Genetic Programming + Unfolding Embryology in Automated Layout Planning

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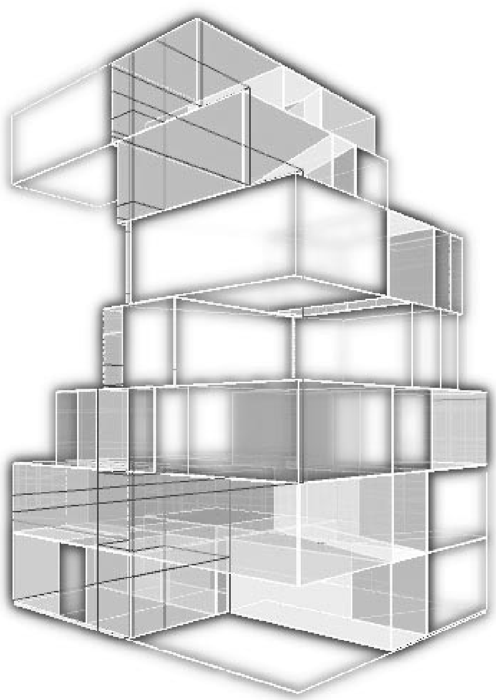

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ABSTRACT

Automated layout planning aims to the implementation of computational methods for the generation and the optimization of floor plans, considering the spatial configuration and the assignment of activities. Sophisticated strategies such as Genetic Algorithms have been implemented as heuristics of good solutions. However, the generative forces that derive from the social structures have been often neglected. This research aims to illustrate that the data that encode the layout's social and cultural generative forces, can be implemented within an evolutionary system for the design of residential layouts. For that purpose a co-operative system was created, which is composed of a Genetic Programming algorithm and an agent-based unfolding embryology procedure that assigns activities to the spaces generated by the GP algorithm. The assignment of activities is a recursive process which follows instructions encoded as permeability graphs. Furthermore, the Ranking Sum Fitness evaluation method is proposed and applied for the achievement of multi-objective optimization. Its efficiency is tested against the Weighted-Sum Fitness function. The system's results, both numerical and spatial, are compared to the results of a conventional evolutionary approach. This comparison showed that, in general, the proposed system can yield better solutions.

Keywords

Genetic Programming, Automated Layout Planning, Permeability Graphs, Space as Program, Recursive Genotype Structures, Multi-objective Optimization

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INTRODUCTION

"The synthesis of design solutions is characterized by uncertainty, unpredictability, the joy of discovery and the frustration of fruitless explorations"

[Kalay,2004,p.199]

Nowadays, architecture has become a field of multidisciplinary influence. Particularly, the encapsulation of computational methods within the design process, has reformulated the traditional approaches to the design problems. Since the early years of the computational era, designers pioneered the implementation of computation in the field of layout planning problem. The layout planning problem is one of great complexity for it seeks to satisfy a set of often conflicting criteria. Additionally, the configurations that result from the combination of even a small amount of spaces constitute a vast search space that makes impossible the enumeration of all the possible solutions and the selection of the best among them. Hence, traditional methods to solve this kind of problems are based on the designer's intuition and creativity.

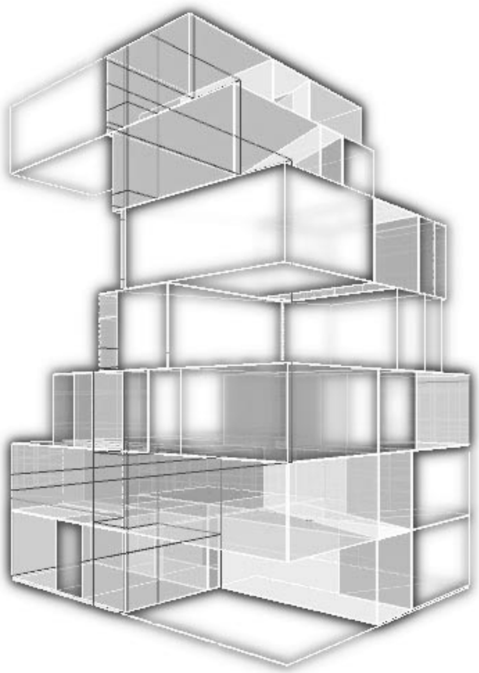
However, the development of sophisticated computational algorithms proposed efficient heuristics for solutions that perform well under the imposed set of constraints. Genetic Algorithms [GAs] in particular, were influenced by the way that natural evolution occurs on populations of individuals, namely through selection and reproduction of the fittest. The implementation of GAs within the field of automated layout planning yielded efficient solutions.

Nevertheless, in most cases of automated layout planning, the researchers seem to neglect the impact that the social and cultural background have over the formation of the layout configuration. This research questions the possibility to guide the evolution of layouts by considering these underlying generative forces.

In order to answer this question, a multi-objective Genetic Programming algorithm is applied over a population of individuals to induct their adaptation to a set of criteria. Genetic Programming [GP], developed by Koza [Koza,1992], is the subset of GAs which is involved with the program induction problem. Hence, the articulation of residential layouts as programs, with values and functions, was necessary for the cooperation with the GP algorithm. Thereupon, the allocation of activities [embryology] to a set of spaces occurs as an independent unfolding procedure that is based on permeability graphs, e.g. Gamma Graphs [Hanson,1998 and Hillier and Hanson,1984].

This report will start with an introduction to the social meaning and the underlying social/cultural rules which generate the houses' layouts. An overview follows along with a classification of the different approaches developed over time for the automated layout planning. A selection of distinctive works which illustrate the different approaches will be presented. Thereupon, the methodology developed for this research will be thoroughly explained, along with its variations and early attempts. Furthermore, the findings of the research will be presented whose meaning and importance will be discussed in respect with the related work and the aims set.

1. LITERATURE REVIEW



1.1 HOUSES' UNDERLYING GENERATIVE RULES

"Buildings are not just objects but transformation of space through objects." [Hillier and Hanson,1984,p.1]

People transform the space of their environment in order to host their activities and their needs. This transformation is not a random aggregation of closed spaces, it rather responds to certain generative rules that vary among the different societies and cultures.

"Buildings, indeed, the entire built environment, are essentially social and cultural products. [...] Their size, appearance, location and form are governed not simply by physical factors but by a society's ideas, its forms of economic and social organization, its distribution of resources and authority, its activities and the beliefs and values which prevail at any one period of time." [King,1980, p.1]

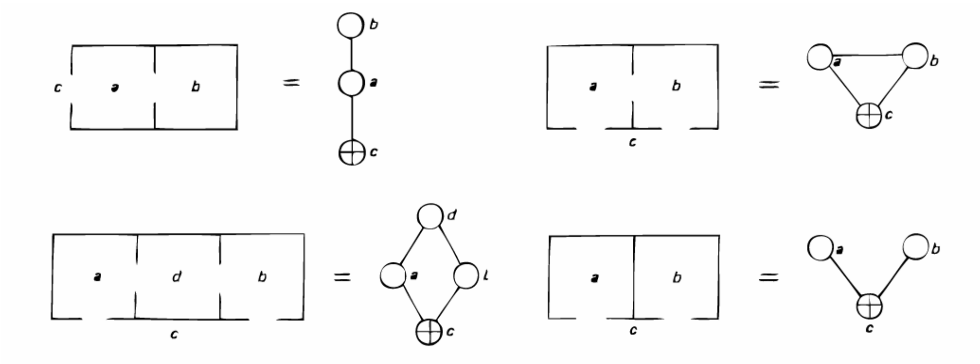


Figure 1 Decoding configurations. [Hillier and Hanson,1984]

In "The social logic of space" Hillier and Hanson [Hillier and Hanson,1984] tried for the first time to decipher the quantitative attributes of a building's inner structure in respect with the social processes that provoked their form and order. This approach was in conflict with the one which several researchers adopted whose main notion was to describe the space and then relate that space to usage [see examples in the next chapter]. As it is argued "the man-made environment through its ordering is already a social behaviour". [Hillier and Hanson,1984,p.8]

Furthermore, according to the authors, the relations in the physical configuration of spaces could describe the social meaning of space. One of the objectives was to find the building rules that produce the resulting spatial configuration. These rules concern the combination of elementary generators in a set of more general rules that constitute the building's genotype. And it is this genotype that makes different instances of buildings to be categorised under the same label. Their similarity or diversity is not based on their geometric attributes, but instead on their underlying generative rules.

"What is realised in every interior is already a certain mode of organising experience, and a certain way of representing in space the idiosyncrasies of cultural identity." [Hillier and Hanson,1984,p.145]

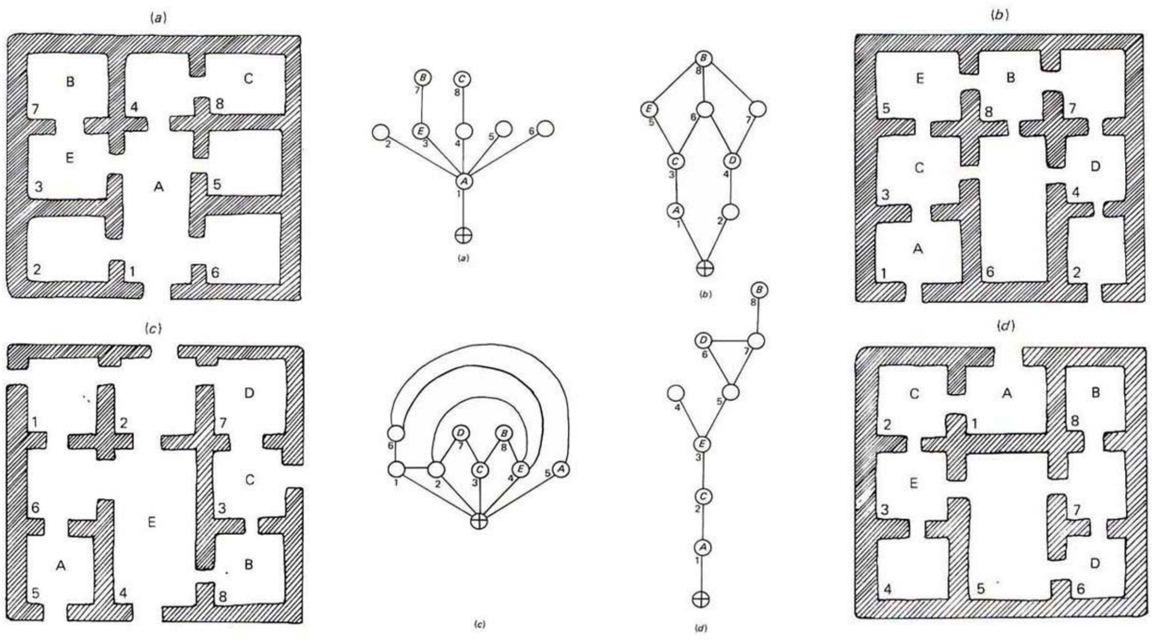
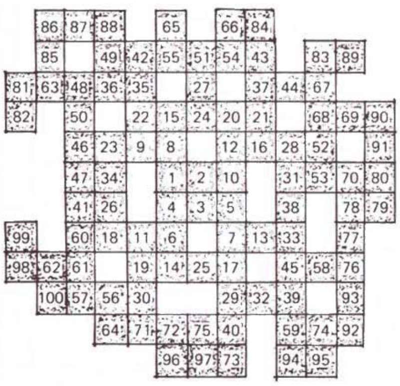


Figure 2 Similar plans generate different patterns of use [Hillier and Hanson,1984]

One of the tools that have been used is the Justified Gamma Map, which is a representational device [Figure2]. Spaces are assigned depth values according to the steps, needed to reach that space from the exterior. Then, these spaces, symbolically represented as circles, are arranged in lines according to their depth; one depth line below the other. Thereupon, the circles are connected with lines which represent the connectivity among spaces, if there is any. Hanson proposes that "the most complex configurational structures are built out of these elementary spatial gestures" [Hanson,1998,p.77]. As it is argued, the power of that representation is a result of the fact that the gamma map deciphers the different underlying syntactic genotypes of buildings [Figure2] whose geometry and adjacency Maps are identical [Hillier and Hanson,1984, p.150].

While their approach has been used for the analysis of the built environment, it has also been used within generative methods, such as the generation of aggregations based on a set of rules. Furthermore, this research was based on Hanson's suggestion that "we can if we so wish use the spatial decodings to generate new designs for houses which share the salient features of the existing collection, each an original, creative, interpretation of the genuine article" [Hanson,1998,p.270].



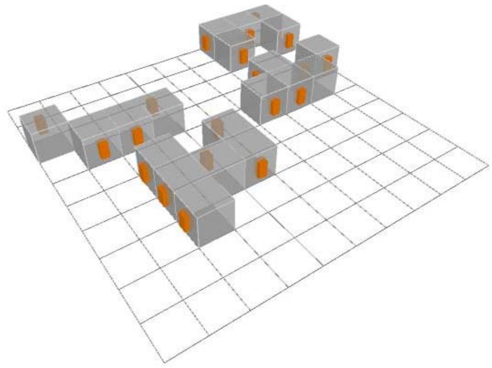


Figure 3 Random aggregation of cells with one face free [Hillier and Hanson,1984]

Figure4 Villager application [Doulgerakis unpublished]

1.2 SPACE LAYOUT PLANNING

In “Decoding homes and houses”, Julienne Hanson mentions that “the same brief for a house may generate solutions of breathtaking sophistication and mind-numbing banality” [Hanson,1998,p.2]. In general, the space layout problem is one of great complexity. Even a small number of spaces give rise to a vast search space as the population of possible solutions augments exponentially.

Since computation made possible the development of search algorithms and optimization strategies, researchers tried to use these new means as an effort to solve that kind of problems [e.g. the Facilities Layout Problem–FLP]. Liggett, in her paper “Automated Facilities Layout: past, present and future” reviews several approaches that aimed to address a demanding design problem. “Facility layout is concerned with the allocation of activities to space such that a set of criteria are met/or some objective minimized” [Liggett,2000,p.197].

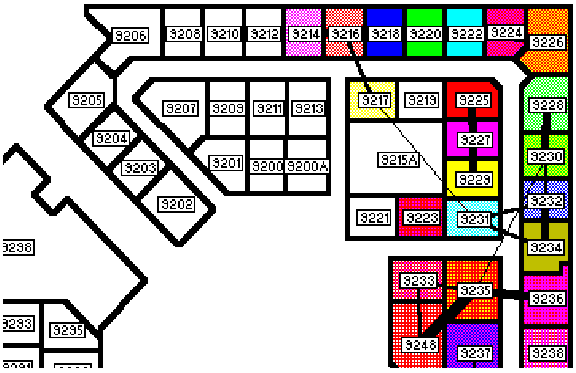
Attempts to build automated solutions for spatial layout problems have their origin in the 1960s. These attempts set different goals and follow various strategies in order to come up with a solution. As the spatial layout planning becomes an optimization problem, the number and the nature of the parameters which have to be optimized, define the complexity of each strategy’s goal. These objectives vary from the optimization of a single criterion function [such as the cost minimization associated with flow of materials between activities], to the finding of an arrangement that satisfies a diverse set of constrains [e.g. position, orientation, adjacency, path, view or distance] [see SEED and LOOS/ABLOOS in Kalay,2004].

1.3 REPRESENTATIONS OF SPACE

Facilities Layout Problems [FLP] can be divided in the following general categories according to the way that the structure of space is considered: the equal-area facility layout problems and the unequal-area facility layout problems.

1.3.1 EQUAL AREAS [One–to–One Assignment]

Early attempts to solve FLP aimed to assign activities to a given set of spaces whose arrangement is predefined by a one-to-one correspondence. This problem is formulated as a Quadratic Assignment Problem [QAP] by Armour and Buffa [Armour and Buffa,1964]. “QAP is a category of problems that is concerned with finding optimal locations for a set of interrelated objects”. [Ligget,2000,p. 200]



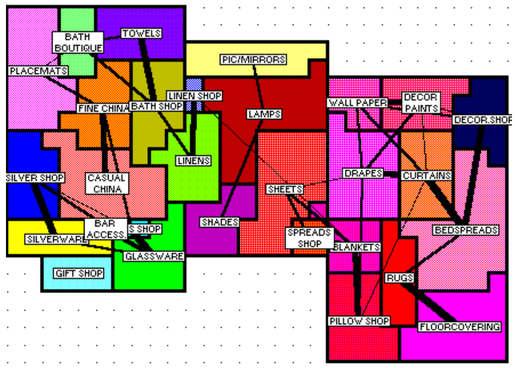


Figure5 One-to-one assignment [Ligget,2000]

Figure6 Modularisation on a block plan [Liggett,2000]

1.3.2 UNEQUAL AREAS [Block Plan]

The Unequal Area FLPs consider that each activity has different area requirements. Consequently, these problems are by far more complicated than those of the first category. However, they are more powerful in solving real world problems, as in reality, activities need host spaces of various magnitudes. The unequal area FLP can be furthermore divided in two categories according to the type of the plan that the FLP is called to solve.

THE GRID-BASED APPROACH

"In the grid-based block plan layout problem the facility layout is constructed on the grid plan, called the grid-based block plan and divided into squares or rectangles having a unit area" [Lee et al.,2005,p.880]. Then, the activities are partitioned into cells of the same unit-area according to their area requirements [Figure6]. Thereupon, as Liggett [Liggett,2000,p.205] stresses, the problem is translated to a one-to-one assignment problem. In this case, the module's attributes influence the results of the automated algorithm. The grid can only approximately create plans whose elements are not rectilinear; the approximation limit is defined by the grid's unit area. Nevertheless, there are examples which show that this method can be efficient in FLP solving [see Jo and Gero,1998 and Rosenman,1996].

THE CONTINUAL APPROACH

Other approaches [see Mitchell et al.,1976] manipulate space based on its geometrical attributes, e.g. the rectangle that describes the given outline. The partitioning of the outline's geometry into smaller, unequal, geometries [rectangles] provides the spaces that host the activities. There are several strategies that lead to the partitioning of space. Tam [Tam,1991] as well as Tate and Smith [Tate and Smith,1995] conclude to the layout by following a tree-structured hierarchical slicing procedure. Namely, the initial rectangle is recursively divided into smaller parts. Each rectangular partition in the slicing structure corresponds to an allocated activity.

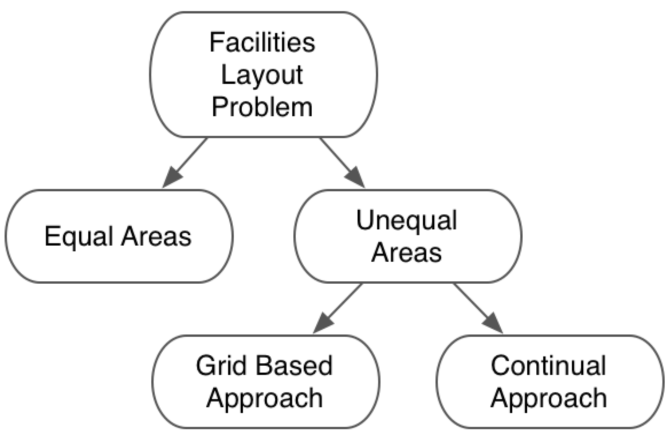


Figure7 Facilities Layout Problem's approaches

1.4 GENERATING SOLUTIONS

Liggett [Liggett,2000,p.202] classifies the existing generative methods in two categories. On the one hand, there are the constructive initial-placement strategies, whereas on the other, there are the iterative improvement strategies.

1.4.1 CONSTRUCTIVE PROCEDURES

According to Jo and Gero [Jo and Gero,1998], a constructive procedure is an n-stage decision process that starts with a set of spaces and a set of activities which are assigned to the spaces one at a time. These activities are allocated the one next to the other according to the predefined design requirements. For each placement, a 'tree-search' is executed and the selection of an activity-location assignment is made. The criteria for the selection of the next element to be assigned can be either local or global. Tree search can either be influenced by the spaces that have already been assigned [local criteria], or by the future search steps as well [global criteria]; thereupon, the assignment that guarantees the most promising evolution is selected.

1.4.2 ITERATIVE IMPROVEMENT STRATEGIES

In order to optimize the outcome of a constructive strategy, improvement procedures are applied at a later stage, i.e. after the completion of the first assignment. The simplest one is the 'pair wise' exchange which is based on the random selection of a pair of assigned spaces and the exchange of their activities. The result is evaluated according to the requirements and if the exchange improves the solution's efficiency, it is accepted as the new solution and so on.

1.4.3 SOPHISTICATED STRATEGIES

There is another category of strategies which are used in order to build more efficient automated solutions for spatial layout problems. This category is characterized by the use of sophisticated algorithms that provide a massively parallel exploration of the solution space. Evolutionary Algorithms attempt to imitate the way that natural evolution generates evolved organisms as offspring of less-evolved ancestors.

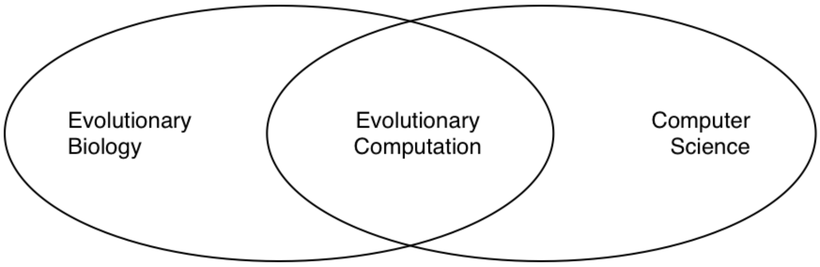


Figure8 Evolutionary computation [Bentley,1999]

As Peter Bentley explains, “evolutionary design has its roots in computer science, design, and evolutionary biology. It is a branch of evolutionary computation, it extends and combines CAD and analysis software, and it borrows ideas from natural evolution” [Bentley,1999,p.35]. Evolutionary design uses as a tool, evolutionary algorithms in order to explore the design solution space, either for the generation of innovative designs or for the optimization of the design’s efficiency according to predefined criteria. It follows the explanation of the evolutionary algorithms that can be used in spatial layout planning and in the next section, paradigms will be described.

GENETIC ALGORITHMS

“Genetic Algorithms [GAs] model natural selection and the evolution process. Conceptually, genetic algorithms use the mechanisms of inheritance, genetic crossover and natural selection in evolving individuals which, over time, adapt to their environment.” [Gero,1996,p.16]

Bentley [Bentley,1999,p.8] mentions that GAs use two kind of abstract spaces. The first space is the solution space, which comprises all the possible solutions of a given problem. As it is impossible for a GA to manipulate the solution space, given that it is merely a computational algorithm, the second space contains a coded version [Genotypes] of all the possible solutions. This space is called the search space of the GA.

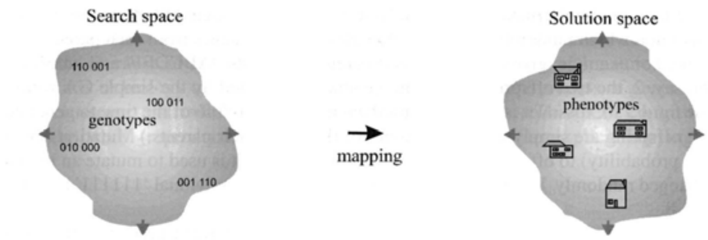


Figure9 Search space and solution space [Bentley,1999]

The genotype is a set of coded parameters that describe the phenotype. These parameters are called the genes, while the values that the genes can take are called alleles. The genotype is often represented as a string of values and each string position corresponds to a single gene.

The efficiency of the algorithm is based on the fact that it is applied to a population of solutions. The search within the solution space is highly parallel as each individual explores a different area of that space. “Evolution operates on no single individual but on entire species.” [Flake,1998, p.340]

The genotypes are then translated to their corresponding phenotypes which are then evaluated according to the predefined criteria. As Jo and Gero [Jo and Gero,1998,p.152] comment, the phenotypes [e.g. the organisms per se] live in the world. Hence, their good or their bad performance depends exclusively on their physical attributes and not on their chromosomes.

The fitness assignment guides the evolutionary algorithm. The individuals that perform better in their environment [e.g. the fittest] are more probable to survive and reproduce themselves. According to John Koza [Koza,1992,p.1], “fitness causes, over a period of time, the creation of structure via natural selection. That is, fitness begets structure.”

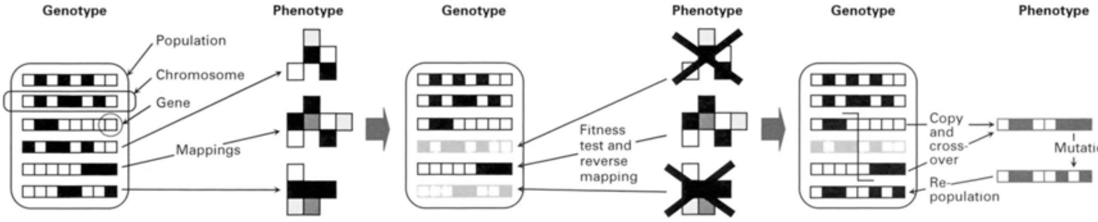


Figure10 Genetic algorithms [Kalay,2004]

On the other hand the evolving power of a genetic algorithm derives from the recombination of the genetic material of well fitted solutions in order to create offspring populations with better-fitted individuals. The recombination and the propagation of the genetic material are executed with the following genetic operations:

a. Survival. Each individual has a probability to survive in the next generation according to its fitness value.

b. Crossover. Two ‘parent’ phenotypes are selected from the entire population. The selection probability of each individual depends on its fitness value, e.g. the fittest are more probable to reproduce. The genetic material of the parents is combined for the creation of an offspring genotype. The genes of this genotype acquire randomly a value between the two corresponding gene values of its parents.

c. Mutation. It is applied with a low probability to the offspring genotype. A single gene discards its value and randomly selects a new value.

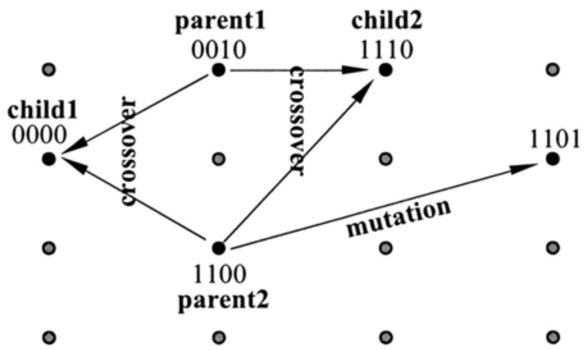


Figure11 Genetic operations in solution space [Gero,1998]

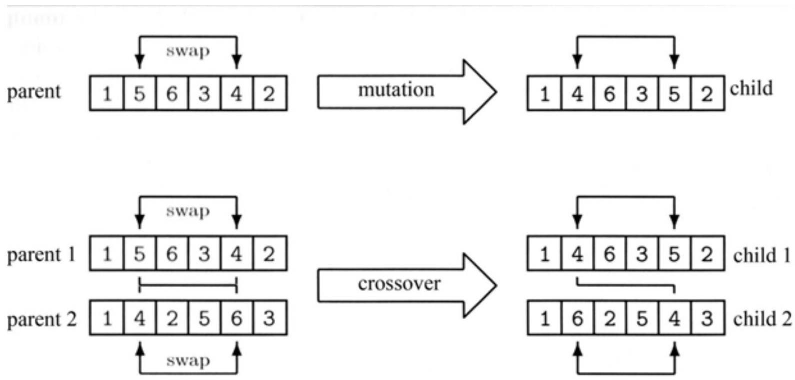


Figure12 Genetic operations [Flake,1998]

The GAs have the ability to evolve their population's organisms and to instruct them to 'adapt' to the requirements which are set by the evaluation criteria. As Flake mentions, "we have both parallelism and iteration as fundamental pieces of the biological equation for adaptation" [Flake,1998,p.340]. The genetic algorithm's efficiency is due to the integration of these two fundamental elements.

GENETIC PROGRAMMING

Genetic programming was developed by John Koza [Koza,1992] as a method to make computers to evolve computer programs. Bentley and Corne [Bentley and Corne,1998,p.17] classify GP as a special kind of genetic algorithm whose individuals are programs and whose genetic operations are modified versions of the operations that GAs implement.

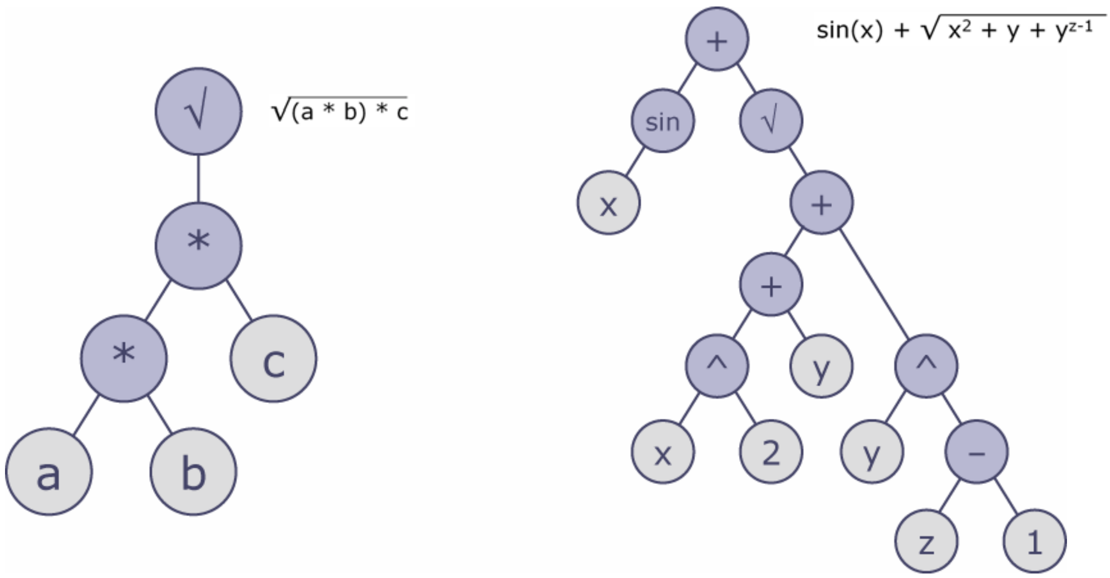


Figure13 Programs in tree-forms [Sean Hanna unpublished]

Koza [Koza,1992,p.2] stresses out that in order to get computers to solve specific problems, the structure of a computer program is required.

Such a structure can:

a. perform operations in a hierarchical way,
b. perform alternative computations depending on the outcome of intermediate calculations,
c. perform iterations and recursions,
d. perform computations on variables of many different types, and
e. define intermediate values and subprograms which can be subsequently reused.

The major difference between GAs and GP is that in the second case the solution to the problem does not have a predefined length and structure. In GAs the genotype of an individual constitutes a fixed length string of genes that include all the necessary information in order to describe each solution. “The initial selection of string length limits in advance the number of internal states of the system and limits what the system can learn” [Koza,1992,p.66]. Within the context of genetic programming “the size, the shape and the structural complexity of the solution should emerge during the problem-solving process as a result of the demands of the problem. The size, shape, and structural complexity should be part of the answer produced by a problem solving technique- not part of the question” [Koza,1992,p.2].

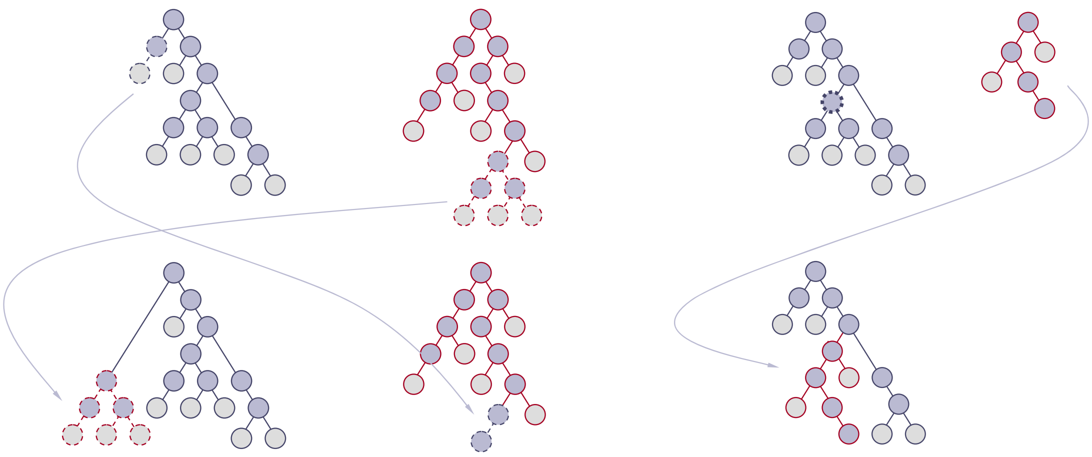


Figure14 Crossover and mutation in GP [Sean Hanna unpublished]

Since a chromosome of a computer program can be of variable length and complexity, a specific solution representation is needed in order to be able to accept the genetic operations, crossover and mutation. Koza [Koza,1992] proposed the arrangement of the solutions in hierarchical tree-structures with intermediate and terminal nodes. The crossover operation selects randomly a node in each parent genotype and swaps their branches. As for mutation, GP selects randomly a node in a tree-structure, and replaces the sub-tree whose root is that node with a new randomly generated sub-tree.

GENETIC ALGORITHMS vs. GENETIC PROGRAMMING

In summary, GP and GAs are both divisions of the evolutionary algorithms and they execute similar heuristics in the solution's induction process. However, their major difference is the kind of solutions that they are involved with. GAs articulate the problem in terms of values required, whereas GP focus on rules describing a method to solve the problem. GAs explore the search space defined by a specific problem in search of a specific optimal solution [data]. On the other hand, GP explores the search space defined by a general set of problems in search of a general solution [algorithm] that responds to the requirement set by such problems.

Hence, the selection for the implementation of the appropriate algorithm, either GAs or GP, depends on the objectives of the research. When a problem is explicitly defined as a single case problem and the desired result is the final values of the variables, the GAs should be implemented. Whereas, when the input that defines a specific problem [e.g. environment values and objectives] is unknown, GP can provide a general set of instructions [algorithm] that solve adequately such problems.

1.5 RELATED WORK FOR THE SPACE LAYOUT PLANNING

1.5.1 CONSTRUCTIVE APPROACH

CRAFT [Armour and Buffa,1964]

Armour and Buffa [Armour and Buffa,1964] formulated the space layout problem as a Quadratic Assignment Problem [QAP]. They created an application called CRAFT [Computerised Relative Allocation of Facilities Technique] whose purpose was to solve the space layout problem as a combinatorial problem in which indivisible activities are to be assigned to fixed locations on a plan.

The algorithm starts with an arbitrary initial layout and computes its 'cost' in interconnection distances according to a predefined matrix of desired adjacencies. Then, CRAFT performs a pair-wise exchange strategy in order to create solutions which perform better in fulfilling the given requirements. This procedure is repeated until there is no possible exchange that can reduce the interconnection cost.

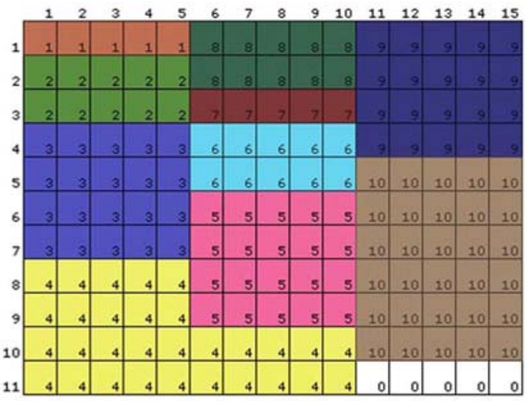


Figure15 CRAFT [//me.utexas.edu/~jensen/ORMM/omie/design/layout/craft.htm]

SMALL RECTANGULAR FLOOR PLANS [Mitchell et al.,1976]

In the 'Synthesis and optimization of small rectangular floor plans' [Mitchell et al.,1976] a combination of algorithms is proposed, aiming to solve a FLP, focused in the case of a small house. It is implied that rectilinear spaces can result from the application of a transformation matrix over a dimensionless representation of rectilinear plan forms. A minimum rectangular grating is superimposed over a rectilinear outline and then, the dimensions of the minimum gratings are adjusted so that each cell becomes square.

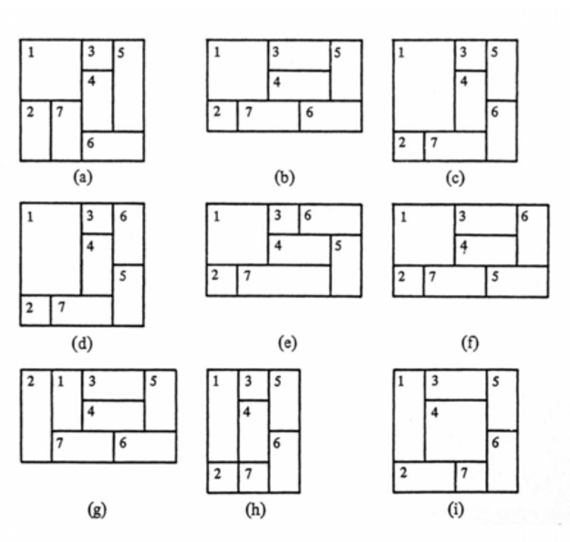


Figure16 Dimensionless dissections of rectangles [Mitchell et al.,1976]

An algorithm has been devised in order to enumerate all possible combinations of dissections that can be made to the initial rectangle so as to produce a given amount of rooms. The user imports the desired connectivity and orientation requirements. Then, the program enumerates all the acceptable assignments which correspond to the given preferences and fit within the several dissections.

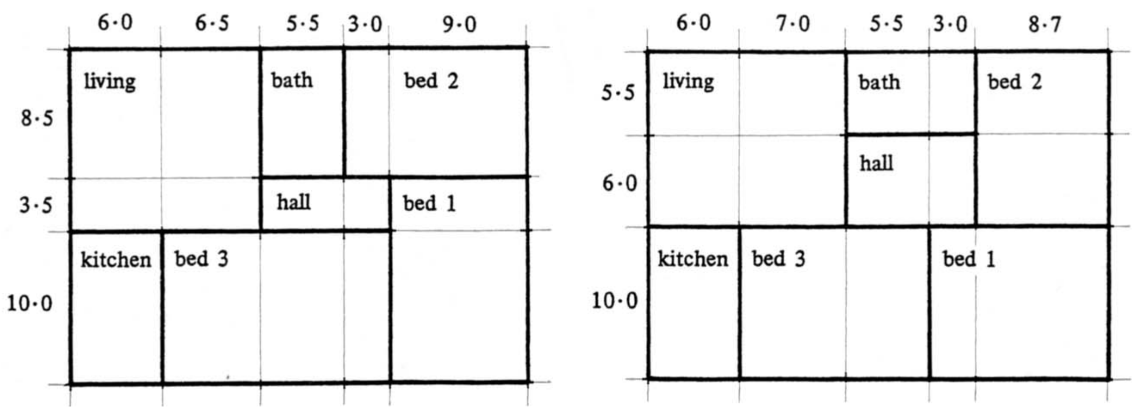


Figure17 Transformations of dimensionless representations [Mitchell et al.,1976]

Having produced a file of plans that satisfy adjacency and orientation requirements [in dimensionless representation], the next step is to consider the application of dimensioning vectors which will produce dimensioned plans according to specified requirements. A nonlinear programming algorithm was applied to each of the plan arrangements generated at the previous step in order to discover the dimensioning vectors which optimise the objective subject to the defined constraints. Only a small amount of arrangements can yield feasible solutions which constitute the final outcome of the method.

SITEWALKER [Doulgerakis,2007]

Sitewalker is an algorithm that was devised at an early stage of that research. The rooms are composed of joined elementary cells. Each room has predefined area-ratio requirements. Additionally, a matrix specifies which rooms should be connected and which should be not connected. Spaces are added one at a time. For each allocation all the possible following spaces and their possible placements are explored and the less ‘expensive’ position, in terms of overlapping areas, is selected.

Some of the produced solutions were promising from an architectural point of view. However, their efficiency can not be assured since the tree search algorithm could not predict future positioning steps. In an effort to include the future allocations in the decision calculations, the limit of the available computational power was reached.

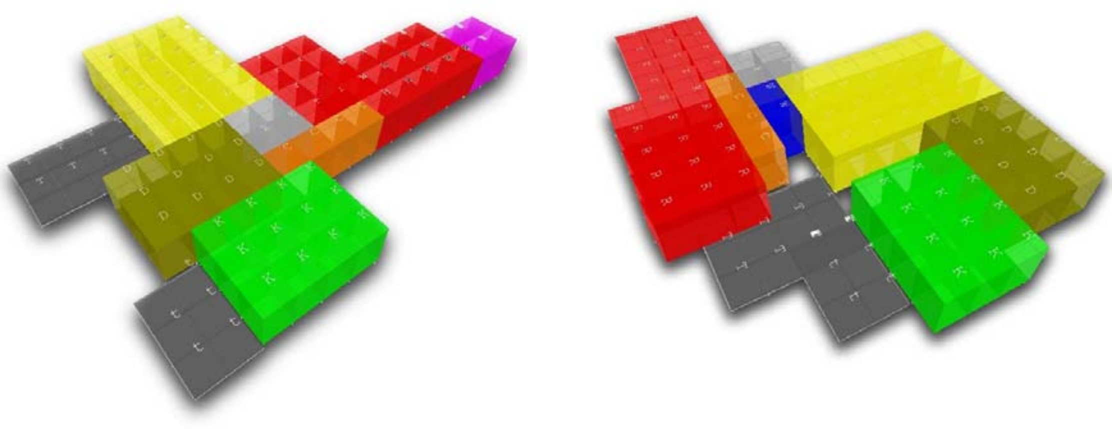


Figure18 Sitewalker [Doulgerakis unpublished]

1.5.2 EVOLUTIONARY APPROACH

EDGE [Jo and Gero,1998]

The Evolutionary Design based on Genetic Evolution system, called EDGE, is based on the evolutionary design model. EDGE is a grid-based approach for block-plan problems. The interaction matrix is based on subjective judgements of the client. The requirements in areas and adjacencies are defined by the user while the perimeter of the building is fixed.

According to the authors, the design elements of the algorithm include:

a. a set of activities or space elements
b. a space in which to allocate the activities
c. an operator to locate a specific activity to a specific location
d. a strategy to control the operator
e. the evaluation criteria.

The activities are placed one at a time within the borders of the building and what remains to be found is the order of the placement. The order of activities is then interpreted into the language of the genetic search system. Each gene includes a distinct activity for avoiding activity duplicates. However, the recombination of the genetic material through the genetic operations of the genetic search process distracts this equilibrium. A reordering function is then required, so as to ensure once again that all the activities of a genotype are unique.

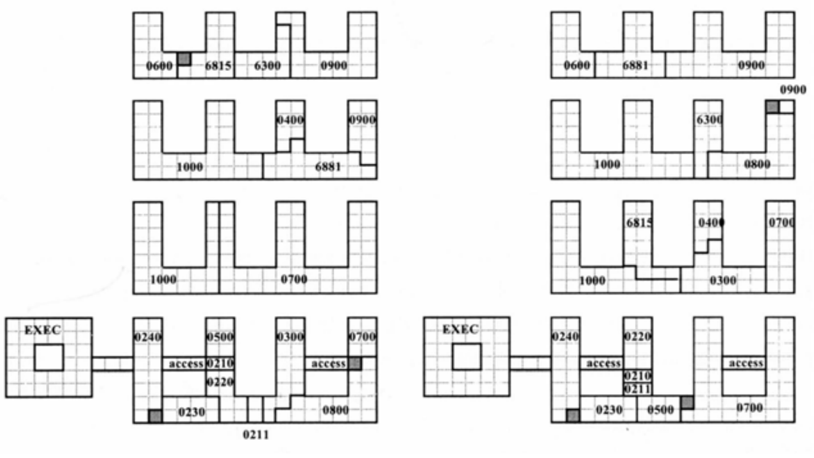


Figure19 Allocated departments within the outline [Jo and Gero,1998]

The system does not converge to a single solution as it is usually the case in evolutionary design; alternatively it provides a series of promising solutions. Then, the user chooses a solution among them.

THE GENERATION OF FORM [Rosenman,1996]

The structure of the designing elements in Rosenman's model is hierarchical. A house is considered to be composed out of zones. Zones are considered to be composed out of rooms which are considered to be composed out of space units. Rosenman's work is a grid-based approach for block-plan problems. Each room is composed of a number of space units. At the room level, the component unit is a fundamental unit of space. At the zone level, the component unit is a room and at the house level the component unit is the zone.

According to the author, the design grammar used here is based on the method for constructing polygonal spaces represented as closed loops of edge vectors. The grammar is based on a single fundamental rule which states that any two polygons Pi and Pj may be joined through the conjunction of negative edge vectors, V1 and V2 [equal in magnitude and opposite in direction]. The conjoining of these vectors results in an internal edge and a new polygon Pk.

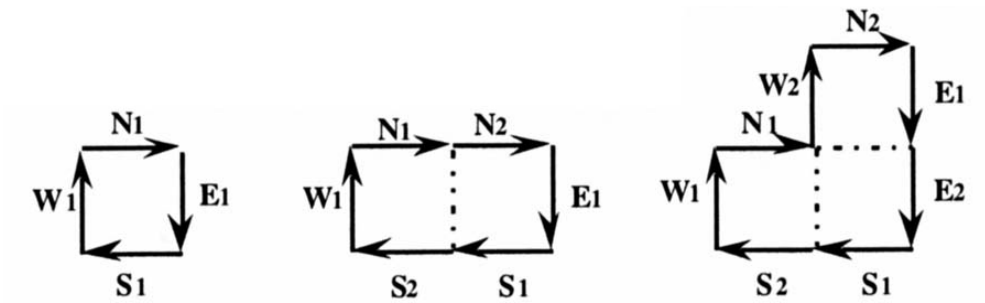


Figure20 Generation of a 'trimino' [Rosenman,1996]

Initially, a population of different rooms is generated for each room type in a given zone through the conjoining of rectangle polygons to 'polyminoes'. Progressively, a population of different zones is generated through the conjoining of rooms. Then, a population of different houses is generated through the conjoining of different zone types.

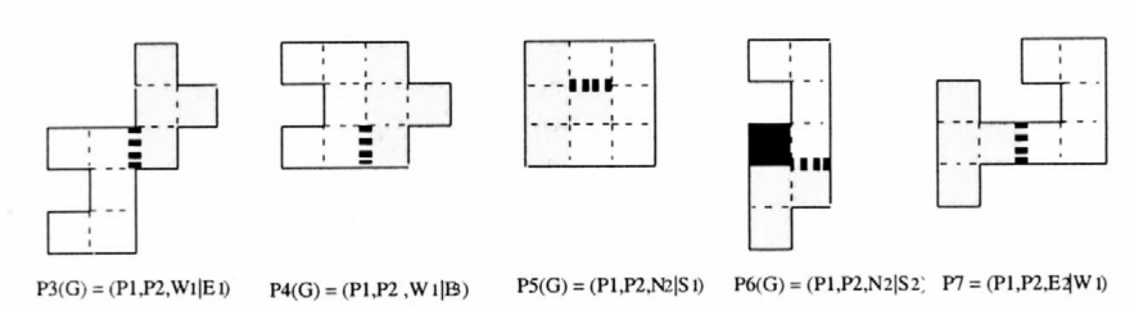


Figure21 Possible arrangements of two rooms [Rosenman,1996]

Each population is then evolved and the solutions are 'adapted' to the predefined requirements. At each level of the spatial hierarchy, different fitness functions apply according to the requirements of that level. By the time that this work was published, only a simple set of criteria had been implemented. According to Rosenman, each evolution-run converges quickly to a dominant solution.

EVOLVING URBAN STRUCTURES [Finucane et al., 2006]

By focusing on a different design scale Finucane et al. developed a sophisticated evolutionary system whose purpose is to produce urban structures within a given site according to a project brief. The system is composed of a genetic algorithm and an 'ant' pheromone trail model. The former sets the basis for the solution while the development of the phenotype [embryology] is achieved through the later.

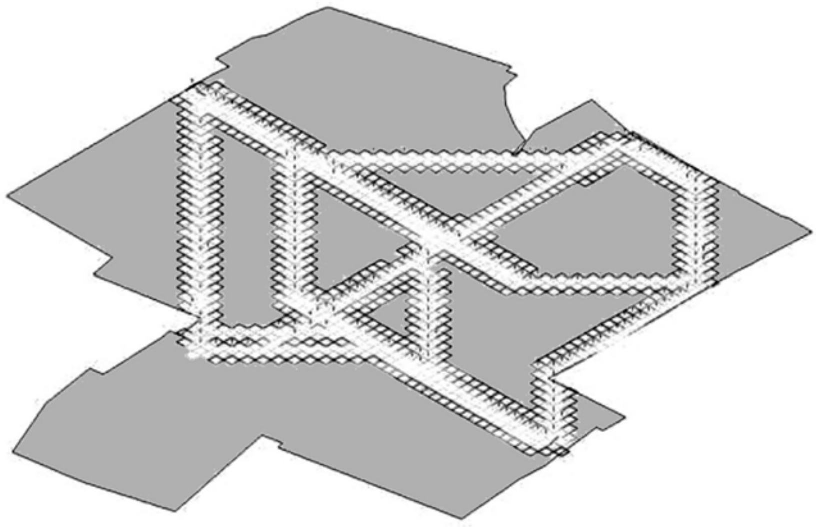


Figure22 Ant's pheromone trail [Finucane et al.,2006]

In particular, the GA randomly locates amounts of ‘food’ that represent the uses defined by the brief. Thereupon, within each evolution run and for each individual, the ‘ant’ pheromone trail model is executed for the determination of the optimal movement paths and building locations [for the particular ‘food’ distribution]. The evolutionary process is guided through the interaction of the intertwined systems.

Additionally, the genetic algorithm executes a multi-objective optimization through the classification of non dominated solutions to ‘Pareto’ fronts. The individual’s fitness value does not depend on its general performance, but rather to the balanced or unbalanced fulfilment of the criteria.

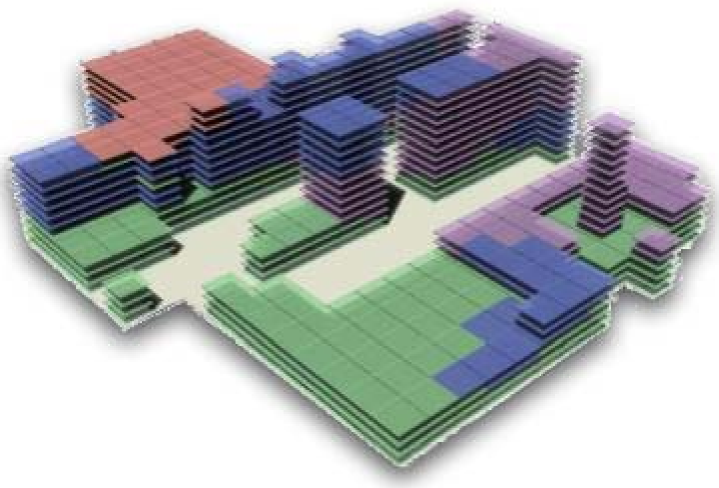
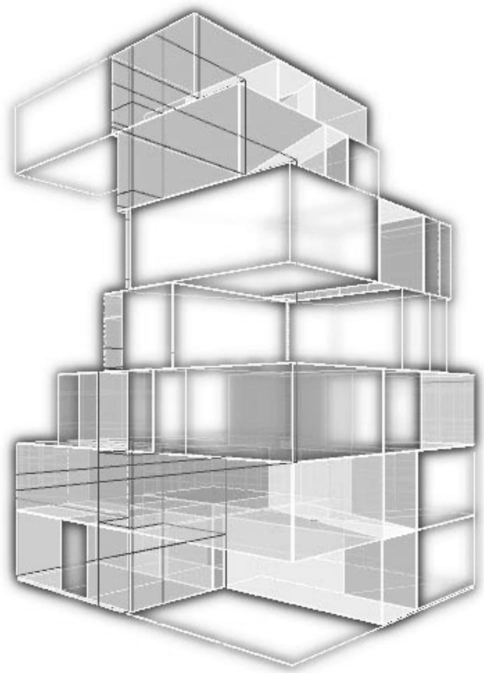


Figure23 Generated urban structure [Finucane et al.,2006]

2. AIMS AND OBJECTIVES



Based on the framework that was described in the literature review, an evolutionary system was created in order to show that a different approach to the automated layout planning is possible.

This thesis attempts to demonstrate that an efficient evolutionary system, whose purpose is to generate floor plans, can be driven by a computationally independent process [embryology] that assigns activities to existing spaces according to a set of rules [preferences]. These rules can be encoded in terms of required dimensional attributes as well as permeability graphs. The evolution of spaces and the assignment process are intertwined in the same system. The space configuration restrains the movement and the decisions of the ‘assigner’. Simultaneously, the ‘assigner’ evaluates the resulted allocation of activities and inducts the evolution of configurations towards the one or the other direction.

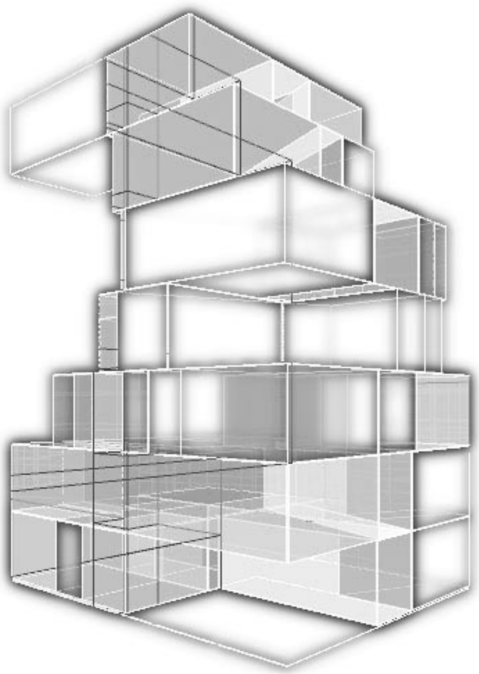
Most of the cases presented earlier [see related work section], implement advanced methods in order to find optimal solutions in the problem of assigning a set of activities within a plan. However, they don’t consider the generative power that the cultural and social structures have over the formation of the built environment.

As it is previously mentioned, Hillier and Hanson [Hanson,1998 and Hillier and Hanson,1984] stress out that there is an underlying social structure that has the role of a ‘genotype’ in the generation of buildings. Different buildings have different layouts because either they host different sets of activities, or the allocation of their activities is inducted by different cultural backgrounds. In both cases, the needs in the implementation of control and power over the given set of activities form a genotypical set of instructions.

In this thesis it is argued that this very set of instructions can be used as the driving force within an evolutionary process in order to direct the evolution towards solutions [e.g. spatial configurations] that can host a set of activities in the same general way that a particular type of buildings already does. It is an effort to create a generative system whose generative power is based on the way that societies have inducted the evolution of their environments.

For the creation of the aforementioned system, the PROCESSING programming language was used. The system was implemented within the context of a real example, namely the typical multi-storey residential building in the centre of Athens. The system's efficiency will be tested against a conventional Genetic Programming algorithm whose activities are randomly assigned during the generation of the individuals.

3. METHODOLOGY



3.1 SPACE AS PROGRAM

Architectural design nowadays strives to adopt the methodologies and the tools of computer science. Some of the uses of computation in architecture include analysis, reproduction, generation and optimization of design artefacts. Regardless of the reason for which one implements computation in the general field of architecture, there is a common basis that is required. Since computation processes information in mathematical terms, there is a need to describe space and spatial attributes in terms of numerical values.

There have been created numerous systems that take as input these numerical values and produce an elaborated output. If we consider these inputs as a representation of space then, the output is consequently an elaborated space. As already mentioned, evolutionary design describes a design solution in terms of a set of numerical values that is the genotype of the solution. The objective of applying genetic algorithms is to evolve an optimized version of these parameters in order to satisfy some criteria.

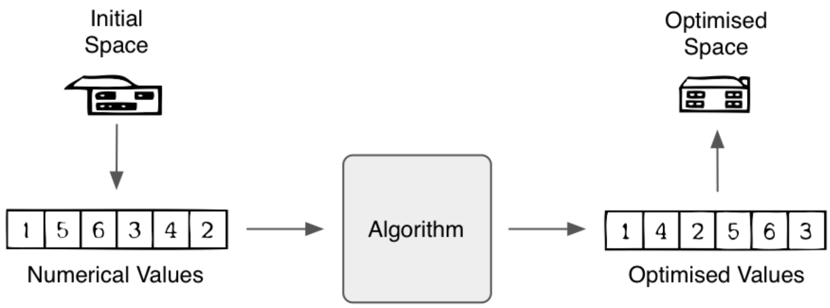


Figure24 Numerical representation and manipulation of space

The restriction of GAs is that they function upon a fixed length genotype. By evolving a predefined set of parameters in a predefined order that compose the genotype, the search space of the evolutionary algorithm is reduced extensively. Consequently, there is no way to ensure that the optimal solution will be within the search space in the first place.

Koza [Koza,1992] proposed, a kind of evolutionary algorithms that they elaborate a genotype of variable size and structure. Genetic Programming [GP] is based on the notion that the magnitude and the structure of the attributes in the optimal solution is part of the answer and not part of the question [Koza,1992, p.2].

A very interesting point that Koza [Koza,1992,p.3] stresses out regarding genetic programming is that a wide variety of seemingly different problems from different fields can be recast as requiring the discovery of a computer program that produces some desired output when there is an appropriate evaluation method. Hence, several different problems can be translated into problems of "program induction".

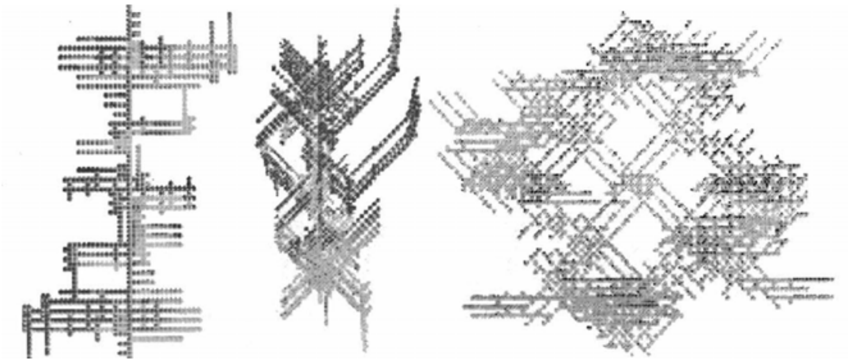


Figure25 Aggregated spheres within an isospatial grid [Coates,1999]

GP has already been implemented in order to generate form either as aggregation of spheres within an isospatial grid [Coates,1999] or as combination of 3D objects [Coates and Hazarika,1999]. Coates proposes that the tree-like structure of programs-genotypes within a GP can be implemented in terms of Lindenmayer-Systems. Both Koza and Coates use LISP for their algorithms. In LISP all the solutions are expressed in terms of S-expressions, tree-like structures whose nodes can be either functions [intermediate nodes] or values [terminal nodes].

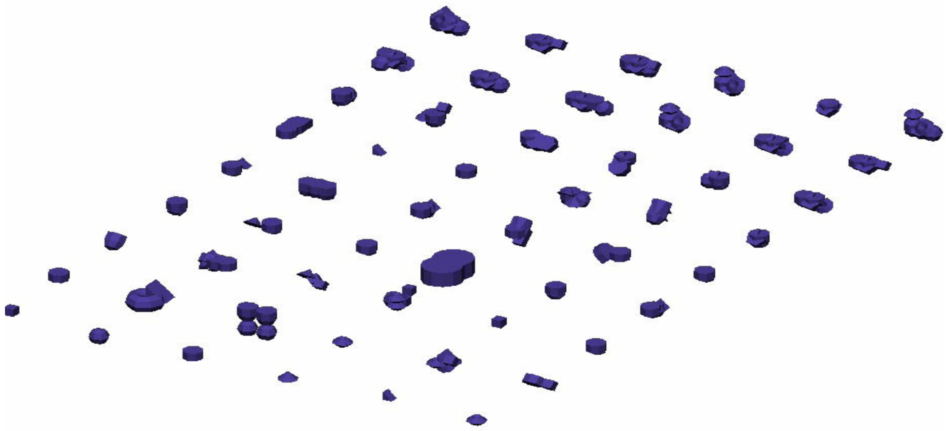


Figure26 GP Population of 3D object's combinations [Coates and Hazarika,1999]

3.2 STRUCTURE OF THE GENOTYPE

Within this research, the problem of layout planning is considered as a ‘program induction’ problem whose tree-like solutions are of unknown size and complexity. The programs’ genotypes are expressed as tree-like recursive structures whose arguments [terminal nodes] are dimensions of spaces and whose functions [intermediate nodes] are manipulating operations over the sub-dependent spaces. The individual’s generation process involves a randomly generated genotype, whose tree structure describes a unique spatial formation.

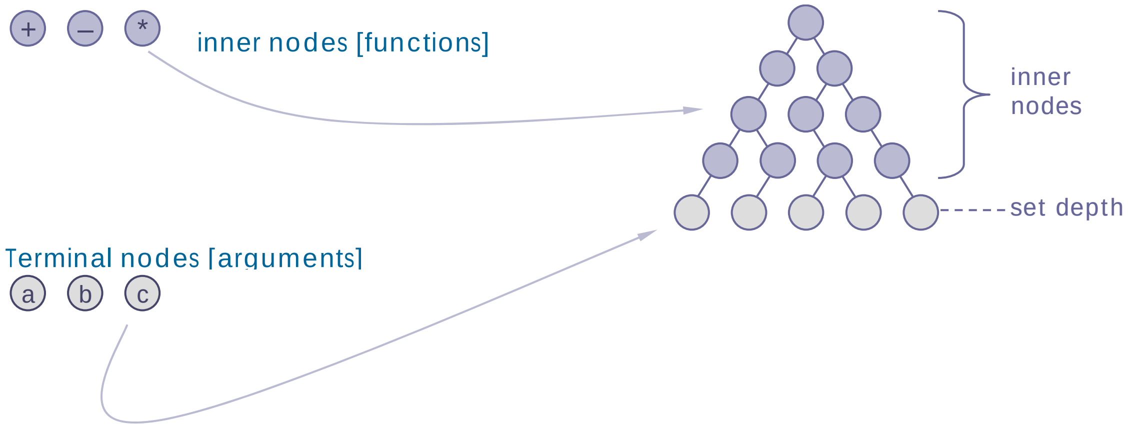


Figure27 GP genotype’s structure [Sean Hanna unpublished]

During the development of the research, two methods were followed for the production of configuration of spaces [aggregation and subdivision method]. Both approaches share the same tree-like genotype representation but they differ in the way their operations manipulate space.

3.2.1 AGGREGATING SPACES

The first attempt to describe a spatial configuration was based on the aggregation of spaces. The program’s genotype is composed by arguments and functions. The arguments are spaces which have two variables [width and height], whereas the functions are transformation operations [move forward, rotate and scale according to variables] that apply to the sub-dependent arguments [e.g. the spaces].

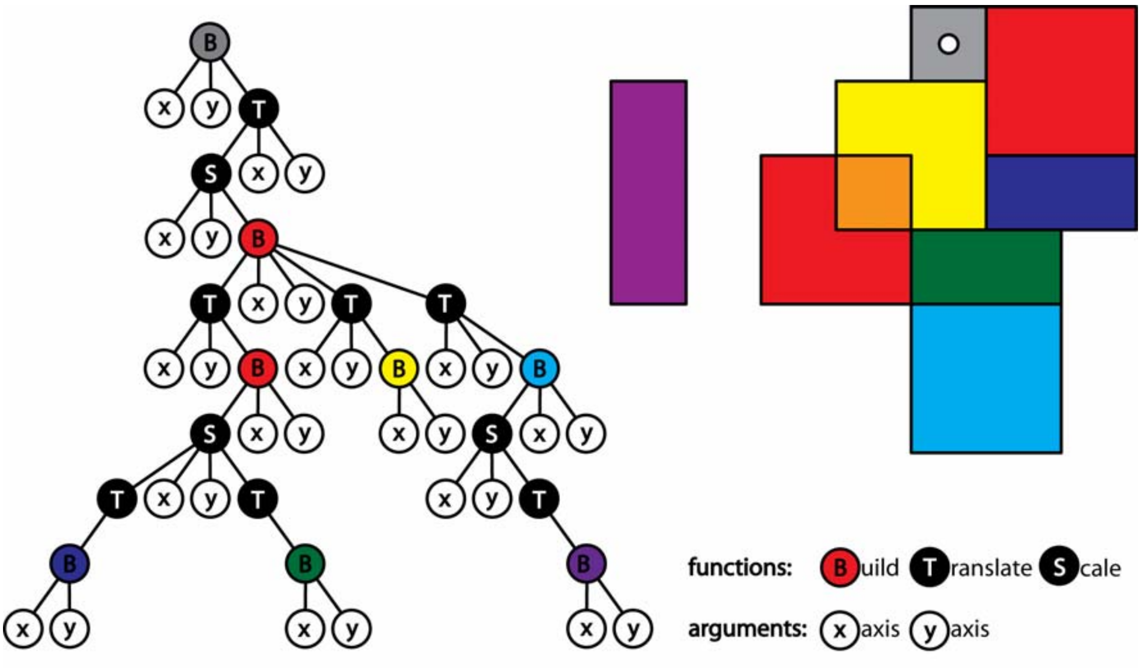


Figure28 Aggregation of spaces genotype-phenotype

Further experimentation with that strategy within the GP algorithm showed that it was extremely difficult to achieve the right distances among the spaces, so as to avoid separation or overlapping. The evolution of solutions seemed a confusing process that punishes the individual genotypes when their spaces were far apart and when they were overlapping. It seemed impossible to reach a point where the connections among spaces would really matter. Additionally, this strategy is rather inefficient when the outline of the site is given, which is the case in most layout planning problems. In order to address these issues, a reversed strategy [subdivision of space] was used.

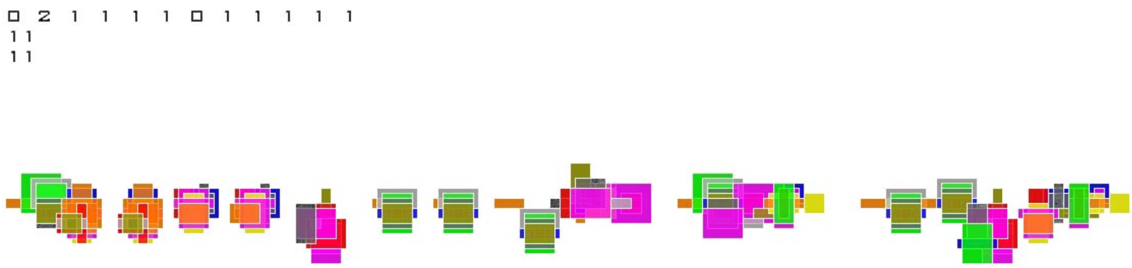


Figure29 GP population [aggregation of spaces]

3.2.2 SUBDIVIDING SPACE

For the creation of configurations of spaces, the second and more efficient approach was to start with an initial rectangle that is recursively subdivided until a certain depth. The spaces which are produced from the final subdivision are the spaces of the configuration. This strategy is more efficient since within a configuration, spaces are separated by walls which constitute a common edge. When a shape is divided into one or more parts, the sum of its parts constitutes the whole, and it is analogous to the subdivision of a given site to a building's spaces [the unoccupied spaces can be considered as spaces of null type].

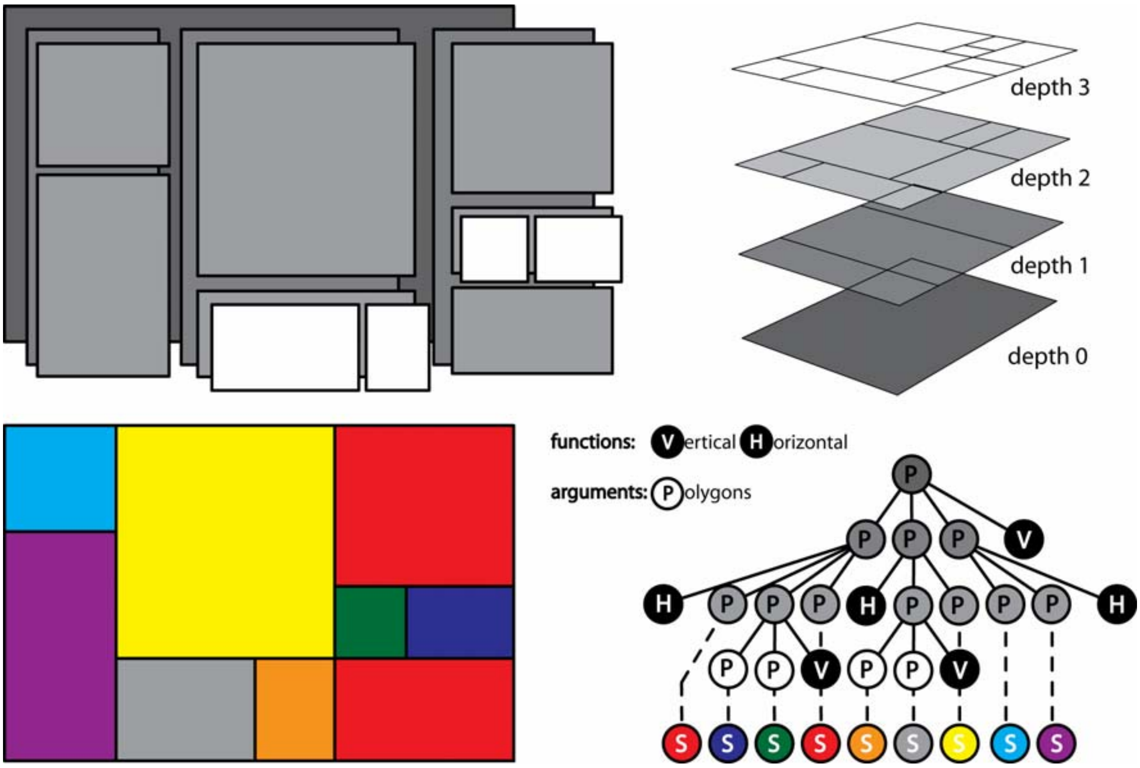


Figure30 Subdivision of space genotype-phenotype

In this case the program genotype is composed out of variables [number of the sub-dependent spaces and the percentage of each subdivision], and functions [direction and angle of the subdivision].

3.3 MANIPULATION OF GEOMETRY

Since the aforementioned tree-like genotype structure can produce the required variations in shape and size of solutions, the next step was to find the way that the tree-structured genotype would describe a configuration of spaces.

3.3.1 RECTANGULAR SPACES

Initially, the subdivision of spaces could occur only rectilinearly. The initial site in that case is always a rectangle and the transformation operations of the genotype describe the analysis of a rectangular space to smaller rectangles.

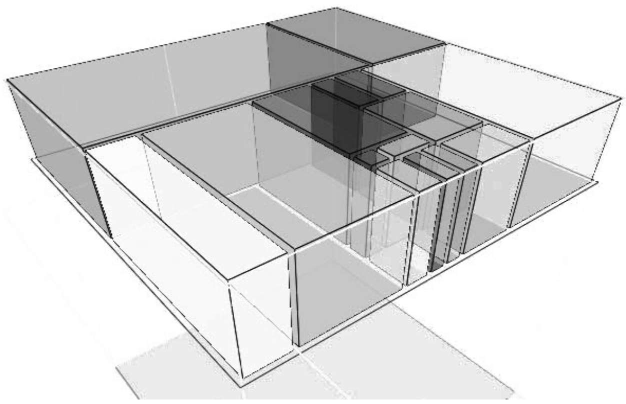


Figure31 Rectilinear subdivision

3.3.2 POLYGONAL SPACES

As already analysed [related work section], most approaches to the automated layout planning problem manipulate rectangular spaces. Even those works that end up with nonrectangular shapes [Rosenman,1996 and Gero,1998], their polygonal spaces are the result of the aggregation of unitary rectangular elements.

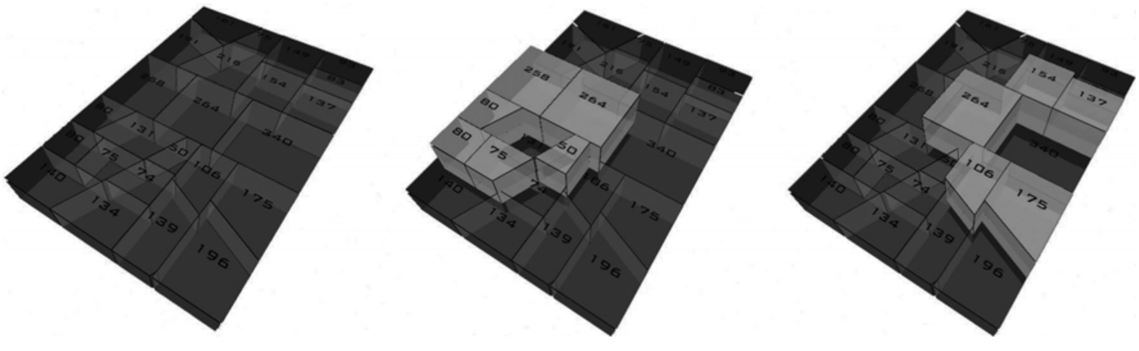


Figure32 Polygonal subdivision

Whereas a rectangular space could efficiently be subdivided to rectangular spaces there was a need for a more flexible strategy that could consider space as a polygon and not as a rectangle. It is worth mentioning that in this case, one could easily remain within the borders of rectangular spaces since a rectangle is a polygon. Nonetheless, by considering space as polygon allows non-rectangular shapes to be included in the generation of solutions and widens the search space towards more realistic configurations.

3.4 EMBRYOLOGY-THE ASSIGNMENT OF ACTIVITIES

The development of the individual's phenotype occurs after the execution of an individual embryology process. Thus, as in Finucane et al. approach [Finucane et al.,2006] the resulting configuration results from the interaction among the evolutionary and the embryology algorithm.

After the spatial aggregations are generated by the GP genotype, the assignment of activities is initialized. This is accomplished through an agent based algorithm that traverses through each configuration and assigns activities to spaces according to geometrical and topological requirements.

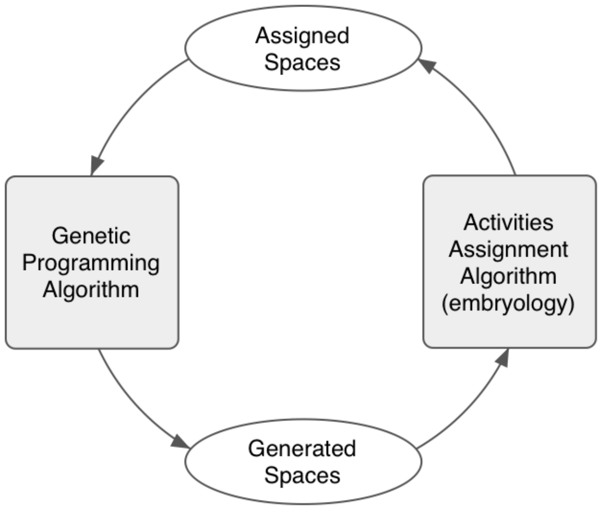


Figure33 intertwined GP and embryology algorithms

3.4.1 ENCODING OF GENERAL PREFERENCES

Initially, a way to encode these requirements was needed. Additionally, as these requirements vary among different social and cultural groups they are referred to as preferences.

In this application model these preferences involve the quantities of activity types, the magnitude for each activity, the ratio of spaces, the preferred locus of each activity [external, internal etc] and the connectivity among the activities. In all the above cases the requirements are encoded in terms of matrices and refer to a set of predefined space-types.

These space types are:

a. vertical communication
b. entrance
c. living room
d. corridor
e. wc
f. kitchen
g. bathroom
h. study-room/workshop
i. diner
j. room
k. terrace
l. storage

The needs in activities are scripted in terms of a one-row matrix. The number at each place of the matrix defines the existence and the number of the space-type that corresponds to that particular place. The area requirements are described with a matrix of floats that defines the minimum and the maximum area value for each space-type.

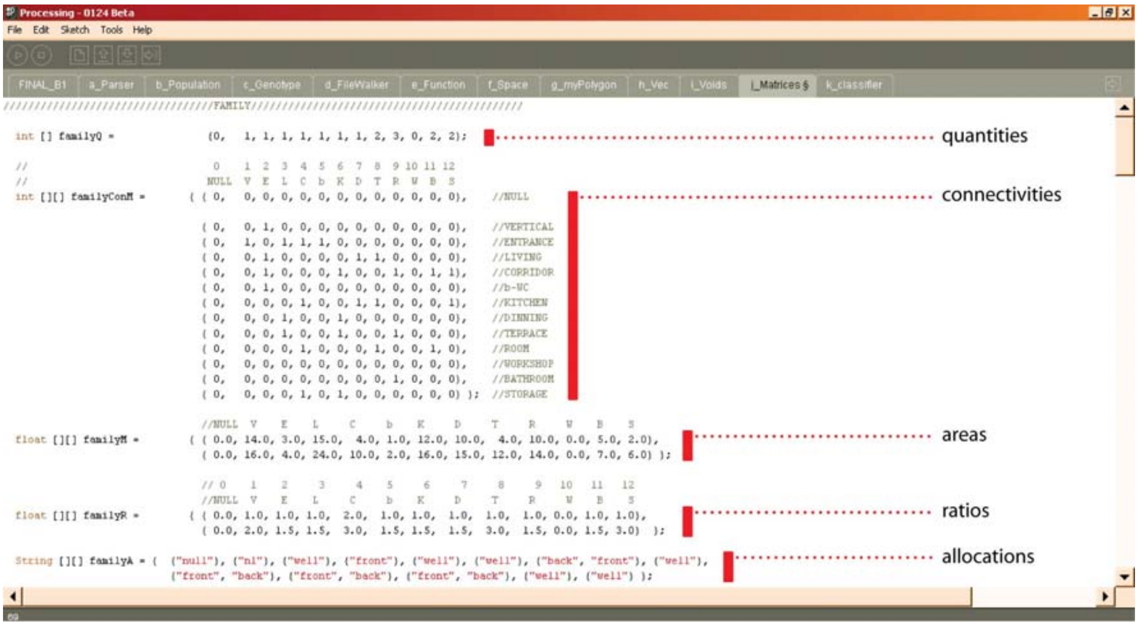


Figure34 Encoding of general preferences

That is also the case for the ratio requirements. As for the connectivity requirements, the correspondent matrix is a square matrix that each space-type corresponds to a row and a column. When an element of the Matrix is 1, the space-types that correspond to the row and the column should be connected, whereas if it is 0, a connection is not required. The locus requirements are described in terms of a matrix that instead of numerical values contains strings. For each position, these strings inscribe the accepted positions of the correspondent space-type [for instance front, back, middle].

3.4.2 ENCODING OF GAMMA MAPS

As it is argued in this research, even though the aforementioned requirements are necessary in order to describe a residential layout, they are not enough. The social and the cultural forces that generate the particular kind of layouts can be scripted through the use of justified gamma maps.

Gamma Maps describe the topological relationship among the activities. This topological relationship can be described through a pair of matrices, a downward and an upward matrix. The downward matrix defines the ensuing activities and for each space-type contains the spaces which this particular activity leads to. The upward matrix defines the preceding activities and for each space-type contains the spaces which this particular activity follows.

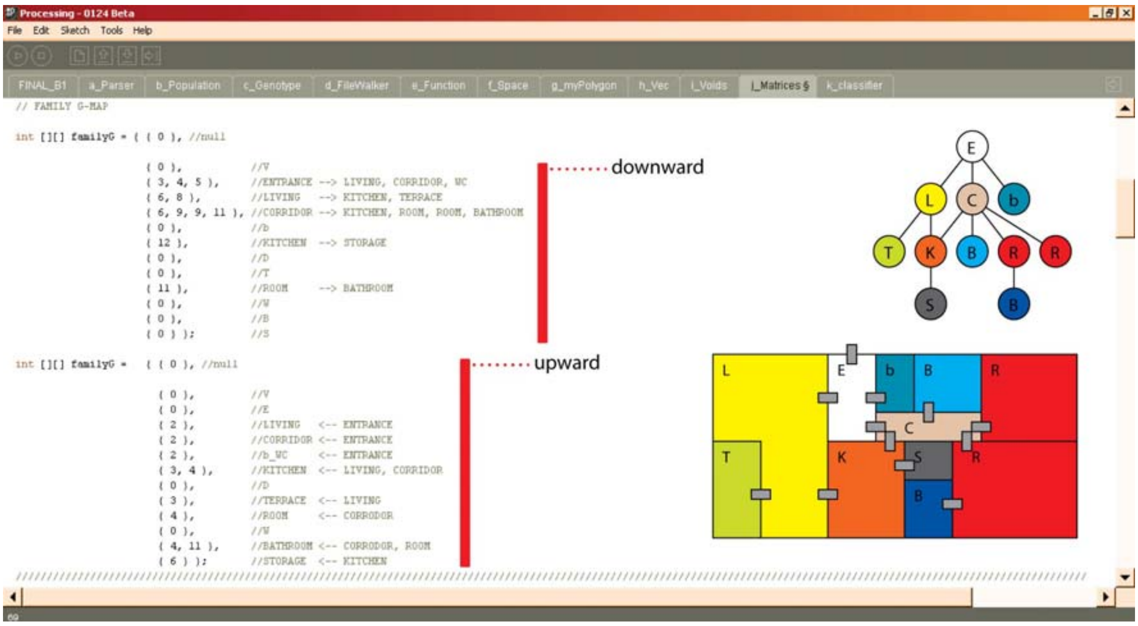


Figure35 Encoding of gamma-maps

3.4.3 ITERATION OF SPACES AND ASSIGNMENT OF ACTIVITIES

In this model the agent's start point is considered to be the entrance even though this is not mandatory. Initially, a search amongst the existent spaces is executed for the most suitable host space for that activity. All the spaces that meet the locus criterion are stored within a vector. Thereupon, each space within that vector is evaluated depending on how it performs against the magnitude and ratio requirements. The fittest space is then selected as the entrance of the layout.

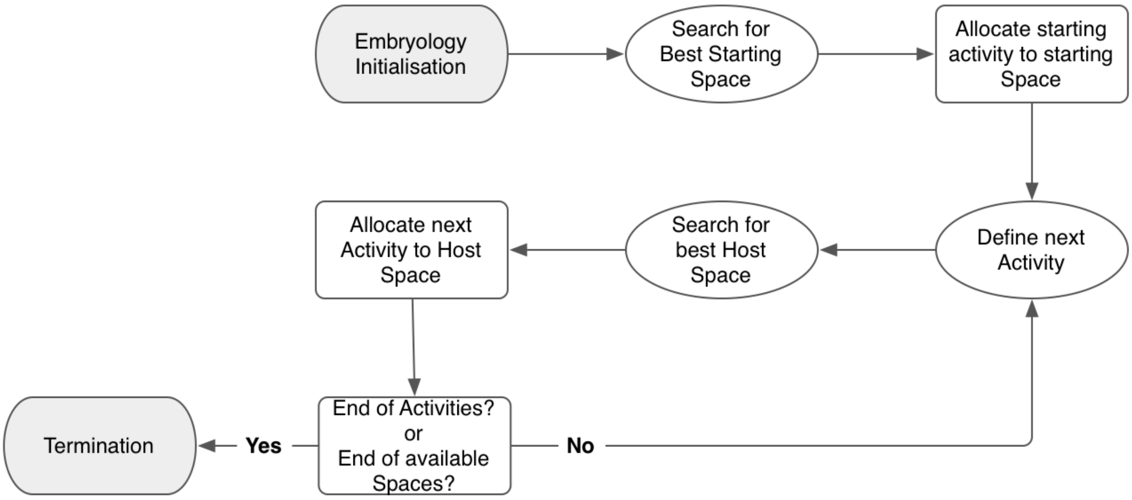


Figure36 Activities assignment algorithm

Successively, the space operates a search for the more appropriate host-space for each activity contained within the downward gamma graph matrix. All the unassigned places that are adjacent to the parent space [initially the entrance] are stored within a vector. Thereupon, each space within that vector is evaluated. The evaluation considers the area of the space, the ratio, the location and the upward gamma graph. The fittest space is then selected to host that particular activity. Once all the ensuing activities are assigned [if they can all be assigned] these activities become the next round's parent spaces and the same procedure is implemented recursively until the assignment of all of the required activities [or the assignment of all the activities that can be assigned within that particular configuration].

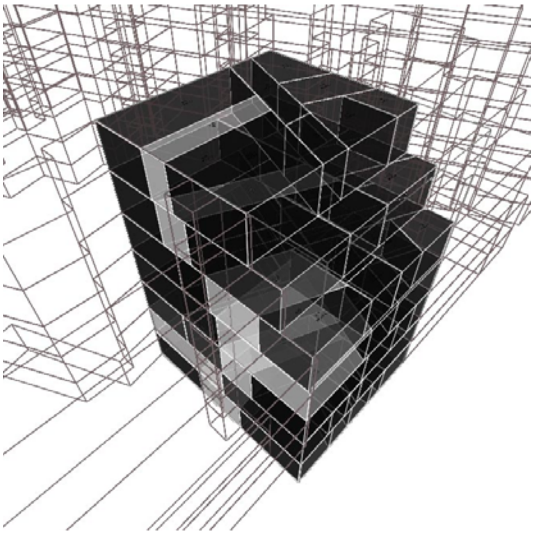


Figure37 Searching for starting spaces.

3.4.4 INITIALIZATION OF THE EVALUATION FUNCTION

Once the assignment procedure is terminated, the final evaluation procedure of the layout is initialised. The evaluation is based on how the predefined preferences have been met through the interaction of the configuration-generation procedure and the activities-assignment procedure. Hence, the fitness is not a direct outcome of the space; rather it is assigned through the performance of an agent within the created space. This is also the approach of Pablo Miranda [Miranda, 2004] in ArchiKluge applet which evolves built forms based on the performance of agents within the environment set by the genotype.

The different approaches to evaluate the result of a multi-objective evolutionary algorithm will be discussed in the next section.

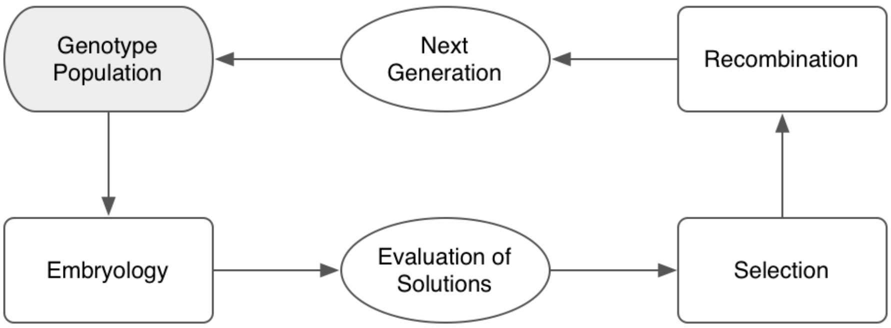


Figure38 Reproduction of the population

3.5 THE EVOLUTION OF CONFIGURATIONS

It is worth mentioning, that within the context of GP there is a problem to produce solutions which are 'valid' and don't cause a system crash when they are executed. The tree-structured genotype can handle the required variations in shape/size of the solutions and its creation method assures the generation of valid solutions, yet most of them are not good solutions. In order to proceed from merely valid solutions to good solutions, an evolutionary algorithm is implemented.

3.5.1 POPULATION OF INDIVIDUALS

Initially, the algorithm produces a population of randomly generated genotypes, whose initial site polygon is loaded from a dxf file. Then, in every run of the algorithm, this population is replaced by an offspring population whose genotype-individuals result from genetic operations applied over the individuals of the population of the previous generation.

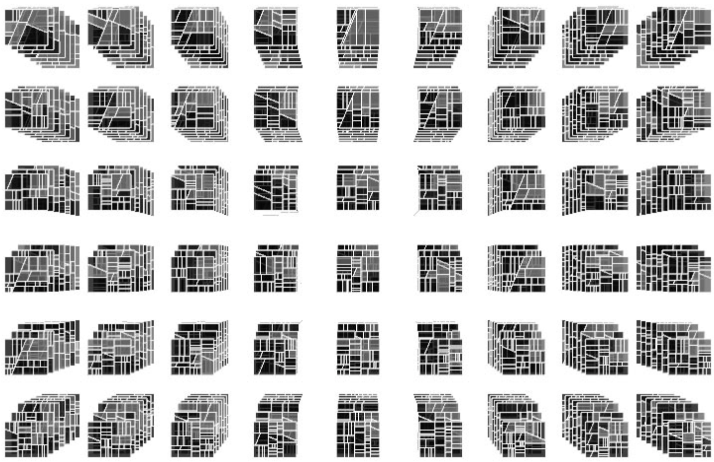


Figure39 One GP algorithm is executed for each floor

3.5.2 MULTI-OBJECTIVE EVALUATION AND SELECTION

The solutions are first evaluated against a set of criteria and they are assigned a fitness value for each criterion. These values are calculated according to the declination from the criteria's ideal values. Hence, the better a solution may perform in respect to a particular objective, the lower this objective's fitness value will be.

There are several methods that calculate the solutions' total fitness value. Particularly, the Weighted Sum, the 'Pareto' Optimisation and the Ranking Sum methods will be discussed in the following paragraphs.

WEIGHTED SUM

In this case, the total fitness value is the weighted sum of the partial fitness values. The individuals are then ranked according to their fitness value and the selection of the parents for each offspring is a probabilistic selection based on the solutions' ranking.

Even though this is a widely used practice, it is often criticised, for the "good-fitted" solutions that it produces can be dominated by a good performance of that solution on a sole objective fulfilment. Moreover, weights' values have a direct impact on the solution's evolution. Nevertheless, it is very difficult to enumerate all their possible 'tunings' in order to find the weights' combination that produces the best results.

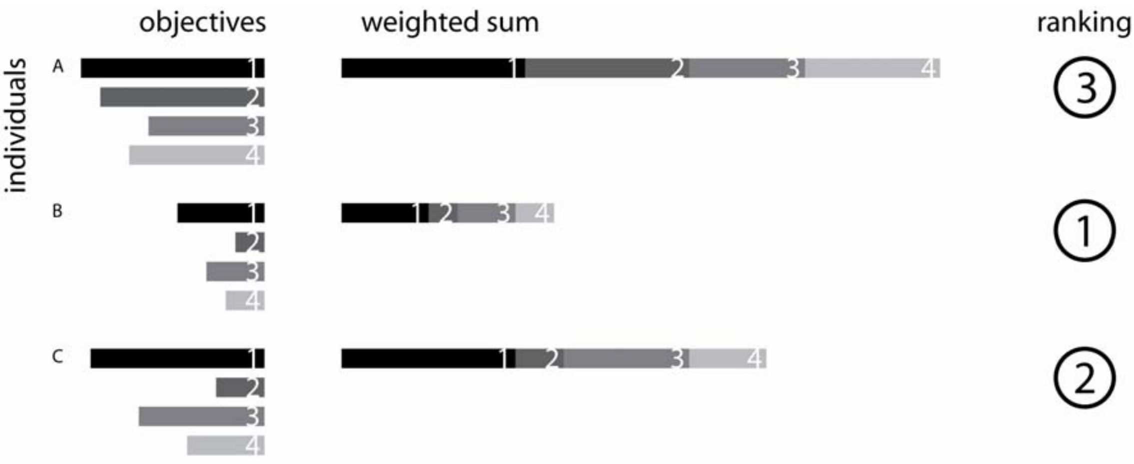


Figure40 Weighted Sum Fitness function

PARETO FRONTS

For the overcoming of these issues, some advanced strategies have been developed that focus on non-dominated solutions. One of these methods classifies the population's individuals among 'Pareto' fronts. The 'Pareto' fronts are groups of solutions with a particular grade of non-dominance. As Cvetkovic and Parmee argue while the application 'Pareto' fronts present very good results, it is extremely computationally expensive to implement [Cvetkovic and Parmee,1998].

RANKING SUM

Another method was instead developed in order to achieve the multi-objective optimization. This method was based on the notion of the ranking selection, only that it extends that idea to each criterion and not only to the total fitness. The individuals are ranked once for each criterion. The performance of each solution is then calculated as the sum of the rankings of that particular solution for each one of the objectives. Then the individuals are ranked according to the total ranking.

This method evaluates the individual's performance based on its relative performance in the satisfaction of each criterion separately. Thus, there is no need to calculate each criterion's weight, because the only thing that matters is the ranking [e.g. the relative performance] for each objective. Additionally, it is more difficult for a sole objective to dominate, though not impossible. Weighted sum and Ranking Sum were both implemented in order to test the efficiency of each method.

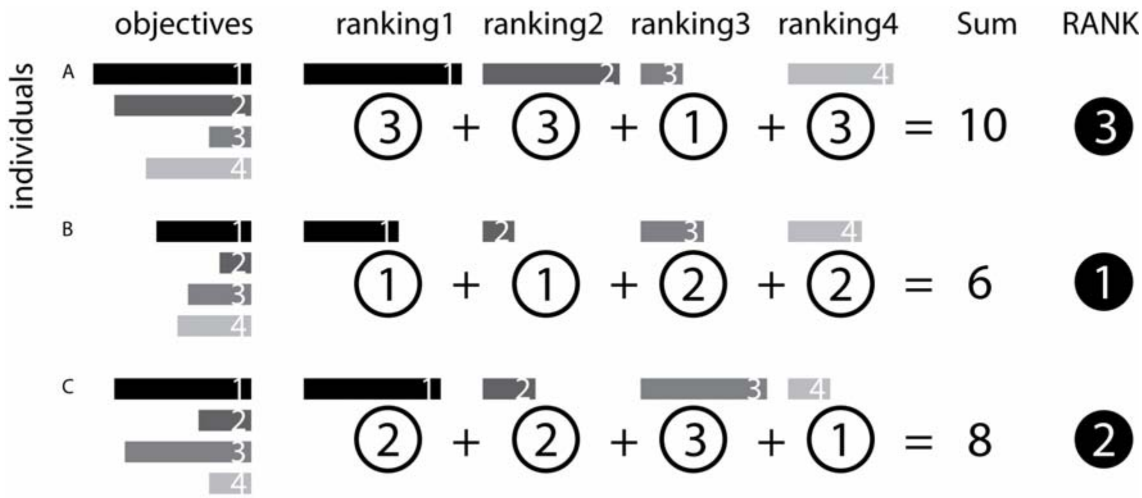


Figure41 Ranking Sum Fitness function

SELECTION

There are several methods to select the parents of the next generation's individuals; for example the probabilistic selection according to their fitness value or the eyeball test where the user selects manually the parents.

In our research the Ranking Selection Method is adopted. Once the evaluation of the individuals is executed, either with the Weighted Sum or the Ranking Sum, the individuals are sorted form the best fit to the worst fit. Thereupon, a probability selection according to the ranking of the solutions defines the parents of the next generation's individuals.

3.5.3 GENETIC OPERATIONS

The genetic operations [GO] which are applied over the parent genotypes aim to recombine the genetic material of the good-fitted solutions in order to produce better-fitted solutions. These genetic operations are divided into the sexual and the asexual GOs. The sexual GOs recombine the genetic material from two parents in order to produce one offspring [e.g. crossover] while the asexual operations recombine the genetic material of one sole genotype in order to produce an altered version of that particular individual [e.g. mutation].

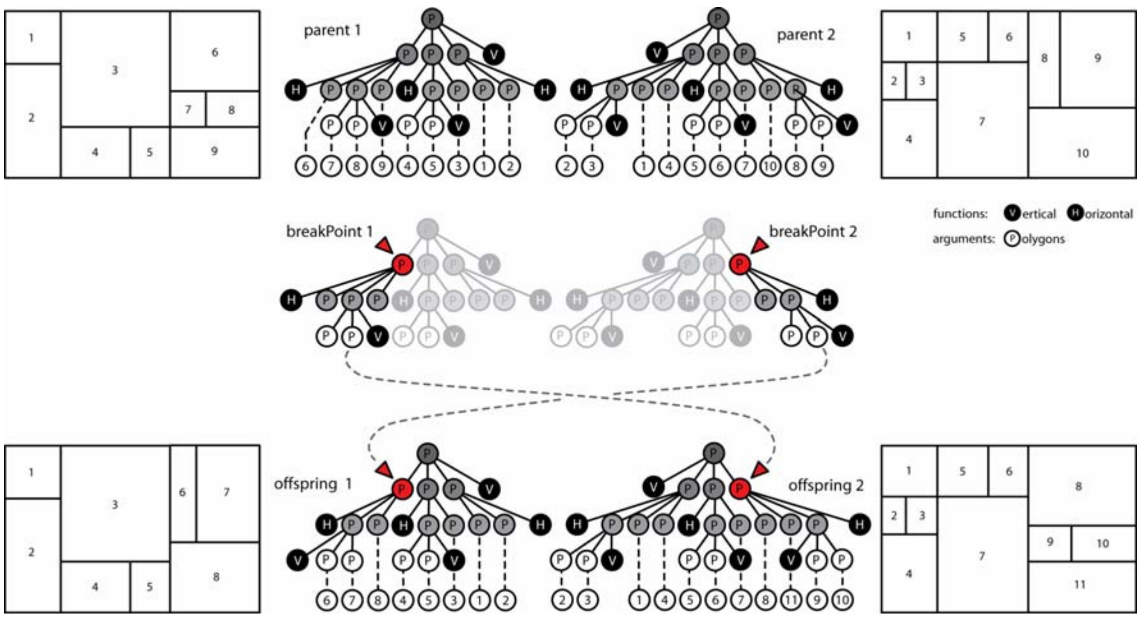


Figure42 Crossover genetic operation

CROSSOVER

The crossover GO is implemented over two parent-genotypes selected as described above [Figure42]. The crossover selects randomly a break-point in each tree-structured parent-genotype and exchanges the sub-trees that depend on these break-points. Hence, the offspring genotypes combine a part from both parents' subdivision instructions.
`

MUTATION

The mutation GO is implemented with a small probability over the offspring genotypes that result from the crossover GO. Mutation selects randomly a break-point in the genotypes' structure and removes the sub-tree that depends on that break-point. Thereupon, a new randomly created tree-structured genotype is added to the offspring genotype as a sub-tree whose root is the break-point.

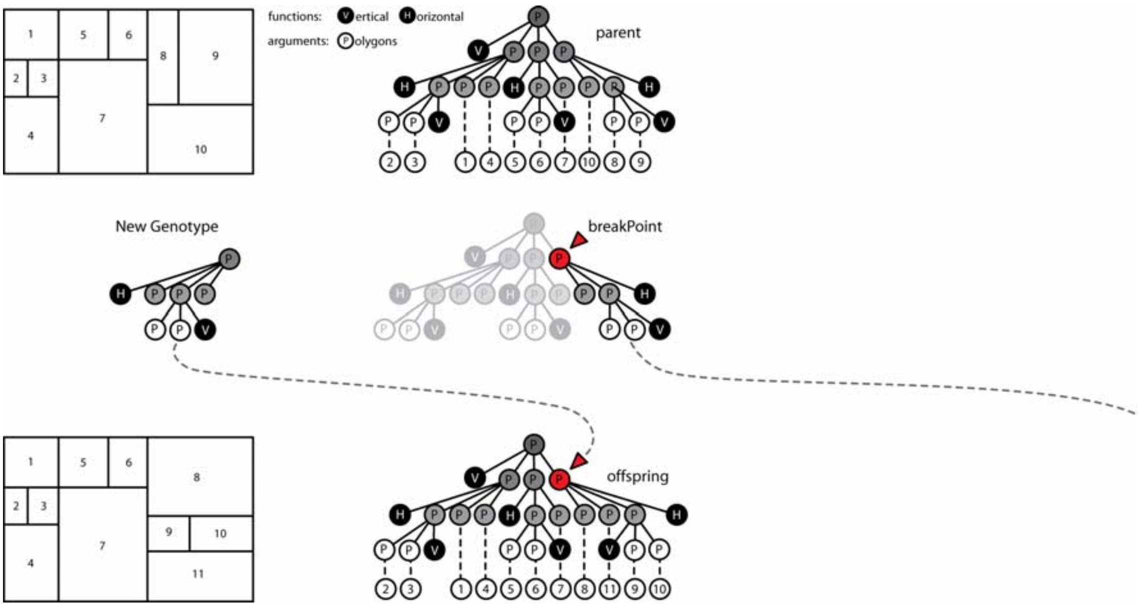


Figure43 Mutation genetic operation

ADF [Automatically Defined Functions]

As Koza [Koza,1991] proposes, sub-structures of programs that perform very well can be considered as useful sub-structures and can be used during a mutation GO instead of a randomly generated program. These sub-structures are called Automatically Defined Functions [ADF].

3.6 THE CONTEXT OF THE APPLICATION

3.6.1 MULTISTOREY RESIDENTIAL BUILDING IN ATHENS

The described methodology is implemented and tested within the context of the typical multi-storey residential building in the centre of Athens. A plethora of social, economic and cultural reasons whose description unfortunately exceeds the framework of this research contributed to the formation of that particular kind of social and built structure.

Figure44 Fragmentation of property in Patisia-Athens [Grigoratos and Sfiriou,2006]

In brief, land property is peculiarly fragmented and distributed amongst the population. The massive demands for residences in Athens alongside with the effort of the state to strengthen the country’s economy [whose one of the main sectors was the construction industry] accelerated the demolition of the old one-floor residences and the massive construction of multi-storey residences.

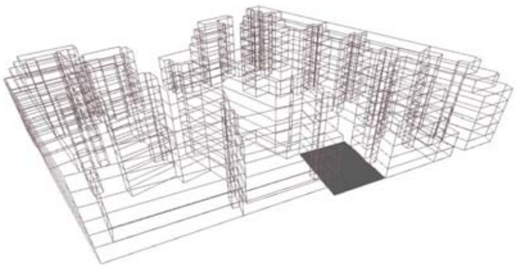
After the expansion of the metropolitan area, a big part of residents moved towards the suburbia. Hence, these buildings started to host non-residential activities. Nowadays, a set of different activities can be found within the same building, distributed among its floors.

Architects struggled to develop innovative and creative ways to design that kind of dense structure. The complexity of objectives and activities along with the demand for maximum use of the available space, restrained peculiarly the factor of aesthetics.

Figure45 Typical multi-storey residential buildings [Grigoratos and Sfiriou,2006]

3.6.2 APPLICATION OF THE MODEL TO THE CONTEXT

The program accepts as input a dxf file with the site and the neighbouring buildings. Then, it calculates the maximum height of the building and the available area for each floor. A set of rules/preferences is scripted for different user profiles and distributed among the floors of the buildings. As it is the case in reality, each floor has a degree of autonomy as each inhabitant can arrange the layout in order to fulfil their needs. However, the whole structure is composed of the aggregation of these distinct floors.



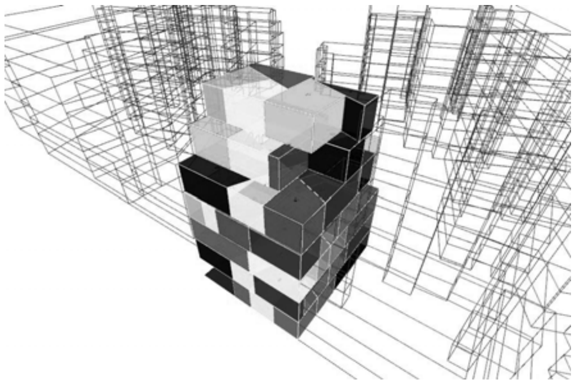
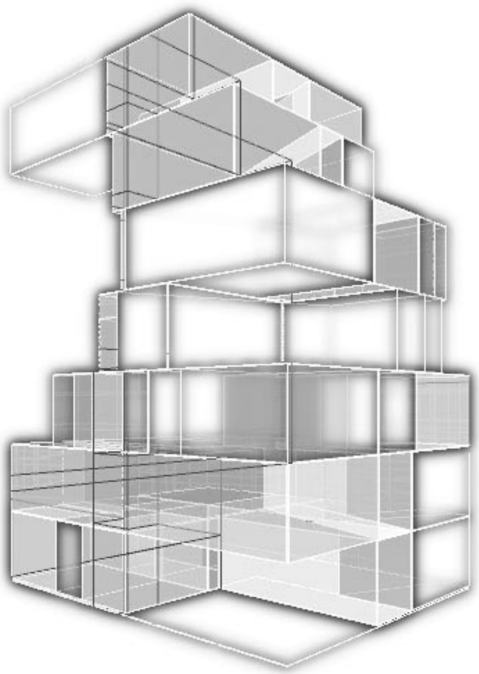


Figure46 Site and environment imported by .dxf file

Figure47 Generate building constrained by site and heights

The implemented user types are selected based on typical examples of inhabitants [see appendix II]. Even though a complete research would provide accurate data for more representative patterns of use, that process is out of the limits of this research due to restrained time and the non-existence of registered data. Moreover, the input data are not considered crucial for that research as its objective is the manipulation of the data for the generation of solutions and not the data per se.

4. FINDINGS



4.1 VERSIONS OF THE APPLICATION

For the testing of the model's efficiency several versions of the program were developed. The differences among these versions aim to compare each one's efficiency in solving the particular problem of automated layout planning as it has been outlined in the objectives and the methodology sections. Therefore, the results are tested against each other.

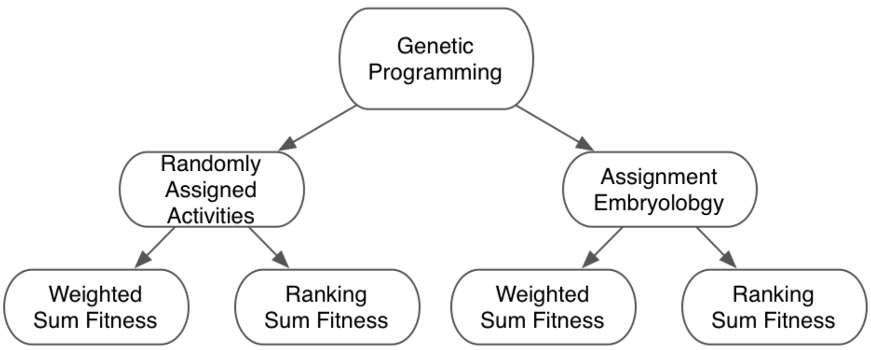


Figure48 Versions of the application

Apart from these variations, all four versions are identical and have been tested under identical conditions. The number of generations is set to 1500. Whereas further fine tuning of the algorithm's details would provide better results, the pros and cons of each strategy are depicted from their comparison.

4.2 PREASSIGNED ACTIVITIES vs. UNFOLDING ASSIGNMENT

An overview of the programs' results, gives the impression that the algorithm which is based on the pre-assigned activities is more efficient than the one which is based on the agent-based activities assignment. The evolution in the total fitness value of the fittest individual is by far more obvious in the first case as it can be observed in the following graph [Figure49].

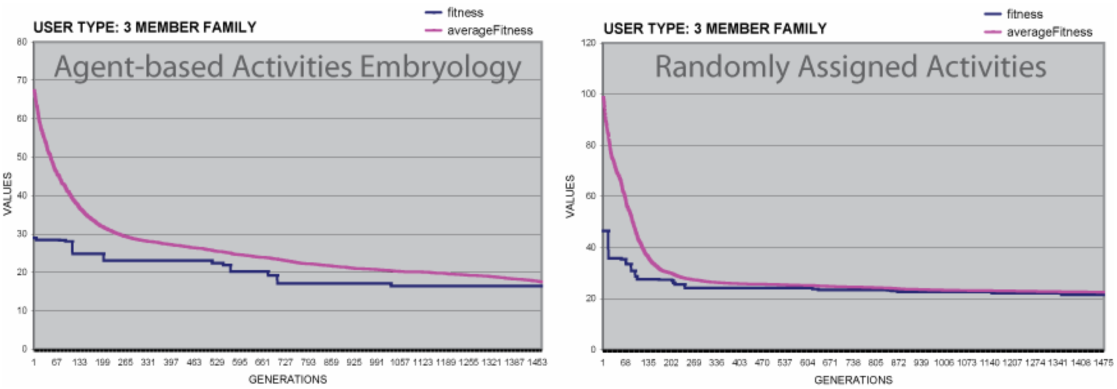


Figure49 Fitness of fittest and average fitness graphs

However, a scrutinised analysis of the data changes that first impression. As it has been explained [see methodology chapter], in the agent-based assignment process, a given configuration constitutes the input. The activities are then assigned to the existing spaces by following rules which define their sequence, and by performing an exhaustive search in order to find the most appropriate host space for each activity. Consequently, it is expectable that even from the early stages of the evolutionary algorithm the solutions will be relatively acceptable.

This is certified by the comparison of the total fitness values in the first generations of the algorithm [Figure49]. While the randomly assigned activities start with a total fitness value around 50, the agent-based assignment process starts with a fitness value around 30. Apart from the difference in the early stages, there is an important difference at later stages. It is observed that the agent-based process reaches better results than the randomly assigned activities. In the first case, the fittest solution reaches values below 18, whereas in the second the best total fitness value is stabilised around 25.

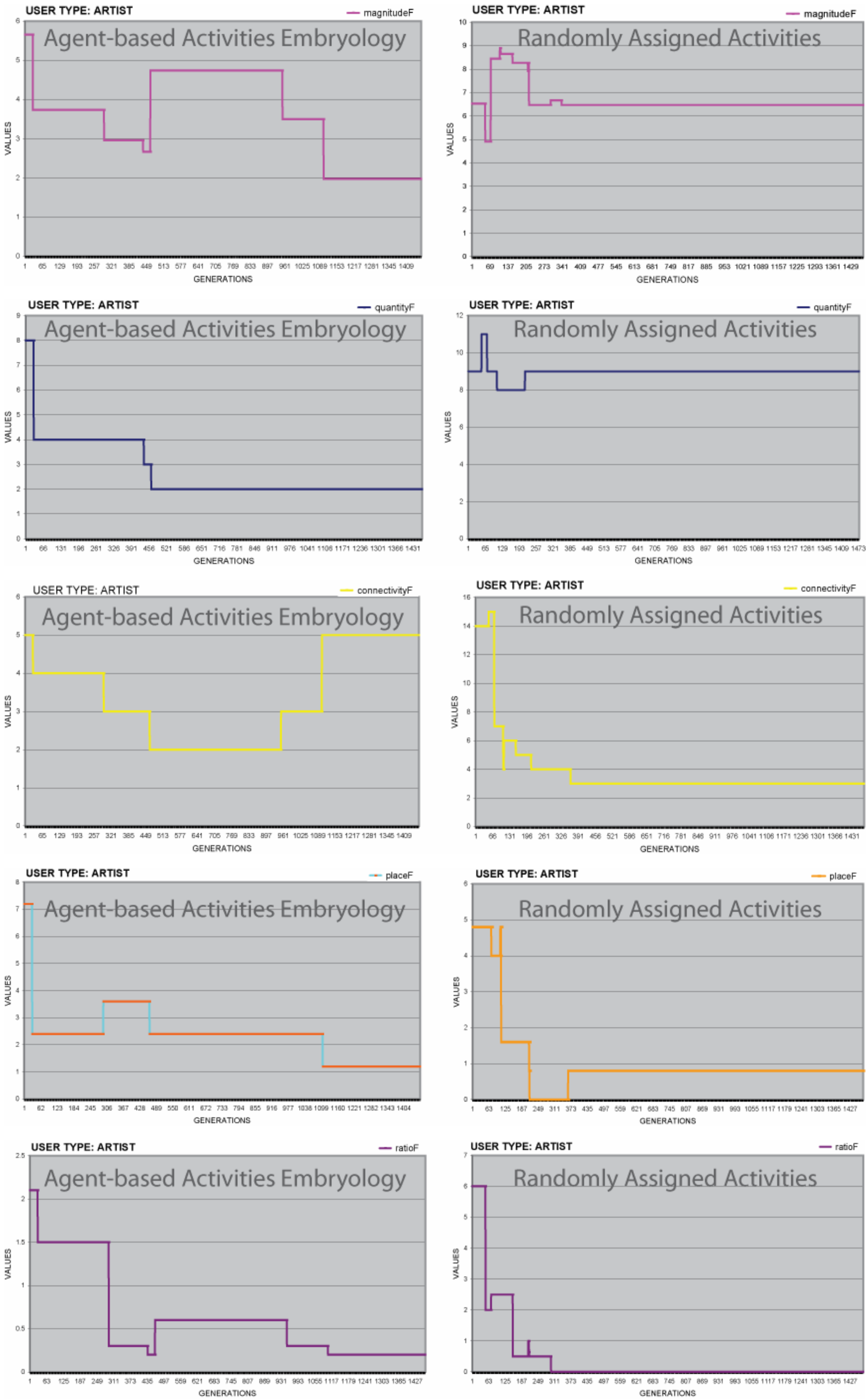


Figure50 Evolution of each objective in the two methods

The evolution of the fulfilment of the several criteria over the generations certifies the above finding [Figure50]. Generally, the starting fitness-values in the case of the agent-based process are better than the values in the random assignment process. In spite of the seemingly unstable [or even negative] course of evolution for some criteria in the first case, their final satisfaction results are better than in the second case. The evolutionary algorithm searches for the best equilibrium among the values of the criteria that produce the best result.

In general, the agent-based assignment of activities process [embryology] performs well in cooperation with the Genetic Programming evolutionary algorithm and produces better results than a merely random-based genetic search. Additionally, as seen from an architectural point of view, the resulting layouts are more rational in the first case than in the second [figures 51,52].

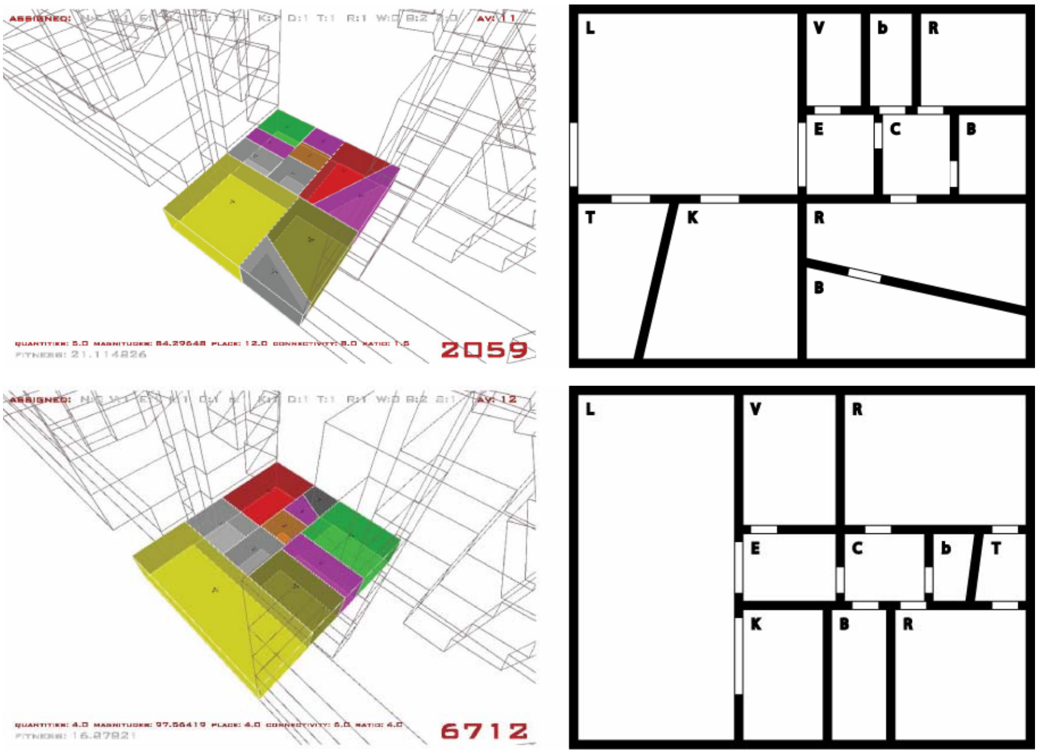


Figure51 Typical layouts [Activities Assignment Embryology]

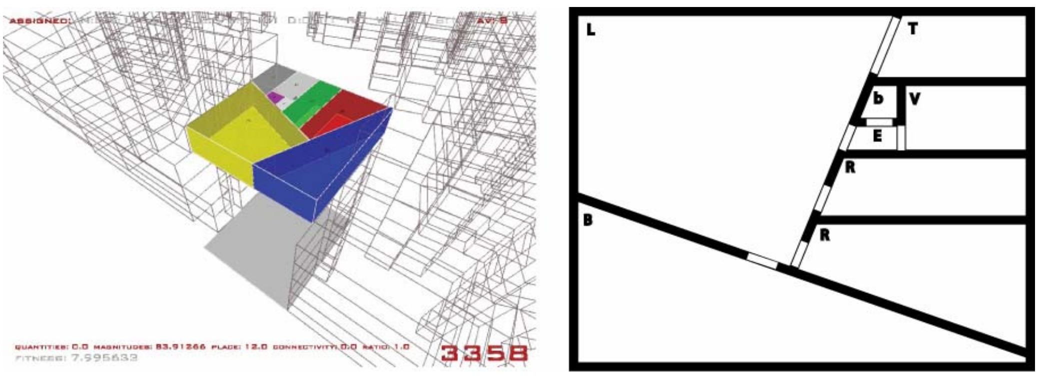


Figure52 Typical layout [Randomly Assigned Activities]

4.3 WEIGHTED SUM FITNESS vs. RANKING SUM FITNESS

There are also some interesting observations concerning the efficiency of the ranking sum classification criterion compared to the weighted sum criterion. As it can be observed in the graphs below [Figure53], even though the criterion for the sorting of the individuals was not the total fitness value [but the sum of the separate rankings, executed for each one of the criteria], the evolution of the total fitness value is evolved towards better values.

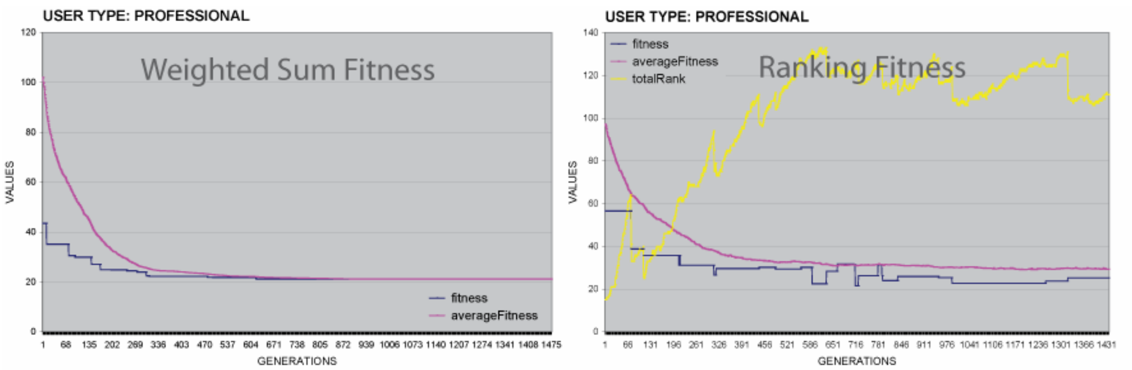


Figure53 Evolution of solutions.

The mechanism of the ranking-sum strategy justifies the temporary negative evolution in the total fitness value. As it has been explained [see methodology chapter], the weighted sum fitness value provides a hint of how well a solution performs within its environment and it's not an undisputable factor. Instead, the fine tuning amongst the several objectives defines the solution's good or bad performance.

In certain cases it might be better to spare a particular objective for a better tuning in return, and the ranking-sum strategy is efficient in taking such equilibrium decisions, as it can be observed through the study of the objective's graph and the produced configurations [Figures 54-57]. Besides, the 'negative' evolution of the total ranking value can be explained from the fact that evolution affects the whole population and not just the fittest solution. Consequently, the total ranking of the fittest solution decreases continuously, for the population is getting better, while it maintains the first position.

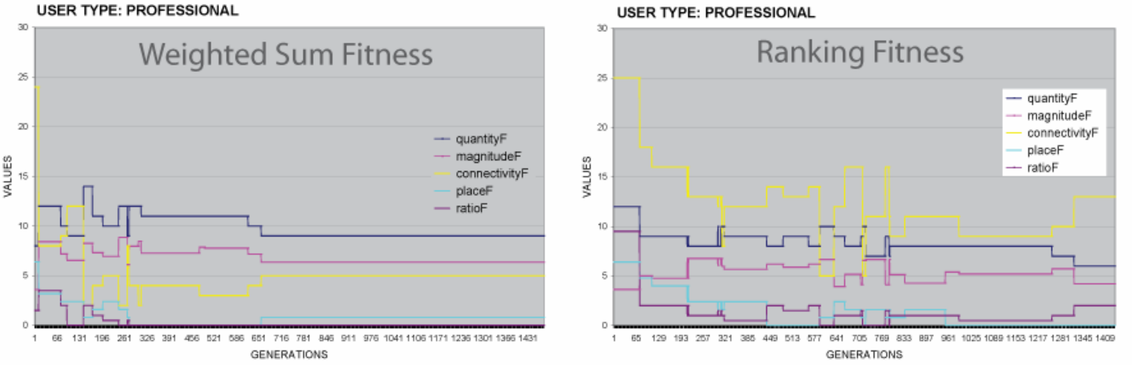


Figure54 Objectives' graph

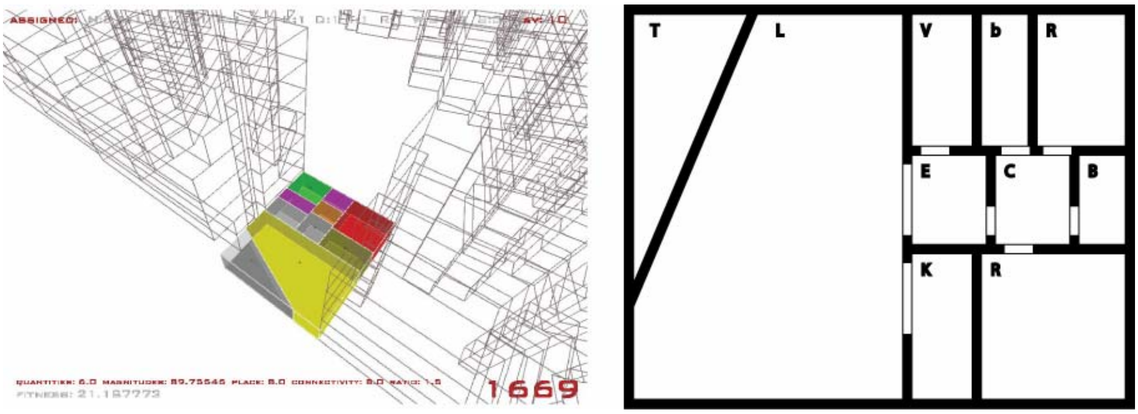


Figure55 Typical layout [Activities Assignment Embryology and Ranking Fitness]

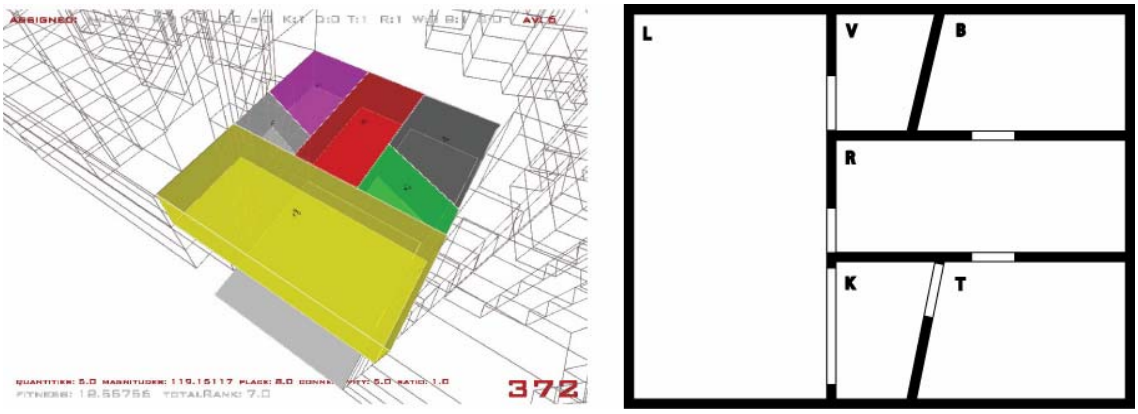


Figure56 Typical layout [Activities Assignment Embryology and Weighted Sum]

In general, the layouts which were produced with the ranking-sum evaluation strategy were more rational than those which were produced with the weighted sum strategy [figures 55-56]. However, the deciphering of the algorithms' data was not trivial, since it seemed that the data were in conflict with the resulting configurations. As it can be seen in the objectives' graphs below [Figure57] the fittest individual reached better total fitness values when the evaluation was based on the weighted sum method. What is really impressing is that even the objectives reach better values with the weighted sum evaluation. A thorough observation of both evaluation mechanisms provides the answer to that riddle.

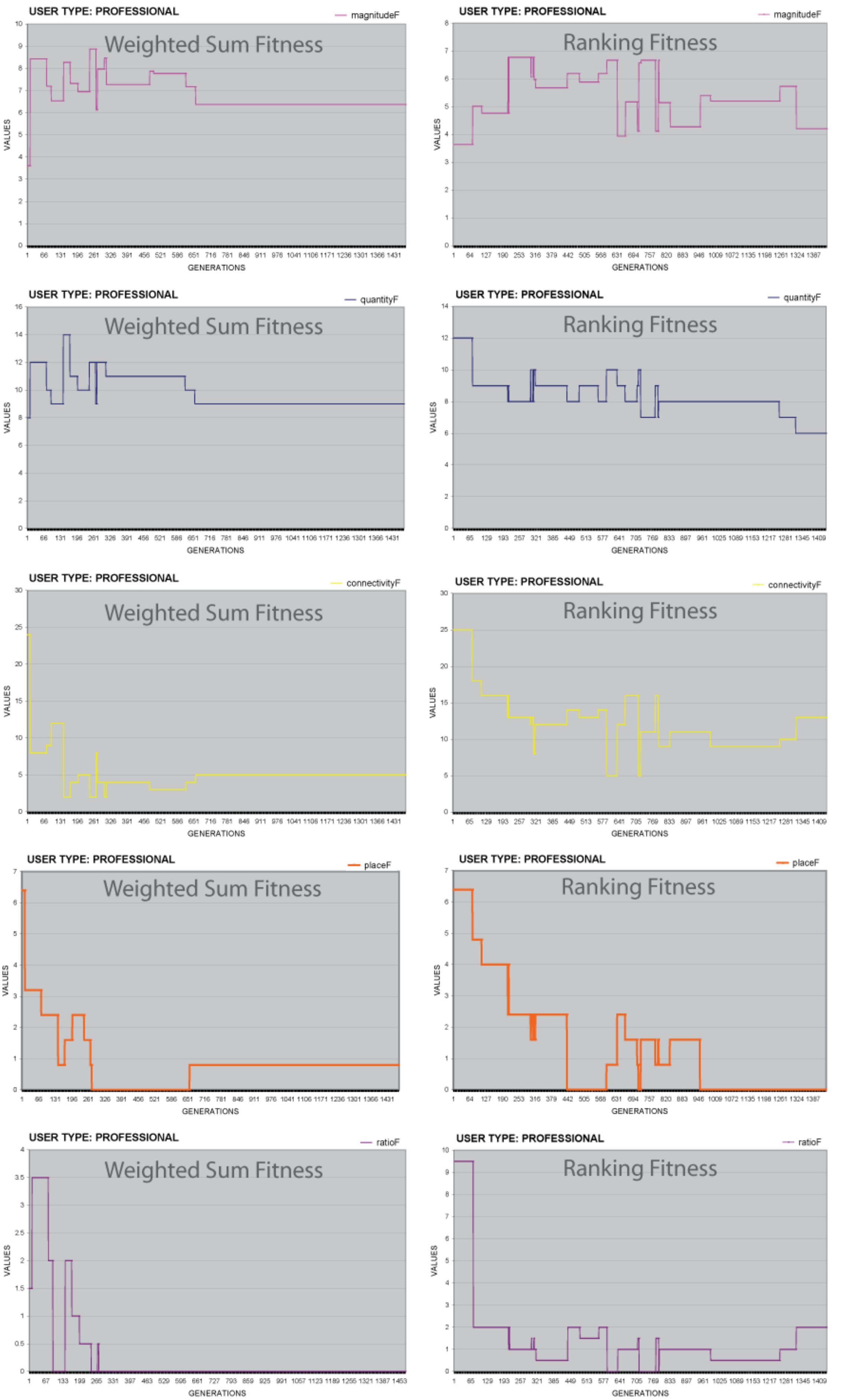


Figure57 Evolution of each objective in the two methods

As it can be verified from the graphs above [Figure57], the less satisfied objective criterion, in the case of the weighted-sum evaluation, is always the quantities factor. This factor is related to the number of hosted against the number of required activities. A trade off in the quantities factor results to a smaller amount of activities to be evaluated and consequently to a lower total fitness value [see also layout Figure56]. It is thus verified that the performance of the solution is not analogous to the total-fitness value.

On the contrary, when the ranking sum evaluation method is implemented, the fittest solutions are the ones whose objectives are well-balanced and that's the reason why its results are better. As it can be observed in the graphs [Figure57] the less satisfied objective is the required adjacencies. Hence, it can be argued that since the ranking sum evaluation method does not need weight calculation, the most conflicting objective is the adjacency requirements.

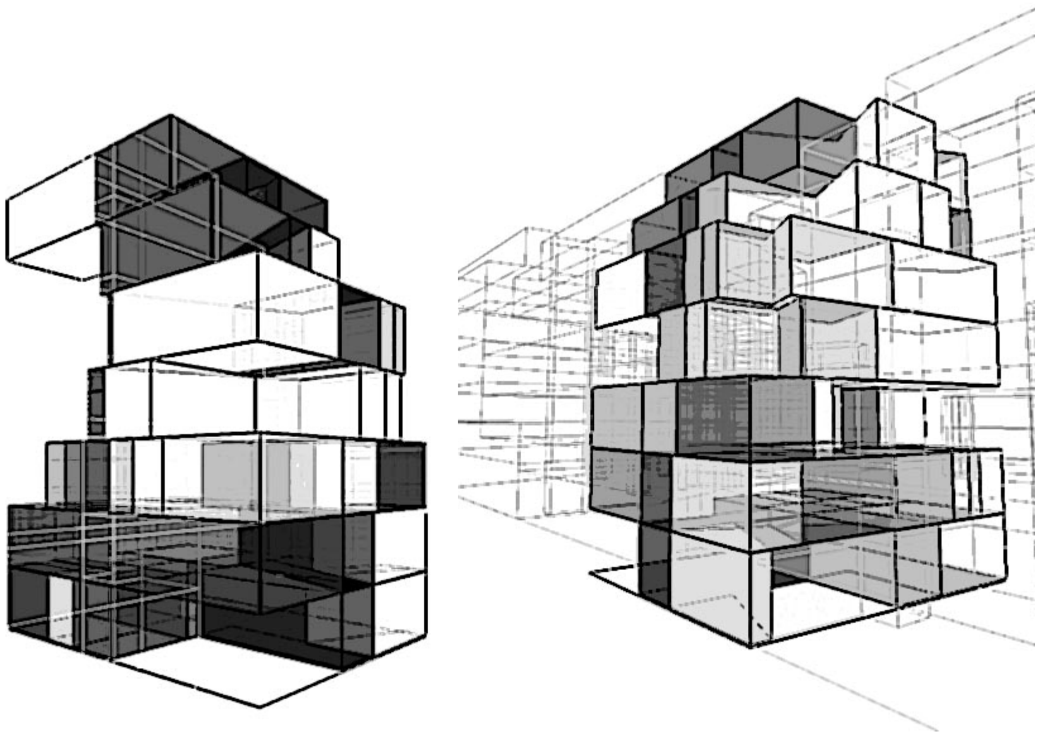
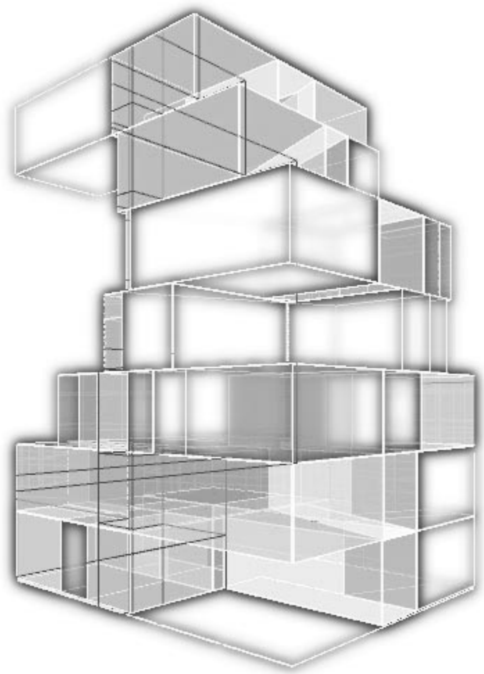


Figure58 Perspective views of solutions

5. DISCUSSION



5.1 GENERAL

As previously discussed [see results chapter], the model used within this research can be considered as successful since relatively good results have been produced regarding both numerical data and spatial configurations. The research's hypothesis that an efficient evolutionary system aiming to generate floor plans can be driven by a computationally independent embryology process is thus verified. This process assigns activities to existing spaces according to a set of rules [preferences] which are encoded in terms of required dimensional attributes as well as permeability graphs. Additionally, it has been shown [see results chapter], that an evaluation method which classifies individuals according to the sum of their rankings [for each objective separately] produces more balanced results than the weighted sum evaluation method.

5.2 COMPARING TO OTHER APPROACHES

The other approaches for the automated layout planning problem that have been studied during the research provided valuable material and helped in the development of the methodology. Particularly, this method is based on the notion that an evolutionary approach is more efficient in the exploration of the search space since the number of possible solutions is extremely high for an exhaustive search for the best solution. Thus, it can be classified within the evolutionary approaches to the automated layout planning problem.

In the case of Sitewalker [Doulgerakis 2007] some of the results produced with exhaustive search in steps were particularly satisfactory. However, when the consideration of future search steps was attempted, the limit of the available computational power was reached. As Jo and Gero [Jo and Gero,1998] argue, in constructive approaches [such as CRAFT [Armour and Buffa,1964] and Sitewalker [Doulgerakis,2007]] there is always the risk that the algorithm will never find its way out of a local optimum and thus, a method such as an evolutionary algorithm which performs a parallel search, is more efficient.

Nevertheless, Mitchell et al. [Mitchell et al.,1976] produce a set of well-fitted solutions with an exhaustive search among all the possible solutions. However, the drawback of that method is its massive computational cost. Hence, as the title of the work proposes, it is efficient only when applied to small rectangular floor plans with a small number of rooms.

However, the way that Mitchell et al. system manipulated space influenced this research. The subdivision of a given rectangle to smaller rectangles constitutes a very capable means of producing spatial configurations. Moreover, these spaces are not the result of aggregated unitary cells; instead they constitute independent geometric elements. Thus, the results are not restrained by the granularity of an underlying grid as it is the case in Rosenman's approach [Rosenman, 1996]. The method which was developed within this research adopts this perspective for the manipulation of unequal-area spaces. Thus, it is classified within the unequal area approach [Block Plan] to the automated layout planning problem and particularly within the continual space block plan approach. However, that research is not narrowed down to rectangular shapes. The subdivision can occur diagonally and the consideration of geometry as polygons allows the manipulation of almost all the possible site outlines and favours the production of even more realistic solutions.

The developed methodology has a similar approach with the Finucane et al. [Finucane et al.,2006] system. Particularly, the development of the phenotype is in both cases an independent embryology process that optimizes the translation of the genotype to the actual configuration. Moreover, both approaches attempt a multi-objective optimization. Finucane et al. yield efficient solutions by classifying the individuals in 'Pareto' fronts. This research's approach to the multi-objective optimization [e.g. the Ranking Sum Fitness] produces efficient results as well.

An element which is neglected in the related approaches is the social and the cultural background, whose forces have an important role in the formation of the buildings' layout. This research aims to prove that it is possible to encode these forces [in this case by means of the gamma-map] and to implement them within a generative system whose purpose is to create floor-layout solutions.

5.3 LIMITATIONS AND FURTHER DEVELOPMENT

Further development of the system was restrained due to time constrains. Additionally, the data which have been used as required attributes for the configurations are not based on statistics. Instead, the preferences of the different user-types have been encoded intuitively. Nevertheless, the objective of this research was to confirm that such an approach can be efficient and thus, these data are not of crucial importance in that branch of the research.

A research could be held concerning the typology and the statistics of this type of buildings. Furthermore, the system's efficiency could be tested against real data by comparing existing typologies and configurations resulting from the implementation of the methodology described.

Moreover, there are several methods to decode the social and the cultural underlying forces that drive the formation of buildings layouts; permeability map being one of them amongst others. Within the context of this research, only the permeability graph [gamma map] has been implemented. A number of other data such as visibility and privacy can also have large impact over the layout's formation forces.

A further development of that research should attempt to implement these data as generative criteria for the assignment of activities, as well as evaluation criteria for the classification of the results.

Furthermore, it must be mentioned that in order to produce more efficient and realistic results, the activities-assignment process should have the ability to join two [or even more] spaces or to further subdivide them if this could make the solution's performance better. This change could be then translated as additional information integrated in the solution's genotype by following the Lamarkistic model of evolution.

While this approach was attempted and managed to produce results within sole individuals, its implementation to the Genetic Programming algorithm was restrained due to the lack of sufficient computational power. Namely, the calculation of the possible additions and subdivisions for every individual and the selection of the best action among the numerous options are excessively demanding in computational power as it approaches exhaustive search algorithms.

Ultimately, it would be very interesting to expand this system as a co-evolutionary system focusing on the interaction of the building's floors. That evolutionary algorithm would generate each floor's configurations independently, but the result would be evaluated according to the feasibility of the solutions as a to-be-built project. For instance the placement of terraces, vertical communications, and wet spaces [bathroom, kitchen], are decisions that should be taken in regards to the whole building in order to achieve functional solutions.

CONCLUSIONS

The development of the application system was based on the ongoing research aiming to address the automated layout planning problem with the use of sophisticated heuristics, such as Genetic Algorithms. However, in most of these cases, the impact of the generative forces that derive from the social and the cultural environment has been neglected. The objective of that research was to illustrate that the encoding of these forces in terms of permeability graphs, can be implemented within an evolutionary process in order to yield meaningful and efficient results.

In order to examine this approach's potentials, two similar multi-objective GP systems have been elaborated. The first one represents the traditional evolutionary approach whose individuals acquire random values during the generation of the initial population. Whereas, the second is a Genetic Programming algorithm implemented for the evolution of residential layouts driven by an independent agent-based unfolding embryology process, which assigns activities to the spaces, generated by the GP, according to a set of spatial and permeability requirements. In the latter, the GP and the assignment process compose a single evolutionary system, as GP generates spaces and the assignment allocates the activities and evaluates the result.

Both systems have been executed within the same context, with the same requirements and for the same time. The context of the experiment was a typical multi-storey residential building in the centre of Athens. As it was justified by the comparison of the results, the co-operational GA-assignment system yielded better results than the conventional GA system. Thus, the hypothesis of the research was verified and the proposed approach can be considered as successful.

Hence, the contribution of this research to the evolution of automated layout planning is that it showed that elements which encode the social meaning of buildings can be used within a generative system and particularly in cooperation with an evolutionary system. Nevertheless, according to Hillier and Hanson [Hillier and Hanson,1984] there is a plethora of such encodings [e.g. visibility and privacy graphs] whose purpose is to decode the social forces that generate configurations. Therefore, a further development should attempt to implement these encodings within the evolutionary system.

To conclude, it is worth mentioning that designers and researchers in the digital era of architecture are vulnerable to consider that computational methods will eventually assure the generation of creative solutions which overpass the human capabilities. However, an efficient generative procedure should not neglect that layouts are not merely hosts of activities. Instead, they reflect social structures and respectively, they induct these structures to their inhabitants. To use Winston Churchill words, ‘we shape our buildings and afterward our buildings shape us’ [Churchill,1944]

Figure59 Backyard at Montessori school, Delft [Hertzberger,1991]

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APPENDIX I: SCRIPTING METHODS

In this appendix some elements of the program will be thoroughly described. The full source code for all the applications developed within this research can be found in the included CD-ROM.

The application is scripted in Processing programming language. However, several elements of the program required methods and classes that overpass processing potentials. In these cases, Java classes have been called within the processing environment. As the classes are named after the object they represent [e.g. the **polygon** class represents polygons], different lettering have used to differentiate the references. Hence, words in bold refer to classes.

GENOTYPE

A **node** class was created that could represent both values and functions. When the generation of a random genotype is initialised, an instance of the node class is called that is the root **node** whose depth value is 0. Then, the root node instantiates a random number of children nodes whose depth value is 1. This procedure is repeated recursively until a certain depth value is reached. The **node** class takes as input the parent node [in the case of the root node the parent node is null] and stores in a Java **vector** the children nodes. In addition, every **node** stores in Java **vectors** all its ancestors and all its descendants. This is achieved when the instantiation of every **node** takes place. Thus, every instance obtains 'knowledge' of its position within the genotype tree by reference to its immediate parent node as well as to its ancestors. Furthermore, in every moment each node is conscious of its sub-dependent tree and nodes.

RECTANGULAR SPACES

When a **genotype** instance is called, it takes as input value the initial space, namely the outline of the building. That space can be either the available part of the construction site, or the site itself. Since this input constitutes a geometry, an appropriate class is needed that can create and manipulate geometry. Initially, the site was strictly rectangular, and the shapes were boxes. A **space** class was then created that used as input the initial point, the width and the length of the rectangular space and produced as output a box whose area was defined by the given width and length values and whose height was predefined.

The initial **space,** which is the input of the **genotype**, is transmitted to the root-**node**. The root-**node** successively decides randomly the number of the children **nodes** and the orientation of the subdivision [vertically or horizontally]. According to each case the root divides the width [horizontal division] or the height [vertical division] while keeping the other value intact. The divisor is the number of the children **nodes**. Then the root-**node** instantiates a number of **nodes** that is equal to its number of children value. The children nodes are called one at a time and they are given as inputs their own **space**, which is composed of the intact value [for instance the width], a part of the other value [for instance the height], and a starting point calculated by the starting point of the parent **node** translated to the sum of the portions of the previous children-**nodes** [if any]. The last child's **space** is the remaining part of the initial **space**.

That procedure is repeated recursively until the maximum depth is reached. All the **nodes** without children-**nodes** are considered as terminal [e.g. the **nodes** of maximum depth and the **nodes** that while their depth value is less than the maximum value, their number of children value was randomly set to 0]. All the terminal **nodes** store a duplicate of the **node**'s **space** within a **vector** in the **genotype.** This duplicate represents a constructed **space**.

While all the **nodes** have each one their **space**, these **spaces** are merely an abstract instance as they do not represent an actual, constructed **space**, but the given **space** that they dispose in order to distribute it among their children. Only the terminal **nodes**' **spaces** are materialized as actual **space**. Thus, by the end of that procedure in lieu of the initial geometry there is a set of rectangles whose areas compose the initial rectangle.

POLYGONAL SPACES

A **polygon** class was created that used as input two arrays of coordinates, the **xPoints []** array for the x-coordinates and the **yPoints []** for the y-coordinates.

Each **space** object has a reference to its corresponding **polygon**. However, while these parameters are sufficient in order to draw the polygon or to calculate its **centroid**, the need for further manipulation [e.g. Boolean operations] led towards the implementation of Java classes.

The notion was that a polygonal space could be subdivided to polygonal spaces with the use of Boolean operations [join, subtract, intersect]. Java's **area** class can perform these operations. In order to render a **polygon** to an **area**, the Java **general path** class was used. Since **general path** implements the java **shape** interface it can provide the **area** of a given **polygon** [polygon->general path->area]. It is worth mentioning that java has its own **polygon** class that implements the java **shape** interface, so it would be easier to get its **area** [polygon->area]. Nevertheless, java **polygon** accepts arrays of integers as coordinates, and for the purpose of subdividing **polygons,** float coordinates were necessary. In brief, in order to perform a Boolean operation over two given **polygons,** the following sequence is used: for both **polygons**, create a **general path** from the **polygons**' points that describe its outline [**general path** gp1, **general path** gp2] -> get the **areas** that correspond to the **general paths** [new **area** a1 = **area**[gp1], new **area** a2 = **area**[gp2]] -> perform the Boolean operation with the **areas** [new **area** rest = a1.subtract[a2]].

Another important method that java **area** class provides is the transform method. By this method one can manipulate the given area [translate, rotate, scale] by use of the **AffineTransform** class that is merely a transformation matrix. The **AffineTransform** matrix can be set by applying its "translate", "rotate" and "scale" methods. In brief, in order to perform a transformation over a given **area** object the following procedure is followed: create an identity **AffineTransform** matrix [new affine transform m] -> apply a transformation method over this matrix [m.translate[x, y]] -> apply this transformation to the initial **area** a [a.transform[m]].

Up to that point, it is achieved to apply transformations as well as Boolean operations to given **polygons**. However, the result of the aforementioned procedures is in terms of an **area** and not of a **polygon**. Consequently, in order to complete the procedure, a final step was necessary: to render the resulted

area to its corresponding **polygon**. That step was achieved by use of the **PathIterator** interface. The **PathIterator** interface provides the mechanism for objects that implement the **Shape** interface [such as area objects] to return the geometry of their boundary by allowing a caller to retrieve the path of that boundary a segment at a time [Java reference]. Hence, the new transformed **polygon** is created by retrieving the transformed **area**'s PathIterator. In brief the procedure is the following: **polygons**-> **areas** of **polygons** -> manipulate the **areas** -> get resulted **areas** -> get new **polygons** from resulted **areas**.

Thereupon, in order to create a configuration the followed procedure is similar with the one that was applied for the creation of configurations of rectangular spaces. The initial **polygon** that is the input of the **genotype** is transmitted to the root-**node**. The root-**node** successively decides randomly the number of the children **nodes**, the orientation [vertically or horizontally], and the angle of the subdivision. The root creates a filter rectangle that is the bounding rectangle of its polygon. According to each case the root scales, rotates and translates the filter in order to produce the children node's bounds. Each child node's space is the intersection of the initial polygon with the filter rectangle. Then the root-**node** instantiates a number of **nodes** that is equal to its number of children value. The children nodes are called one at a time and they are given as input their own **polygon**. The last child's **polygon** is the remaining of the initial's **polygon**.

CROSSOVER

In order to perform the crossover GO, first a **genotype** copy function is needed. That function's role is to generate an identical duplicate of a **genotype** so as when the crossover occurs to the copies of the **genotypes**, the original **genotypes** remain intact. The copying is achieved by recursively 'reading' the original **genotype**'s **nodes** and creating in the same time identical duplicates of these **nodes** to the duplicate **genotype**.

Successively, the crossover function selects randomly a breaking point **node** for each **genotype**. Every **genotype** stores within a **vector** every node that is created from its root-**node**. Thus, the selection of breaking points occurs by randomly selecting a **node** among the **nodes** that are stored within the nodes-**vector** of each **genotype**. Once the selection of break-points is made, the **genotypes** exchange the sub-trees that have as roots the breakpoints **nodes**.

A re-creation function is then applied to the **genotypes** in order to update the changes that have occurred. Particularly this re-creation function removes the **nodes** from its initial **genotype**'s and adds them to its current **genotype**'s node-**vector**, updates the depth value of each **node**, updates the genealogy relations that are inscribed within each **node**'s allAncestors and allDescendants **vectors**, and updates the **polygons** of each **node**. Each **node** object has memory of the way that its parent filter-**polygon** was manipulated [translated, scaled and rotated] for the production of that exact **node**. Consequently, the same transformations are applied but in different filter-**polygons** this time resulting to different **polygons**.

Eventually, the two offspring **genotypes** are evaluated and the fittest is selected as the offspring, whereas the other one is rejected.

MUTATION

The mutation GO is occasionally applied, with a small probability factor, over the offspring **genotype** of the crossover operation. The mutation GO selects randomly one break point [as in the crossover] and removes the sub-tree that has as a root the break point **node**. Then, a new random **genotype** is generated that is added to the first **genotype** by replacing the break point **node** with the new genotype's root-**node**.

In order to produce solutions that are considered within the acceptable boundaries, the new **genotypes** maximum depth allowance is equal to the general maximum depth allowance minus the break point's depth value. Successively, the recreation function is applied again in order to update the final **genotype**.

ADF [Automatically Defined Functions]

In our model, the **genotypes** that have a very good performance, store to a **vector** a new **genotype** that is a duplicate **genotype** of a sub-tree. Thereupon, when the mutation GO is applied, instead of generating a new random **genotype**, the mutation has a chance to occur by adopting randomly one of the ADF **genotype**.

APPENDIX II: USER TYPES

The user types and their preferences which were implemented for the purpose of this application are considered to be a three member family type, a two member family type, a professional type, and an artist type.

Usertype: 3 Member Family

Activities Quantities

```
int [] familyQ =          {0,   1, 1, 1, 1, 1, 1, 1, 2, 3, 0, 2, 2};
```

Connectivity Matix

```
                         // 0     1  2  3  4  5  6  7  8  9 10 11 12
                         //NULL   V  E  L  C  b  K  D  T  R  W  B  S
int [][] familyConM =    { { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},  //NULL

                           { 0,   0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //VERTICAL
                           { 0,   1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0},    //ENTRANCE
                           { 0,   0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0},    //LIVING
                           { 0,   0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1},    //CORRIDOR
                           { 0,   0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //b_WC
                           { 0,   0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1},    //KITCHEN
                           { 0,   0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0},    //DINING
                           { 0,   0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0},    //TERRACE
                           { 0,   0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0},    //ROOM
                           { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //WORKSHOP
                           { 0,   0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0},    //BATHROOM
                           { 0,   0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0} };  //STORAGE
```

Activities Areas

```
                         // 0     1    2     3     4    5     6     7     8     9   10   11   12
                          //NULL  V    E     L     C    b     K     D     T     R    W    B    S
float [][] familyM =     { { 0.0, 14.0, 3.0, 15.0,  4.0, 1.0, 12.0, 10.0,  4.0, 10.0, 0.0, 5.0, 2.0},
                           { 0.0, 16.0, 4.0, 24.0, 10.0, 2.0, 16.0, 15.0, 12.0, 14.0, 0.0, 7.0, 6.0} };
```

Activities Ratios

```
                          // 0    1    2    3     4    5    6     7     8     9   10   11   12
                          //NULL  V    E    L     C    b    K     D     T     R    W    B    S
float [][] familyR =     { { 0.0, 1.0, 1.0, 1.0,  2.0,  1.0, 1.0,  1.0,  1.0,  1.0, 0.0, 1.0, 1.0},
                           { 0.0, 2.0, 1.5, 1.5,  3.0,  1.5, 1.5,  1.5,  3.0,  1.5, 0.0, 1.5, 3.0}  };
```

Activities Allocation

```
String [][] familyA =    {  {"null"}, {"nl"}, {"well"}, {"front"}, {"well"}, {"well"}, {"back", "front"}, {"well"},
                            {"front", "back"}, {"front", "back"}, {"front", "back"}, {"well"}, {"well"} };
```

Downward Gamma Map

```
int [][] familyG_D =     { { 0 },                    //null

                           { 2 },                    //VERTICAL
                           { 4, 3, 5 },              //ENTRANCE
                           { 7, 8 },                 //LIVING
                           { 6, 11, 9, 9, 9, 12 },   //CORRIDOR
                           { 0 },                    //b_WC
                           { 12 },                   //KITCHEN
                           { 0 },                    //DINING
                           { 0 },                    //TERRACE
                           { 11, 8 },                //ROOM
                           { 0 },                    //WORKSHOP
                           { 0 },                    //BATHROOM
                           { 0 } };                  //STORAGE
```

Upward Gamma Map

```
int [][] familyG_U =     { { 0 },                    //null

                           { 0 },                    //VERTICAL
                           { 1 },                    //ENTRANCE
                           { 2 },                    //LIVING
                           { 1 },                    //CORRIDOR
                           { 1 },                    //b_WC
                           { 4 },                    //KITCHEN
                           { 3, 6 },                 //DINING
                           { 3, 9 },                 //TERRACE
                           { 4 },                    //ROOM
                           { 0 },                    //WORKSHOP
                           { 4, 9 },                 //BATHROOM
                           { 4, 6 } };               //STORAGE
```

Usertype: professional

```
int [] professionalQ =         {0,   1, 1, 1, 1, 1, 1, 0, 2, 2, 1, 1, 2};
```

Activities Quantities

```
                           // 0     1  2  3  4  5  6  7  8  9 10 11 12
                           //NULL   V  E  L  C  b  K  D  T  R  W  B  S
int [][] professionalConM = { { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},  //NULL

                              { 0,   0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //VERTICAL
                              { 0,   1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0},    //ENTRANCE
                              { 0,   0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0},    //LIVING
                              { 0,   0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0},    //CORRIDOR
                              { 0,   0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //b_WC
                              { 0,   0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1},    //KITCHEN
                              { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //DINING
                              { 0,   0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0},    //TERRACE
                              { 0,   0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0},    //ROOM
                              { 0,   0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1},    //WORKSHOP
                              { 0,   0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0},    //BATHROOM
                              { 0,   0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0} };  //STORAGE
```

Connectivity Matix

```
                            // 0     1     2     3     4     5     6     7     8     9    10    11    12
                            //NULL   V     E     L     C     b     K     D     T     R     W     B     S
float [][] professionalM =  {{ 0.0, 14.0, 12.0, 15.0, 10.0, 1.0, 12.0, 0.0,  4.0, 10.0, 25.0, 5.0, 4.0},
                             { 0.0, 16.0, 15.0, 24.0,  4.0, 2.0, 16.0, 0.0, 12.0, 14.0, 30.0, 7.0, 6.0} };
```

Activities Areas

```
                            // 0    1    2    3     4    5    6     7    8     9   10   11   12
                            //NULL  V    E    L     C    b    K     D    T     R    W    B    S
float [][] professionalR =  { { 0.0, 1.0, 1.0, 1.0,  2.0,  1.0, 1.0,  0.0,  1.0,  1.0, 0.0, 1.0, 1.0},
                              { 0.0, 2.0, 1.5, 1.5,  3.0,  1.5, 1.5,  0.0,  3.0,  1.5, 0.0, 1.5, 3.0}  };
```

Activities Ratios

```
String [][] professionalA = { {"null"}, {"nl"}, {"well"}, {"front"}, {"well"}, {"well"}, {"back", "front"}, {"null"},
                              {"front", "back"}, {"front", "back"}, {"front", "back"}, {"well"}, {"well"}};
```

Activities Allocation

```
int [][] professionalG_D =  { { 0 },           //null

                              { 2 },           //VERTICAL
                              { 4, 3, 10, 5 }, //ENTRANCE
                              { 8 },           //LIVING
                              { 6, 9, 9, 11 }, //CORRIDOR
                              { 0 },           //b_WC
                              { 12 },          //KITCHEN
                              { 0 },           //DINING
                              { 0 },           //TERRACE
                              { 8 },           //ROOM
                              { 12 },          //WORKSHOP
                              { 0 },           //BATHROOM
                              { 0 } };         //STORAGE
```

Downward Gamma Map

```
int [][] professionalG_U =  { { 0 },           //null

                              { 0 },           //VERTICAL
                              { 1 },           //ENTRANCE
                              { 2 },           //LIVING
                              { 2 },           //CORRIDOR
                              { 2 },           //b_WC
                              { 4 },           //KITCHEN
                              { 0 },           //DINING
                              { 3, 9 },        //TERRACE
                              { 4 },           //ROOM
                              { 2 },           //WORKSHOP
                              { 4 },           //BATHROOM
                              { 6, 10 } };     //STORAGE
```

Upward Gamma Map

Usertype: artist

```
int [] artistQ =            {0,   1, 0, 1, 0, 1, 1, 0, 2, 1, 1, 1, 2};
```

Activities Quantities

```
                         // 0    1  2  3  4  5  6  7  8  9 10 11 12
                         //NULL  V  E  L  C  b  K  D  T  R  W  B  S
int [][] artistConM =    { { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},  //NULL

                           { 0,   0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //VERTICAL
                           { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //ENTRANCE
                           { 0,   1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0},    //LIVING
                           { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //CORRIDOR
                           { 0,   0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //b_WC
                           { 0,   0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1},    //KITCHEN
                           { 0,   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},    //DINING
                           { 0,   0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0},    //TERRACE
                           { 0,   0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0},    //ROOM
                           { 0,   0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1},    //WORKSHOP
                           { 0,   0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0},    //BATHROOM
                           { 0,   0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0} };  //STORAGE
```

Connectivity Matix

```
                           // 0    1     2     3     4    5     6     7     8     9    10    11   12
                           //NULL  V     E     L     C    b     K     D     T     R     W     B    S
float [][] artistM =     { { 0.0, 14.0, 0.0, 15.0, 0.0, 1.0, 12.0, 0.0,  4.0, 13.0, 30.0, 5.0,  4.0},
                           { 0.0, 16.0, 0.0, 24.0, 0.0, 2.0, 16.0, 0.0, 12.0, 14.0, 50.0, 7.0, 10.0}  };
```

Activities Areas

```
                           // 0    1    2    3     4     5    6     7     8     9   10   11   12
                           //NULL  V    E    L     C     b    K     D     T     R    W    B    S
float [][] artistR =     { { 0.0, 1.0, 0.0, 1.0,  0.0,  1.0, 1.0,  0.0,  1.0,  1.0, 1.0, 1.0, 1.0},
                           { 0.0, 2.0, 0.0, 1.5,  0.0,  1.5, 1.5,  0.0,  3.0,  1.5, 2.0, 1.5, 3.0}  };
```

Activities Ratios

```
String [][] artistA = { {"null"}, {"nl"}, {"null"}, {"front"}, {"null"}, {"well"}, {"back", "front", "well"}, {"null"}
                        {"front", "back"}, {"front", "back"}, {"front", "back"}, {"well"}, {"well"}};
```

Activities Allocation

```
int [][] artistG_D =     { { 0 },              //null

                           { 3 },              //VERTICAL
                           { 0 },              //ENTRANCE
                           { 5, 9, 6, 10, 8 }, //LIVING
                           { 0 },              //CORRIDOR
                           { 0 },              //b_WC
                           { 12 },             //KITCHEN
                           { 0 },              //DINING
                           { 0 },              //TERRACE
                           { 11, 8 },          //ROOM
                           { 12 },             //WORKSHOP
                           { 0 },              //BATHROOM
                           { 0 } };            //STORAGE
```

Downward Gamma Map

```
int [][] artistG_U =     { { 0 },              //null

                           { 0 },              //VERTICAL
                           { 0 },              //ENTRANCE
                           { 1 },              //LIVING
                           { 0 },              //CORRIDOR
                           { 3 },              //b_WC
                           { 3 },              //KITCHEN
                           { 0 },              //DINING
                           { 3, 9 },           //TERRACE
                           { 3 },              //ROOM
                           { 3 },              //WORKSHOP
                           { 9 },              //BATHROOM
                           { 6, 10 } };        //STORAGE
```

Upward Gamma Map

Usertype: 2 member family

Activities Quantities

```
int [] coupleQ =             {0,   1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1};
```

Connectivity Matix

```
                            // 0    1  2  3  4  5  6  7  8  9 10 11 12
                            //NULL  V  E  L  C  b  K  D  T  R  W  B  S
int [][] coupleConM =       { { 0,  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},  //NULL

                              { 0,  0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //VERTICAL
                              { 0,  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //ENTRANCE
                              { 0,  1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0},   //LIVING
                              { 0,  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //CORRIDOR
                              { 0,  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //b_WC
                              { 0,  0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1},   //KITCHEN
                              { 0,  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //DINING
                              { 0,  0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //TERRACE
                              { 0,  0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //ROOM
                              { 0,  0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //WORKSHOP
                              { 0,  0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0},   //BATHROOM
                              { 0,  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0} };  //STORAGE
```

Activities Areas

```
                              // 0   1     2    3     4    5    6     7    8    9     10    11   12
                              //NULL V     E    L     C    b    K     D    T    R     W     B    S    V
float [][] coupleM =        { { 0.0, 14.0, 0.0, 15.0, 0.0, 0.0, 12.0, 0.0, 4.0,  13.0, 13.0, 5.0, 4.0, 14.0 },
                              { 0.0, 16.0, 0.0, 24.0, 0.0, 0.0, 16.0, 0.0, 12.0, 15.0, 15.0, 7.0, 6.0, 16.0 }  };
```

Activities Ratios

```
                              // 0   1    2    3     4     5    6     7     8     9    10   11   12
                              //NULL V    E    L     C     b    K     D     T     R    W    B    S
float [][] coupleR =        { { 0.0, 1.0, 0.0, 1.0,  0.0,  0.0, 1.0,  0.0,  1.0,  1.0, 1.0, 1.0, 1.0},
                              { 0.0, 2.0, 0.0, 1.5,  0.0,  0.0, 1.5,  0.0,  3.0,  1.5, 1.5, 1.5, 3.0}  };
```

Activities Allocation

```
String [][] coupleA = { {"null"}, {"nl"}, {"null"}, {"front"}, {"null"}, {"well"}, {"back", "front"}, {"null"},
                        {"front", "back"}, {"front", "back"}, {"front", "back"}, {"well"}, {"well"}};
```

Downward Gamma Map

```
int [][] coupleG_D =        { { 0 },                 //null

                              { 3 },                 //VERTICAL
                              { 0 },                 //ENTRANCE
                              { 6, 9, 10, 11, 8 },   //LIVING
                              { 0 },                 //CORRIDOR
                              { 0 },                 //b_WC
                              { 12 },                //KITCHEN
                              { 0 },                 //DINING
                              { 0 },                 //TERRACE
                              { 0 },                 //ROOM
                              { 0 },                 //WORKSHOP
                              { 0 },                 //BATHROOM
                              { 0 } };               //STORAGE
```

Upward Gamma Map

```
int [][] coupleG_D =        { { 0 },                 //null

                              { 0 },                 //VERTICAL
                              { 0 },                 //ENTRANCE
                              { 1 },                 //LIVING
                              { 0 },                 //CORRIDOR
                              { 0 },                 //b_WC
                              { 3 },                 //KITCHEN
                              { 0 },                 //DINING
                              { 3 },                 //TERRACE
                              { 3 },                 //ROOM
                              { 3 },                 //WORKSHOP
                              { 3 },                 //BATHROOM
                              { 6 } };               //STORAGE
```

CD-ROM