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EMO-based Architectural Room Floor Planning

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***Abstract*—We propose a spatial plan generator based on our spatial planning algorithm and spatial growth rules, combine it with evolutionary multi-objective optimization, apply the system to architectural room floor planning, and evaluate its potential as a support tool for planning. We also introduce a framework for combining the architectural room floor planning support system with an interactive evolutionary computation component that constitute the next step of our research. The system executes two test runs, evolving the generated room floor plans with four and six objectives, respectively, while we monitor the convergence of each of these objectives. The results show that all objectives converged and a great variety of architectural room floor plans was produced. Obtained plans include a variety of unexpected plans for an architect, which implies that this system is useful for not only beginners who need design support but also for architectural professionals.**

***Index Terms*—room floor planning, architectural planning, evolutionary multi-objective optimization.**

I. Introduction

Spatial layout plans are a part of the design process in architecture, landscape architecture, urban and even LSI design. With such tasks, it is necessary to take into account multiple planning restrictions and evaluation criteria, and planners are required to be skilled and experienced in their respective domain areas. It is difficult for ordinary client users to embed their preferences into the professional planning process.

One possible solution is to make a spatial planning support system that generates a variety of preferable plans for client users. Such a support system should also be useful for professional planners who wish to improve the efficiency of their planning; the planners can obtain hints from various generated plans and shorten the time required for fine-tuning the plans, thereby easing the timely production of plans that will meet with the approval of their clients.

As many planning conditions and restrictions must be considered for architectural room floor planning, the support system must have an optimization function for multi-objectives. This can be realized by embedding evolutionary multi-objective optimization (EMO). EMO has come to be applied to structural and environmental engineering, scheduling, and other construction areas recently. However, its applications to design and planning, especially architectural planning, are still few.

One of reasons why evolutionary computation (EC) approaches are not extensively used in this area is the difficulty

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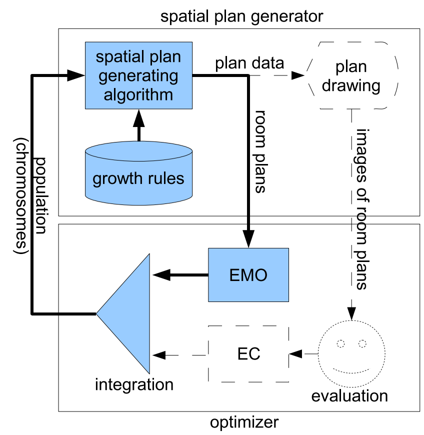

Fig. 1. The architectural room floor planning support system consisting of a spatial plan generator (upper) and an optimizer (lower). The part of the IEC surrounded by broken lines on the lower right side is an extension for the next step of research and is not handled in this paper.

of arranging rooms or subspaces. It is necessary for EC-based spatial planning to model its target spaces, and some architectural planning models have been proposed to do this.

In one system, the floor plans of a detached house were modeled by combining cells and then optimized [10]. It is difficult for this approach to remove gap spaces between rooms and make rooms rectangular, however. In another study, the floor of a detached hospital building was planned by combining fixed room shapes [4], with the inherent limitation that it was impossible to change the room shapes freely. A simple way to generate a variety of room floor plans is to optimize only the lengths of the rooms [1], but this does not consider the arrangement of room positions. Another floor planning method is to divide a space into two and repeat the division until a desirable room floor plan is obtained [7], but the obtained room floor shapes created by this method will only be rectangular. In yet another model room shapes are formed by combining square modular cells [8]. One side of a cell of a room becomes a doorway and connects the room to the next room, and this connection makes a whole room floor layout. A drawback of this method is that gap spaces appear easily in its room floor plans, and it is not easy to make it fit within a rectangular outline of the entire planning area, i.e. an entire building.

To solve these problems and realize an architectural room floor planning support system, we propose a method for gener-

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ating plans for generalized spatial planning in section II, apply the method and EMO to architectural room floor planning in section III, and show that our approach can optimize room floor plans experimentally in section IV. More specifically, we construct an architectural room floor planning support system as shown in Fig. 1. The system can be extended to combine an interactive evolutionary computation (IEC) [9] to embed human experiences and domain knowledge into the optimization process of the room floor planning in order to meet subjective planning objectives. This forms the next step of our research.

Some abbreviations used in this paper are as followed: CC=common corridor, V=veranda, L=living room, K=kitchen, B=bedroom, W=water area, Pass=hallway, and S=gap space. B1–B3 means bedroom 1, 2, and 3.

II. Algorithm and Rules for Generating Space Plans

A. Proposed Algorithm for Generating Spatial Plans

We propose an algorithm for generating spatial plans that meet the following two specifications: (a) the sizes, shapes and positions of planned subspaces should be changeable, and (b) useless gap spaces in the planning area should be minimized.

Our algorithm first scatters *seeds* that are starting points for growing spaces in the planning area and then merges cells around the seed cells. Different spatial plans are generated by controlling seed coordinates and changing the definition of distance used for growing the spaces.

We apply the algorithm to generate architectural room floor plans. In this application, the entire planning space corresponds to the whole residential area of an apartment or a house, and subspaces correspond to rooms within the dwelling. Mesh cells are the metric we use for room space because actual architectural room floor plans are designed based on architectural modules or a basic unit length. Coordinates and lengths in our room plans are thus expressed in terms cell units. *Growth* in this paper means that a room space expands gradually by merging with neighbor cells based on its distance from the seed coordinates.

Our algorithm [5] is realized by the following steps.

1) Initialize the seed coordinates on $m \times n$ cells randomly or based on our domain knowledge, where the coordinates are the starting cells of rooms.
2) Grow each room into its neighboring cells.
3) If a growing room hits an obstacle, such as another room or a wall, stop growing the room in the direction of the obstacle encountered.
4) Repeat 2) and 3) until all rooms stop growing.

Fig. 2 shows a sample room growth process. The whole area represents a residential space, and the growing subspaces starting from seed coordinates become rooms.

B. Growth Rules

Growth rules determine how subspaces expand within the framework of the algorithm described in the previous section II-A [5]. The rules determine growth directions, growth order,

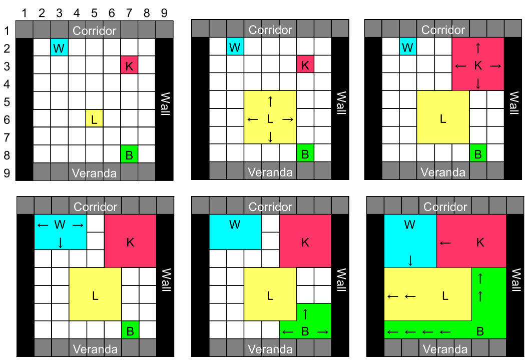


Fig. 2. A sample growth process for an architectural room plan based on our proposed algorithm. The sequential growth order is from left to right, top to bottom. See section I for L, K, W, and B.

growth speed, how to suppress the growth when a growing subspace hits other subspaces, and other aspects of growth. The growth rules describe how subspaces are formed, and different rules may be defined for each application task, while the algorithm in section II-A outlines our unique common philosophy for all spatial planning that can be used in various fields. We can form several shapes for the subspaces formed from the same seed coordinates by changing the definition of distance and the method for measuring the distance from the seed coordinates. The growth rules and the method for coping with collisions between subspaces enable the generation of various subspace shape outcomes.

The growth rules for architectural room floor planning used in this paper are as follows.

- Room spaces do not grow simultaneously but rather in sequence.
- Growth directions for each room:
  - a room can grow into any of the cells in the four directions of up, down, right, and left if the growth does not hit obstacles or other rooms,
  - room growth stops in the direction of collision when the room hits obstacles or other rooms, and
  - a room grows into the cells in the diagonal directions, which are synthesized from the growth directions of up, down, left, and right if there are no obstacles or other rooms.

C. Gene Coding

We define a chromosome with a set of the seed coordinates of rooms and optimize room floor plans using EC. The chromosome for the room floor plan in the upper left of Fig. 2 is expressed as [(6,5),(3,7),(2,3),(8,7)], for example, where each of four "( )" is (*a vertical coordinate*, *a horizontal coordinate*) of L, K, W, and B in this order, and the origin of this metric space is the upper left cell of a room floor plan.

D. Application to Room Floor Planning

We apply the algorithm and growth rules proposed in this section to the task of generating architectural room plans.

Although applicable in a variety of planning areas, in this study we concentrate on generating room floor plans for a residential space measuring $12m \times 7m$ in an apartment. The system generates room floor plans including L, K, B1–B3, W, and Pass in the space. This setting is more practical for architectural room floor planning, since our former research examined optimizations on setting to plan only four rooms into $7m \times 7m$ area [6]. Let the upper direction in the plans be north. To the north of the residential space there is a common corridor, to the east and west there are walls, and a veranda lies to the south. These surroundings become obstacles to the growth of rooms in our algorithm and growth rules.

III. Evolutionary Multi-objective Optimization of Room Plans

A. Objectives of a Room Floor Planning Task

We define six objectives below to be satisfied by the EMO and conduct two experimental evaluations, using respectively four and six objectives. The system calculates objective fitness values for each generated room plan and normalizes all fitness values onto the range [0,1] before Pareto ranking, where 1 is the best. We will introduce IEC to incorporate qualitative objectives in the next step of our research in near future.

Objective1*: Room Floor Size*

We set the entire floor area of the residential space at $84m^2$ and set the target floor area of each room as follows: L = $20m^2$, K = $16m^2$, B1 = $12m^2$, B2 = $12m^2$, B3 = $12m^2$, W = $9m^2$ and Pass = $1m^2$. Fig. 3(a) shows a fitness function, $f_i^1(a_i)$, for the room i, where a_i and $\hat{a}_i$ are the floor areas of the actual rooms i and their targets, respectively. The fitness of the room floor size specification for entire floor plan is expressed as the sum of the fitness values for its six rooms and hallway: $f^1 = \sum_{i=1}^{7} f_i^1(a_i)$.

Objective2*: Room Shape*

The fitness function for Objective2 consists of three components: sub-fitness for the aspect ratio of the shape of the room, sub-fitness for the degree to which the shape is regular rectangular, and the degree to which rectangular shape is important for each of the six rooms. The first sub-fitness of shape aspect ratio is defined as $f_i^2(r_i)$ as shown in Fig. 3(b), where r_i is *short side length / long side length* of the room i. In the second sub-fitness expression for the degree to which the room is rectangular, g_i^2, is defined as *room floor area, a_i / minimum rectangle area that contains the entire shape of the room i*. When a room i is exactly rectangular, then $g_i^2 = 1$; if some parts of the rectangular shape are missing, then $0 < g_i^2 < 1$. For the third component, which determines the importance given to rectangular shape for the room, w_1 – w_7, are 1.0, 0.75, 0.5, 0.25, and 0.0 for B1–B3, L, K, W, and Pass, respectively; the requested level to the rectangular shape depend on rooms. The fitness function for the Objective2 is defined as $f^2 = \sum_{i=1}^{7}(w_i \times f_i^2(r_i) \times g_i^2)$.

Objective3*: Circulation: Relationships between Rooms*

We categorize rooms and hallways as being public spaces or private spaces. Public spaces refers to spaces that we can pass through and includes L, K, and Pass, while private spaces refers to other spaces including B1–B3 and W. When gap spaces are generated between rooms, we may use them as hallways or storage areas. Correct architectural room plans must have one or more paths from an entrance door at a common corridor to the veranda passing through only public spaces. One point is accumulated to a fitness value, f^3, when each of the below seven room adjacency relationships is satisfied, and the total points become the fitness value for the Objective3. Here ↔ indicates that there is a connection between adjacent spaces through which we can pass.

- (CC↔(Pass or L or K)) or (CC↔S ↔(Pass or L or K))
- (B1↔(Pass or L or K)) or (B1↔S↔(Pass or L or K))
- (B2↔(Pass or L or K)) or (B2↔S↔(Pass or L or K))
- (B3↔(Pass or L or K)) or (B3↔S↔(Pass or L or K))
- (W↔(L or K or Pass)) or (W↔S↔(L or K or Pass))
- (V↔(L or K or Pass)) or (V↔S↔(L or K or Pass))
- ((L↔K) and (L↔Pass)) or ((L↔K) and (K↔Pass)) or ((L↔Pass) and (K↔Pass))

Objective4*: Legal Window Sizes*

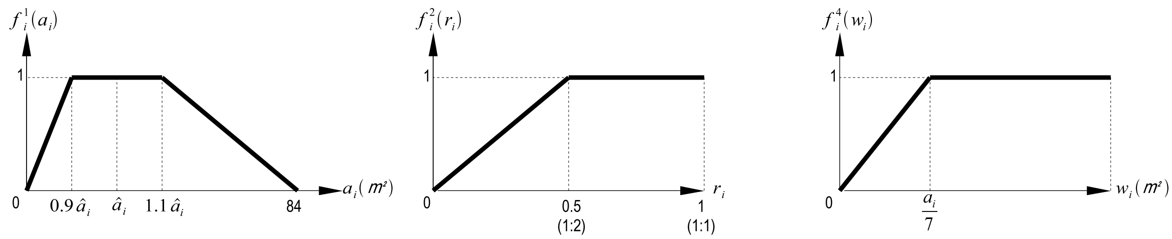
Japanese Architecture Standard Law demands that for their to be sufficient natural light, the surface area of the window must be more than or equal to 1/7 the surface area of the floor in all rooms except the kitchen or passes. When a kitchen and a living room are connected, a kitchen without a window is acceptable; we assume that the natural light from the living room reaches the kitchen and an exception to the law is applied in this case. We let the window sizes on the walls at the common corridor side and veranda side be $1m^2/m$ and $2m^2/m$, respectively. Fig. 3(c) shows the fitness function for window size required for natural lighting of room i, f_i^4. It becomes 1 when the size is more than equal to 1/7 of the room surface area and takes on a value between 0 and 1 in other cases. We define the fitness value for the Objective4, f^4, as the sum of f_i^4.

Objective5*: Wall Lengths*

We calculate total lengths of walls by counting the number of cells at the boundary between two rooms and using it as an index to its economic cost. In the other objectives, a higher value means a better or more desirable solution, so the inverse of this number is used as the fitness value, f^5, for the Objective5. Because inner walls are not load bearing, their economic impact is small in comparison with the construction of the dwelling's structural frame, and Objective5 is not used in the EMO experiment with four objectives.

Objective6*: Water Duct Lengths*

We calculate the total lengths of water ducts by calculating the average Euclidean distances between each cell in a kitchen or water area and use it as an economic index. As with Objective5, its inverse is used as the fitness value f^6. Since



(a) The sub-fitness function for Objective1. (b) The sub-fitness function for Objective2. (c) The sub-fitness function for the Objective4.

Fig. 3. (a) a_i and $\hat{a}_i$ are floor areas of the actual room i and its target, respectively. (b) r_i is shape aspect ratio of the room i. (c) a_i and w_i are respectively the surface areas of the floor and the window providing natural light for room i.

duct cost is relatively small, Objective6 is also excluded from the EMO experiment with four objectives.

B. Optimization Procedure

The optimization procedure of EMO is to:

1) evaluate each of the generated room plans with respect to the objectives,
2) calculate Pareto rank [3] based on the obtained evaluation values,
3) calculate Niche count [2] for the distance between individuals, i.e. similarity of the room plans,
4) calculate the fitness of each individual based on its Pareto rank and Niche count,
5) select individuals based on their fitness and generate offspring individuals using genetic operations, and
6) confirm whether the seed coordinates, i.e. growth beginning points, of the offspring individuals are in the range of the planning area and there is no overlap of the seed coordinates. If these conditions are not satisfied, the offspring individual is culled, and an alternative offspring is generated again.
7) The above mentioned steps are repeated until the necessary number of offspring individuals is obtained, and then they are sent to the spatial plan generator in Fig. 1.

We use multi-objective genetic algorithms (MOGA) as the EMO in our experiment. The reason why we adopt MOGA is that its structure is simple and suitable for the maintenance of solution diversity in the objective space by using the Niche technique [2].

There are two differences between our MOGA and the ordinary implementation [2]. The first difference is the use of the Pareto ranking method; our ranking is decreased even when an individual is a weak Pareto optimal solution, while that of the ordinary one [3] is decreased only when an individual is dominated by a comparable individual. The reason why we use this ranking is that some objectives in our room floor planning optimization task tend to have similar values.

The second difference is in how we calculate the distance d between individuals during niching. A requirement for diversity of architectural room floor plans is not in the *objective space* but among 2-dimensional *room floor plans*, i.e. phenotypes, such as Fig. 4, 5, 7 or 10. Our distance d is calculated by comparing corresponding cells of two room plans on the same Pareto rank and counting the number of cells that correspond to different rooms in the two plans; this is accomplished by overlapping two 2-D room floor plans and calculating the number of cells where the room type is different.

IV. Experiments

A. Experimental Conditions

We generate room plans consisting of 6 rooms (L, K, B1-B3, and W) and Pass in a residential space of $12m \times 7m = 84m^2$. The growth order of the algorithm in section II-A is that of L, K, B1-B3, W and Pass. The experimental conditions of MOGA are shown in Table I.

TABLE I
EXPERIMENTAL CONDITIONS

trial runs	10
# of objectives	4 and 6
max. generations	50
population size	21
selection method	roulette wheel selection
mutation rate	1%
crossover rate	100%
crossover method	uniform crossover
niche boundary σ_{share} [2]	# of cells = 84/4

B. Results

Fig. 4 shows the initial room floor plans that the spatial plan generator generated from randomly initialized room seeds' coordinates before EMO runs. They show that our algorithm and growth rules proposed in section II-A can overcome the conventional problems of room shapes and gap spaces and generate a variety of room plans.

Room plans obtained at the 50th generation with four-objective MOGA in Fig. 5 show that optimization with four objectives worked well in general although there are exceptions. A hallway locating in the northeast corner can function as an entrance hall. Average fitness convergences of 10 trial runs for each of 4 objectives in Fig. 6 show that they are almost saturated at around the 25th generation.

Fig. 7 shows room floor plans obtained at the 50th generation with six-objective MOGA. A kitchen and water area have become adjacent in all plans except two due to the introduction of Objective6, which optimizes lengths of water supply and drainage ducts. The fitness convergences for six-objective MOGA gradually increase but were slower than those of four-objective MOGA (Fig. 8). The fitness values of the

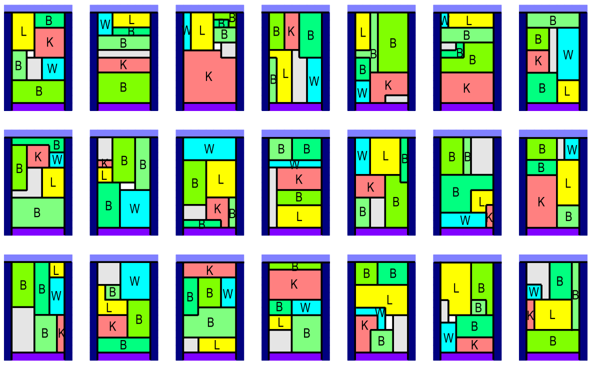


Fig. 4. Initial generated room floor plans at the 1st generation of the 5th of 10 trial runs. Spaces of yellow (L), red (K), green (B), light blue, gray and white are L, K, B1–B3, W, Pass and S. Note that the positions of the L, K, B, and W in this figure do not mean those of the seed coordinates, unlike Fig. 2.

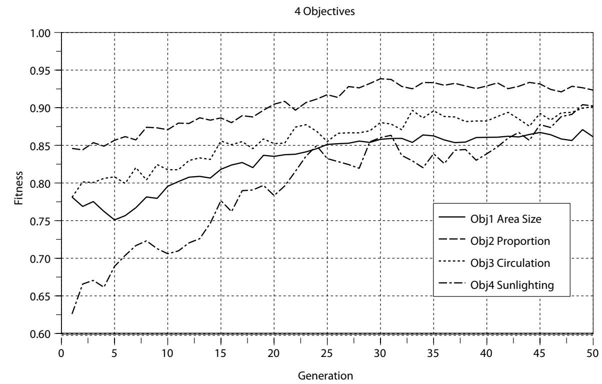


Fig. 6. Average convergence characteristics of 10 trial runs for 4-objective MOGA with 21 individuals. Curves of Obj1–Obj4 show fitness convergence of room floor size, room shape proportion, circulation in residential unit, and sun lighting window size, respectively.

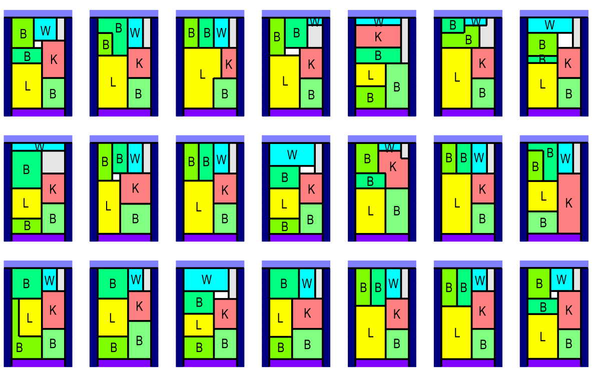


Fig. 5. Evolved room floor plans with 4 objectives at the 50th generation of the 5th of 10 trial runs. See abbreviations in the caption of Fig. 4. The Pareto front solutions are the 1st, 9th, 13th, and 21st plans in the order of top left to bottom right.

Fig. 7. Evolved room floor plans with 6 objectives at the 50th generation of the 5th of 10 trial runs. See abbreviations in the caption of Fig. 4. Solutions of Pareto rank 2 are the 15th and 16th plans in the order of top-left to bottom-right, and others are the Pareto front solutions.

Objective1–Objective4 at the 50th generation of six-objective MOGA were about 0.05 worse than those of four-objective MOGA. Those of the Objective5 and Objective6 were low from the first generation. This may be due to the design of these objectives; for example, the best Objective6 is obtained when a $1m^2$ kitchen and a $1m^2$ water area are connected, which is not realistic.

Because we intend to use IEC in future experiments, a population size of 21 was chosen so that it would be manageable for the human evaluations required with IEC. This population size is quite small, however, and it is not in fact necessary to use the same population size in EMO when we combine IEC with EMO, because human evaluations are only required for the IEC process. We conducted 4-objective MOGA with 100 individuals to compare with the performance of Fig. 6. Fig. 9 shows the results. Although MOGA with 100 individuals performed slightly better than MOGA with 21 individuals, e.g. about 0.05 at the 50th generation, the difference is so small that the latter is also acceptable for practical applications.

V. Discussions

Fig. 10 shows the room floor plans selected from each trial run. The variety of plans generated exceeded our imagination, and they could not be obtained from the planning conditions alone. Both the spatial plan generator and the optimizer in Fig. 1 generated hallways using the same conditions used to generate the six other rooms, except for the conditions for the floor size and shape. Nevertheless the support system seems to have optimized the shape and function of the hallway well; one end of the hallway became an entrance hall from the common corridor, and the hallway connected the kitchen with the living room or alternatively connected two rooms. These are good functions for a hallway, and we did not expected to find them before the experiments.

The convergence of four-objective MOGA was comparatively fast, but still there is space to improve the diversity of obtained room floor plans (Fig. 5). The population size, which was made small at 21 to take into account the introduction of IEC for qualitative objectives in the next research step, may be one reason; reducing the rank of weak Pareto optimal

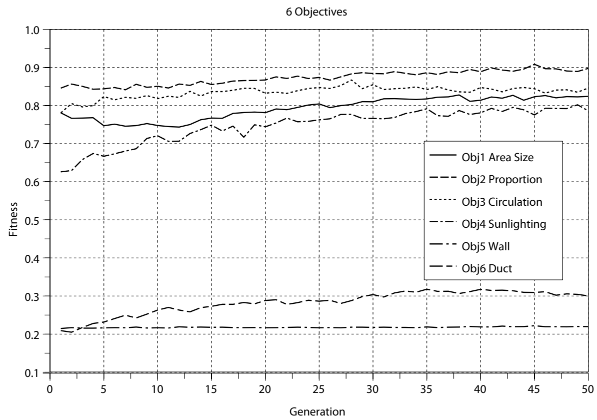


Fig. 8. Average convergence characteristics of 10 trial runs for 6-objective MOGA with 21 individuals. The curves of Obj5 and Obj6 show fitness convergence of wall length and duct length, respectively. For the other curves, refer to the caption of Fig. 6.

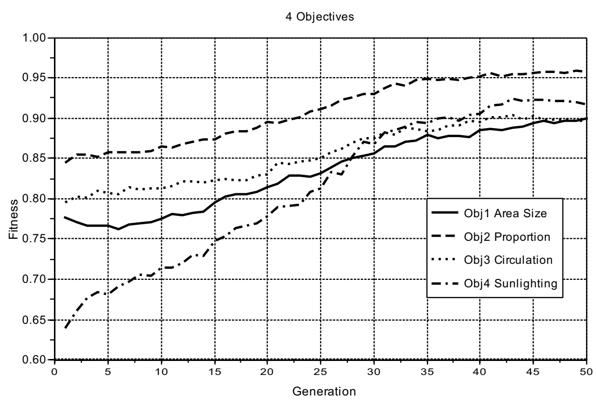


Fig. 9. Average convergence characteristics of 10 trial runs for 4-objective MOGA with 100 individuals. See Obj1–Obj4 in the caption of Fig. 6.

solutions may another other reason. We should be able to increase the diversity of results by adjusting the combination of objective functions and niche parameters. In addition, we need to evaluate other EMO methods for this task.

VI. Conclusion

First, we proposed an algorithm and growth rules for generating spatial plans by arranging subspaces within a planning area. The system allows variable sizes, shapes and positions of subspaces, minimizes useless gap spaces among subspaces, and its flexibility is higher than several previously proposed models for spatial planning. Secondly, we showed the framework of an architectural room floor planning support system consisting of a spatial plan generator using the proposed algorithm and growth rules and optimized using EMO.

We applied the framework to generate room floor plans for a housing complex with six rooms and a hallway and confirmed that the system generated useful and practical room floor plans using both four objectives and six objectives. The same algorithm and growth rules were able to optimize a

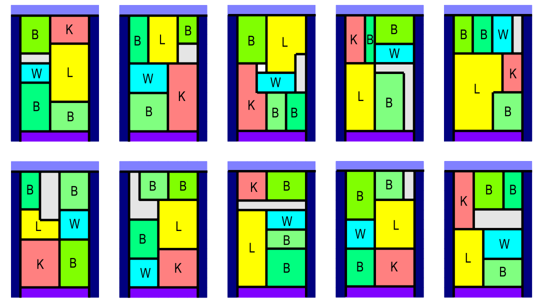


Fig. 10. Typical room floor plans selected from each of 10 trial runs; the plans from left to right in the upper row are obtained from the 1st to 5th trial run, and those in the lower row are obtained form 6th to 10th trial run.

hallway as they did the rooms, which increased the practicality and the diversity of the room floor plans. Another advantage of this system is that it can provide emergent hints to architects. The system generated several varieties of room floor plans that may not be sufficient to satisfy all objectives but some of them exceeded the plans that we consider in general. Although they may not be used as they are for the final room floor plans, they act as good starting points for architects, and therefore we can conclude that the capability of generating a variety of room plans is practical and useful.

Our future steps are to combine IEC with EMO for qualitative objectives, introduce area partitioning with curves, which is demanded in planning gardens or landscaping, and update our system for 3-D spatial planning for tasks such as planning multi-story buildings.

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