

To appear in the *Journal of Experimental & Theoretical Artificial Intelligence*
Vol. 00, No. 00, Month 20XX, 1–28

Online/Offline Evolutionary Algorithms for dynamic urban green space allocation problems

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(v5.0 released November 2016)

Urban-planning authorities continually face the problem of optimising the allocation of green space over time in developing urban environments. The problem is essentially a sequential decision making task involving several inter-connected and non-linear uncertainties, and requires time-intensive computation to evaluate the potential consequences of individual decisions. We explore the application of two very distinct frameworks incorporating evolutionary algorithm approaches for this problem: (i) an 'offline' approach, in which a candidate solution encodes a complete set of decisions, which is then evaluated by full simulation, and (ii) an 'online' approach which involves a sequential series of optimizations, each making only a single decision, and starting its simulations from the endpoint of the previous run. We study the outcomes, in each case, in the context of a simulated urban development model, and compare their performance in terms of speed and quality. Our results show that the online version is considerably faster than the offline counterpart, without significant loss in performance.

Keywords: Optimisation; Green Spaces Allocation; Evolutionary Algorithms; Planning; Uncertainty; Sequential Decision Making Problem

1. Introduction

From the planning perspective, open space management is a challenging task that should be analysed as a complex system (Boyd, 2008), due to the fact that different plausible policies and management objectives may lead to multiple future scenarios. Many factors contribute to the complexity of open space planning, including the inherent ill-structured nature of the problem, the existence of spatial dependencies, the presence of multiple conflicting objectives, non-linear relationships between decisions and their consequences, and varied forms of uncertainty (Janssen & Rietveld, 1990).

In urban land-use allocation, the consequences of allocating a land-use type to a particular area are highly context dependent. In the concrete case of green spaces, spatial relationships between residential locations and adjacent natural environmental units create dependencies among activities in surrounding areas; in turn, these introduce new non-linearities (Stewart, Janssen, & van Herwijnen, 2004). These types of complex dependencies and uncertainties often presented in objective functions, constraints, and system predictions, may severely affect the robustness of the underlying allocation processes. This could result in sub-optimal or even infeasible green area network designs, with the outcome being a significantly reduced overall level of provision.

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The aim of green space planning is to select an efficient sequence of green-space facilities over a defined period of planning time. This task can be viewed as a Sequential Decision Making (SDM) problem where a sub-optimal finite set of N sequential alternatives has to be found in a discrete-time system. In a green space planning scenario, each of these N alternatives can be seen as an embedded location-allocation (LA) problem. LA problems, first described by Cooper (1963), can be defined as the optimal placement of a set of new facilities or units in such a way that a series of goals is met.

Standalone LA problems have been tackled using various traditional optimisation techniques, especially linear, non-linear and integer programming (Ligmann-Zielinska, Church, & Jankowski, 2005; Moore & ReVelle, 1982), and branch-and-bound methods (Daskin, 2011; Kuenne & Soland, 1972; Malczewski, 1999). However, exact solutions are not computationally tractable for real-world problems. As such, research on these problems over the past 20 years has mainly focused on robust meta-heuristics such as Evolutionary Algorithms (EA) (Shariff, Moin, & Omar, 2012), Simulated Annealing (Murray & Church, 1996) and Tabu Search (Brimberg & Mladenovic, 1996; Ohlemüller, 1997) amongst others. Studies comparing these approaches on different tasks have reported contradictory results (Bettinger, Sessions, Chung, Graetz, & Boston, 2003; Pukkala, Carneiro, Trasobares, & Lozano, 2004). However, formulation, implementation and parameter settings can significantly affect the final performance of the algorithms which could introduce bias in the analysis (Crowe & Nelson, 2003).

Nonetheless, when moving from solving single LA problems to complex SDM problems under uncertainty, the suitability of the aforementioned algorithms has to be revisited. In the case of EAs, their performance under uncertainty has been questioned (Rieser, Robinson, Murray-Rust, & Rounsevell, 2011; Wu, Zheng, Chien, & Zheng, 2006). To equip an EA to solve this kind of problem, it is necessary to engineer appropriate mechanisms which help maintain suitable search progress without being misled by noisy decisions, or unacceptably decelerated by time-consuming simulations. Existing methods that can be applied to evolutionary systems to cope with such circumstances include tools such as noisy fitness, fitness approximation, and dynamic fitness functions. A useful survey of such mechanisms appears in Jin and Branke (2005), while a brief update of the state of the art is covered in (Qian, Yu, & Zhou, 2013).

However, despite the availability of such techniques, very few studies have taken advantage of them for applying EAs to the SDP under uncertainty. Instead, this type of problem has been solved traditionally using decision trees (Garcia & Sabbadin, 2006; Jeantet, Perny, & Spanjaard, 2012), influence diagrams (Guezguez, Amor, & Mellouli, 2009) and more commonly different types of Markov Decision processes like Partially Observable Markov Decision Processes (POMDPs) (Pineau, Gordon, & Thrun, 2006; Sabbadin, 1999). The main drawback, in these cases, is that such strategies cannot be generally scaled to large problems (Krause, Golovin, & Converse, 2014).

This paper investigates the viability of two distinct approaches using evolutionary algorithms as alternatives for generating open space plans by solving this SDM problem in a stochastic urban scenario. In what we call the 'offline' approach, a complete plan is proposed at the outset; that is, at time=0, it has already been decided which parcels of land are slated to be purchased at all future time-steps (if it turns out to be feasible in the ensuing simulated circumstances). In contrast, the 'online' approach makes its land-acquisition decisions one at a time, each time benefiting from the reduced uncertainty arising from the previous step. Both approaches are empirically evaluated and compared in response to a set of physical and ecological constraints using the same software structure for all methods. To measure the suitability of each approach, three criteria have been simultaneously taken into account: the computational time used, the objective function

value and the spatial patterns generated. Additionally, we also show the efficacy of Monte Carlo sampling on this complex planning problem.

The remainder of this article is organised as follows: Section (2) provides a brief overview of the proposed urban growth model. Section (3) describes the evolutionary algorithm techniques, introducing the online and offline algorithms by describing their properties and discussing their general advantages and disadvantages. Section (4) presents the methods that allow both evolutionary algorithms to cope with the uncertainty. Results are presented and discussed in Section (5), delivering a quantitative comparison between the policies generated by both methods developed in this research, as well as comparing the approaches in terms of computation time. Lastly, the paper ends with some general conclusions and a discussion of future work.

2. Urban Growth Model

In the considered hypothetical urban growth model created by Vallejo, Corne, and Rieser (2014), a Cellular Automaton (CA) is used to simulate land dynamics by means of a two-dimensional regular discrete lattice of 50×50 cells with i - and j -axes and stochastic transition rules. A traditional CA can be defined as a finite state machine in which the state of each cell at time $t + 1$ is dependent on two factors: its state at time t and its neighbours according to a set of decision rules. Formally this can be expressed as follows:

$$S^{t+1} = f(S^t, \Omega, T) \quad (1)$$

where S is the set of all possible states and Ω is the neighbourhood of all cells. Both aspects provide input values for the transition function T that defines the state changes from t to $t + 1$.

Each cell in the model represents a unit of the landscape identified by its location (i, j) and by a unique land-use class whose value is dynamic through time. The general classification of land types under consideration comprises urban, rural and protected areas which, in turn, can be subdivided into more specific types.

Let C be the set of all single parcels of land in the considered geographic area represented in the CA, then the more general land-use subdivisions $N_U^t, N_R^t, N_P^t \in C$ can be summarised by the following set of cells: N_U^t denotes all the urban parcels in the grid, N_R^t groups the type of rural land units and N_P^t represents the open spaces protected at a determined time-step t . All subsets are always mutually disjoint which can be formalised as:

$$c_k^t(i, j) \in \{0, 1\} \quad (2)$$

where $k \in K$ is the land use type, K is the set of all possible land uses states $\{U, R, P\}$. Then, at a determined time t every cell $c_k^t(i, j)$ is equal to 1 if the land-use k is present at location (i, j) and 0 otherwise. Those values are dynamical through the time and influences other internal characteristics of the cell like its price and its ecological value. The city and its hinterland are capacitated in such a way that:

$$N_U^t + N_R^t + N_P^t = NC \quad \forall t = 0, 1, 2, \dots, T \quad (3)$$

where NC is a constant value that represent the total number of cells in the grid and T is the maximum time horizon of the simulation.

Cellular automata have been shown to be powerful qualitative tools for modelling not only urban phenomena (Ligmann-Zielinska et al., 2005; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Santé, García, Miranda, & Crecente, 2010) but also for addressing other spatial simulation problems such as robot path planning (Ferreira, Vargas, & Oliveira, 2014), pedestrian modelling (Crociani, Piazzoni, & Vizzari, 2015) or fluid dynamics (Lafe, 2012).

Following an extension of the classical canonical economic model of Alonso (1964), where multi-centricity and green externalities are included, householders modelled by an Agent-Based Model (ABM) look for an economic competitive equilibrium between housing space and commuting costs. The individual aggregated decisions and the defined transition rules combine to lead the city to stochastically expand its peri-urban boundaries over time. Green externalities are defined as the spatial relationships between green areas and household prices (del Saz & García, 2007), which induce preferences for housing locations close to green amenities and, consequently, modifies urban patterns in the long term.

The model starts with a completely undeveloped grid, where every transformation of activity is new to the parcel under consideration. A similar initial configuration was used in previous models (Church, 2002; Ogawa & Fujita, 1989, p.10), while other approaches start with an initial landscape arrangement (Ligmann-Zielinska et al., 2005; Nalle, Arthur, & Sessions, 2002). The final topological patterns and the speed of the urban process depend mainly on the CA transition rules, the residential choices of the inhabitants and the location of green areas within the city, where people generally prefer to live (del Saz & García, 2007). From this perspective, the model is therefore dynamic in time and space, and each simulation run will yield a different result.

To further test the potential of evolutionary techniques in this area, the stochastic model is configured to use a topologically non-trivial city with several Central Business Districts (CBDs) and different price gradients. This type of arrangement complicates the search and decision landscapes and provides a scenario where EA can better show its potentiality (Pukkala & Kurttila, 2005; Vallejo, Corne, & Rieser, 2015). A CBD represents not only clustering of jobs and business interdependences, but also shopping locations generated by consumers' choices. Price gradients can be divided into two different dynamics according to the type of land they represent, broadly subdivided into rural and urban. Urban prices are higher the closer the patch of land is to a CBD, and also depend on household agents' preferences and on the current level of demand for this particular parcel of land. On the other hand, rural prices are basically different if the corresponding area is classified as a forest or as an agricultural cell. They are also influenced by the distance to the closest peri-urban area, due to the influence of the expected profit derived from its urban transformation. Rural land, located in the surroundings of the borders of the city, achieves a peak in prices, decreasing from this point with distance (Plantinga, Lubowski, & Stavins, 2002). Meanwhile, the continuous urban growth expansion narrows the amount of available land, and this diminishing supply increases the price of the remaining land as time passes.

In this urban scenario, the uncertainties and variabilities arise mainly from the following sources: (1) multiple choices for transforming rural areas into green parcels; (2) uncertainty about urban growth evolution; (3) lack of knowledge of the future total population and its distribution; (4) uncertainty regarding urban and rural land price dynamics; (5) land resource availability.

The provision of green services is performed following a covering model, sometimes

also called maximum service distance (Toregas, Swain, ReVelle, & Bergman, 1971). The principle of this approach is to maximise the number of users who are located relatively close to the defined type of service, in this case green areas.

Some key assumptions made in the definition and development of the model include the fact that cells have an homogeneous size and shape. Each is considered an independent unit and no clustering techniques to group them are included explicitly in the model.

3. Application of Evolutionary Optimisation Strategies

Evolutionary Algorithms have been proved to be a flexible and powerful tool to solve nonlinear, nonconvex, multimodal objective functions in discrete decision spaces (Davis, 1991; Goldberg, 1989). This stochastic metaheuristic, not based on neighbour search, echoes aspects of the mechanism of natural selection (Darwin, 1861) by following the assumption that nature evolves by preserving the species most suited to their environment. To accomplish that behaviour, the method uses a set of robust problem-specific tools (Datta, Deb, & Fonseca, 2007) such as selection, reproduction, crossover and mutation that are capable of adaptively exploring the search space in order to find near-optimum solutions.

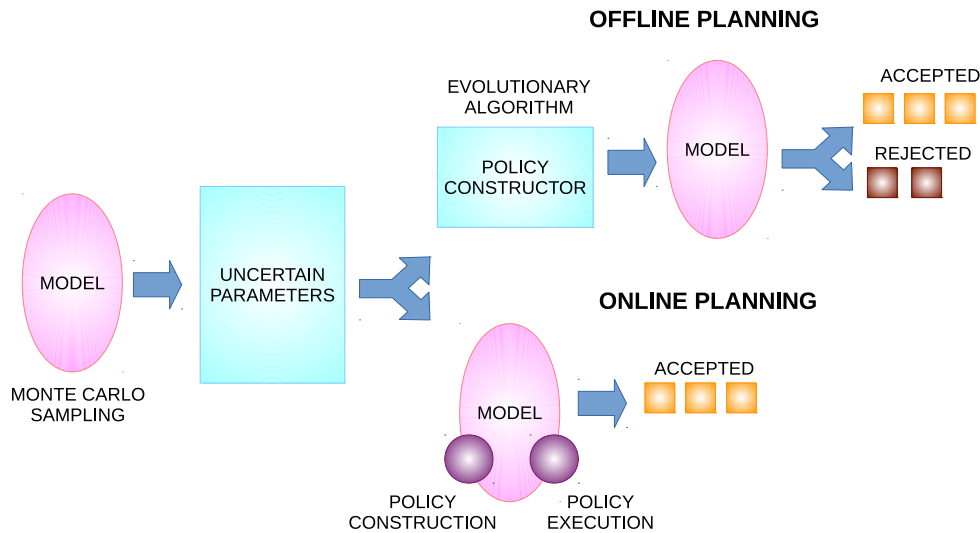


Figure 1. The schema of all the elements included in both planning processes is depicted in this figure. The previous generation of uncertain parameters, how these different components are linked with the hypothetical urban model and the different nature of the results in each approach are also included.

Based on this evolutionary strategy, the proposed optimisation framework includes a variety of components as can be observed in Fig. (2). In that figure, the two different EA workflows for our scenario, an ‘online’ and an ‘offline’ approach, are described. The main goal of the optimisation process is to select a series of patches of rural land, within a determined time horizon, to be transformed into green areas as the city develops over a number of years. The general objective pursued with this purchasing policy is to attempt to ensure that each land allocation decision fulfils both the present needs of the urban population, along with estimated needs of the larger population as it develops in future time-steps.

The optimisation process starts in both cases with the definition of two initial con-

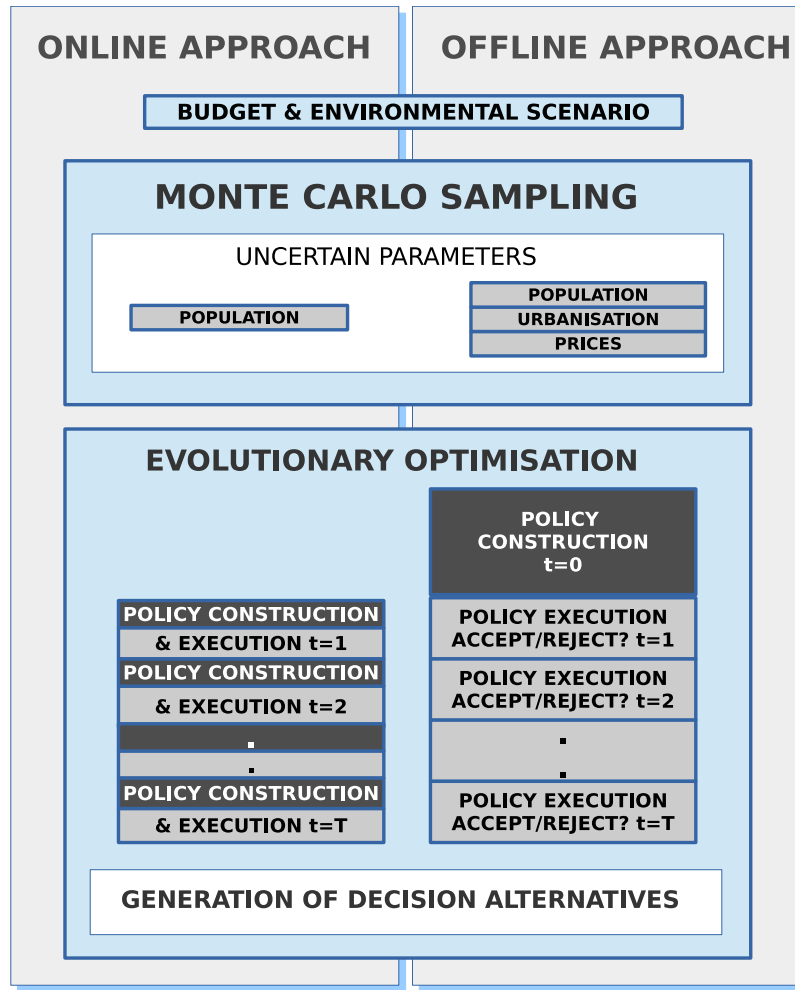


Figure 2. The online & offline optimisation workflows are depicted highlighting the characteristics that these two strategies have in common. Both approaches share a common budget and an initial environmental scenario. By means of Monte Carlo sampling techniques the offline approach will gather the required information about the most probable population density and its distribution, the urbanised areas and the rural prices for each time-step considered in the simulation. The online counterpart only needs the population information to calculate the fitness function. Based on that data, the optimisation procedure depicts the adaptive and non-adaptive nature of the corresponding online and offline approach. Finally the generation of the final decision alternatives is performed which describe the concrete policies resulted from the process.

straints that are imposed on the algorithms at the beginning of the simulation: a common *budget* which limits the acquisition process, and an environmental layout whose values are attached to every cell of the grid, see Fig. (3). In both cases the constraints are generated in advance by a uniform random process. The budget takes values in fixed intervals for the entire duration of the simulation. The ecological values measure the natural resources richness of the land and determine the rural land type: cells with the highest 'eco' values are classified as forest, while rural cells with the lowest eco values are classified as agricultural.

The ecological value of a cell (and hence its land-use classification) is also influenced by the values assigned to the cells in its neighbourhood. This leads to a dynamic diffusion/feedback process within the model, which is capable of mimicking the ecological degradation process provoked by urban expansion over the remaining open space (Alberti

& Marzluff, 2004). Both of the initial constraints (budget and environmental layout) directly affect the land purchase mechanism. The budget limits the locations and amounts of cells that the system is able to acquire, and the ecological values influence rural prices and the non-urban land-use type.

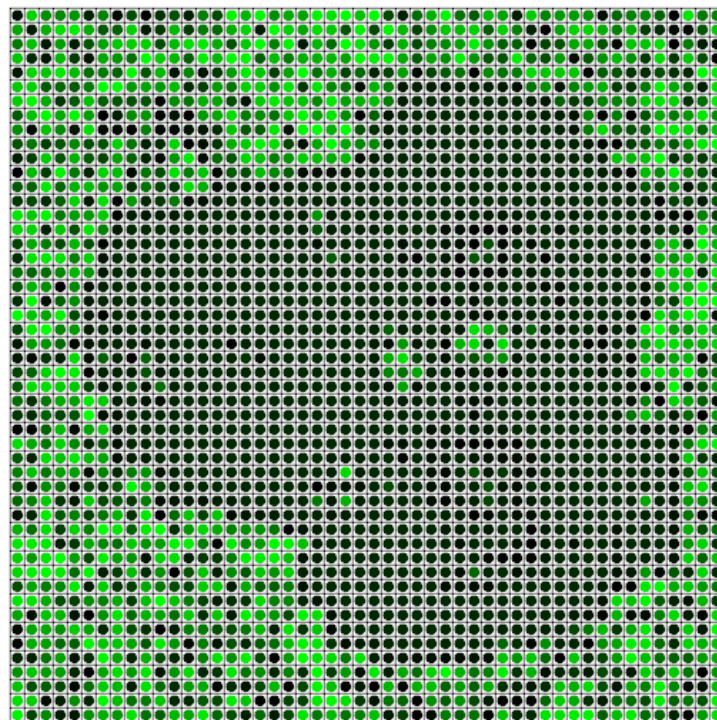


Figure 3. Visualisation of a determined configuration of ecological values linked to each cell where black cells represent very degraded areas and green cells describe rich environmental zones. The range of green tones represent intermediate states, with brighter colours depicting more valued areas. From a general point of view, this lattice shows the ecological value degradation effect caused by urban development in a city of three CDBs. The small green areas within the urban cores depict the protective impact of allocating green parks in the city.

In terms of their formulation, the two algorithms vary in line with the nature of their overall approaches, which, respectively, are adaptive and non-adaptive. The main difference between them is that during the execution of the online approach, local policies are computed at each decision step; whereas, in the offline algorithm, all policies are decided and fixed at the beginning of the simulation.

3.1. *The Offline Algorithm*

The algorithm starts with the random generation of an initial population of potential solutions (referred to in the following as ‘chromosomes’). A relatively small population size of 25 is used (for both approaches), following preliminary work in which we concluded that this enabled both algorithms to converge relatively quickly, and (considering each algorithm individually), was not surpassed in solution quality by larger population sizes. Each chromosome stores the information needed for encoding a complete solution to the problem. The construction process has to satisfy some initial constraints in terms of budget and land availability. Protection is not allowed in urban areas and the budget must be strictly positive at any time.

Every individual chromosome, Cr , is composed of ‘genes’, each one denoted by β and

referred to in the following as a ‘selection’ (since it is a selection of specific rural cells for protection). These chromosomes can be formally expressed as follows:

$$Cr = [\beta_0, \beta_1, \dots, \beta_{T-1}] \quad (4)$$

where $T = 600$ is the number of time slots defined in the simulation, in which the algorithm has the opportunity to perform a purchase if it is considered appropriate. An individual time unit in the simulation can be thought of as equating to one month of simulated time. A given β_t represents the selection of rural cells to be protected at a certain time t that, in turn can be defined as:

$$\beta_t = \{[c_{(x_1, y_1)}, c_{(x_2, y_2)}, \dots, c_{(x_m, y_m)}], B_t\} \quad (5)$$

where $c \in C$ is the set of $[0, m]$ cells selected for protection, each spatially located in a different pair of coordinates (x, y) to be transformed into a park in turn t . In the formula B_t denotes the remaining budget that was not spent in time t and accumulates for the next selection β_{t+1} .

This chromosome representation is order-dependent, with a total number of possible facilities to be protected not fixed in advance. The fact that some of the selections could be empty, implies that chromosomes could also be considered of variable length. However, for simplification purposes we treat them as regular.

The selection operator emphasises good solutions to the detriment of weaker alternatives by the implementation of an elitism mechanism. Elitism in an EA context, is a mechanism that ensures that the best-so-far individuals survive from generation to generation. For selection purposes we use Tournament Selection (TS), which has shown to lead to good performance, despite its simplicity, and it is frequently used (Nicklow et al., 2009). The method selects a parent from the population by first choosing four chromosomes uniformly at random, and selecting the best of those four (breaking ties randomly).

A fitness function computes the objective fitness metric of each solution. The posterior ranking of the population according to its value is used to assess the suitability of the chromosomes, to implement the elitist matting and to select the final best solution. In the model, the fitness is defined to reflect how close agents’ homes are to green spaces, and involves measuring the distance from the dwelling of each agent to the closest green area located in the surroundings. This metric is based on the fact that distance is the factor that mainly determines the access and the frequency of use of green areas (Giles-Corti et al., 2005).

In detail, fitness f is formulated as follows: if $\delta(a_i, g_j)$ is the function that calculates the distance from an agent a_i to a green area g_j using a Manhattan distance metric, then the fitness value $f(a_i, g_j)$ at a time t that measures the satisfaction achieved by this concrete agent a_i in relation to the green area g_j can be denoted by:

$$f_t(a_i, g_j) = \begin{cases} 3 & \text{if } \delta(a_i, g_j) = 1 \\ 2 & \text{if } \delta(a_i, g_j) = 2 \\ 1 & \text{if } \delta(a_i, g_j) = 3 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

From an urban planning perspective, to appropriately assess the suitability of a planning policy, it is not enough to know how effective the plan is for a given moment in time. Instead it is necessary to determine its adequacy for the entire interval covered by the planning procedure. To accomplish this goal the fitness of each parcel of land included in each selection β_i is measured from the moment t^* that is acquired to the end of the simulation T . Formally this can be represented as:

$$F(g_j) = \sum_{t=t^*}^T \sum_{i=1}^n (f_t(a_i, g_j)) \quad (7)$$

where n is the total number of inhabitants in the city at time t and $F(g_j)$ is the fitness of a single green area g_j calculated for the entire population of the city for the period $[t^*...T]$. If the fitness is finally collected for the entire set of protected areas, then:

$$F_T = \sum_{k=1}^m F(g_k) \quad (8)$$

where F_T is the total aggregated fitness of the entire green area network and m is the number of green areas planned to be purchased within the policy.

The mutation mechanism works by modifying slightly the structure of a chromosome and it is used to maintain diversity and prevent premature convergence to local optima. The implemented mutation method randomly selects one non-empty selection β_i and searches for a new set of cells that improves the fitness with respect to the same selection i in the parent. Let β_i be the selection i picked for be mutated in time t , then β'_i will be the new selection to substitute β_i if:

$$\begin{aligned} f_t(\beta'_i) &> f_t(\beta_i) \\ \beta'_i &\notin Cr^* \\ p^R(\beta'_i) &\leq p^R(\beta_i) \end{aligned} \quad (9)$$

where f defines the fitness function, Cr^* the chromosome which represents a copy of the current parent solution Cr and p^R is the total rural price of the patches of land included in a given selection.

These conditions can be interpreted as the fact that only if the new selection of cells β'_i , strictly disjoint from the cells already selected within the entire policy, achieves higher satisfaction than the previous one, at the same time that the affordability terms are not violated, then the change is accepted and hence the mutation is successful.

Apart from those conditions, there is another factor that complicates the consequences of the mutation procedure. The time-dependent nature of the budget further constrains the price requirements for the new selection. The amount of resources assigned to each slot of time t is compounded by the corresponding budget for this time slot plus the remaining resources resulted from previous purchases. Then, due to the fact that the part of the budget that the selection β_t has not spent in time t is accumulated for time $t + 1$, it could easily happen that any of the next non-empty selections from β_{t+1} to β_T use these extra resources for its own purchase. If the mutated selection β' uses

more resources than β , then future infeasibilities can occur when the next acquisitions are carried out, invalidating some of the future purchases when the policy is finally executed. If the number of generations that the algorithm uses to evolve its population is large, this effect can easily spread which can provoke numerous rejections when finally the policy is implemented. Other reported approaches eliminate the consequences of this aggregate behaviour by discarding the budget that was not spent in each time slot (Golovin, Krause, Gardner, Converse, & Morey, 2011).

The existence of infeasibilities at the level of single selections, on the other hand, could be positive under certain circumstances. It was empirically proven that this mechanism may boost the final performance of the algorithm by incrementing the final number of protected cells and compensates the ones finally rejected by failing to foresee the urbanisation dynamics. In the execution of the policy, a cell can be rejected due to two factors: a lack of budget or when the objective cell has been already urbanised. The algorithm includes a parameter which may slightly relax the budget constraints in the mutation process, introducing a reduced number of infeasibilities. In the case of a urbanisation failure, the resources assigned to the purchase will not be used and can be invested in some extra cells selected by this mutation mechanism.

The crossover operator is an evolutionary mechanism that allows the recombination of partial structure from multiple (usually two) chromosomes. In the present implementation, the selected structural representation of individuals introduces difficulties for crossover operations. Firstly, as a rural cell cannot be protected twice, a feasible crossover needs to ensure that the sets formed by the cells included into the segments to be integrated in the new chromosome should be strictly disjoint.

Again, as was the case with the mutation operator, a further complicating factor to consider is the time-dependent nature of the remaining budget. The consequences of this effect for crossover can be described as follows: having selected a pair of parental chromosomes Cr and Cr' to mate and recombine in such a way that β_i is the binding crossover point and B_i the remaining budget for Cr , and in the same way, β_j and B_j are the corresponding parameters for Cr' , then the following condition $B_i > B_j$ should be met to minimise the number of possible infeasible selections. The high likelihood of joining two incompatible chromosomes provokes difficulties in easily finding a suitable combination to compose the new offspring. In this regard, this search of compatible individuals causes an exponential increment in the computational time of the algorithm. As a conclusion, the crossover operator was removed from the system, even if this decision could also reduce the time performance of the algorithm (Jansen & Wegener, 2002).

A steady state replacement method is used to generate the new population in each generation, where fitter offspring is inserted into the current population, replacing less profitable parents. Finally, the selected stopping criterion is twofold: the algorithm stops when a maximum number of generations (10,000) is reached or if a certain number of generations (200) have passed without improvement. The latter value was selected after observing, in preliminary work, that once this threshold is reached it is unlikely that further evolution occurs. When the algorithm finishes, the individual solution with the highest fitness is accepted as the optimum result. The offline approach always allows the system to run until convergence is reached.

3.2. *Purchasing Decisions in Offline Planning*

Due to the time-dependent nature of the budget, the monetary resources available in a given time t , are partially the result of the previous land purchase history. Hence, the

selection of the time-steps where the land acquisition should be carried out is one factor that severely influences the effectiveness of a given policy. There are different criteria that could be applied to decide if it is a good choice to spend the current budget in a given time-step or whether it is more convenient to accumulate it for the future in order to select a more appropriate and expensive patch of land. In the offline algorithm two different approaches were implemented to solve this problem:

- **FIXED**

Every time the budget is bigger than the cheapest cell in the grid the system tries to make a purchase. If in 100 attempts the algorithm is able to find a suitable selection of cells, the acquisition is performed. In general this approach can only afford to buy a reasonable amount of cheap cells located far from the CBDs, due to the fact that the continuous acquisition of land refrains the strategy from being able to save enough financial resources to buy other kind of patch of land.

- **STOCHASTIC**

In this case, purchase decisions are limited not only by the available funds, but also by a variable which restricts the purchases to the 70% of the times that these actions can be potentially successful. The strategy allows the system to focus on a more qualitative type of cells than the previous approach at the expense of dropping the total number of cells transformed into green spaces.

Both methods treat the entire set of decisions as equally as important. However earlier purchases are more critical than the later ones, due to the fact that at the beginning of the simulation, when the city is small in size there are promising empty areas close to the CBDs that will soon be urbanised. These areas will potentially be highly populated in the near future and the amount of satisfaction collected will be much higher than in zones closer to the outer limits of the grid.

3.3. *The Online Algorithm*

The online approach performs a series of optimisation runs, one for each time-step, to support the decision at that time-step. In contrast to the offline approach, each of these individual optimisations requires a much simplified chromosome Cr , which only needs to represent the current state of the system since it can exploit the complete knowledge of the current belief at any moment. Consequently its structure is reduced to the following information:

$$Cr_t = [c_{(x_1, y_1)}, c_{(x_2, y_2)}, \dots, c_{(x_m, y_m)}] \quad (10)$$

where each cell c_i , spatially located in a different pair of coordinates (x, y) , belongs to the set of $[0, m]$ cells selected for being transformed into parks in the present time-step t . Notice the variable-length nature of the chromosome. Another difference from the offline approach is that, in this case, it is not necessary to accumulate any remaining budget because the available funding, shared by the entire population, is known at each moment. This property of the budget allows the system to completely remove this source of uncertainty.

Regarding the mutation operator, the online approach uses the same mechanism as the offline strategy, but with a different level of granularity: instead of searching for a selection β to mutate among the entire set of selections, the generation of a complete

new individual is considered in each generation.

Contrary to the previous approach, all the selected cells included in the population at any time-step are feasible. The optimisation module is aware of the current state of the system and the entire set of chromosomes constructed and evolved under these circumstances are valid and can be checked at the time the policy is decided.

Due to time restrictions, the online stopping criterion is halted prematurely, reducing the maximum number of generations that the algorithm is allowed to run without improving to 50 and the total number of generations to 450.

3.4. *Purchasing Decisions in Online Planning*

As a result of the simplified nature of each online individual, the question raised is if it is possible to implement a more efficient mechanism to discern whether it is convenient to look for a feasible candidate patch of land to purchase, which means to evolve the current EA population in this turn or save the resources for the future.

One possible way to answer this question is by analysing the nature of the search space and the way it is constrained by external factors at the current point in time. The method we use is referred here as a *threshold-based strategy*, and it simply involves recording the mean fitness of the initial population of random solutions at the current time-step. The quality achieved at this initial point provides a useful hint about the potential capacity for improvement by evolution, subject to the current budget and land price constraints. Such use of information retrieved in the first generation was also explored in Ratle (1998) to create a global approximation of the fitness function.

Purchasing decisions are therefore taken by comparing the averaged fitness of the current time-step's initial population with a pre-defined threshold. If the threshold level is not met, it is assumed that, even by the use of an evolutionary process, the algorithm will not be capable of finding enough attractive choices in this current generation, presumably due to the gap between the current budget compared to the current prices.

In the case that the initial population check passes the threshold, and consequently we evolve a population at the new time-step, a second threshold comes into play. This time based on the averaged fitness of the evolved population compared to the average fitness of the initial population. If the second threshold is not reached, we take the view that purchases made in this time-step are likely to be suboptimal due to a lack of evolution, and may cause a cascade of further difficulty in future time-steps simply through poor use of budget in this round. Not reaching this second threshold therefore leads to rejection of this result, and we reinstate the budget and proceed to the next time-step, where the current budget will be accumulated. Both thresholds were defined and calibrated by empirical observation of the algorithm's behaviour in preliminary work.

In Fig. 4 we depict the behaviour of the evolution resulting from the application of this strategy. Successful attempts peak at around 200 generations, where almost 50% of the time the initial population of solutions was accepted. From this point, there is a clear decline in successful attempts; at generation 400 only small gains are made in terms of patches of land selected and protected. The evolved and not selected set of solutions are rather significant option executed around 40% – 50% of the times during the first half of the simulation, increasing the frequency up to more than 60% in the second third part of the simulation, decreasing drastically to less than 20% at the end. Meanwhile, rejected generations reach 20% – 30% in the first third of the simulation, climbing up to 40% in the second third, until, towards the end of the run, all generations are rejected, since rural prices are extremely high due to the lack of supply.

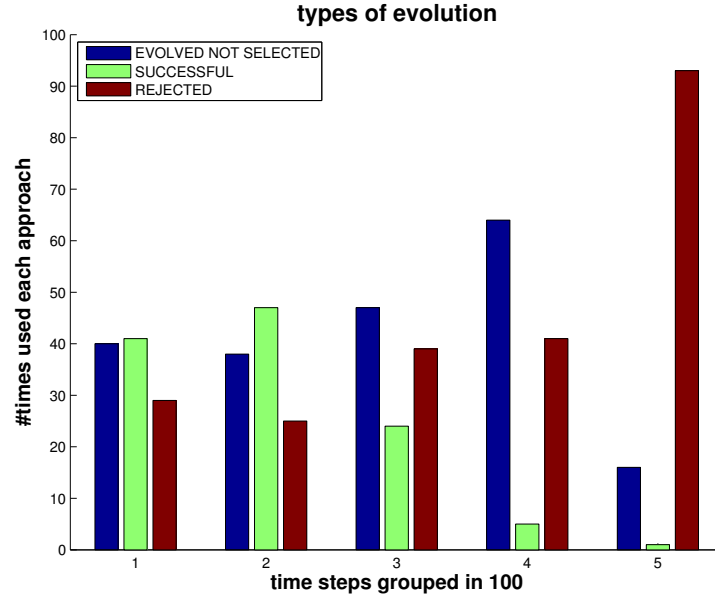


Figure 4. Amount of different type of evolutions of the population according to the nature of the search space in each concrete time-step. Green values represent successful evolutions, where the policy was decided and executed and consequently a patch of land was protected. Red values represent generations with an insufficient level of quality in the initial population, where the population was not evolved. Finally blue values illustrate promising generations in which the level of improvement was not enough to be considered as a suitable solution for being included into the final policy.

In terms of time consumption, the first threshold speeds up the algorithm, avoiding the exploration of certain generations meanwhile the second threshold wastes the time taken in evolving a population that perhaps is not going to be used within the final policy.

4. Evolutionary Algorithms and the tools to deal with the Uncertainty

In general, online approaches alleviate the computational complexity and the level of uncertainty by only considering the state of the present situation and the current time horizon, whereas an offline search would compute a large contingency plan prior to its execution, considering all possible situations that could occur (Ross, Pineau, Paquet, & Chaib-Draa, 2008).

A step-by-step planning strategy is significantly more flexible and it allows the online version to handle possible changes in the environment without extra computation. This characteristic permits planners to take the potential advantage of analysing and responding to the stochastic dynamics of the system. On the other hand, the offline approach can get benefit from, effectively, being able to look further ahead, acquiring at lower prices patches of land that are located in more remote areas. These locations, that currently are not very attractive for the online strategy, can be unaffordable when the level of interest increases.

An additional advantage of the modular structure of the offline EA is that it can be easily applied to any urban growth model, even if an increment in the complexity of the model may require substantially more computational effort than the one reported in this paper. The online counterpart, on the other hand, would need to be integrated into the code of the objective urban growth model. Consequently its applicability would generally

require further coding in order to include the policy constructor considered here in the execution module, which is particular of each individual urban model.

4.1. *Fitness Approximation*

As shown in Eq. (8), in both approaches, the fitness calculation needs to know the expected population distribution. However, obviously we cannot know in advance the future spatial configuration of the population within a city, especially since such a city is a system with complex spatial and temporal dynamics (Jacobs, 1961). We therefore need to find good approximations to this expected distribution; specifically, the (future) distance from each agent to its closest green area.

To address this need, a Monte Carlo sampling strategy is adopted, and integrated into the EA, to recreate a plausible population distribution. Monte Carlo sampling is a widely used tool, that by means of controlled randomised sampling, allows the study of the properties of random natural systems when analytical solutions are not easily available. This technique was developed in the 1940s by Metropolis and Ulam (1949). Formally, if ρ_i is the function that defines the population distribution dynamic for a determined city i , then a noisy population distribution ρ'_i can be described as:

$$\rho'_i = \rho_i + rnd[N(0, \sigma^2)] \quad (11)$$

where $rnd[N(0, \sigma^2)]$ denotes the random noisy component added in each evaluation. Based on the central limit theorem, the sampling mechanism reduces the amount of noise by calculating the mean of multiple function evaluations.

$$\rho_{i,n}^* = \frac{1}{n} \sum_{j=1}^n \rho'_{i,j} \quad (12)$$

where $\rho'_{i,j}$ is the sampling realisation number j of the population dynamic i and $\rho_{i,n}^*$ is the distribution of ρ resulted from the mean of n samples of ρ' . As larger as n is defined, the standard deviation is reduced.

In the model, the fitness sampling is implemented using the generation of a sample set of equally likely realisations that captures the spatial population dynamics through time (Rada-Vilela, Johnston, & Zhang, 2014). The source of these realisations is a parallel version of the same model that is statistically similar to the actual site without the inclusion of green externalities (Vallejo, Corne, & Rieser, 2013). Excluding externalities implies reducing the extent to which non-linearities result from the relationship created between urban prices and green areas (Wu & Plantinga, 2003), but at the same time, maintain other aspects of the general evolution of the system, and, across multiple realisations, capturing salient aspects of the inherent variability and statistics of the modelled system. Analogous approaches have been successfully applied in other fields including dialogue systems (Rieser & Lemon, 2011) and in environmental studies (Kennedy et al., 2006). By means of this method, the framework is capable of performing the offline sampling. Since it is demonstrated that sample size describes a function that is pareto-optimal in terms of the speed and the accuracy of the algorithm (Srinivas & Deb, 1994), the offline procedure permits the system to focus mainly on the accuracy factor.

To test the appropriateness of the method, the collected population distribution was

compared with the real counterpart, gathered once the optimisation terminated. In order to calculate the degree of similarity between distributions, we used appropriate correlation measures. By means of canonical correlation techniques it is possible to estimate a symmetric measurement of the congruence of two matrices (Ramsay, ten Berge, & Styan, 1984). In this concrete case we analysed the Pearson's linear correlation matrix resulting from comparing the Monte Carlo pregenerated matrix M' with the matrix composed by the real population distribution M . The dimensions of both matrices are 600×2500 , resulting from vectorising the grid of (50×50) values that represents the population within the city in each time-step. $T = 600$ is the time horizon considered. Every value of M and M' is based on averages of 20 different observations (simulation runs). The resulting correlation matrix is shown in the following table:

	M	M'
M	1	0.7634
M'	0.7634	1

Table 1. Correlation matrix calculated from the real population distribution (M) and the simulated sampling distribution (M').

These values show a strong correlation between both sources of data. To validate this conclusion the matrix of p-values for testing the hypothesis of no correlation was calculated:

	M	M'
M	1	0
M'	0	1

Table 2. p-values resulted from testing the hypothesis of no correlation between both matrices, M and M' .

Based on the values derived from testing this hypothesis, it can be concluded that the assumption that the correlation is caused by random sampling can be rejected. Consequently, the use of the approximate fitness function within our EA makes the final results reasonably reliable in comparison with real fitness evaluations, if the system is supported by a robust and consistent urban model able to mimic reality suitably well. In previous studies, it was also concluded that, in an evolutionary scenario, the Monte Carlo method performs even better without extensive sampling (Miller & Goldberg, 1996; Vallejo et al., 2013). The reduced number of samples is a computational advantage compared to other approaches that requires the generation of a much larger number of samples to achieve good results (Murray & Church, 1995).

Due to the fact that our noisy fitness function uses sources of information generated by Monte Carlo sampling, the fitness function can be seen as a type of sampling fitness function (Smalley, Minsker, & Goldberg, 2000) even if this sampling procedure is done offline.

4.2. Offline Constraints & Testing

When a sequential set of decisions has to be taken in advance with no information about the state of the environment at these times, highly constrained conditions can easily arise at the time the policy is implemented. In this regard, the offline algorithm ideally needs to receive as inputs accurate information about which cells are urbanised during the entire period considered and the dynamics of the rural prices. By using Monte Carlo sampling techniques analogously, as was previously done for the urban population, this information is collected. Finally this urban information will be used to constrain the

set of available parcels of land, meanwhile non-urban prices will limit the cells that the budget can afford during the simulation.

In Fig. (2) it is shown that the offline optimisation approach is divided into two main independent parts: the policy constructor implemented by the EA, and the policy execution which is incorporated within the code of the urban model represented by a CA. A disadvantage of placing the unique policy execution after the planning phase is that some of the expectations and assumptions of the policy constructor could be found wrong when facing real conditions. This may lead to cases where certain selections of cells included in the planning cannot be transformed into green areas, due to a lack of budget compared with the real price of the parcel at this time, or also because of incompatibilities in the objective land class in the case the parcel is already urbanised. The policy execution, responsible for checking the final set of cells, is allowed to dismiss the candidate green areas which are incompatible with the real instance of the problem. Once the filtering is performed and the final set of cells is defined, the policy executor will calculate the real satisfaction of the offline algorithm based on this successfully applicable subset of cells.

5. Results & Discussion

The results shown in this article are the averages over 20 independent optimisation runs for each approach. The algorithms were executed in a Linux operating system with an Intel core i5-3210M processor and 8GB DDR3 of RAM memory and they were coded in Java using a Eclipse compiler and the open source software Repast Symphony version 2.0 (North, Howe, Collier, & Vos, 2005) (RS). RS is an agent-based modelling and simulation toolkit commonly used in the CA-ABM community. Previous publications have validated the software in different contexts (Griffin & Stanish, 2007; Parry, Evans, & Morgan, 2006).

A hypothetical CA-ABM urban growth framework was implemented, with the main objective of making use of the complexity of its dynamics (Batty, Xie, & Sun, 1999) in order to test and measure the suitability of EA techniques in a stochastic scenario under uncertainty in two different versions, the described online and offline approaches. The model is configured to develop an urban area with three main CBDs growing in parallel with different price gradients.

5.1. Computation Time

The CA-ABM model, as previously mentioned, was implemented using the RS framework. This is an important aspect to take into consideration when the computation time of both algorithms is analysed. The RS framework requires a significant amount of computational resources to simulate the dynamics of the city, the representation of all its inhabitants and their interactions.

The resulting time statistics are shown in Table (3). It is intuitively clear that offline approaches would need considerably more time to come up with a final plan in comparison with an online version of the same algorithm (Ross et al., 2008). In the present work, computer simulations show that the proposed algorithm exhibits the expected behaviour in terms of time. It should be noticed that there are two main factors that can significantly affect the behaviour of the time consumed. Firstly the offline version can run alone in the system terminal using all the available resources, meanwhile the online version has to share memory and processor resources with all the infrastructure created by Repast Symphony and Eclipse. This means that, at the same time that the EA population is

Approach	Policy Time (sec)	Total Time (sec)	Time Factor	#Generations
Offline	41011.8	41923.12	2.145	1682
Online	19118.3	20723.1	0.466	450

Table 3. Offline vs. Online results in terms of computation time and the number of generations in which the population of solutions is evolved. Column 1 represents the running time that both algorithms require to construct their policies without taking into account the policy execution. The policy execution comprises the implementation of the planning process and the evolution of the rest of the model dynamics. Column 2 illustrates the total used processor time: which includes the previous policy construction time plus the policy execution. Column 3 shows the factor of increase in speed in each case and, finally, Column 4 depicts the average number of generations used in each evolutionary algorithm.

evolving, thousands of objects which represent agents, cells and other type of elements of the urban growth model will typically coexist. Secondly the number of generations that the online version is allowed to evolve in comparison with the offline version, aids the algorithm to show better time performance at the expense of decreasing the quality of its final individual solution.

One drawback associated with online planning is that, in a practical setting, it would generally be required to meet real-time constraints; this means that the algorithm would need to greatly reduce the available planning time to satisfy the requirements of a real-time environment. For instance, this could be the case of robot motion planning or anytime learning scenarios (Gaschler, Petrick, Giuliani, Rickert, & Knoll, 2013; Vargas, Di Paolo, Harvey, & Husbands, 2014). However the system, in any of its versions, cannot properly cope with the requirements of a real-time system, basically because the nature of EA requires long computational times until convergence is achieved and it is not considered in general a suitable approach for these kind of scenarios (Ciesielski & Scerri, 1998) unless the algorithm is strictly time-bounded.

Other external characteristics that can be associated with the time calculation is the convergence rate and the internal design of the EA. Changes through better areas of the search space require time in terms of number of generations. In the present offline implementation, since the crossover operator is dismissed, every generation the algorithm is able to modify a single allele of one individual of the entire population, which means that the mutation rate p_{of} can be at maximum:

$$p_{of} = \frac{1}{T} \frac{1}{N_{pop}} \quad (13)$$

where T is the number of time-steps of the simulation and N_{pop} is the number of individual solutions evolving together in the evolutionary population. In turn, in the online approach the mutation rate, denoted by p_{on} , will change the information of one single individual in each generation:

$$p_{on} = \frac{1}{N_{pop}} \quad (14)$$

Following from that, the mutation operator in the online approach allows further jumps in the search space, converging faster than its offline counterpart. This aspect also means that it is more likely that the online algorithm falls into local maxima. However, since the evolving time assigned to the evolution of each generation is rather limited, a faster improvement of the solutions compensates for this effect, since in general chromosomes do not have enough time to properly converge.

In conclusion, the offline algorithm navigates the search space slowly, making a large number of small steps; it is essentially a highly exploratory and ‘careful’ approach, capable of finding near-optimal results, but generally requiring many generations to do so. Meanwhile, the approach used by the online algorithm is more an exploitative approach, taking a small number of large steps; it is a strategy that can provide excellent results in a short time, but generally runs the risk of not achieving the best results available.

5.2. Performance

In Fig.(5) the performance of the fitness function of both algorithms is visualised. This performance is calculated by measuring the satisfaction achieved by the population using the formula 6. At this point it is important to recall that a person living in the city is ‘satisfied’ if he/she lives close to a green area.

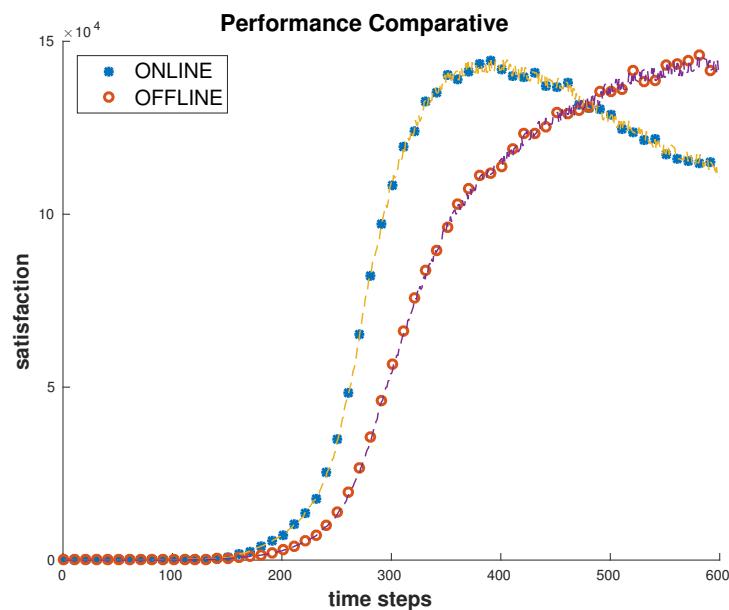


Figure 5. Comparing the online & offline algorithms’ performance in terms of the satisfaction achieved by the urban population during the complete time horizon of the simulation. Regarding the purchasing strategy, the offline approach uses a **stochastic strategy** to decide the moment in which the purchase decisions are taken and the online approach uses a **threshold-based strategy** that takes the information from the fitness of the random population of EA solutions as it is explained in Fig. 4

The functions plotted show that the offline version marginally outperforms its online counterpart, but only towards the end of the simulation, where the online satisfaction figures decay. This behaviour can be explained after the analysis of the pattern of land resulted from the purchases of both approaches. As we will see, key relevant factors in this behaviour turn out to be the spatial positioning of the selected green areas, particularly the distance from the protected cells to the different CBDs, and also the numbers of cells protected.

The Alonso (1964) urban model adopted in this work has a general tendency to concentrate most of the population close to the CBD. Consequently, the measurement of how many of these protected patches of land are close to the three defined central areas of the lattice can provide significant information about the level of satisfaction achieved

by the inhabitants of the city. This distance concept is called in the present work the ‘closeness’ factor. The closeness factor is defined as a measure which averages the distance from the protected cells to each corresponding CBD, see Fig.(6). The mean is calculated by grouping the cells of the lattice in concentric annuli around its CBDs. Each ring is considered of distance one. Finally each group is multiplied by its distance and averaged for each time-step.

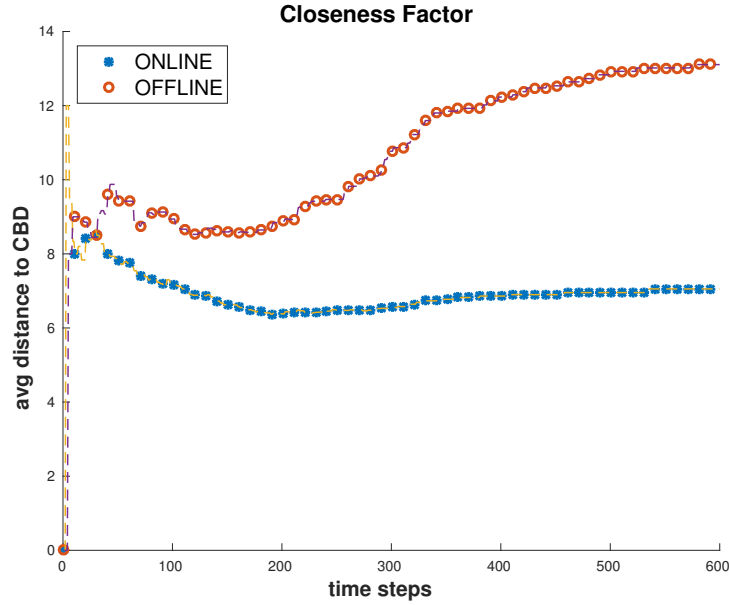


Figure 6. This figure represents the average closeness of each protected cell to the corresponding CBD in both algorithms. This factor is calculated using the number of concentric circles between them. Closeness is a key element in the analysis of the performance of both algorithms and consequently, this aspect can be seen as a qualitative measure of a given solution.

Here it is important to mention that the difficulty in allocating green parcels of land close to the peri-urban areas of the city, which would improve the closeness factor and better serve more populated areas, is mainly related to the quantitative difference between the available budget and the rural prices of the peri-urban areas of the city. However, in response to its immediate urban development, the price of these patches of land increases significantly (Plantinga & Miller, 2001).

In terms of the ability of the algorithms to allocate their green cells in more efficient areas of the grid, Fig. (6) shows the different values of the *closeness* factor for both approaches. The functions depict noticeable differences in terms of the shape and the average distance from the protected cells to their corresponding CBD. The online approach is a more intelligent strategy, capable of allocating the selected green areas closer to the city centre. This tendency, that can be almost described as constant from time-step 200, is valid for the entire simulation period. On the other hand, the offline algorithm displays consistently higher values than the online approach, with a steady monotonic increment throughout the process.

Along with the spatial position of the cells, the total number of purchased green areas is also a salient factor which influences the final level of satisfaction. As shown in Fig. (7), at the beginning of the simulation, both algorithms have very similar behaviour. However from about halfway into the simulation, around time-step 350, the online algorithm starts to fall behind in terms of the number of protected cells. This effect is caused by the

restrictive purchasing schedule strategy selected for the online approach, which does not consider any affordable non-urban cell profitable enough to be purchased. In contrast, the offline policy constructor is able to more efficiently manage its budget in the latter half of the simulation, buying some affordable cells in the outskirts of the city.

One conclusion that can be drawn from these figures is that, if the analysis considers the moment in which the protection purchase was carried out, it can be seen that actions taken at the end of the simulation have less impact on the final performance. This arises from the aggregate nature of the definition of the fitness function. Since the online algorithm needs a certain level of satisfaction to allow a purchase, these late-stage acquisitions are rejected, and consequently we see the offline strategy catching up and overtaking the online strategy in terms of protection decisions late in the city's development.

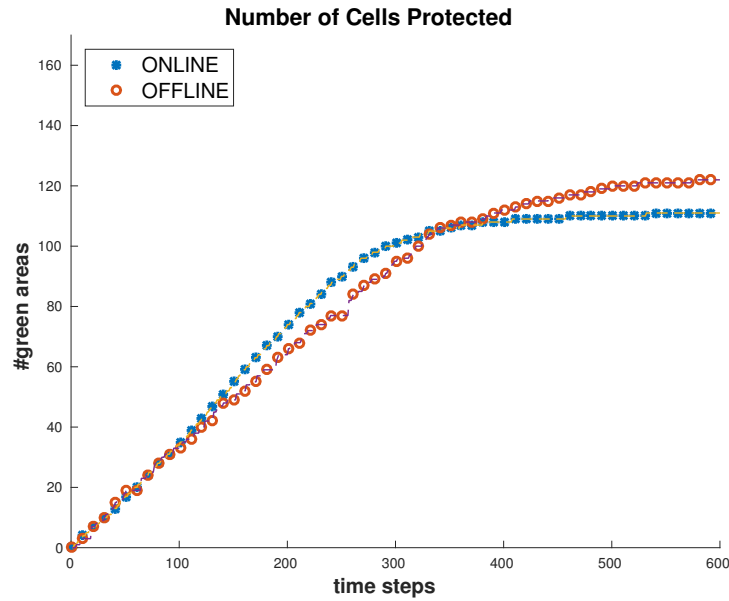


Figure 7. This figure shows the performance of both approaches in terms of the number of green cells protected at each time-step during the simulation.

Future analysis needs to be done to better understand the causes and dynamics of these behaviours, however it also should be mentioned that the limited number of generations allowed for the online EA may be an important factor. With more generations allowed, for example, it could be that we would see even better protection decisions made at early stages by the online EA, and, although we might still expect the slowdown in purchasing at later stages, the earlier boost may keep it ahead of the offline algorithm in terms of the number of areas protected.

5.3. *Spatial Distribution of Cells*

Visually, the spatial arrangement of the protected cells resulted from the application of the policy constructor of both approaches, captured in time-step 300, shows some noticeably different spatial arrangements. It is interesting to see how these patterns vary according to the different variants of the approaches: the fixed and stochastic purchase mechanisms for the offline approach and the threshold-based strategy for the online algorithm. The corresponding figures showing the topological distribution of green areas are in Fig. (8), which represents the final offline spatial distribution with a fixed purchase

schedule plan, Fig. (9) with a stochastic schedule plan and finally Fig. (10), which uses the threshold-based strategy to decide when is the best time to buy.

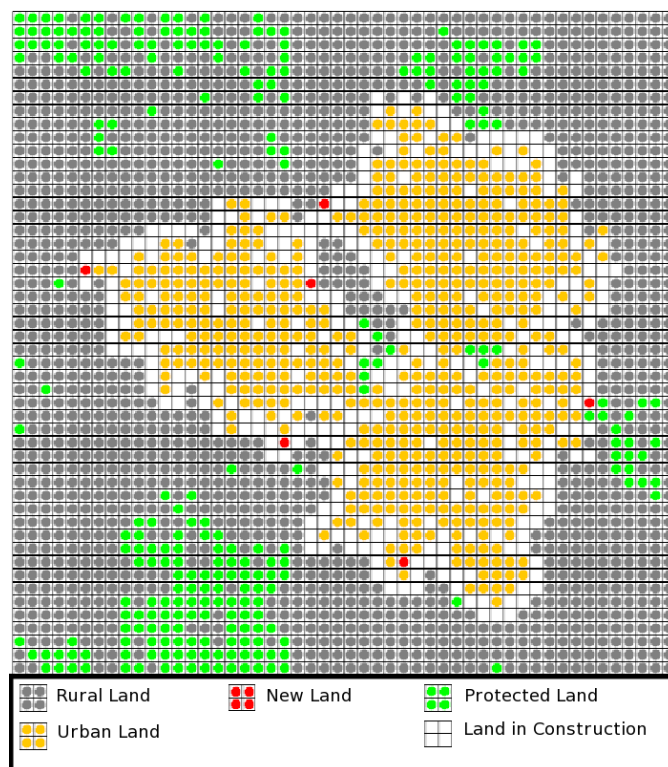


Figure 8. Offline algorithm: The lattice shows the spatial distribution of green cells in time-step 300 with a **fix purchasing schedule** strategy. In this case, green areas are located generally further from the CBDs. The approach achieves to protect a large number of cells, however only a small number of them are placed between the urban cores.

General observations about the distributions of green cells in these three approaches can be made as follows. The offline approach implements two strategies: a fixed and a stochastic variant. From its qualitative characteristics, the fixed purchasing schedule strategy manages to protect its green areas in locations generally further from the CBDs. This fixed approach also manages to protect a large number of cells, however only a small number of them are placed between the urban cores. Since the approach tries to protect cells as soon as it has funding for any of the available areas, it is complicated to save enough resources to buy expensive cells close to very populated areas.

In the stochastic purchasing schedule, on the other hand, the total number of protected cells is lower than in the fixed purchasing schedule. Recall that in this strategy the algorithm avoids any purchase the 70% of the time that the algorithm has enough resources to do it, which seems responsible for this behaviour. However, the accumulation of money allows the algorithm to invest in more expensive patches of land. Hence, the majority of these cells are located in more populated areas, closer to the CBDs. Then, in conclusion, the stochastic approach surpasses the fixed approach due to the fact that the higher number of cheap protected cells of the fixed approach cannot compete with the higher quality of the ones selected by the stochastic strategy.

The online approach implements a threshold-based purchasing schedule to decide when to buy and when to save the budget for the next generation. This approach is capable of protecting a slightly lower amount of cells than the stochastic procedure of the offline

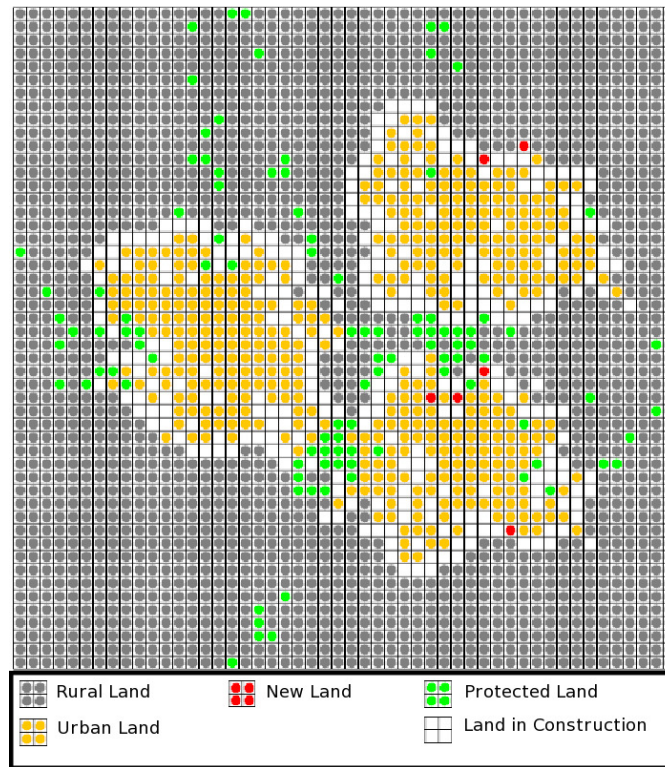


Figure 9. Offline algorithm: The grid depicts the spatial distribution of green cells in time-step 300 with a **stochastic purchasing schedule** implementation. The total number of protected cells are remarkably reduced if it is compared with Fig. 8, a fix purchasing schedule, but the majority of them are located in more populated areas, closer to the CBDs.

approach at the end of the simulation. It achieves a compact distribution of green areas and connects the majority of them. The quality of these cells also tends to be high, being mostly placed close to the most crowded areas of the city.

If a comparison between the stochastic offline approach and the threshold-driven online algorithm is carried out, it can be concluded that even if there is a general tendency in both strategies to place more green areas in the zones of confluence amongst CBDs, the offline topological distribution is rather more scattered, with some of the cells located in the extremes of the lattice. In contrast, the offline approach groups the green areas in some well-formed clusters, even though factors like size and compactness of the protected land were not explicitly included as objectives in the definition and calculation of the fitness function.

Focussing now on the offline approach, we can analyse the difference between the fixed and stochastic purchasing strategies (Fig. (8) and Fig. (9)). A conclusion that results from the inspection of these very distinct patterns is that the purchase strategy seems to be a critical factor for the entire land protection process. The differences, at least based on visual inspection, between the selection of the fixed and stochastic purchasing mechanisms appears to be as relevant as the differences between the offline and online strategies themselves. Further consideration allows this to be traced back, again, to the time-dependent nature of the budget, and the strained relationship between budget level and the general dynamics of rural land prices, since the distance to CBD and the amount of cells are strongly linked with the purchase strategy. Clearly, the purchasing strategy is crucial in shaping the overall outcomes. This leads to the suggestion that ongoing

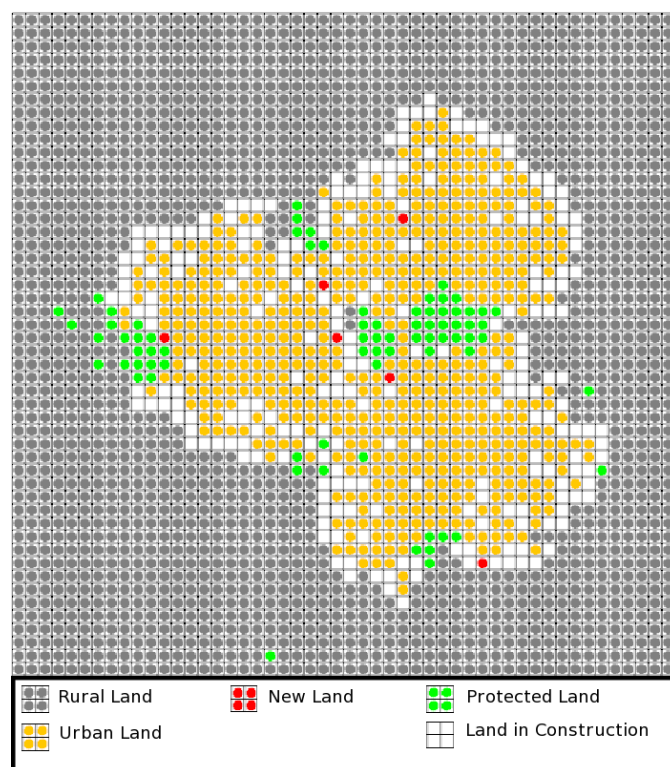


Figure 10. Online algorithm: Visualising the spatial distribution of green cells in time-step 300 with a threshold-based purchasing schedule implementation. The adaptive strategy achieves the most compact distribution of green areas compared to the other two approaches. With a number of green cells similar to the stochastic strategy, the approach allows to connect the majority of them.

research in this area might usefully consider separating the overall task into two phases, as shown in Fig. (11).

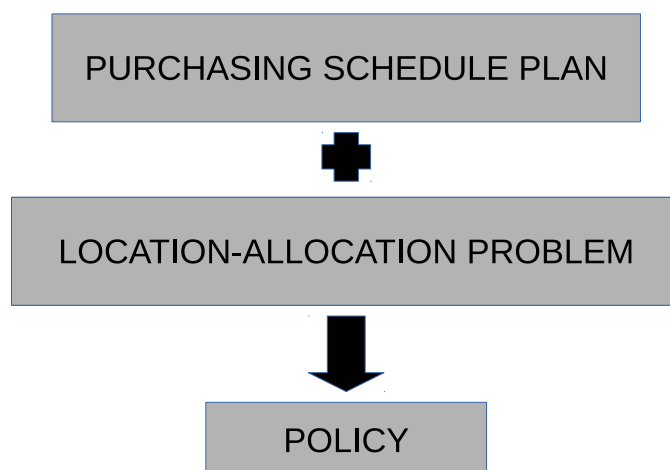


Figure 11. Simple depiction of what we propose to be an optimal way to engineer effective green planning practice, based on our experiments and results. A key conclusion is the crucial role of the purchase schedule plan, given that purchase decisions are dependent on a restrictive budget which limits the amount of land possible to acquire.

Size is an important factor in the pattern of use of a given green area, linked with

the visit frequency and the type of activities undertaken in parks (McCormack, Rock, Toohey, & Hignell, 2010). However, even if larger areas are capable of supporting a more diverse type of uses and activities, which increases their attractiveness (Broomhall, 1996), other studies conclude that it is better to design a layout with numerous small green areas than a few large parks (Morancho, 2003). In this particular aspect, the final spatial pattern distributions linked to the study of the population's needs, as done in this work, clearly produce a contrary conclusion. Even if other more complex factors can be included into the calculation of the fitness that could contribute to partially modify the spatial results, such as crowdedness, security or level of amenities of each green area, our results can contribute to the discussion towards more effective designs of green area layouts within the green planning community.

6. Conclusions

In abstract terms, the field of study of this paper is Sequential Decision Making problems under uncertainty in stochastic domains. These type of problems are normally addressed with a variety of non-evolutionary strategies. Our goal is to assess the suitability of EA techniques for this task, particularly in the context of its application in a green space allocation planning model. The main goal of the developed optimisation framework is to determine an investment strategy which ensures a proper provision of a given kind of resource, in this case parks, for the population of a city within a predefined period of time.

We illustrate how two different EA methodologies, an online and an offline approach, are implemented and how they are equipped to cope with the uncertainty in constraints and objective functions, by means of a specific implementation of Monte Carlo sampling. In the online version, the algorithm is able to see the state of the system at any time, being capable of taking decisions in real time. A second offline strategy has to look ahead in order to forecast all the possible situations and create an entire plan for a long period of time. Both approaches were tested in a complex version of the urban growth model, configured with three CBDs and multiple price gradients to take more advantage of the application of the evolutionary technique. Finally, we compare their performances, the computational time used and the emerged spatial patterns, explaining in each case the behaviour of both approaches.

The empirical experiments show that both algorithms achieve similar results; the offline version out-performs the online at the expense of using significantly more time to converge. Disparity in factors like the number of cells protected, the average closeness to a CBD and the final spatial size and distribution of green areas shows the different nature of both algorithms. Due to the aggregated nature of the budget, different purchasing strategies are tested, concluding that the details of the purchasing policy are critical factors within the problem.

Finally, from the research conducted here we believe that evolutionary techniques can be considered a valid option to solve sequential decision making problems under uncertainty in complex environments.

7. Future Work

Location allocation problems are in nature multiobjective (Nelson et al., 2009; Watts et al., 2009) and optimizing a single objective with respect to the others can produce

unacceptable results. However, in a realistic planning scenario, these objectives conflict each other, and a consequently clear and interesting direction for future work is to investigate multi-objective optimisation formulations to achieve an efficient open space planning policy. In the next version of our framework, new criteria will be added to the system, focusing mainly on environmental protection policies, maximising the number of green areas and minimising budget expenses amongst others.

Additionally, it is also interesting to consider how the planning and optimisation strategies are also influenced by the ‘quality’ of the green area. Currently each green area is homogeneously defined without including further characteristics that could influence the visitors’ frequency of use, such as noise levels, biodiversity, size, level of greenery, proximity to shopping, and others. Future work could investigate these factors by enriching the description of green spaces when these concepts are included in the characterisation of each park. At the same time, the purchasing strategy could also be enhanced by taking into account the potential for additional spending, to raise the quality to desired levels, and consider the tradeoffs involved, noting that the general absence of such factors could discourage visitors from using these areas (Vallejo, Rieser, & Corne, 2015).

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