International Journal of Urban Sciences
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rjus20

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Version of record first published: 08 Mar 2013.

To cite this article: Shih-Kung Lai , Haoying Han & Po-Chien Ko (2013): Are cities dissipative structures?, International Journal of Urban Sciences, DOI:10.1080/12265934.2013.766504

To link to this article: http://dx.doi.org/10.1080/12265934.2013.766504

International Journal of Urban Sciences, 2013
http://dx.doi.org/10.1080/12265934.2013.766504

Routledge
Taylor & Francis Group

Are cities dissipative structures?

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(*Received 28 August 2012; revised version received 26 November 2012; final version accepted 5 December 2012*)

The new emergent paradigm of urban development theory that is based on complexity sciences allows us to understand and analyse cities in a new way. Theoretically, complexity sciences enable us to depict the fundamental characteristics of urban development, including nonlinearity, self-organization, and emergence. Empirically, the agent-based modelling (ABM) approach can help us to conduct simulations of complex systems, including cities, in an effective way. In the present paper, we demonstrate a computer simulation of urban growth based on the spatial garbage can model represented in an ABM framework. In the simulation, we treated the city as an open system in that the fundamental elements of the system flow in and out of the system over time. We then computed over time the levels of entropy as a measurement of the degree of structural order of the systems, namely, decision and spatial structures. The results showed that these entropies decreased over time, indicating that the city self-organizes itself reminiscent of a dissipative structure.

Keywords: cities; open systems; entropy; self-organization; dissipative structures

1. Introduction

Complexity theory has been a new paradigm to study urban development since the founding of the Santa Fe Institute in the 1980s. Considering the interaction of different types of agents in urban development, complexity theory can simulate many aspects of urban development that are characterized by cities in the real world and explain urban phenomena that cannot be described or solved by traditional mathematical models. Although the models based on complexity theory could display the self-organization of cities to some extent, no model of complexity, however, can perfectly restore the process or explain the mechanism of urban development until now. That is mainly because a city is a very complex system, which comprises almost an infinite number of elements and agents interacting with each other. Therefore, a conceptual framework rather than a large and comprehensive model is needed to simulate and explain urban development in research.

The spatial garbage can model (SGCM) looks at urban development from a particular perspective. It considers a city as a collective of accumulated stocks of buildings, which results from numerous interacting development decisions made both by the public and private sectors. These decisions are interrelated functionally, geographically, and institutionally (Lai, 2006). It also views the emergent development pattern as being derived from

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*Corresponding author. Email: lai@mail.ntpu.edu.tw the interplay among five almost independent streams of elements, namely, decision makers, solutions, problems, decision situations, and locations (see, for example, Cohen, March, & Olsen, 1972). Those five elements flow and mix with each other. On specific occasions, decisions are made and activities take place. The structural constraints (to be explained shortly) are the crux in determining whether decisions can be made through the interactions of agents, which move according to some rules in a fictitious hyper-space, similar to the concept of agent-based modelling (ABM). What differentiates mostly the SGCM from traditional urban development models is that the former focuses mainly on the impact of structural constraints, such as the institutional and spatial designs on urban development, while the latter on the explanation of the patterns and changes of urban space without regard to intangible impacts, such as institutions. The present research is distinct from the previous one mainly in the design of the simulation in that while the previous simulation viewed the urban system as closed, in the present research the system is treated as open in that the elements are free to flow into and out of the system. In addition, in the present research the structural constraints co-evolve with the urban system as endogenous, while in the previous design these constraints were fixed and given as exogenous.

In Section 2, we review some ideas about ABM and the SGCM. In Section 3, we depict the research design, followed by the simulation results in Section 4. In Section 5, we discuss the implications of the simulation and then conclude.

2. Spatial garbage can model

The SGCM was first developed by Lai (2006). It adds the element of place and two structural constraints (solution and spatial structures) into the traditional garbage can model to simulate and explain the process of urban development. The SGCM views cities as organized anarchies. In the system with these organized or regular structures, there are five elements: decision situations, decision makers, issues (problems), solutions, and places (Figure 1). These elements flow independently in a hyper-space (Figure 2). Because of the ‘disconnections among problems, solutions and decisions’ caused by ‘problematic preference’, ‘unclear technology’, and ‘fluid participation’ of organizational choice behaviour as observed by Cohen et al. (1972), in the current formulation there is no clear, definite, and causal relationship between the five elements in the urban context, owing to the complexity of the interaction among them. In other words, the interdependence among the five elements in the SGCM is manifested indirectly by the complex decision-making process that is derived from the chance meeting of these elements and the interrelationship of the structural constraints. When all the five elements (at least one of each type) meet in a particular cell and the amount of energy supply associated with these elements is greater than that of energy demanded, a decision is made.

Taking the decision-making in land development as an example, decisions are unpredictably made in this process. A decision maker may have usable land as a solution at the beginning, but does not know how to use it. When the interest rate decreases or the land value increases due to the construction of new roads, the decision maker(s) may decide to develop the land as a problem to gain profits. That means the solution (land available) may exist before the problem occurs (intended development). In addition, a decision made may not result in a resolution of the problem(s), that is, the land does not get developed. In the decision-making process, problems are sometimes, but not always, solved. New additional problems will also be brought out after the resolution of the existing problem. For example, the development of the land could cause traffic congestion.

The SGCM can further explain the occurrence and evolution of urban events. A city comprises many types of continuously changing events which bring about activities. The supply of public services in cities will influence the activities of families and the places constructed for housing, shopping, working, walking, recreation, watching movies, hospitals, and schools, etc. Regardless of whether plans are followed or not, decision makers, solutions, problems, decision situations, and places will interact with each other to give rise to complex outcomes. A family could have a budget for shopping (a decision situation), a search for the commodities in the stores at different locations (a problem), and find the favourite one(s) in a specific store (a solution). The shopping decision relies on the meeting of different elements of the family: the budget, the searching, the commodity, and the store. When decision makers, solutions, problems, and locations meet in a specific decision situation, whether a decision can be made depends first on the structural constraints. Such structural constraints include both formal and informal rules and institutions. An apparent example of such a type of structural constraint is zoning, which prescribes what type of development (solutions) is permissible where zonal areas (places) with specific location and density of construction (attributes of solutions). It also demands what type of use is prohibited; for example, facilities other than apartments, town houses,

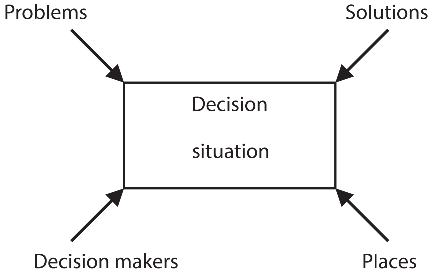

Figure 1. Building block of SGCM.

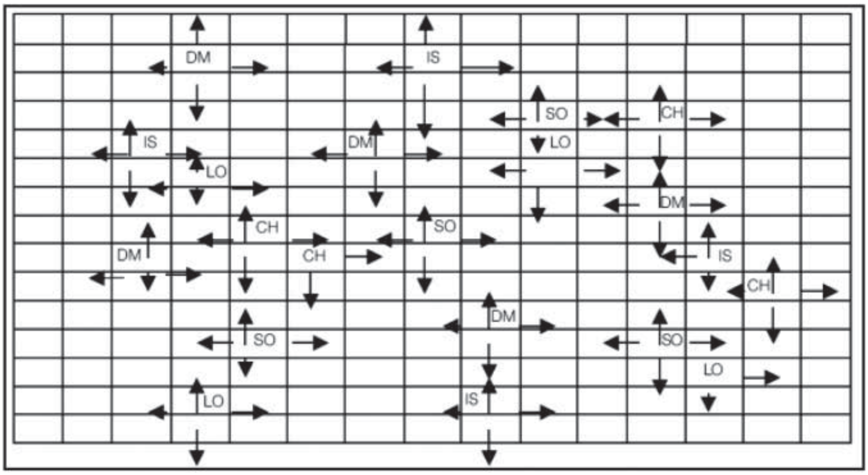

Figure 2. Simulation of SGCM.
Notes: DM, decision maker; LO, location or place; IS, issue or problem; CH, choice opportunity or decision situation; SO, solution.

single-family houses or similar residential uses are not allowed to be constructed in a residential area.

3. Simulation design

We set four structural constraints in the simulation of this research: decision structure, access structure, solution structure, and spatial structure. Consistent with the settings in the SGCM, a decision structure was defined in terms of a 0–1 matrix between decision makers and choice opportunities, an access structure between problems and choice opportunities, a solution structure between solutions and problems, and a spatial structure between choice opportunities and locations. The decision structure was reminiscent of an institutional constraint, while the spatial structure represented a spatial constraint. Both of the structures were adaptive in this simulation, capable of evolving with the change in the system over time. The access and solution structures each had three forms of constraint: unsegmented, hierarchical, and specialized as depicted in Section 3.2. These three forms were fixed and did not evolve with the change in the system over time.

3.1. *Parameters*

We used a grid of 50 × 50 = 2500 cells in this computer experiment, in which five types of elements moved and interacted, including decision situations (choice opportunities), decision makers, solutions, issues (problems), and locations

3.1.1. *Agents, grids, and time frame*

At the beginning of the simulation, 500 decision makers and 500 locations were randomly distributed on the grid. At each ensuing time step, a new solution, issue, and decision situation were added into the system. No new elements were added when the number of elements of any type reached 500. The simulation stopped at the 20,000th time step.

3.1.2. *The energies of agents*

In the SGCM, each element was allocated an amount of energy, which represented the relative contribution to make a decision. The energy could have either a positive or a negative value. A positive value indicates the amount of supplied resources/capability, such as time and labour, while a negative one represents the amount of resources/capability demanded. In the present simulation, we used the same energy levels set in the SGCM. The amount of energy supplied was given randomly from 0 to 1 for each solution. The amounts of energy supplied by each decision maker and location were set to 0.55 and 2.55, respectively, and the amounts of energy demanded by each problem and choice opportunity were both set to 1.1. These figures did not correspond to any empirical meanings of decision-making in the real world; they were specified for computational purposes so that generalized observation could be derived from such computation.

3.2. *Structural constraints*

When at least all the five elements, each of which from a different type, met in a particular cell and the amount of energy supply associated with these elements was greater than that of energy demand, a decision was made. Whether a decision could be made also depended on the structural constraints. If the value of the corresponding number in the array was 0, a decision could not be made, meaning that the element could not appear in the corresponding choice opportunity or location. Otherwise, a decision could be made if the value was 1. The settings for different structural constraints are as follows.

3.2.1. *Access/solution structure*

There are three prototypical types of constraint in access structures: unsegmented, hierarchical, and specialized as shown in matrices A_0, A_1, and A_2, respectively (Cohen et al., 1972). A '1' entry in the matrices means that the problem in the corresponding row can be attended to in the choice opportunity for the corresponding column, whereas a '0' means that there is no such relationship. The reason for applying the three prototypical types of constraint is because they are different enough to investigate into how such structures would affect the simulation outcomes. For example, in the spatial structure, zoning could be considered as a hierarchical structure in that more intensive land uses, such as commercial, are not allowed in spatial units with less intensive uses, such as residential.

$$A_0 = \mathrm{A}_0 = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}, \quad \mathrm{A}_1 = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathrm{A}_2 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

In the unsegmented structure, all active problems have access to any active choice opportunities; in the hierarchical structure, important problems (the upper part of the matrix) have access to more choice opportunities; in the specialized structure, each problem has access to only one choice opportunity. The application of a hierarchical structure means that more important problems can enter into more choice opportunities than less important problems. Following Fioretti and Lomi (2008), in the present paper this structure was constructed through a comparison of the identifications (IDs) between problems and choice opportunities. Before its movement, a problem would search for whether there was any choice opportunity in its eight neighbouring cells. If no choice opportunity was found, it moved one step randomly towards one of its eight neighbouring cells. If a choice opportunity was found, a comparison between the ID of the problem and that of the choice opportunity was made first. If the former was smaller, the problem moved at that time step, meaning that decision-making was possible. Otherwise, it stopped to render decision-making impossible. The same rule applied to the choice opportunity. If the ID of the choice opportunity was greater, it moved. Otherwise, it stopped. In the specialized structure, a choice opportunity could only meet a specific problem. If the ID of a problem was equal to that of a choice opportunity, the problem moved. Otherwise, it stopped. The rule for the movement of agents in the solution structure was similar to that in the access structure.

3.2.2. *Decision/spatial structure*

Similar to the agents in access structure, a decision maker searched for whether there was any choice opportunity in its eight neighbouring cells before its movement. If no choice opportunity was found, it moved one step randomly towards one of its eight neighbouring cells. If a choice opportunity was found, the decision array of the decision maker was examined. If the corresponding number of the decision array associated with a decision

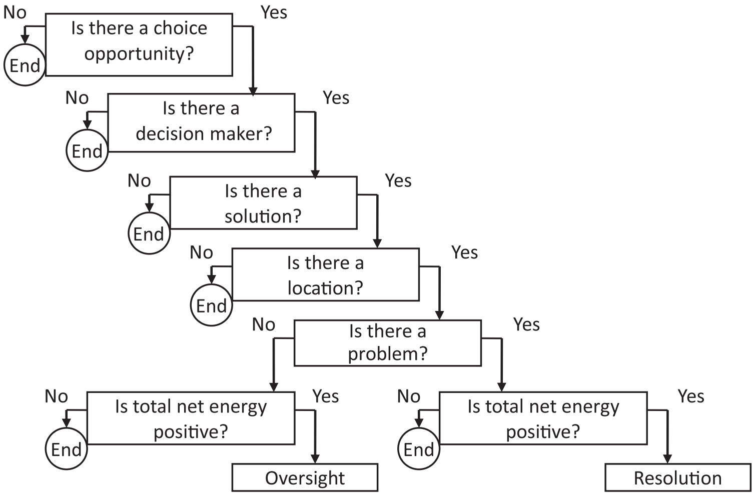

Figure 3. Decision-making rules in the simulation.

maker was 1, the decision maker moved. Otherwise, it stopped. For the choice opportunities, there was no such restriction. The rule for the movement of agents in the spatial structure was similar to that in decision structure.

3.3. *Rules for decision-making*

In addition to the decisions in the SGCM, the present simulation distinguished oversight decisions in the original garbage can model. An oversight decision means that if a choice opportunity was activated when problems were attached to other choice opportunities and if there was energy available to make the decision quickly, it would be made without any attention to existing problems and with a minimum of time and energy. In other words, if a decision was made when the four types of elements other than problems met at a particular cell, the problem(s) was not resolved. Therefore, oversight decisions can be regarded as an inefficient way of decision-making.

Whether a decision has been made was judged at the cells (Fioretti & Lomi, 2008). At each time step, a judgment was made at all the cells based on the following rules (Figure 3):

(1) If at least one decision maker, one choice opportunity, one solution, and one location met at a particular cell, no problem existed, and the total net energy of all those agents was positive, an oversight decision would be made. If there were more than one decision makers at a particular cell, all these decision makers would participate in the decision-making. If there were more than one choice opportunities, solutions, or locations at a particular cell, one of them would be randomly selected.
(2) If at least one decision maker, one choice opportunity, one problem, one solution, and one location met at a particular cell, and the total net energy of all those agents was positive, a resolution decision would be made.
(3) After a decision was made, the problem and solution would be thrown out of the system, while the decision maker, choice opportunity, and location would remain within the system. Moreover, the energy of the choice opportunity would be set to

be 0 and marked so that it would not participate in the future decision-making and the calculation of entropy, which will be discussed shortly in the next section.

In the present research, we hypothesize that self-organization of decision and spatial structures can emerge and evolve in the SGCM, or in other words, these structures are adaptive. This is based on the concept of 'adaptive efficiency' explained by North (1998). It implies that different rules evolve over time with respect to two basic abilities of an organization: the ability to innovate and learn. In the present simulation, the rules for adaption were not given, but evolved in the decision-making process as follows:

(1) If the total net energy of the five types of agents at one cell was positive (resolution), the corresponding values of structural constraints would be assigned a value of or remained to be 1. This means that after a resolution, the agents of decision makers and locations would have a greater probability of meeting choice opportunities in which resolution decisions were likely to be made.

(2) If an oversight had been made, or if the total net energy of the five types of agents at a particular cell was negative, the corresponding values of the structural constraints would be assigned to a value of or remained to be 0. It means that an inefficient decision had been made during that process. Therefore, when the decision makers or locations met the same choice opportunities in the future in which a resolution decision had not been made, they would choose not to participate in the decision-making in order to increase the efficiency.

In essence, the more decisions that decision makers and locations participate in, the more knowledge or capability they can acquire to make more efficient decisions in the future.

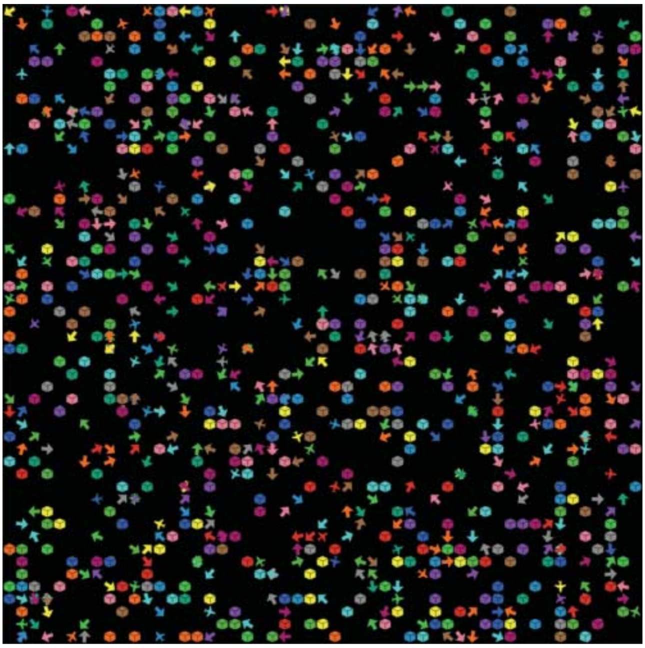

Figure 4. A snapshot of the simulation.

3.4. *Data recording and interface*

The total net energy of the system, the entropy of the decision structure, the entropy of the spatial structure, and the numbers of oversight and resolution decisions were recorded in the simulation. We used the entropies to measure the degree of order in decision and spatial structures. Following Shannon (1948), entropy is calculated through the following formula:

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log_b P(x_i), \tag{1}$$

where b is set to be 2, H is the entropy for x_i which is a random variable of row I in the structure; P is the probability that x_i occurs.

In each of the initial arrays of decision and spatial structures, there were 50% of 0's and 1's, respectively. With the unfolding of the simulation over time, the proportions of 0's and 1's changed over time. The greater the entropies were the more chaotic the system tended to be. We can regard the system as self-organizing and evolving towards order if the entropies of both the decision structure and the spatial structure decreased.

The fluctuations of the entropies were recorded dynamically in the plots. Through the plots, we can visualize the trends and patterns for the evolution of the entropies so as to judge whether the structural constraints were stable or not. The computer experiment was implemented on the NetLogo 4.0.3 platform on a personal computer. Figure 4 shows a snapshot of the simulation where different shapes of objects represent different elements of the SGCM. In the present study, we aimed at examining whether order would emerge within the decision structure and the spatial structure over time.

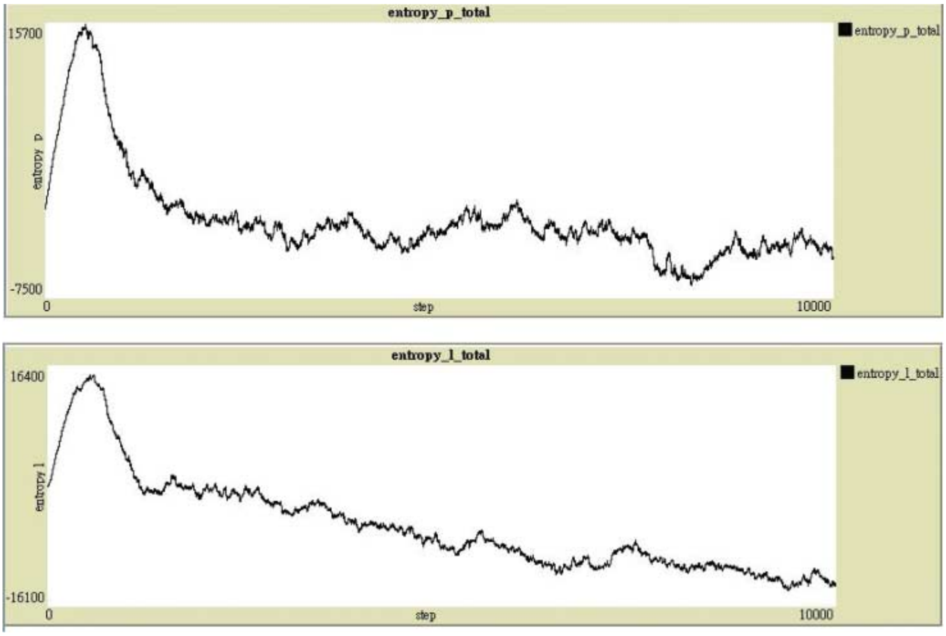

Figure 5. Trajectories of entropy for decision (top) and spatial (bottom) structures with the maximum number of locations set to 1500.

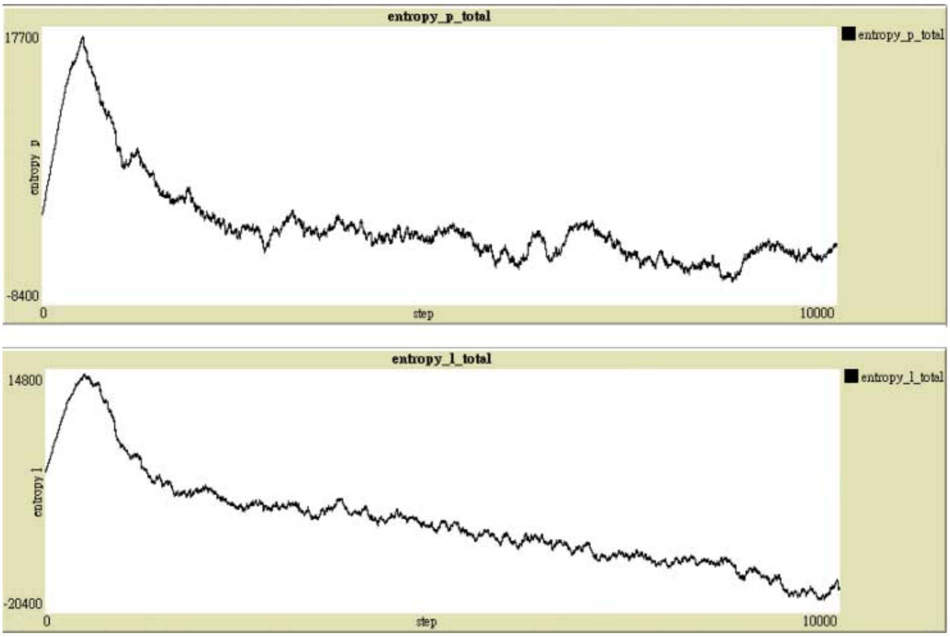

Figure 6. Trajectories of entropy for decision (top) and spatial (bottom) structures with the maximum number of locations set to 2500.

4. Results

The trajectories of the entropy of the decision and spatial structures of the system over the 10,000 time steps are shown in Figures 5 and 6. It is clear that the level of entropy decreased over time for both the decision and spatial structures, when the maximum number of locations was set to 1500 or 2500. In addition to the initial values of energy, we tried in the simulation various values (0 or 2.5) of energy for the five elements and the trends of entropy trajectory were robust. In addition, the total net energy of the system increased over time. We can conclude that when the city is treated as an open system and its fundamental elements, including decision makers, solutions, problems, and decision situations flow in and out of the system, the city tends to self-organize itself as manifested by the decrease in entropy in the decision and spatial structures and the increase in the total net energy of the system. In other words, the city can be viewed as a dissipative structure (Allen, 1997, p. 10).

5. Conclusions

Are cities dissipative structures? Our answer is tentative ‘yes’. Policy implications can be derived from this simulation on how much we should plan for urban development and how. For example, too much planning might destroy the intricate socio-economic and physical structures that are derived from the self-organization of the dissipative structure (Jacobs, 1993). One such case is the renovation of a circular night market in Taipei’s old central business district in that the government reconstructed the once prospering market by providing a new structure, resulting in nothing but a deteriorating business area because the old connections of various activities no longer existed. Planning and complexity are two seemingly conflicting notions in that planning brings about order whereas complexity reduces order. In the present paper we show, however, that a city without planning intervention manifests itself as order; that is, self-organization. On the other hand, planning brings about order (Lai, 1998, 2003). The subtle but important distinction is that the order brought about by planning and that generated by complex systems are different in nature. The order brought about by planning is man-made and Euclidean whereas the order generated through self-organization of complex systems is natural and fractal. Both types of order can be measured through entropy. However, this observation does not render planning useless; instead it should strengthen the need for planning. The main reason is that the order brought about by self-organization alone might not meet the needs of human beings. For example, zoning has been applied in Asian cities for a long time, but most of such systems fail because the market forces in determining land use patterns seem stronger than the zoning regulations (Lai & Han, forthcoming). It is planning *and* self-organization that makes a city work. On the other hand, the debate on whether zoning should be adopted by large cities is controversial (see, for example, Saltzman, 2012), but we argue that in order for planning to be effective, the order brought about by planning must enhance the order generated by complex systems. Otherwise, the outcomes resulting from planning are doomed to fail (Jacobs, 1993). Future work is needed to confirm this claim.

Acknowledgement

The authors are grateful to the three anonymous referees for their very useful comments.

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