An Evolutionary Model for Urban Development

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Abstract

In the context of the rapid growth of urbanized population as well as the effects of climate change and diminishing natural resources, the methodology by which cities are designed in the next 30 years is crucial to the success or failure of sustaining the growing numbers in the population. In this perspective, population based evolutionary algorithms, driven by biological evolutionary principles, excel over conventional problem solving strategies through their ability to optimize for multiple conflicting objectives, therefore generating multiple optimal solutions rather than a single optimized solution, allowing for a diverse solution set to a problem that has no clear single solution. To test this, a computational multi-parameter approach driven by an evolutionary model of development is implemented on an urban patch in the city of Barcelona.

Introduction

In the opening statement of Stephen Marshall's, '*Cities, Design and Evolution*', he states that "Among all species – it is perhaps only humans who create habitats that are not fit to live in" (Marshall, 2009, p.1). Marshall argues that the 'unplanned' cities of the past have proven to be more habitable, economical and sustainable; creating a correlation between how complex cities function and how functional order is achieved through evolution in nature. In this perspective, the conventional method of urban planning implemented in the 20th century, in which the city was designed not unlike a machine, adhering to an idealistic notion of planning a generic city that is applicable regardless of region, climate or topography, commonly resulted in dire impacts on both global and local scales. This has triggered a reassessment and revision of traditional urban design methods in order to establish a more sustainable modus operandi for urban development.

In recent years, this has propagated an in-depth analysis of understanding a city within a biological context, an approach introduced as early as the late 19th century by Patrick Geddes (Batty and Marshall, 2009). Thus, developing a city as an organism, through a biological evolutionary model, attempts to establish a substantial and applicable methodology for cities that develop through adaptation rather than optimization, reflecting traits – already acquired by natural systems – of energy efficiency, environmental response, regeneration and climatic (and cultural) adaptation. Marshall clarifies that "the 'argument from evolution' suggests that adaptive incremental change can lead to great transformations and a diversity of forms in the long term" (Marshall, 2009, p.14).

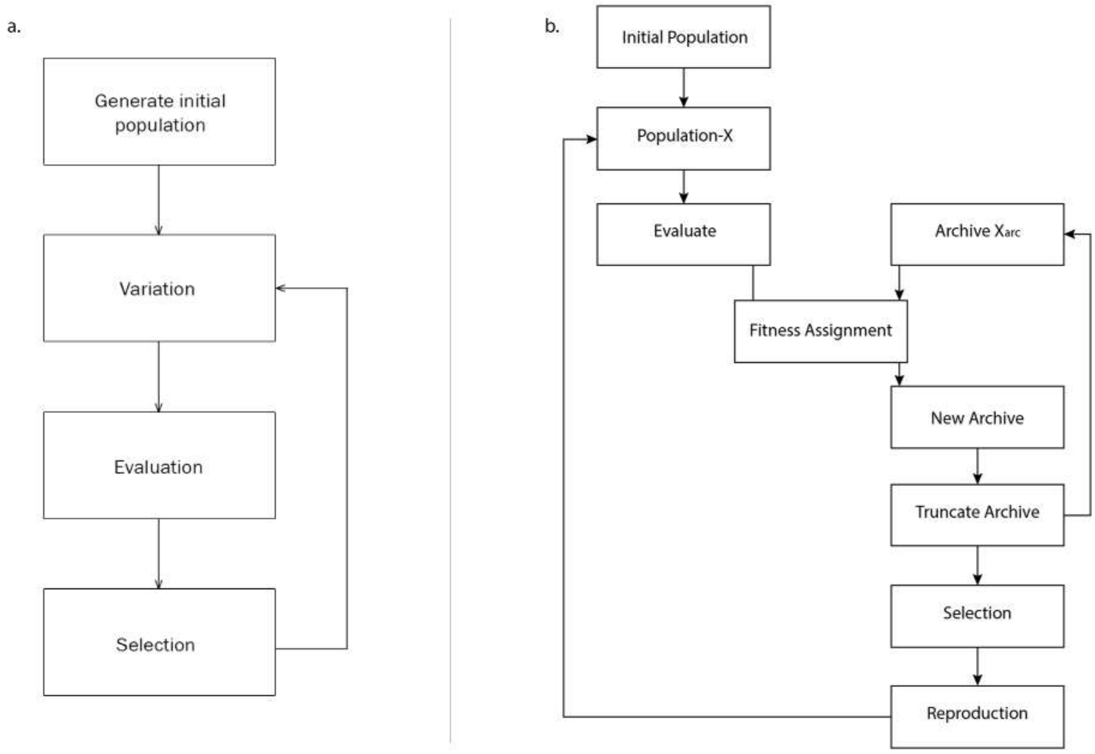
Therefore, the paper engages the application of an evolutionary model, through the utilization of evolutionary algorithms, to develop an urban patch that aims to adhere to several conflicting objectives by generating multiple optimal solutions rather than a single solution. Evolutionary computation and the principles that drive the field form the foundation of the experiments, as such, a description of the algorithmic process is expanded upon to ensure a clear understanding of the factors that drive the experiment presented within this paper.

The Biological Argument

The conventional definition of cities in the past half-century has been formulated around treating a city as both a system that is independent from its environment and one that is usually in an equilibrium state. This top-down approach to cities reflected a process of planning and management; the master plan was implemented with the notion that once constructed, the city was perceived to be 'complete'. However, 'completion' was seldom achieved, as it was a substantially idealistic perception. The factors that dictate the growth rate and development of a city cannot be expressed and implemented through a 2-dimensional representation of location and space distribution. This has been proven in an array of examples that range in scale and timeframe. Two of which are Brasilia and Milton Keynes (Makki and Schizas, 2010). The former was designed in the mid 20th century to accommodate a population of 500,000 people, however by the year 2000, the population of Brasilia reached 2 million and has reached close to 3 million in 2014. Milton Keynes on the other hand was designed primarily as a poly-centric plan through the distribution of different business centers throughout the city; however, the unexpected rapid growth of one business center during the city's development resulted in the failure of the remaining business centers to compete, thus transforming the city into a mono-centric one.

Such unexpected outcomes are due to the fact that cities are governed by the stakeholders that comprise the city as well as the efficiency of the networks and flows between these individuals. Thus, rather than approaching cities as machine systems, Batty (2013) contends that a city must be considered as an organism, a system that is ever-evolving, one that is in a perpetual dialogue with its environment, continuously adapting to changes dictated by the individual and group decisions that comprise the city. Brasilia and Milton Keynes exemplify the lack of control over the growth rate and final outcome of a

Figure 1. a.) The principal flow of evolutionary algorithms b.) SPEA2 Algorithm – to increase the efficiency of reaching a diverse optimal set, algorithms incorporated different techniques and variations to the basic interpretation of the principles of natural evolution. The evolutionary solver employed in the experiment implements the algorithmic flow diagrammed in figure b. (Reproduced from Weise, 2008)

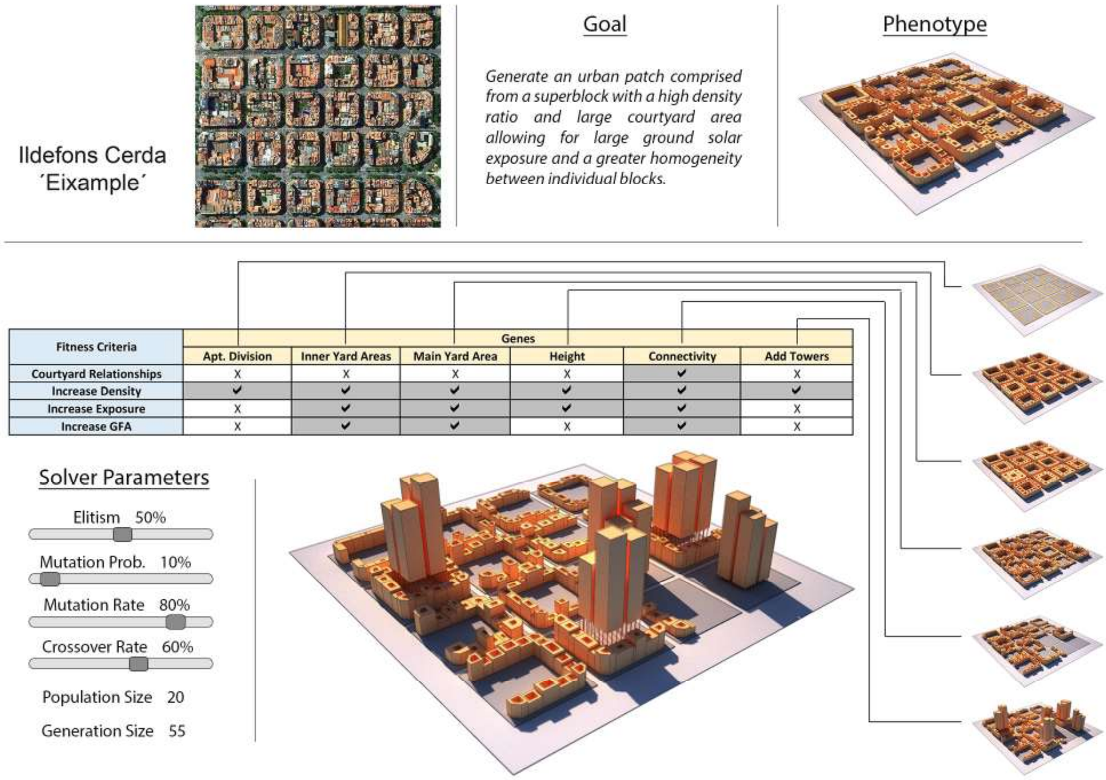


city; cities designed with idealistic goals that could only have been achieved were they in isolation from their environment.

In line with Batty's argument of approaching the city as an organism rather than a machine; understanding the relationship between a biological natural system to its environment is crucial in translating the factors that govern the evolution of natural systems towards city growth and development. Contrary to the conventional planning methods of the 20th century, natural systems do not evolve towards a predefined goal, as this deems the system to be one that is self-contained; therefore, rather than optimization, natural systems evolve and develop through adaptation. Emphasis must be placed on the term *adaptation* as it greatly signifies the fact that the evolution of a natural system is completely dependent on the ability of the system to successfully transform itself and adapt to its environment. Ernst Mayr (2001) emphasized the significance of a natural system to adapt to its environment by attributing it as a relationship of "perfection", although the use of this term may be construed as a teleological one, Mayr clarifies that by perfection he means "the seeming adaptodness of each structure, activity and behavior of every organism to its inanimate and living environment" (Mayr, 2001, p163). The adaptation between a system and its environment is one of the corner stones of a biological model of evolution, as it results in an efficient exchange of resources between the two; thus the significance of a city's morphology to adapt to its environment (climatic, cultural, geographic, etc.) is crucial in developing the sustainable longevity of a city; further signifying the need for the shift from understanding a city as a machine to that of an organism.

Therefore, rather than attempting to predict and define the final outcome of a city's urban fabric, the application of an evolutionary model to generate design solutions that

Figure 2. Diagrammatic Summary of the application of the gene pool onto the phenotype, including a cross-reference between the genes and the fitness criteria highlighting the required transformations for the evolution of the phenotypes. Also summarized are the parameters driving the solver. The experiment was conducted with team members Ali Farzaneh (Architectural Association) and Diego Navarro (Universitat Internacional de Catalunya)



Fitness Criteria	Genes					
	Apt. Division	Inner Yard Areas	Main Yard Area	Height	Connectivity	Add Towers
Courtyard Relationships	X	X	X	X	✔	X
Increase Density	✔	✔	✔	✔	✔	✔
Increase Exposure	X	✔	✔	✔	✔	X
Increase GFA	X	✔	✔	X	✔	X

evolve towards fitter individuals to their environment serves as an efficient design strategy for a problem whose conflicting objectives necessitate multiple solutions rather than one single optimal solution. Back, Hammel and Shwefel (1997) argue that "the most significant advantage of using evolutionary search lies in the gain of flexibility and adaptability to the task at hand", and while the optimal solution for a single objective problem is clearly defined, multiple objective problems require the "robust and powerful search mechanisms" (p.13, Zitzler, 1999) of evolutionary algorithms to find the fittest solution candidates that take into consideration all of the assigned objectives.

The Evolutionary Strategy

Evolutionary Algorithms have been used extensively in recent years to mimic the principles of evolutionary science to solve common real world problems through search and optimization procedures of single or multiple objectives. Ranging from the fields of economics to politics and music to architecture, evolutionary algorithms have proven to be an efficient problem solving technique to find multiple trade-off solutions for problems that possess multiple 'fitness criteria' (objectives) that are in conflict with one another.

Although evolutionary algorithms are derived from evolutionary principles, the algorithmic process by which a population of individuals 'evolve' towards a local or global optimum may be viewed as a teleological process that is driven towards an end goal.

There is yet to be a consensus to justify this fundamental difference between the algorithm and its biological counterpart; some authors in the field attribute it as a "change in semantics" (p.48, Weise, 2008), while others outline the process of evolutionary algorithms as one that is similar to the "selective breeding programs of animals and plants" (p.5, Paterson, 2002), rather than one that attempts to evolve new species or employ natural selection (Paterson, 2002). However, De Jong (2006) argues that if an evolutionary system is viewed as a "complex, adaptive system that changes its makeup and its responses over time as it interacts with a dynamically changing landscape," then an evolutionary algorithm is represented as a "feedback control mechanism responsible for maintaining some sort of system stasis in the face of change" (p.23, De Jong, 2006). Therefore, when comparing the local optimum in an evolutionary algorithm to a biological evolutionary process, Weise (2008) argues that achieving the local optimum in an evolutionary algorithm corresponds to a "well-adapted species that dominates all other animals in its surroundings" (p.3, Weise, 2008).

Nevertheless, several applications of an evolutionary model as a computational process have been developed throughout the mid-20th century; the most prominent of these algorithms were Rechenberg and Schwefel's 'evolutionary strategies', Fogel's 'evolutionary programing' and Holland's 'genetic algorithm' (De Jong, 2006). Although each of these models have been founded and developed almost independent from one another, the establishment of several evolutionary algorithm (EA) conferences in the 1990's resulted in highly beneficial interactions between the domains of evolutionary computation. De Jong (2006) clarifies that "the result of these first interactions was a better understanding of the similarities and differences of the various paradigms, a broadening of the perspectives of the various viewpoints, and a feeling that, in order to continue to develop, the field as a whole needed to adopt a unified view of these evolutionary problem solvers". *Figure 1a* illustrates the basic principles associated with evolutionary algorithms.

The 'integration' of different evolutionary paradigms, as well as the challenge associated with finding a solution to mul¬¬tiple conflicting objectives, led to an upsurge in different evolutionary algorithms. Each employed a different evolutionary strategy driven by a different interpretation of evolutionary principles with the ultimate objective of achieving the most optimal solution-set to a problem in an efficient timeframe. However, the two basic evolutionary principles of selection and *variation* remain the main driving force behind most evolutionary algorithms. Zitzler (1999) explains that:

"In evolutionary algorithms, *natural selection* is simulated by a stochastic selection process. Each solution is given a chance to reproduce a certain number of times, dependent on their quality. Thereby, quality is assessed by evaluating the individuals and assigning them scalar fitness values. The other principle, *variation*, imitates natural capability of creating "new" living beings by means of recombination and mutation."

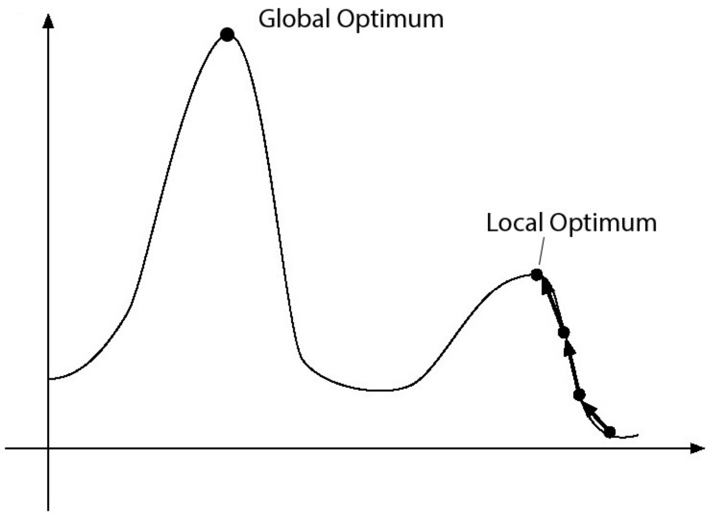
The progression of different evolutionary strategies over the past few decades has revolved around the efficiency of an algorithm to apply these two basic principles in order to achieve the two most fundamental objectives of multi-objective optimization (Zitzler, 1999):

- Application of the most efficient assessment and selection methods to achieve the optimal set of trade-off solutions – the *Pareto optimal* set.
- Maintain a diverse population throughout the simulation run in order to minimize the probability of premature convergence as well as maintain a dispersed Pareto optimal set.

Thus, the methods by which different evolutionary strategies apply the principles of selection and variation are notably diverse in different evolutionary algorithms. However, the most progressive evolutionary algorithms (e.g. NSGA-2, SPEA-2) excelled through their ability to achieve the most diverse Pareto optimal set in both an efficient timeframe as well as a reasonable computational environment (Luke, 2014). As such, the algorithm associated with the evolutionary solver utilized (Octopus 3D) for the following experiments is the Strength Pareto Evolutionary Algorithm 2 (SPEA-2) (*figure 1b*).

As the biological paradigm may be perceived as foreign to many designers, a brief description of the terminology interpreted within the solver is crucial for a comprehensive

Figure 3. An abstract 2-dimensional single objective optimization fitness landscape



understanding of the experiment carried out in the following chapter (the following definitions correspond to their relevance within the CAD software and therefore are not to be interpreted as the biological definitions of the terminology):

- *Generations* – The number of iterations per simulation run.
- *Population* – The number of individuals per generation.
- *Phenotype* – The geometry onto which the simulation will run.
- *Gene* – Parameter that controls the intensity by which the phenotype is modified.
- *Fitness Criteria* – The criteria by which the phenotype will be evaluated and selected.
- *Mutation* – Random modifications to the gene pool.
- *Mutation Rate* – The intensity of the mutation.
- *Mutation Probability* – The probability of a gene to mutate.
- *Crossover* – Exchange of genes of different phenotypes.
- *Elitism* – The number of dominant solutions selected to generate the next population.
- *Pareto Front* – The most optimal solutions in the population.

Experiment

Experiment Setup

Contrary to a single objective optimization algorithm, the use of evolutionary population based algorithms empowers the possibility to modify, evaluate and select a set of candidate solutions per each iteration rather than a single solution. Thus avoiding the conventional preference based approach that required the solver to "convert the task of finding multiple trade-off solutions in a multi-objective optimization (*problem*) to one of finding a single solution of a transformed single-objective optimization problem" (Deb, 2001, p.7). Therefore, the following experiment utilizes Ildefon Cerda's unique Eixample block as the main component that comprises the 16 block *phenotype* onto which the solver will run. The experiment's objectives aim to generate an urban patch that achieves an efficient courtyard relationship, a high density ratio, a high ground solar exposure ratio and an increase in the size of courtyards. To accomplish this, the gene pool detailed in *figure 2* transforms the phenotype's morphology through modifications to courtyard size (main courtyards and inner courtyards), building heights, unit divisions and courtyard connectivity between individual blocks. In addition to this, the genepool also allowed for the emergence of towers, should the solver find it a viable solution to generate higher density ratios while simultaneously maintain large open areas.

Unlike single objective algorithms, each individual in the population is evaluated according to each fitness criterion independent from one another (*figure* 2). Therefore, the same individual may score a high fitness value in one criterion, while simultaneously score a low fitness value in relation to another fitness criterion. Therefore, the *Pareto optimal set* – the fittest individuals in the population that are not dominated by any other individual, is comprised from a diverse set of individuals that are all considered to be optimal solutions within the population (Deb, 2001).

Solver Setup

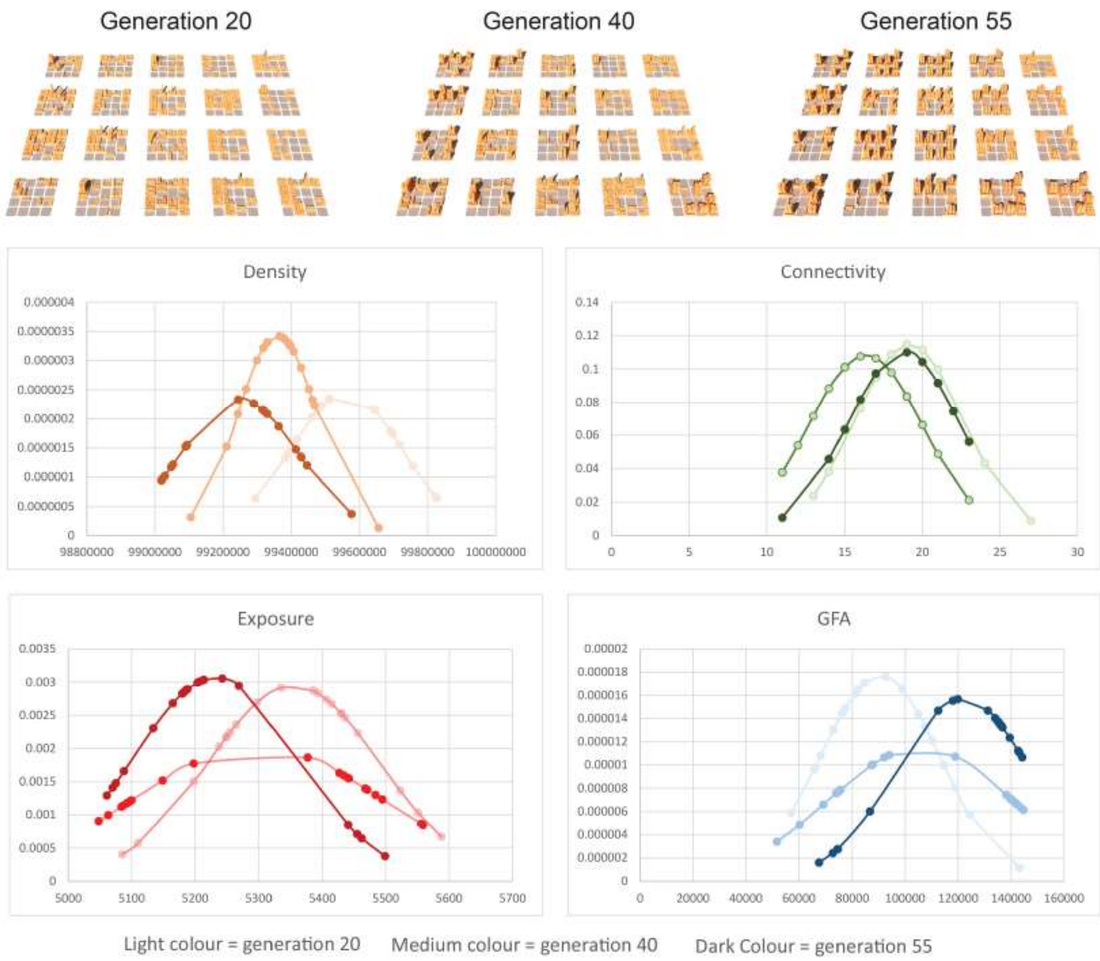
Although the algorithm mimics natural evolution by incorporating variation and selection strategies to *evolve* the population towards an optimal solution set, the intensity of their application plays a pivotal role in generating a diverse solution set within an efficient timeframe. Ideally, the algorithm setup should balance a search and optimization strategy that is both *explorative* – adequate mutation and crossover to allow for a diverse population of candidate solutions; as well as *exploitative* – employing an efficient selection and variation strategy that directs the algorithm towards an optimal solution set within a feasible number of generations (Luke, 2014). This is best represented through a 2-dimensional single objective optimization fitness landscape (figure 3). Depending on the complexity of the *fitness landscape*, what may be initially perceived as the optimal solution is in reality a local optimum. Therefore, in order to avoid the solver converging towards a local optima, the biological parameters driving the algorithm are modified throughout the simulation to achieve the most efficient balance between exploration vs. exploitation.

To ensure the population in the simulation *evolves* towards one that is both diverse as well as optimal, the solver parameters are set to the following: An elitism value of 50% is implemented which ensures half the population is bred from the most optimal solutions while the other half is randomly bred from the remaining solution candidates. A high mutation rate coupled with a low mutation probability, complimented with a moderate crossover rate ensures adequate variation is applied to the individuals in the population to generate diversity while simultaneously evolving the population towards 'fitter' individuals. However, constraints to the computational environment limit the experiment to a population of 20 individuals and a simulation run of 20 generations (*figure* 2).

Experiment Results

The simulation was interrupted, analyzed and modified at three stages throughout the experiment; generation 20, generation 40 and generation 55. The conflicting objectives set in the experiment aimed to ensure a diverse Pareto optimal set was achieved while simultaneously converging towards the global optima. At each 'analysis point' in the simulation, the objectives driving the experiment were modified in response to the fitness results of the phenotypes. At generation 20, the objective optimizing for larger courtyards was suppressed as it was evident that three of the four objectives (courtyard connectivity, courtyard area and ground solar exposure) complemented one another and thus have directed the simulation towards early signs of premature convergence. As a result, at generation 40, towers emerged throughout the majority of the individuals within the population. Rather than achieving a high density through a uniform height distribution within the population, the independent evaluation of each fitness criterion run by the solver generated an array of geometric diversity within the population. Finally, at generation 40, the objective optimizing for large courtyard areas was reintroduced to the simulation, while the objective optimizing for ground solar exposure was simultaneously suppressed. The results of which showed a significant shift in the population towards individuals that comprised predominantly from towers. Eliminating the objective optimizing for solar exposure allowed for a spike in towers and thus an increase in the density ratio as the overshadowing on ground level no longer played a role in the experiment (figure 4).

Figure 4. Geometric and Statistical comparison of the results of the fitness values of the three generations analyzed. As with most evolutionary algorithms, the fitness of an individual is determined by its proximity to '0'. In the results above, density and exposure have optimized throughout the simulation, while connectivity has maintained a relatively uniform fitness throughout. Finally, as a result of suppressing the objective optimizing for large courtyards (gfa) early on in the experiment, the fitness values of courtyard areas have decreased throughout the simulation.



Conclusions

The distinct evolution of phenotypes from a population comprised from low rise geometry, to one predominantly comprised from towers may be viewed as the extinction of one species and the emergence of another. The solver attempted to generate the most optimal solutions to the objectives defining the experiment, thus the Pareto optimal front was directed towards a phenotype that utilized open spaces and high density towers to achieve high fitness values relative to all of the analysed criteria. However, the fitness values of the four objectives did not achieve a uniform increase in fitness throughout the simulation. Although this was partly due to changes applied to the objectives at different stages in the experiment, it was also a result of the limits imposed by the computational environment which constrained the simulation to a small population and generation count, consequently restraining the results to a limited solution set. Although alterations to the parameters driving the solver at different stages throughout the simulation play a significant role in directing the experiment towards diversity and optimization, the length of the simulation is pivotal to ensure that the applied changes manifest themselves in the population.

Further Applications

The foundations of evolutionary computation have been significantly contingent on the principles of evolution established in the modern synthesis in the 1940's. Although evolutionary algorithms apply key principles of an evolutionary model within a computational environment, these principles reflect phenotypic variations through statistical gene frequencies in populations (Carroll, 2008). However, the advancements in the field of evolutionary development in the 1980's pertaining to the effect of mutations of gene regulation and regulatory sequences on the evolutionary process of organisms is severely lacking from the field of evolutionary computation. Although the discoveries in developmental biology have greatly challenged the principles established in the modern synthesis, these discoveries are yet to manifest themselves in genetic algorithms, thus resulting in an incomplete translation of how evolution functions on the genetic level and consequently an incomplete portrayal of a biological evolutionary model through evolutionary computation. Preliminary experiments carried out at incorporating algorithmic gene regulation on a simple phenotype have yielded successful results in generating a significantly diverse population in an efficient time frame. However, a thorough application of modern evolutionary principles within the field of evolutionary computation is yet to be realized.

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