Journal of Computational Science 9 (2015) 57–63

Contents lists available at ScienceDirect

Journal of Computational Science

journal homepage: www.elsevier.com/locate/jocs

Genetic algorithm evaluation of green search allocation policies in multilevel complex urban scenarios

Marta Vallejo*, Verena Rieser, David W. Corne

Heriot-Watt University, Edinburgh, Scotland, UK

ARTICLE INFO

Article history:
Available online 17 April 2015

Keywords:
Green area
Genetic algorithm
Green space allocation
Agent-based model
Optimisation

ABSTRACT

This paper investigates the relationship between the underlying complexity of urban agent-based models and the performance of optimisation algorithms. In particular, we address the problem of optimal green space allocation within a densely populated urban area. We find that a simple monocentric urban growth model may not contain enough complexity to be able to take complete advantage of advanced optimisation techniques such as genetic algorithms (GA) and that, in fact, simple greedy baselines can find a better policy for these simple models. We then turn to more realistic urban models and show that the performance of GA increases with model complexity and uncertainty level.

1. Introduction

Landscape covered with natural or man-made vegetation inside or close to urban zones can be seen as green lungs that significantly contribute to a varied range of social, economical and environmental aspects [10,8] in densely populated areas. Numerous studies highlight how human interactions with nature are beneficial for physical, social, and mental wellbeing [29,32].

However, the rapid growth of urban population worldwide [37] and spatial densification planning policies not only may provoke a narrowing of park areas [14,25] but also can seriously threaten ecosystem services [7]. As such, this unsustainable process needs to be controlled by nature conservation plans and green belt legislations. The consequences derived from the application of a range of possible planning approaches lead us to envisage the evolution of multiple hypothetical future scenarios. The analysis of the plausible implications of each of these future scenarios can give support to experts, planners and political decision-makers to understand the socio-economics and biophysical driving forces involved in this complex system [9] in order to elaborate guidelines or other kinds of legal mechanisms to mitigate the negative effects of urban development.

One of these tools widely recognised is spatial optimisation [11], which aims to optimise the topological arrangement of a kind of resource to meet a set of goals. Possible optimisation techniques vary from traditional optimisation methods, such as linear, non-linear and integer programming [18,17], to advanced heuristics like simulated annealing and genetic algorithms (GA) [1,16]. GA approaches can provide to the policymakers the capability of evaluating alternative land-use configurations [30], calibrate parameter values and transition rules [33,13] and improve the accuracy of the model [12,15]. However, while there is numerous research in location-allocation of varied kinds of facilities, green space allocation as such, has received very little attention so far [38], with some exceptions [28,31,21].

The present study provides new insights into the green space planning problem, exploring the behaviour of adaptive and non-adaptive optimisation approaches in relation to the complexity of a dynamic spatio-temporal urban growth simulation.

The rest of this article is organised as follows. Section 2 presents the definition and context of the problem. The urban simulation is described in Section 3. Section 4 explains the implementation of the optimisation procedures. Finally, results are presented in Section 5 and discussed in Section 6 with some perspectives on future research in Section 7. Finally, Section 8 summarises the findings and concludes.

2. Definition of the problem

The present study is based on a theoretical green location-allocation planning model [34] successfully designed as an exploratory tool to analyse the potential use of GA techniques into an urban growth framework under uncertainty. This model follows the classical microeconomic equilibrium model of Alonso [2] within a canonical mono/multicentric framework in which externalities, in form of green areas, have been introduced.

* Corresponding author.
E-mail addresses: mv59@hw.ac.uk (M. Vallejo), v.t.rieser@hw.ac.uk (V. Rieser), d.w.corne@hw.ac.uk (D.W. Corne).

http://dx.doi.org/10.1016/j.jocs.2015.04.004
1877-7503/

The space provision is performed by a land banking mechanism where the purchase of parcels is done in advance according to the expected population distribution and density projections. The acquisition is based on the assumption that green areas constitute a case of market failure which requires public intervention mechanisms to ensure optimal allocation [3]. The planning strategy follows a demand approach [19] which assumes that people get beneficial from the presence of recreational areas in the surroundings of their residences. Access and frequency of use are mainly determined by the distance between the dwelling to the park [4].

A successful allocation strategy should be based firstly, on finding the amount of parcels which ensures enough space provision and secondly, on how efficiently these areas are distributed. Even if there is a lack of consensus about how to achieve these goals [19], a trade-off between the available budget and the selection of the most expensive areas with expected highest impact on population should be found to achieve, through all the period considered, a higher service reward for the current and future urban population. From this point of departure, optimisation strategies can be analysed focusing on two main factors: the total amount of cells that can be purchased with the predefined budget and the efficiency that, under Alonso's assumptions, could be measured by the closeness rate to the Central Business District (CBD). However the simplicity of the model [36,6] affects the nature of the search space and may condition the optimisation process. GA approaches, compared to other methods, have been shown to be specially suitable for large and complex (nonconvex and nonlinear) search spaces with a very large number of parameters [1] and, within a simple environment, GA cannot use all its potential and other less sophisticated methods can outperform it [26].

3. Model description

The proposed theoretical model was implemented in Java & Repast Simphony [23] for analysis and visualisation purposes. A Cellular Automata (CA) [22] is used to model how urban cells spread out from a determined point to adjacent neighbouring cells through time on a 50×50 grid space.

The model can depict a city with one or several CBDs where cells tend to absorb most part of the population. These cores represent, not only employment centres, but also shopping points generated by consumer decisions, business interdependences and clustering of jobs. Each heterogeneous cell has a single land cover class that comprises: urban, protected and rural areas. This land-class classification is stochastically dynamical in time and influences its price and ecological value.

The CA is combined with an Agent-Based Model (ABM) to emulate the heterogeneous urban population, capable of interacting among them and with their own environment. CA-ABM has been extensively used to study land use change and urban growth phenomena [5,20]. Future socio-ecological trends like the emergence of urban patterns can be derived from their endogenous economical choices and interactions. Agents look for the maximisation of a utility function in the pursue of an economic competitive equilibrium for space between housing and community costs. As an externality, the model includes the willingness to pay more for the residence if it is close to a park (10%), which increases the demand of the nearest dwellings and, as a consequence, provokes the modification of urban patterns.

3.1. Prices dynamics

Prices of parcels, along with their availability are the two major factors to consider when the land purchase strategy is planned. According to Alonso's conception, urban land prices increase as long as they get closer to the CBD where jobs are concentrated and population prefers to live to avoid commuting costs, meanwhile the non-urban counterpart expresses an opposite behaviour with more expensive areas located in the physical boundaries of the city and decaying with distance. Plantinga et al. postulate that agricultural prices are influenced by the agricultural exploitation and by the expected future urban transformation profitability. For our purposes and based on a Plantinga's simplification [24, Eq. (9)], the final price of a rural cell, $P_t^R(z)$ located in z at time t is the following:

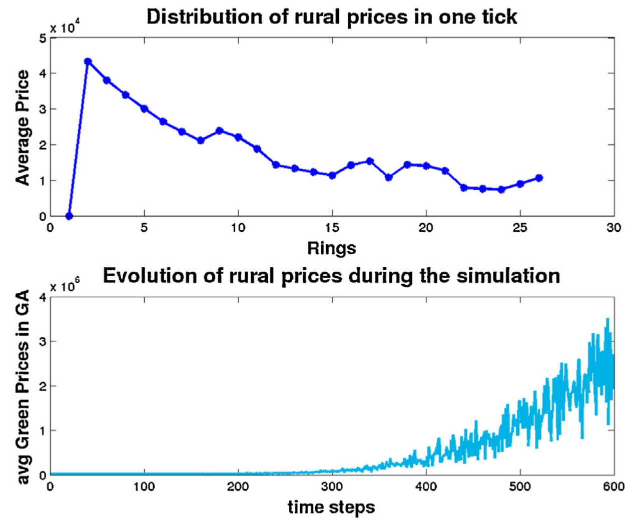

Fig. 1. Rural Prices dynamics: distribution of the prices within the lattice in a single tick of the clock. The grid is divided into concentric annuli or rings and rural prices are averaged accordingly (top). Rural prices of the entire lattice are averaged for each tick of the clock (bottom).

$$\rho_t^U(z^*(t)) = P_t^U(l) \cdot 100$$
$$P_t^R(z) = \left(\frac{P_{base}}{5} + \rho_t^U(z^*(t))\right) \cdot e^{-\alpha[z-z^*(t)]} \tag{1}$$

where $P_t^U(l)$ is the price of the urban cell l most recently urbanised in time t, α is the *change rate* that measures the declining urban rent gradient from the CBD. $z-z^*(t)$ defines the physical distance from the cell z to $z^*(t)$ where $z^*(t)$ is the placement of the peri-urban area at time t such that $z > z^*(t)$. $\rho_t^U(z^*(t))$ depicts the estimation of the profitability of the future urban transformation. Finally, P_{base} is based on rural land prices (agricultural and forest) in the UK [27].

Apart from the price dynamics at a given time, prices of the entire set of non-urban cells increase with the time as the total number of rural cells becomes less numerous by cause of the urbanisation and hence there is a decrease in supply (Fig. 1).

4. Optimisation procedure

Two adaptive baselines were used, called "closest to the CBD" (CLO) and random (RAN), to compare the performance of our non-adaptive evolutionary approach. Notice that, comparing adaptive approaches which are free from the influence of the uncertainty and are always fully aware of the state of the system may be unfair for the non-adaptive strategy. In this case the GA, when its offline results are applied to the real problem, can see how a percentage of its candidate cells are rejected because the objective area to protect is already urbanised or the final price of the cell is higher than expected and unaffordable for the current budget.