban systems. To answer these questions, firstly, this paper analyzes the solutions of AI supplying for urban land systems and how these solutions can be used to assist urban land simulation. Secondly, a concept framework which incorporates the three most important dimensions in urban systems: urban land dynamics, planning support and intelligent infrastructure is presented. It is helpful to understand the process of how AI approaches, as intelligent infrastructure, is used in order to simulate urban land dynamics in order to and provide planning support for planners. Phase-transition and bifurcation are two important elements in complexity analysis. They are very useful to identify the waves of complexity which can be represented with trajectory in graphics and, with them, we can analyze the move of solutions within the three dimensions. In this way, we try to understand some specific phenomena in urban systems from the perspective of complexity systems. For example, policy changes can be seen as the trigger points which produce phase transition or bifurcation in the trajectory of complexity in urban systems.

2 AI solutions for urban land dynamics
From the published literature, it is possible to observe that many AI approaches have been used in urban studies, which supply us with new insight into the dynamics of land use change processes. According to their application and properties, we classified them into five groups as following.

1. Artificial life
Cellular automata, Agent based modeling, Swarm intelligence: Ant colony optimization, particle swarm optimization, bee colony optimization.

2. Intelligent stochastic optimization processes
Genetic algorithm, simulated annealing, hill climbing algorithm, tabu search and path relinking, OptQuest engine, stochastic diffusion Search.

3. Evolution computing and Spatial DNA
Artificial neural network, spatial DNA, shuffled complex evolution, artificial immune system.

4. Knowledge based intelligent systems
Fuzzy logic, expert systems, heuristics, rule based reasoning, case based reasoning.

5. Others

Reinforcement learning, analytical learning.

The previous approaches are at the basis of many of today’s models and can be grouped in terms of their implementation characteristics accordingly to four different groups: spatial and a-spatial dynamic representation; optimization solutions; knowledge engines; integrated solutions.

2.1 Spatial and a-spatial dynamics representation

Cellular automata (CA), due to its ability to fit complex spatial nature using simple and effective rules, are very apt to model dynamics of urban systems at spatial scale. CA works as a framework incorporating geographic based information sets to supply spatial oriented data processing and visualization. The lattice structure and the link to geographic data make CA models highly visual. CA allows modellers to view urban systems growing over time in increments [2].

In contrast with CA’s abilities on spatial dynamics of land change, Agent Based Modelling (ABM) has presented its strong representation on a-spatial dynamics. Particularly when integrated with genetic algorithm, ABM plays a major role in explaining decisions making processes that leads to specific spatial actions [3]. Agent based modelling are usually used to simulate social-economic or human systems in urban studies where individual agents represent households, vehicles and pedestrians.

Urban land dynamics is driven by the combination of synergetic spatial and a-spatial factors, which trigger the dynamic process with their interactions. The stationary transition probabilities and less a-spatial representation of CA have limited its ability to reflect feedbacks in this system, as, in some of the CA models, global changes in the system do not influence transitions at the cellular level [4]. This can be improved by incorporating agent based model for its ability of representing the impacts of autonomous, heterogeneous, and decentralized human decision making on landscape. Thus, the hybrid model, which is composed of CA and ABM, is a more appropriate method for urban modelling since it possesses the advantages of both CA and ABM [5]. In this context, urban and land dynamic models include two important components: cellular model that is used to describe spatial dynamics and agent based models that represent social interactions. ABM, as complementarities to spatial model, makes modelling of urban and land systems more comprehensive in an entirely nonlinear way. Mainly, this is because it offers a way of incorporating the influence of human decision making on urban land dynamics and the ability to analyze the response of a system to exogenous influences: urban-rural dynamics, and policy and institutional changes and spatially explicit way.

2.2 Optimization solutions

The approaches in the group of intelligent stochastic optimization processes and swarm intelligence are mainly used to solve optimize problems in simulation processes. Genetic algorithm (GA) is one of the most commonly used approaches. Generally, GA was implemented in three areas: global optimization, auto-calibration and combinatorial optimization. Recently, a promising solution of GA to explaining decision making processes and behaviour of agents have been noticed. Silva presented that GA is important for its behavioural roles that are very apt to model individual agents and their behaviour [3]. In this way, GA works as a high level pattern of ‘human behaviour’, which produces solutions for the behaviours choice of ‘human’ (agents) under social-economic environment. This could be introduced into the original concept of GA model to make it a more inclusive structure, which includes agents that represent entities (households, vehicles and pedestrians) in land system and the behaviour regulations (e.g., optimization on transport cost function of agents) that GA imposes on them. When incorporated with agent based system (ABS), the decision making properties of agents in GA models were tailored for different applications. This combination multiplies the optimization scheme of GA on explaining decision making processes as well as the behavioural and their social-human interactions.

2.3 Knowledge Engine

Knowledge based intelligent systems mainly work as knowledge engine for urban land simulation. Expert systems incorporated with other relevant technologies (e.g., GA in [6, 7]; ANN [8]) allows for handling both quantitative and qualitative data and facilitating the process of decision making. When integrated with agent based systems, knowledge systems will work as decision engine behind the agent’s behaviors. For example, fuzzy logic’s ability to handle natural information and rules that code people’s perception and behaviors are very helpful when set up the agent’s calendar map.

Knowledge management and some of the ideas behind systems thinking promise to alleviate those issues through recognizing organizational/cultural influences on planning activities, learning and
adaptation, making efforts to consider tacit knowledge and linking planning objectives with actionable planning problems [9]. When these knowledge engines are embedded into modeling methodologies, a comprehensive framework for urban planning will emerge.

**2.4 Integrated solutions**

Different approaches of AI make their individual contributions towards urban dynamics research. However, each of these techniques has their limitations. Many of these limitations are potentially overcome by the integration of AI. Hence, there have been increasing demands for more integrated approaches in addition to the need for sophisticated models and exploring the capabilities of different approaches.

Spatial and temporal dynamics are two important driving forces of the complex adaptive process. The key to integrating AI approaches into urban models is to understand the interaction and synchronization of spatial and temporal processes. High level architecture (HLA) and Geo-Spatial Analyzer [10] have demonstrated their abilities to facilitate different simulators to take place at their specified applications. An ideal framework for simulation should be reusable and interoperable for different use cases. The framework should maximize the composition forces and minimize the cost of interaction between the components in it. HLA and Open Geospatial Consortium specifications [11] might be potential solutions for promoting the interoperability of AI framework and supply two watches to the behaviours of humans and cells in the integration processes.

**3 Waves of complexity in urban land dynamics with AI solutions**

Theoretically, the study of urban/land change modelling with artificial intelligence should be considered as an interdisciplinary study, which is at the intersection of such fields as complexity theory, GIS/RS, urban geography, land use/cover modelling, artificial intelligence, and high level architecture. Understanding the dynamics of land change and applying this knowledge to planning are both closely linked with these areas. And their systematic and synergetic combinations foster the theory foundation for the solutions to land change problems.

As Batty and Torrens [12] described, complex systems give rise to “surprise” for the observer. Urban complexity evolves through geography phenomena under the interaction between the human society and the nature. The individual groups (e.g., social-economics, infrastructures, geography factors, etc.) as a whole emerge many surprising to urban complexity, for example, sustainable development and land use change. Because of the size of operation, urban systems are difficult to understand without complexity modelling. Under the formulism of complex systems theory, many models (e.g., Artificial intelligence models) have been conducted to clarify the complexity hidden in processes of spatial and a-spatial in land change. Phase-transition and bifurcation are two most important elements to describe complexity, and the understanding on them provides promising solutions for us to identify the waves of complexity and to choose suitable approaches to represent specific phenomena in urban systems. Artificial intelligence models, such as CA and GA are the best modeling approaches to represent complexity in terms of phase-transitions or in terms of bifurcations [3].

Mainly, dataware, dynamic urban processes and technical infrastructure are the foundation stones of AI infrastructure in urban dynamics. The composition forces of the three components supply
us more robust and sophisticated solutions for modelling urban land dynamics. The ‘dataware’ for urban dynamics simulation is usually provided by GIS, which supplies spatial data for analysis. The ‘knowledge engine’ for urban planning is a comprehensive concept, which can include expert systems, data mining tools (for data analysis, model calibration or AI approaches), and visual interfaces, but it can also be described as a framework of high level data-sets and logical reasoning that, in this paper, will work as the environment/structure for the Spatial/temporal integration of different simulators. Finally, ‘dynamic urban processes’ stands for the dynamic phenomenon of urban sprawl and land use change (the variables, indicators, metrics, and theory from which we are going to perform data analysis and extract data-led theory).

In order to understand urban dynamic processes, it is necessary to develop data models, which include dataware and data analysis processes. In this context, data analysis and simulation process are executed by AI approaches. So AI approaches work as the techniques infrastructure embedded with dataware to simulate urban/land dynamics. For example, in coupling GIS with CA, CA can serve as an analytical engine to provide flexible framework for the programming and running of dynamic spatial models.

Based on the literature review and on the detailed exploration of the hybrid models explored in the previous points, it was possible to construct Figure 2. The intersect points in Fig.2 represent the implementation of AI in data analysis of urban land dynamics. In this figure it is possible to observe that CA and Agents were used to represent and deal with spatial-temporal interaction of urban dynamics. GA, SA, ANN and heuristic search, and swarm intelligence can be used as parameters optimization and calibration methods. Fuzzy logic, expert systems and heuristic search are termed as knowledge engine in urban land dynamics. GIS or expert systems can be seen as dataware of an integration framework, and they are able to interact with the underlying data sources directly.

The concept framework of AI solutions for urban planning comprise of three dimensions: urban land dynamics (which can mainly be understood by data analysis); intelligent infrastructure (which mainly includes AI approaches and GIS); and planning support - expert systems (planning support systems), which are mainly supported by modelling processes. As is shown in Figure 3, the overview of three previous dimensions represents how AI approaches as intelligent infrastructure are used to simulate urban land dynamics in order to supply planning support for planners. Such conceptual framework covers many different features of urban simulation, from data and software integration to internet operation and simulation processes.

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Fig. 2 AI approaches in urban land dynamics

Fig. 3 The concept framework of AI solutions for urban land planning
3.2 Waves of complexity in urban land dynamics with AI solutions

Generally, the understanding of increasing complexity of urban dynamics requires increasing level of intelligent infrastructure to support urban planning, because the dataware level and knowledge engine level for urban dynamics require more intelligent data analysis supplied by intelligent infrastructure. This can be illustrated by Fig. 4. Q (A', B', C') and P (A, B, C) are two points in the three dimensions solution space. They represent two different solutions, for example, point P represents that intelligent infrastructure (in A level intelligence) was used to simulate the complexity of urban dynamics (in B level of complexity) in order to give support to urban planning (supplying C level planning for decision making). There are two cubes defined by two points Q and P, which represents different solutions space. The projections of P (A, B, C) in three facets are P' (A, B), P'' (A, B) and P''' (B, C) respectively. Curve 1 shows the change of solutions (including the solution point Q and P) for urban planning. Curve 2 shows the change of urban dynamics with intelligent infrastructure through curve (Q'-P') - the projection of curve 1 in facet (X,Y). We can see it clearly that with the change of solutions in curve 1(Q-P), the Curve 2 (Q'-P') in facet (X, Y) addresses the increasing urban dynamics is accompanied by the increasing level of intelligent infrastructure. Curve 3 (Q''-P'') shows the increasing level of urban planning (decision making) which requires increasing level of intelligent infrastructure.

However, one point of concern is that it is not correct to integrate as many as AI approaches into urban land dynamics as we might want or require (at least at this stage of development), because the more AI approaches are used in urban planning model, the more interference and synchronization problems we need to deal with, the more parameters and inner-operation we need to optimize. As a result, the cost of optimization, computing time and complication of models may exert negative influence on the representation of urban dynamics. This could be depicted in Figure 5, which is based on the work of Silva [3] on waves of complexity. Silva explored complexity with phase-transitions and bifurcations and defined four ways of representing waves of complexity and best models that will study them. When introduced these concepts into our case as shown in Figure 5, it demonstrates which approaches in the intelligent infrastructure are the best choice for the four ways of representing waves of complexity in urban/land dynamics.

- Class membership [P4, P1] --- CA and Fuzzy sets.
- By the curve (P1-P3) --- any statistic package
- Moment of transition (P4) --- GA and Neuronal nets
- Intersection of trajectories (<P2, <P3) -- Fuzzy sets

With the waves of complexity in urban dynamics, the level of intelligent infrastructure required will change according to the group. This can be described by the formula:

\[ \frac{dx}{dy} \] (Y describes the level of dynamics which is represented by intelligent infrastructure)

This formula depicts the velocity of the change of intelligent infrastructure on the waves of complexity in urban dynamics. So as is shown in Fig. 5, P4 and P2 can be seen as the two highest levels of dynamics which are represented by the two levels of intelligent infrastructure in a2, and a4. Clearly, with the least level of combination, P4 is the best solution for the balance.

Fig. 4 Solutions Cube of Artificial intelligence for urban land dynamics
Fig. 5 Waves of urban dynamic complexity and intelligent infrastructure

4 Conclusions
Artificial intelligence approaches are playing an increasingly important role in urban studies. They are very apt to capture the spatial and a-spatial dynamics in urban land change process. With AI approaches, we tried to build a concept framework which includes both spatial and a-spatial dynamics analysis. And this concept framework will be used in our future research in modelling urban land use processes. With the complexity coming into urban studies, it has been used to explain many phenomena and with it we can understand much more clearly the intrinsic properties of urban systems. However, how to represent complexity and how to identify the relationship between the right level of complexity required for urban studies are two important challenges in this research area. With our analysis, we think it is possible to include waves of complexity and the dynamics of urban land use change into a concept framework, which may provide us a new viewpoint to explain some specific phenomena with concepts such as phase-transition and bifurcation. Although the complexity analysis with AI solutions for urban land dynamics is at an introductory level, it potentially provide us with a method to clarify the way of explaining complexity with AI approaches at quantitative formulation.

References: