A utility study of Ant Colony Optimization for automated calibration of Land Use Cellular Automata Models

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Abstract

Land use models are used to provide valuable scientific knowledge as part of decision support systems, but the present manual calibration approach, both knowledge and time intensive, has limited the ability to apply such models. One approach to automate calibration has been to formulate the problem in an optimisation context, and this research serves as a preliminary investigation into the utility of an ant colony optimization algorithm for this task, applied to a transition potential based Cellular Automata land use model.

Keywords: Land use Cellular Automata models, Automated calibration, Ant Colony Optimization.

1. Introduction

A number of generic integrated decision support systems have been developed to support policy analysis in the field of land use and spatial planning. An important component of such systems are transition potential land use (allocation) models based on Cellular Automata (CA), used to simulate the dynamics of land use change as part of scenario analysis and discovery (Van Delden and Hurkens, 2011). Part of applying support systems requires calibration of the land use model to the specific region being investigated. In spite of recent efforts to generate automatic calibration procedures (García et al., 2013, Van Vliet et al., 2013), this is still commonly a manual process, which is both knowledge and labour intensive (Van Delden et al., 2012). Given the benefit land use models provide as part of decision support systems, there is value to automating this procedure.

Land Use Cellular Automata (LUCA) models are mostly calibrated to reproduce historical land use patterns or changes, adjusting model parameters to improve the agreement between model output and given data sets (Rykiel Jr., 1996). Calibration is complex because LUCA models feature a relatively large number of parameters and the interplay between them drives land use changes. Thus isolating specific parameters for tuning is difficult. Therefore manual calibration uses an iterative process that normally follows a standard order of tuning a few parameters at a time, generally on a process by process basis. Modellers draw on a heuristic knowledge base to ensure parameters generate realistic model results. The key to improving automated calibration methods lies in incorporating this theoretical knowledge into such procedures as well as being able to tune parameters of more than one process (Van Vliet et al., 2013).

This research aims to investigate the utility of an automated calibration methodology for a transition potential based, CA land use model using Ant Colony Optimization (ACO). Based on a theoretical construct that promotes rapid discovery of good solutions, ACO can be used to solve nonlinear optimization problems effectively (Dorigo, 1992). Recently modellers have adopted ACO into different CA based land use models to define explicit transition rules (Liu et al., 2008, Yang et al., 2012) as Boolean statements. The objective of this research was to investigate a more comprehensive ACO framework for LUCA model calibration in four ways:

1. Incorporating heuristic knowledge about the values and shapes (Hagoort et al., 2008) of neighbourhood interaction curves to define potential pathways for the ACO application (Figure 1);
2. Incorporating heuristic knowledge about other processes, such as the strength of policy intervention to limit or stimulate developments and accessibility requirements, to define potential pathways for the ACO application;
3. Incorporating significance testing for when performance is sufficient to progress to the next process; and
4. Testing different metrics that quantify accuracy and realism (Brown et al., 2005) for use (either individually or in combination) as an objective function for optimization.

2. Methodology

This research used the constrained CA, transition potential based land use allocation model Metronamica (www.metronamica.nl). Metronamica is a generic forecasting tool that has been applied extensively to study city, regional and national spatial development. Metronamica is a constrained CA that acts on the basic assumption that actors and land uses are in competition for space with each other. Three types of land use classes are defined: passive, which only change as a result of other land use dynamics; active, which are actively modelled based on exogenous demand for land use classes; and static, which do not change but influence dynamics. Land use demands are defined exogenously for different scenarios, and given demand for a certain type of land use, the model allocates land use based on transition potential, calculated as the weighted sum of four processes and a stochastic (random) component, shown in Equation 1.

$$P_{k,i} = v \times A_{k,i} \times S_{k,i} \times Z_{k,i} \times N_{k,i} \tag{1}$$

Where $P_{k,i}$ is the potential for land use k in cell i, v is a scalable random perturbation term, $A_{k,i}$ is the accessibility, the effect of the distance and importance of different types of transport networks and infrastructure, for land use k in cell i, $S_{k,i}$ is the suitability, the effect of a location's physical properties, for land use k in cell i, $Z_{k,i}$ is the zoning status, the influence of policy and restrictions, for land use k in cell i, and $N_{k,i}$ is the neighbourhood rule, defining the influence of different land use classes exerted at varying distances, for land use k in cell i.

ACO considers the optimization problem as a directed graph, where the nodes are the decision points and the edges are the decision options, iteratively constructing solutions as paths through this graph. Figure 1 illustrates an example formulated for neighbourhood interaction curves, an important component of transition potential based LUCA models. Initially a selection of values for an inertia/conversion point are the decision points. When one has been selected as optimal, the next set of decision points are the possible shapes taken from empirical knowledge (Hagoort et al., 2008, Van Vliet et al., 2013) of the neighbourhood interaction tail curve.

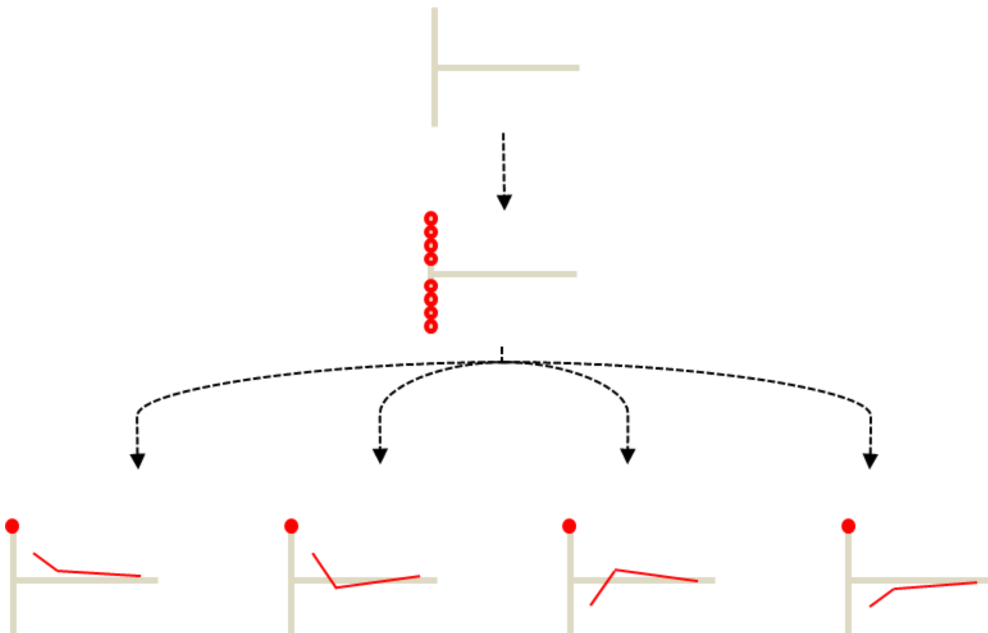

Figure 1. Formulation of neighbourhood rule definition as an optimization problem for solution by ACO.

3. Goals

To evaluate the utility of ACO to automatically calibrate LUCA models requires a correct formulation of the problem graph to incorporate all facets of the calibration problem; and defining what constitutes acceptable performance. Modellers have also adopted baseline models as a means of comparison, either null models of no change or neutral models from landscape ecology (Hagen-Zanker and Lajoie, 2008) as a benchmark for acceptable calibration performance. However, research into other automated procedures (Van Vliet et al., 2013) has also used the results of manual calibration as a baseline for comparison. Thus, utility will be graded as either:

1. Insufficient: The ACO formulated parameters generate land use maps that return global metric values that are significantly worse than a neutral model or patterns of land use that are unrealistic;

2. Reasonable: The ACO formulated parameters generate land use maps that return global metric values sufficient to the degree they can be manually fine-tuned more efficiently than a purely manual process; or
3. Acceptable: The ACO formulated parameters generate land use maps that return global metric values equal to or exceeding manual tuning.

Determining the utility of ACO as an optimization methodology will be beneficial to modellers by providing greater understanding of the problem formulation and defining the extent of automated calibration usefulness.

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