Evaluation of Hybrid Optimization with EMO and IEC for Architectural Floor Planning

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***Abstract*— We investigate the combinatorial effect of evolutionary multi-objective optimization (EMO) with interactive evolutionary computation (IEC). The purposes and combination ways of several presented EMO and IEC researches are different. We evaluated seven combination ways of four EMO objectives given by fitness functions and one IEC objective given by a pseudo-IEC user outputting stable evaluation regardless repeated experiments in our previous experiments. In this paper, we extend experimental conditions to 39 and evaluate them: 3 pseudo-users × 13 combination ways of 4 + 1 objectives. We also consider features of this system.**

Keywords—interactive evolutionary computation , evolutionary multi-objective optimization , soft computing , architectural planning.

I. INTRODUCTION

Design field and application to real problems are treated as multi-objective problems, because they have many conditions or requirements. In particular, architectural planning and design require determination based on the planners' experience, knowledge, sensitivity and aesthetic sense also at the same time. We have already proposed an architectural floor planning support system, using a computer, puts subjective evaluation or judgment into multi-objective optimization. A method of the incorporation is interactive evolutionary computation, IEC [10].

This study's goal is to carry out fusion of IEC and evolutionary multi-objective optimization, EMO. The computer evaluates objectives preset in EMO, a user subjectively evaluates in IEC. There are not so many studies on the combination of IEC and EMO so far, their purposes and combination methods are different in various ways [1, 5, 9]. Reference [11] was the first research of IEC with EMO.

Many previous researches have considered that user fatigue is problem in IEC evaluation. Too many evaluations give fatigue the user and disturb stable optimization. On the other hand, insufficient number of evaluations does not bring desirable solutions. We have conducted experiments of the combination to examine whether it is possible to sufficiently optimize in moderate number of evaluations. We have set seven combinations that changed four objective evaluations in EMO and one in IEC in each generation with one pseudo-user [5]. Generally, humans evaluate a task in IEC. However, we use a function that evaluates artificially instead of human-user in order to obtain stable evaluations in repeated experiments of this research.

Setting conditions of [5] is insufficient. Therefore, we extend experimental conditions to 39 and evaluate them: 3 pseudo-users × 13 combination ways of 4+1 objectives in this paper in order to further deepen discussion.

II. SYSTEM OVERVIEW AND CONFIGURATION

A. System configuration

Architectural floor planning support system of this study uses three methods, spatial generation algorithm, EMO and IEC. The system is composed of two parts roughly, optimization unit and spatial plan generation unit. The spatial plan generation unit has growth rules and spatial generation algorithm and generates architectural floor plans. Optimization unit consists of EMO for multi-objective optimization under constraint of required specifications and IEC for the design to satisfy difficulty qualitative objectives such as experience, knowledge and sensitivity [7, 8].

B. Spatial generation algorithm

Spatial generation algorithm that we have already proposed [6, 7] is as follows.

1. Initial placement of growth starting points, seeds of each room is based on knowledge or at random to cells on m × n.
2. Space of each room grows into adjacent cells.
3. The space does not grow in direction if there is an obstacle such as a wall or other rooms in the growth direction.
4. The above 2 and 3 are repeated until it is no longer able to grow.

When we apply the spatial generation algorithm to the architectural planning support system, we regard a subspace as a room and whole space as planning area. We call descriptions how to grow the subspaces growth rules. For example, there are directions, order or amount of growth, restriction at the time of collision with the other subspaces, etc…. The rule determines shapes of the generating spaces. We define a chromosome a set of seeds' coordinates of each room, subspace in order to optimize the floor plans by evolutionary computing (EC) in this study [7, 8].

C. Application to architectural floor planning

Planning target is a floor plan of an apartment dwelling unit. The system plans six rooms (a living room, a dining kitchen, three bedrooms and a water area) and a corridor within area of $84m^2$ (12m × 7m). A smallest unit of planning or module is a cell of 1m × 1m. If the north direction is above the plan, a public pathway is on the north side, walls of adjacent dwellings are on the east and west side and a veranda is on the south side, around the planning area. The peripheral part functions as limits of growth or obstacles in spatial generation algorithm. We regard a boundary between the rooms as a wall. Although it is necessary to install doors and windows to the wall in an actual building, this planning support system will not determine their locations.

D. Objectives of architectural floor planning problem

We set five objectives for the optimization. They are four objectives to be satisfied as limited architectural plans and one objective by user evaluation. Their definitions are as follows.

Objective 1: room floor area. We define desirable floor area that living room = 20 m^2, dining and kitchen = 16 m^2, each bedroom (1-3) = 12 m^2, water area = 9 m^2, corridor = 1 m^2. We have already defined a fitness function to be one if floor area of room *i* is within ± 10% of the desirable floor area $\hat{a}_i$ [8]. A fitness value of the entire plan about room floor area is the sum of the fitness values of the six rooms and corridor (1).

$$f^1 = \sum_{i=1}^{7} f_i^1(a_i) \tag{1}$$

Objective 2: room floor shape. We have already defined a fitness function $f_i^2(r_i)$ for aspect ratio to be r_i stands for short side length / long side length of the room *i* floor [8]. g_i^2 is defined (room floor area a_i) / (the smallest rectangle area that contains all room *i* area), for rectangular degree of the room floor shape. And each g_i^2 is weighted w_i [8] because room floor shape importance differs in room type. Thus (2) stands for a fitness value of the entire room floor shape.

$$f^2 = \sum_{i=1}^{7} (w_i \times f_i^2(r_i) \times g_i^2) \tag{2}$$

Objective 3: Circulation. We have already set some check items to satisfy architectural circulation about adjacencies between rooms or between a room and the around for the whole room floor plan [8]. Fitness value f^3 for the circulation is obtained by counting the satisfied conditions.

Objective 4: Sun lighting. The building standard law of Japan, article 28 requires that window area for sun lighting is 1/7 or more of the floor area of each living room, dining and kitchen, bedroom. We set that every one meter of wall contacting the public pathway can take sun lighting area $1m^2$ and every one meter of wall contacting the veranda can do $2m^2$. We have already defined a membership function that if the sun lighting area is 1/7 or more of floor area, fitness values for sun lighting are ones, if not, the values are between 0 and 1 depending on the degree [8]. And their sum is fitness value f^4 for the sun lighting of the entire room floor plan.

Objective 5: Qualitative evaluation by pseudo-users. User evaluation by the pseudo-user is the fifth objective in this paper.

E. Pseudo-user

Repetition of an evaluation in a subject experiment fatigues human-users. And they also get used to the experiments. This human instability interferes with accurate data collection and greatly influences the experiments. Therefore it is said that the pseudo IEC user are effective for stable experiments [4]. We examine proposed methods using pseudo-human as a user evaluation in IEC in this research.

We set the pseudo-user evaluation according to the five-grade. At first, we have some room plans as pseudo-user's ideal goals beforehand. The room plan of an individual is compared with the aim room plan by a cell unit. And the difference is smaller; its evaluation value becomes higher. When the differences between individual and aim plan are the same in all individuals at a generation, all those evaluations value is given three. We prepare type I, II and III as the aim room plans for the pseudo-user (Fig. 1). Furthermore, each symmetric room plan for the aim are prepared because there is no difference in condition of right and left around the planning area. We set three types of I, II and III for the pseudo-users, and define three aim room plans I, II and III for the each pseudo-user. The system compares the target individual's room plan with the right and left symmetric aim plans, and then it takes the smaller difference of those for an evaluation. Because the objective about bedrooms is common to three bedrooms, we let the system judge it to be the same if it is a bedroom. In addition, the floor area of room plans that the pseudo-users aims for are the following. Living room = 18 - 20 m^2, dining kitchen = 15 - 16 m^2, bedroom 1 - 3 = 9 - 12 m^2 for each, water area = 9 m^2 and corridor = 4 - 7 m^2.

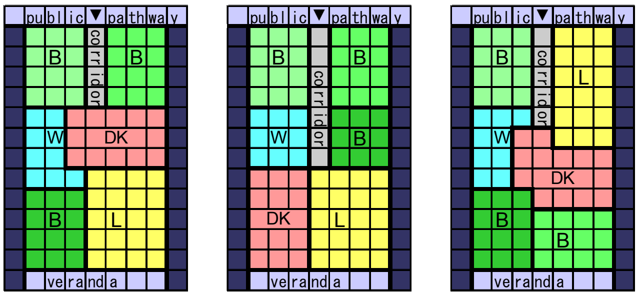


Fig. 1. Floor plans that pseudo-users aim for. (Room plan I, II and III from the left. L, DK, W, B stand for a living room, a dining kitchen, water-area and a bedroom. However, those letters' position is not a position of the seeds. Gray area means a corridor. The system uses the right and left inverse plan for the evaluation.)

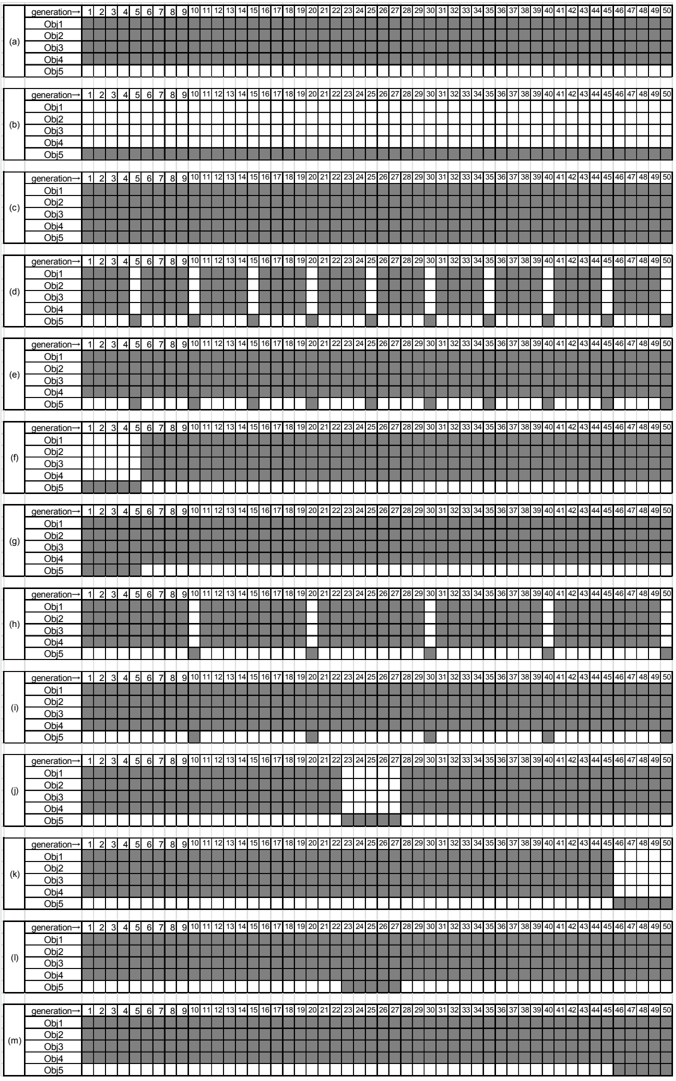


Fig. 2. Combinations of the objectives to use for Pareto rank every generation. *(Gray cells show that Pareto rank uses the objectives.)*

III. Optimization Experiments

A. Experiment setting

Five objectives set in section II-D are combined for the evaluation. The other settings are 50 samples, 50 generations, 21 individuals, roulette selection, mutation rate 1%, crossover rate 100%, uniform crossover and niche size σ_{share} [2] 49/4. Growth order of the spatial generation algorithm are living room, dining kitchen, bedroom 1, bedroom 2, bedroom 3, water area, corridor. We use multi-objective genetic algorithm (MOGA) [2, 3] as EMO in the optimization part. In addition, each objective fitness value is normalized so that the best becomes one.

B. Interactive evolutionary multi-objective optimization

This study's method to introduce IEC into EMO is a combination with next two.

1. A user evaluation value in IEC is incorporated in the Pareto ranking [3] process as one of the multi-objective fitness values in EMO.
2. Generations optimized for multi-objective by normal EMO and generations optimized by normal IEC are combined every EC generation.

It is necessary to consider user's fatigue in real evaluations and there are some precedence researches [9] on EMO and IEC combinations for the reducing user fatigue. An experiment aim of this study is to verify how we combine a few user evaluations with EMO. We confirm relationship between the user (pseudo-user) evaluations and the objectives in the EMO part and consider it. We set 13 ways of combinations, of four objectives and the pseudo-user evaluation as another objective, like a Fig. 2 (a) – (m). It is said that the fewer number of user evaluations helps to reduce user fatigue. We set the number of human evaluations to 5 and 10 as our experimental conditions. Then, we prepared several combinations of objectives, (a) - (m), and investigated the best timing or generation of human evaluations.

IV. Results

Fig. 3 – Fig. 6 show relations of the five objective fitness (averages of 21 individuals and 50 samples) and the generations in case of evaluation objective combination from (a) to (m) and pseudo-user I and II. We leave figures of pseudo-user III out.

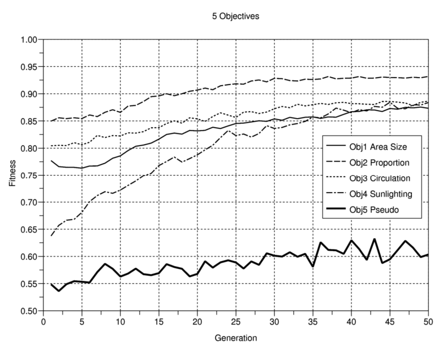
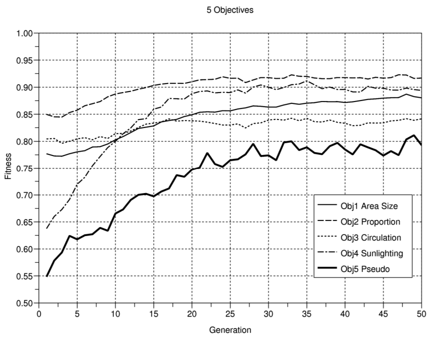
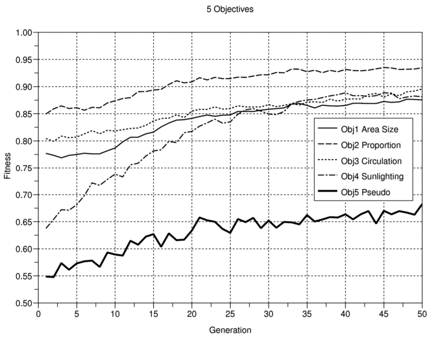


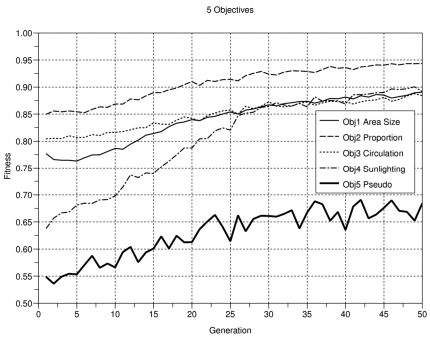
Fig. 3. Fitness changes for objective combination (a) and pseudo-user I.



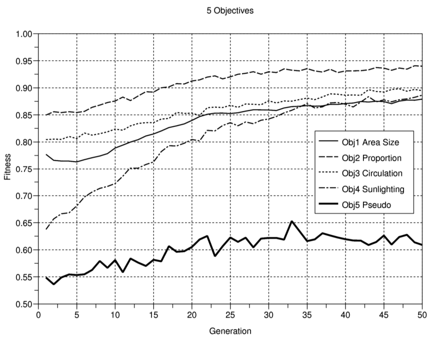
I - (b)



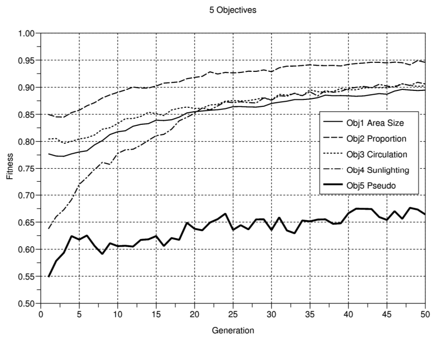
I - (c)



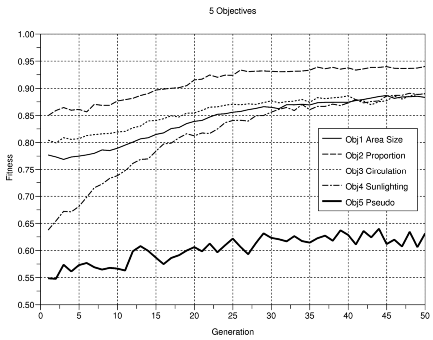
I - (d)



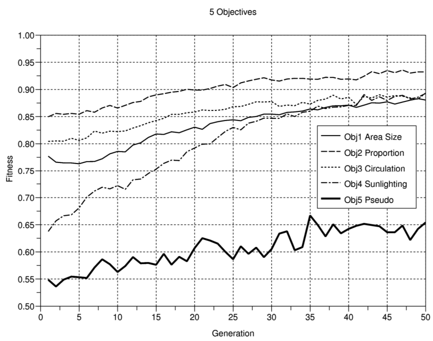
I - (e)



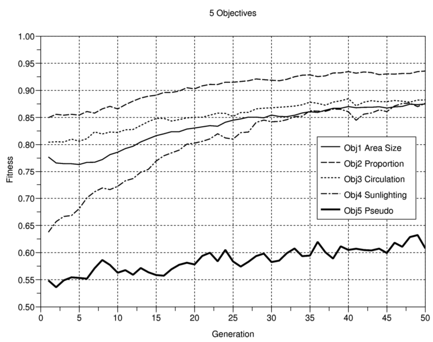
I - (f)



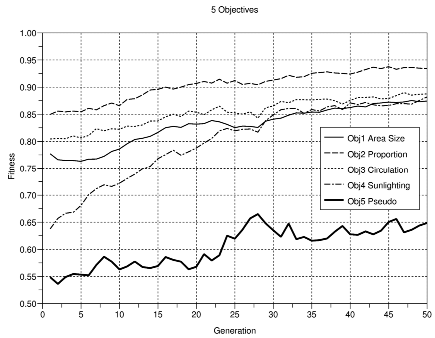
I - (g)



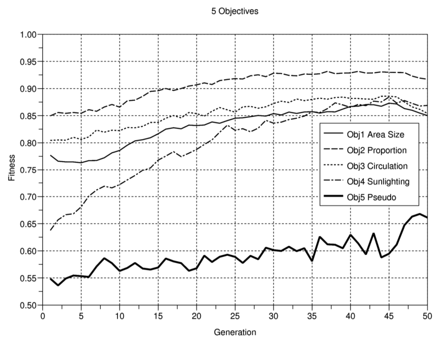
I - (h)



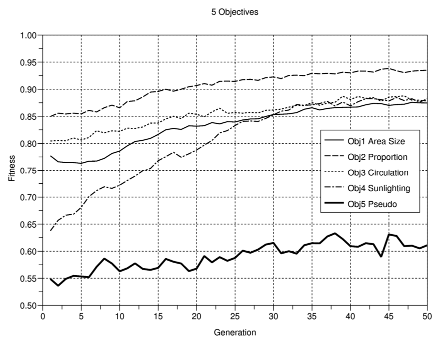
I - (i)



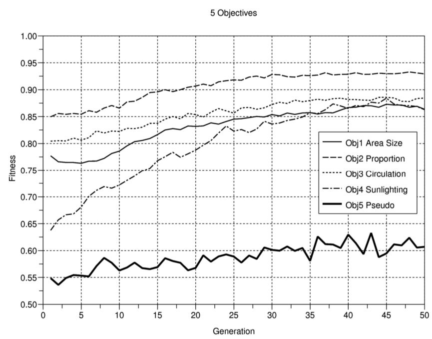
I - (j)



I - (k)

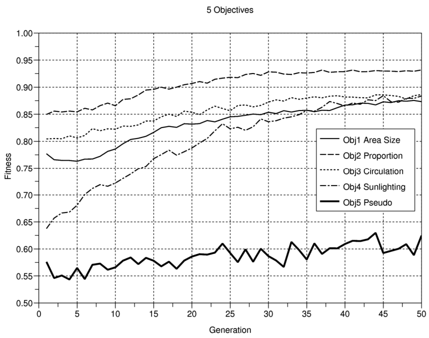


I - (l)

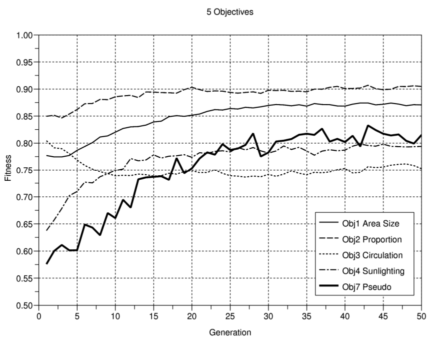


I - (m)

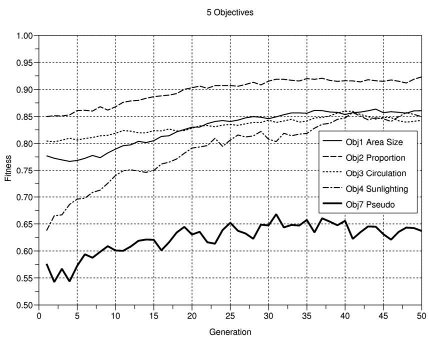
Fig. 4. Fitness changes for objective combinations (b) – (m) and pseudo-user I.



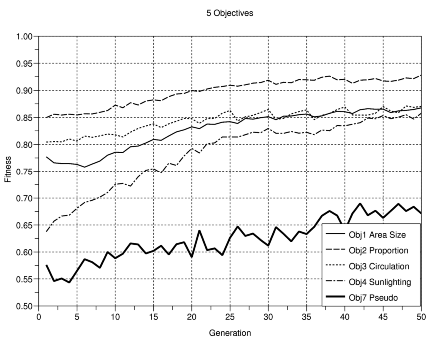
II - (a)



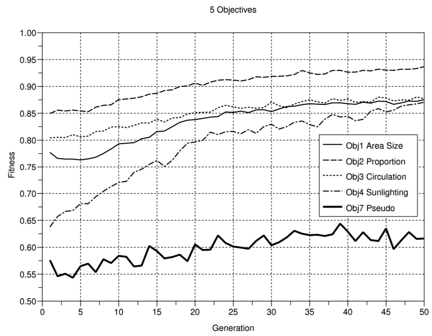
II - (b)



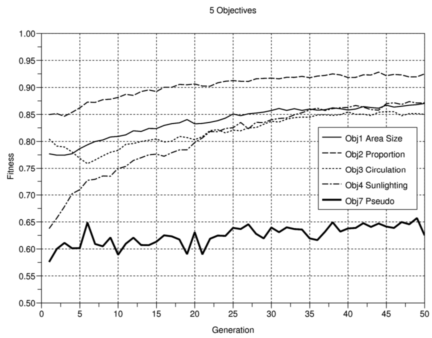
II - (c)



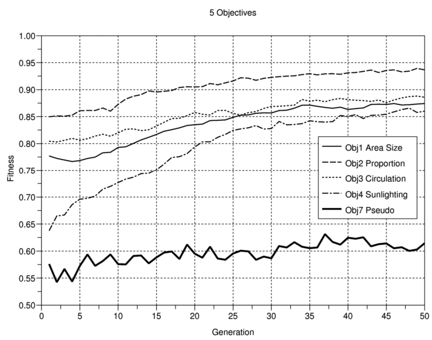
II - (d)



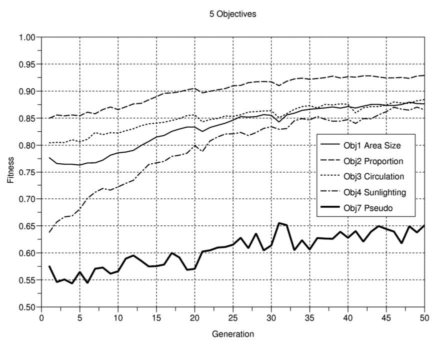
II - (e)



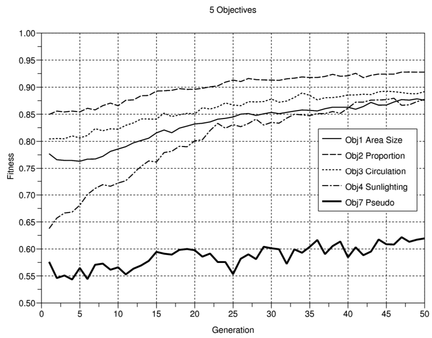
II - (f)



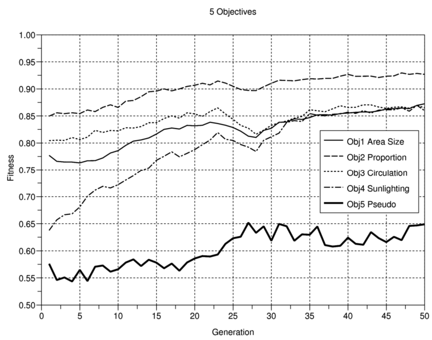
II - (g)



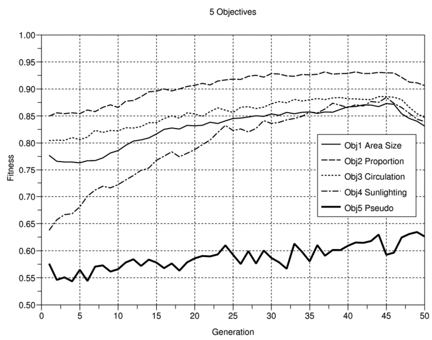
II – (h)



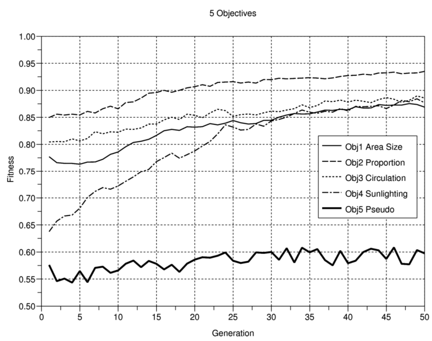
II - (i)



II - (j)



II - (k)



II - (l)

Fig. 5. Fitness changes for objective combinations (a) – (l) and pseudo-user II.

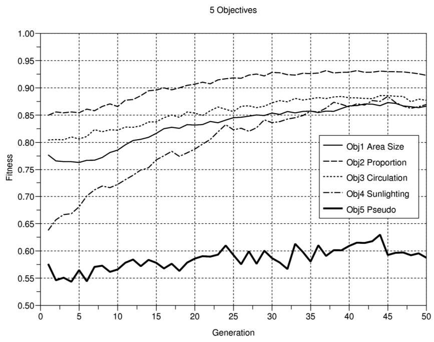


Fig. 6. Fitness changes for objective combination (m) and pseudo-user II.

V. CONSIDERATIONS

Judging from Fig. 3 to 6, fitness convergences of (f) seem to be relatively good (Fig. 4 (f)) about pseudo-user I. (f) is a combination that optimize the objective by the pseudo-user evaluation from the first to the fifth generations and optimize the four objectives from the sixth to the 50th generations (Fig. 2 (f)). Compared with (a) (Fig. 3) which optimized the four objectives in all generations, fitness progresses of (f) are fast to the 15th generation and the values are high after the 35th generation also. This shows that the user evaluation in an early generation might be effective for the optimization. And, user evaluation five times in combination (f) is relatively few. It shows a possibility to reduce the user's fatigue.

We examined sign tests that compared combination (f) with the other 12 combinations for average fitness values of 21 individuals and 50 samples every five objective, every five generation step. As a result (TABLE I), significant differences that mean combination (f) is better compared with the others were seen at relatively many points. On the other hand, significant differences that mean combination (f) is worse were only some part of the 15th and the 20th generation.

We examined the same sign tests about pseudo-user II also. As a result (TABLE II), significant differences that mean combination (f) is worse particularly for objective 3 (circulation) compared with many others were seen at relatively early generation. The plans of pseudo-user II have no circulation problem and it is also unknown whether it is because of affinity between the aim plans and the EMO's four objectives. In addition, there were good significant differences in only comparison with (b). Only the result of the pseudo-user II was different from the others. We think that it was due to the different characteristic of its targeted floor layout from others. In addition, it might be hard for our layout generation algorithm to target the layout II task that the Objectives 1-4 might not match.

We examined the same sign tests about pseudo-user III also, because the fitness convergence properties of (f) seemed to be relatively good. As a result (TABLE III), good significant differences were seen in many cases like pseudo-user I.

The fitness of objective 2 and 3 with pseudo-user I, II and III were bad (Fig. 4 (b), TABLE I - III) in (b) evaluating only pseudo-user for all generations. It may be natural because the system did not evaluate four objectives set in EMO part. On the other hand, the fitness of objective 5 rose with generation progress in all combinations. The user's aim and the quantitative objectives' aim do not always go together. Therefore, we should consider that they have bad influences each other depending on the combinations.

We terminated our EC search at the 50 generation regardless it reached to the global optimum but discussed the results till the 50th generation using a statistical test.

The fitness fluctuation of the Objective 5 is bigger than those of other objectives in Fig.s 4-6. We think that its reason is that most of objective combinations often evaluate populations about only objective 5.

TABLE I. SIGN TEST ABOUT PSEUDO-USER I

Compared combination (f) with the other 12 combinations for average fitness values of 21 individuals and 50 samples every five objective, every five generation step. ++ shows that (f) is better with significant difference level 1%, + does 5%, -- does (f) is worse with significant difference level 1% and – does 5%.

I (f) vs	generations→	5	10	15	20	25	30	35	40	45	50
(a)	Objective 1	++	++		++				++		++
	Objective 2		++					++			+
	Objective 3										
	Objective 4	+	++	+	++	++			++		
	Objective 5				++	+					
(b)	Objective 1										
	Objective 2								++	++	+
	Objective 3			+		++	+	++	++	++	++
	Objective 4				--						
	Objective 5			–							
(c)	Objective 1		++	+			+				+
	Objective 2										
	Objective 3									+	
	Objective 4				+		+				
	Objective 5										
(d)	Objective 1	++	++	++	++						
	Objective 2		++								
	Objective 3		++					++	+	+	++
	Objective 4	+	++	++	++	+					
	Objective 5		+								
(e)	Objective 1	++	++	++					++	+	++
	Objective 2		+	+					+		
	Objective 3		+						++		+
	Objective 4	+	++	++			+				
	Objective 5				+						
(g)	Objective 1		++	++							
	Objective 2		++								
	Objective 3		+	+				++			
	Objective 4		+		+				+		
	Objective 5										
(h)	Objective 1	++	++	++	++		+		+		++
	Objective 2		++		+	++			+		
	Objective 3							+		+	
	Objective 4	+	++	++	++	+					
	Objective 5				++	++					
(i)	Objective 1	++	++	+	+				+	++	+
	Objective 2		++		+			+			
	Objective 3					+					
	Objective 4	+	++	+	++	++					
	Objective 5				+						
(j)	Objective 1	++	++		++	++	++	++		+	
	Objective 2		++								
	Objective 3					+				+	+
	Objective 4	+	++	+	++	++			+		
	Objective 5				++						
(k)	Objective 1	++	++		++				++		++
	Objective 2		++					++			+
	Objective 3										++
	Objective 4	+	++	+	++	++			++		
	Objective 5				++	+					
(l)	Objective 1	++	++		++	+					+
	Objective 2		++								
	Objective 3							+			++
	Objective 4	+	++	+	++						
	Objective 5				++	+					
(m)	Objective 1	++	++		++				++		++
	Objective 2		++					++			+
	Objective 3										
	Objective 4	+	++	+	++	++			++		+
	Objective 5				++	+					

TABLE II. SIGN TEST ABOUT PSEUDO-USER II

Compared combination (f) with the other 12 combinations for average fitness values of 21 individuals and 50 samples every five objective, every five generation step. ++ shows that (f) is better with significant difference level 1%, + does 5%, -- does (f) is worse with significant difference level 1% and – does 5%.

Ⅱ (f) vs	generations→	5	10	15	20	25	30	35	40	45	50
(a)	Objective 1	++	++								
	Objective 2								-		
	Objective 3	--	--	--	--	-		--			
	Objective 4										
	Objective 5										
(b)	Objective 1				-						
	Objective 2								+	+	
	Objective 3		++	++	+	++	++	++	++	++	++
	Objective 4					+	++	++	++	++	++
	Objective 5			-	--						
(c)	Objective 1	++	++	+							
	Objective 2		+								
	Objective 3	--	--	-							
	Objective 4	+									
	Objective 5										
(d)	Objective 1	++	++								
	Objective 2										
	Objective 3	--	--	--	--	--					
	Objective 4							+			
	Objective 5										
(e)	Objective 1	++	+								
	Objective 2										
	Objective 3	--	--	--	--	--	--				
	Objective 4										
	Objective 5										
(g)	Objective 1	++									
	Objective 2							-			
	Objective 3	--	--	--	--	--	-	--	-		--
	Objective 4	+									
	Objective 5										
(h)	Objective 1	++	++								-
	Objective 2										
	Objective 3	--	--	-	--	--					--
	Objective 4										
	Objective 5										
(i)	Objective 1	++	++								
	Objective 2										
	Objective 3	--	--	--	--	--	--	--		-	-
	Objective 4										
	Objective 5										
(j)	Objective 1	++	++			++	++				
	Objective 2										
	Objective 3	--	--	--	--						
	Objective 4										
	Objective 5										
(k)	Objective 1	++	++								++
	Objective 2								-		
	Objective 3	--	--	--	--	-		--			
	Objective 4										
	Objective 5										
(l)	Objective 1	++	++								
	Objective 2										-
	Objective 3	--	--	--	--						-
	Objective 4										
	Objective 5										
(m)	Objective 1	++	++								
	Objective 2								-		
	Objective 3	--	--	--	--	-		--			
	Objective 4										
	Objective 5										

TABLE III. SIGN TEST ABOUT PSEUDO-USER III

Compared combination (f) with the other 12 combinations for average fitness values of 21 individuals and 50 samples every five objective, every five generation step. ++ shows that (f) is better with significant difference level 1%, + does 5%, -- does (f) is worse with significant difference level 1% and – does 5%.

Ⅲ (f) vs	generations→	5	10	15	20	25	30	35	40	45	50
(a)	Objective 1		+			+	+	+	+		
	Objective 2				++						+
	Objective 3										
	Objective 4				++						
	Objective 5					+					
(b)	Objective 1		+							++	
	Objective 2			++	++	++	++	++	++	++	++
	Objective 3		++	+	++	++	++	++	++	++	++
	Objective 4		++	++	++	++	++	++	++	++	++
	Objective 5										
(c)	Objective 1		++	++	+	++	++	+	+	+	
	Objective 2			+	+		++				+
	Objective 3			+							
	Objective 4					+		+	+		
	Objective 5										++
(d)	Objective 1		+		+						
	Objective 2			+							
	Objective 3										
	Objective 4			++	+	++					
	Objective 5										
(e)	Objective 1		++	++		+					
	Objective 2			+	+						
	Objective 3										
	Objective 4			++		+			+		
	Objective 5					+					
(g)	Objective 1			+		+					
	Objective 2										
	Objective 3										+
	Objective 4				+						
	Objective 5					+					
(h)	Objective 1		+	++		++					
	Objective 2				+						
	Objective 3										
	Objective 4				+						
	Objective 5										
(i)	Objective 1		+	+	++	++	++	+	++		
	Objective 2				++		+				
	Objective 3					-					
	Objective 4			+				+			
	Objective 5										
(j)	Objective 1		+			++	++	++	+		
	Objective 2				++	++	+				
	Objective 3										
	Objective 4				++	+	++	+	+		
	Objective 5										
(k)	Objective 1		+			+	+	+	+		++
	Objective 2				++						++
	Objective 3										++
	Objective 4				++						++
	Objective 5					+					
(l)	Objective 1		+			++					
	Objective 2				++	++	+		+		+
	Objective 3										
	Objective 4				++	++	+	+	+		
	Objective 5										
(m)	Objective 1		+			+	+	+	+		++
	Objective 2				++						
	Objective 3										
	Objective 4				++						
	Objective 5					+					

VI. CONCLUSIONS

We tried fusion of IEC and EMO, examined the combinations with plural setting and tested its effectiveness. Combination (f) made some fine room plans in relatively early generation in two with two setting of the three pseudo-users even as for a few evaluation times, probably because the user evaluation in early generation gave good influence for the later. However, a result of the combination which seemed to be the best was different about one of three pseudo-users. And it turned out different from the precedent study [9] that assumed MEMS as a task. It is necessary to make experiments changed characteristics of subjective objectives and objective objectives of EMO for clarification these questions.

We set the differences with the aim room plans to the fitness values, but the question whether it is good as evaluation functions. Only differing from the aim plans may greatly influence the evaluations in this setting to always aim for the fixed room plans, even if the individual has good fitness values for four objective of EMO. If a search space has many peaks characteristic by a pseudo-user aiming at plural room plans, some proper individuals appearing in middle generations may succeed to later optimization. We have to conduct the experiments at such points of view in future.

In addition, these sign tests compare the combinations every objective, however we should use Pareto ranking for multi-objective problem.

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