

A Review Study on Urban Planning & Artificial Intelligence

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Abstract— AI Techniques are best techniques for dealing with complex and dynamic problems of urban studies. They give a better way for analysis of urban growth. Major objective of this study is to review recent developments in the field of urban planning & AI. The purpose of this article is to explore how artificial techniques have been applied for urban dynamic planning processes. For this, the authors have reviewed the application of AI techniques in urban land dynamics. This paper discusses how cellular Automata, Fuzzy Logic, Neural Networks have been applied for Urban Planning due to the unpredictability, instability, uncomputability, irreducibility and emergence that exists in the process of urban evolution. The authors conclude that AI based approaches offer possible solutions for urban dynamics.

Index Terms— Cellular Automata, Fuzzy Logic, Neural Networks.

I. INTRODUCTION

Urban modeling was initiated in late 1950's & in 1960's in USA & European countries. But In late 1970's & 1980, it gradually faded. At that time, the techniques used for urban planning were static, linear, cross-sectional, deterministic approaches, such as regression analysis, mathematical programming, input-output analysis etc. These techniques were not enough for the complex, dynamic and non-linear factors inherent in urban systems or subsystems [9]. Consequently, a new challenge emerged that a focus of modern urban modelling be shifted from macro to micro, from static to dynamic, from linear to non-linear, structure to process, from space to space-time. In this paper we are discussing how AI techniques have been applied in the area of urban planning.

II. CELLULAR AUTOMATA

A cellular automaton system consists of a regular grid of cells, each of which can be in one of a finite number of k possible states, updated synchronously in discrete time steps according to a local, identical interaction rule. The state of a cell is determined by the previous states of a surrounding neighborhood of cells.

In urban planning, Cell states usual represent land use or land cover.

CA has proven to be useful for dynamic modeling. Urban planning being a complex system is beyond the capability of standard CA. It has a no. of limitations such as its homogeneous cellular structure and synchronous time

advancement are too rigid to easily accommodate the diversity of processes that interact of overall system.[1]

Urban systems include a variety of spatial objects that interact with each other in complex, non-linear, and often surprising ways. Therefore, the current CA urban models are needed to be adapted for their use in Urban Planning to a large degree limited to physical processes. Table 1 shows the comparison of the tradition urban models (CA) & CA for Land Use (Adapted one). [12]

Basis	Traditional CA	CA for Land Use
Space	Regularity	Irregularity
State Set	Uniformity	Non Uniformity
Neighborhood	Stationary	Non stationary
Transition Function	Universality	Non Universality
Time	Regularity	Non Regularity
System Closure	Closed	Open

Many attempts have been made to develop a more general and flexible CA. Couclelis (1985) extended CA by separating the neighborhood set and transition rules from each cell. In other words, each cell can possess its own set of neighborhood and transition rules.

Li and Yeh (2000) developed a sustainable urban model based on constrained CA. They argue that CA can be used to model compact cities and sustainable urban forms based on local, regional, and global constraints. In addition, the concept of grey state of a cell was proposed, which can overcome the limitations of absolute black and white cells (i.e. dead or alive) that are used in standard cellular automata.[6]

Engelen (1997) developed a model-based support tool in complex urban areas. The model based on constrained CA. They constrained the overall dynamics of the CA model by means of coupling with more traditional dynamic spatial interaction models, operating on a set of regions much larger than individual cells. Also, the transition functions are written as distance functions and represent the push and pull forces between pairs of land use. The simulation operates on urban activities using rules for spatial interaction among these activities, including predefined and changeable constraints.[2]

Takeyama and Couclelis (1997) adopt the concepts of Geo-Algebra in generalizing and extending CA. In their work, CA is generalized and extended using the representations and operators of Geo-algebra.

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[10] However, these extended versions of CA still operate on a regular array of square cells. The neighborhood relations among spatial objects with irregular shape and sizes, is still major problem for any spatial system. Standard CA should be integrated with more states, infinite neighborhoods, and more constraints with complex transition rules. More integrated technology is required for urban simulation modeling. The use of intelligent agents is the currently the best approach to model the dynamic behavior of the land-use system. But the question remains, what type of spatial model can be integrated with agent system to overcome the irregularity and other limitations of CA.

III. CELLULAR AUTOMATA WITH GIS

The integration of CA and GIS has demonstrated considerable potential. The studies that have included GIS have had varying degree of success. The limitations of contemporary GIS include, its poor ability to handle dynamic spatial models, poor handling of the temporal dimensions (Park and Warner). 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. However, to build models that represent more practical geographical problems, it seems that more complex CA is required and that their dynamics need to be constrained [2]. Moreover, GIS are an inherently static tool, and are limited for use in dynamic modelling in both their updating of cellular data and implicit cellular nature. [11]. They do not include procedures for explicitly handling time, are designed to process entire arrays of data, and cannot easily address varying localized operations across the spatial grid (Gimblett, 2002).

IV. FUZZY LOGIC

The ability of fuzzy inference systems to embed expertly guided rules makes it a good choice to model uncertainties arising in urban planning due to a complex array of interacting agents in fuzzy logic. The implementation of fuzzy logic to urban planning and decision support was initially investigated during the late 1990s. Following table summarizes some of the work done in the field of Fuzzy Systems and urban planning.

Author	Outcome of the work
Sui(1992)	raised the importance of a “fuzzified” approach to the analysis of GIS based data.
Stefanakis et al. (1996)	Proposed a distance based location assessment based on fuzzy measures.
Zheng and Kainz (1999).	Neuro-fuzzy based rule extraction for a constraint based analysis of GIS data
Wu (1998)	GIS/cellular automata based visualization platform that employed fuzzy logic to capture the features of land conversion

	behavior
Feng and Xu (1999)	Hybridization of knowledge based systems, neural networks and fuzzy systems
Mraz et al. (2000)	Concept of fuzziness in cellular automata

Khalid Al-Ahmadia and his team presented a fuzzy cellular automata urban growth model for simulating the complex dynamics of urban growth in Riyadh, Saudi Arabia. This urban model differs from earlier work by its construction of transition rules using fuzzy logic. The use of fuzzy logic provided a more efficient and accurate means of calibrating the model. The inclusion of fuzzy logic allowed for the formulation of more realistic transition rules. It also allowed for a much more generic, extensible and adaptable approach than previous methods reported in the literature.[5]

An expert system based on fuzzy logic (Netweaver software) and the ArcGis EMDS extension (Ecosystem Management Decision Support) has been implemented that has been designed to help in the process of making decisions related to locating industrial areas. A GIS platform has been used to spatially analyze the suitability of a municipality to locate an industrial area, and considering the fuzzy logic attributes. The creation of an expert system based on Netweaver and the flexibility of ArcGis EMDS package allow the user to query the system using different groups of criteria. The fuzzy logic gives to the system a type of evaluation closer to the complex reality of regional planning. [13]

M. Roscia, D. Zaninelli, Gh. Lazaroiu ‘s work includes the assignment of the weights to the different indicators that can be taken in consideration in an environmental impact using fuzzy logic, so to obtain a significant homogeneity and objectivity.[7]

Fuzzy logic are used in knowledge modeling but they have a drawback i.e. direct employment of fuzzy logic lies in the way knowledge is captured, i.e. by employing man-made rules. Pure fuzzy logic based systems may not offer a feasible solution. This is generally due the fact that because of a high number of inter-dependent variables, construction of a manual, expertly guided rule-base that robustly maps input/output relationship becomes a cumbersome task [3]. In order to overcome the shortcoming of manual knowledge acquisition to create such a rule base, Artificial Neural Networks (ANNs) are extended to automatically extract fuzzy rules from numerical data.

V. NEURAL NETWORKS

Neural networks have the capacity to recognize and classify patterns through training or learning processes. They have been used in urban studies, such as journal to work flows and airline and telecommunication traffic. These studies indicate that neural networks provide superior levels of performance. Application of Artificial Neural Networks (ANN) to modelling urban growth is quite relevant due to following reasons:



- 1) They can solve highly non linear problems.
- 2) Mixture of data types can be input into the ANN.
- 3) They make no assumptions regarding the distribution of the data.
- 4) They can use many variables or factors some of which may be redundant.

The development of an artificial neural network (ANN) model requires the specification of a "network topology", learning paradigm and learning algorithm. Unlike the more commonly used analytical methods, the ANN is not dependent on particular functional relationships, makes no assumptions regarding the distributional properties of the data, and requires no a priori understanding of variable relationships. This independence makes the ANN a potentially powerful modeling tool for exploring non-linear complex problems.

Artificial Neural Network has the capability to learn dynamic behavior and performs Prediction based on its learning process. The emergence of artificial neural network (ANN) as one of computational intelligence, has added more processing power when ANN is used within the spatial analysis.

Li and Yeh (2002) presented a method for integrating NN, GIS and Cellular Automata for the purpose of simulating different development patterns based on the planning objective. Li and Yeh (2001) implemented NN to determine the Cellular Automata simulation parameters through importing the parameters values from the training of NN into the cellular automata models. Liu adapted a new method to detect the change from non-urban to urban land use through using artificial neural network (ANN).

In urban growth, (Pijanowskia et al., 2002) integrated both the artificial neural network and geographic information systems for the purpose of forecasting the change in land use. The scheme of their work starts with design of the neural network and identify the inputs using a historical data, using subset of the inputs the network was trained, then neural network testing was performed using the full data set of inputs and the final stage was using the information from the neural network to forecast changes.[8]

Artificial neural networks arise as an alternative to assess such probabilities by means of non-parametric approaches. As stated by Fischer and Abrahart (2000), these mechanisms are able to learn from and make decisions based on incomplete, noisy and fuzzy information, and that is the reason why they can be suitable to handle spatial problems. This information is important for planners and resource managers in developing better decisions affecting the environment and local and regional economies.

Dr. Kamal Jain and Mulugeta Feyissa used a methodology for simulating urban growth phenomenon through utilizing remote sensing imagery and neural network (NN) algorithms. Backpropagation Neural Network was used to classify the images to different land use categories. To implement NN algorithms for simulating the urban growth; focus was directed to the urban class and its growth. Results showed that the ANN model has succeeded in simulating the growth trends and the testing of similarity between simulated and real growths was better. [4]

Li and Yeh in their research paper "Urban Simulation using neural networks and cellular automata for land use planning" have applied Integration of neural networks, GIS and cellular Automata (CA) that can be used in land planning for simulating alternative development patterns acc to different

planning objectives. Neural networks are used to simplify model structures and facilitate the determination of parameter values. Unlike traditional CA models, it does not require users to provide transition rules, which may vary for different applications. Historical remote sensing data are used as the training data to calibrate the neural networks. With neural networks, the structure of networks remains easy and the calibration is also easy. With traditional CA, studies related to the calibration issues are very limited. Neural networks can be used to replace the transition rules used by conventional CA models in a simple & effective way.

Neuro fuzzy systems exhibit the noise robustness and learning capabilities of neural networks together with the ability of fuzzy systems to explicitly model uncertainties of linguistic concepts and the knowledge of human experts.

However, the major drawbacks of ANN, including its black-box and static nature, result in a deficiency in modeling the urban growth process.

VI. CONCLUSION

Urban planning being a complex system is beyond the capability of standard CA having a no. of limitations such as its homogeneous cellular structure and synchronous time advancement are too rigid to easily accommodate the diversity of processes that interact with overall system. In order to build models that represent more practical geographical problems complex CA emerged. The major drawback of direct employment of fuzzy logic lies in the way knowledge is captured, i.e. by employing man-made rules. The construction of a manual, expertly guided rule-base is a complex task due to the presence of a high number of inter-dependent variables. In order to overcome the shortcoming of manual knowledge acquisition to create such a rule base, Artificial Neural Networks (ANNs) are extended to automatically extract fuzzy rules from numerical data.

The major drawbacks of ANN include its black-box and static nature that results in a deficiency in modeling the urban growth process.

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