Computers and Concrete, Vol. 11, No. 3 (2013) 183-199
DOI: http://dx.doi.org/10.12989/cac.2013.11.3.183

Genetic algorithm in mix proportion design of recycled aggregate concrete

W.J. Park[1], T. Noguchi[2] and H.S. Lee*[3]

[1]Sustainable Building Research Centre, Hanyang University, Ansan, Korea
[2]Faculty of Engineering (Architecture), the University of Tokyo, Tokyo, Japan
[3]School of Architecture, Hanyang University, Ansan, Korea

(Received January 9, 2012, Revised December 11, 2012, Accepted January 3, 2013)

Abstract. To select a most desired mix proportion that meets required performances according to the quality of recycled aggregate, a large number of experimental works must be carried out. This paper proposed a new design method for the mix proportion of recycled aggregate concrete to reduce the number of trial mixes. Genetic algorithm is adapted for the method, which has been an optimization technique to solve the multi-criteria problem through the simulated biological evolutionary process. Fitness functions for the required properties of concrete such as slump, density, strength, elastic modulus, carbonation resistance, price and carbon dioxide emission were developed based on statistical analysis on conventional data or adapted from various early studies. Then these fitness functions were applied in the genetic algorithm. As a result, several optimum mix proportions for recycled aggregate concrete that meets required performances were obtained.

Keywords: mix proportion design; recycled aggregate; recycled aggregate concrete; genetic algorithm

1. Introduction

Recycling concrete waste has become more important for sustainable building material due to the reduction of waste disposal, depletion of natural resources and the lack of final disposal area. However, almost recycled aggregates (RA) made from concrete waste are consumed for roadbed gravel and landfill. Therefore, it is significantly important to expand the use of RA for concrete such a recycled aggregate concrete (RAC). To obtain various performances that cannot be obtained from conventional concrete and by the current mix proportion method, a large number of trial mixes are required to select the desired composition of materials that meets desired performances for concrete (Wang 2012)

Design of RAC mix proportion can be solved as the multi-criteria problem to meet the various required performance (Shin 2006). In this study, genetic algorithm (GA) that is well known for the advantage of solving the combination problem was used to solve the multi-criteria problem like mix design of concrete (Lim 2004, Peng 2009, Parichatprecha 2009). GA, known as a very efficient heuristic algorithm that has been widely used in the various fields of engineering, is based

*Corresponding author, Professor, E-mail: ercleehs@hanyang.ac.kr

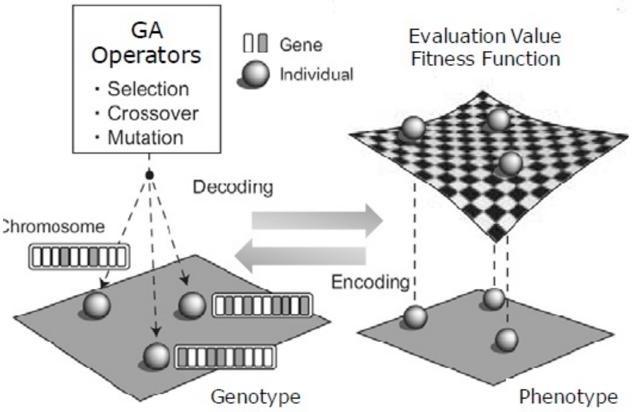


Fig. 1 Process of genetic calculation on GA

on the mechanism of natural selection and natural genetics (Goldberg 1989). The general form of GA is composed of three major operators, i.e., selection, crossover, and mutation throughout optimizing, learning, and searching algorithms (Holland 1975). GA deal with genotype which is coded as a finite-length string with binary digits containing information of various materials of concrete. Process of genetic calculation on GA is illustrated in Fig. 1 (Park 2011).

2. Pareto optimal solution

Problems of mix proportion for RAC are difficult to solve using the typical methods that basically search for the best solution with a single objective function, i.e., linear and non-linear problems. The purpose of a multi-objective optimization is to optimize multiple conflicting objectives such various required performances at the same time. The general form of a multi-objective optimization problem (MOP) is as follows (Shin 2006).

$$\text{optimize} \quad f_i(\mathrm{X}),\ i= 1, \ldots, M$$
$$\text{subject to} \quad g_j(\mathrm{X}) = 0,\ j= 1, \ldots, N$$
$$h_k(\mathrm{X}) \geq 0,\ k= 1, \ldots, \mathrm{O}$$
$$\mathrm{X} = (x_1, \ldots, x_n),\ x_l^{(\mathrm{L})} \leq x_l \leq x_l^{(\mathrm{U})};\ 1 = 1, \ldots, n \tag{1}$$

where f, g, h, M, N and O represents the objective, the equality constraint, the inequality constraint, the number of objectives, the number of equality constraints, and the number of inequality constraints. $x^{(L)}$ and $x^{(U)}$ are the lower and upper bounds of decision variable x, respectively. And n is the number of variables. To compare the different solutions in a MOP and judge the superiority of a solution, Pareto optimality is usually used. The Pareto optimal can be defined as follows. In the case of maximization, a solution X is said to dominate another solution Y when

$$\forall i \in \{1, \ldots, \mathrm{M}\}, \qquad f_i(\mathrm{X}) \leq f_i(\mathrm{Y}) \tag{2}$$

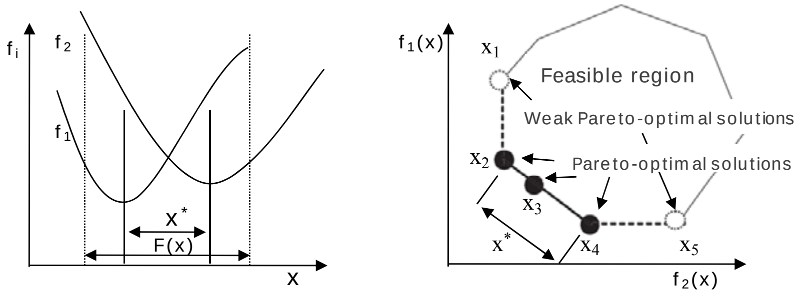


Fig. 2 The concept of Pareto-optimal solution

$$\exists\, i \in \{1, \cdots, M\}, \qquad f_i(X) \leq f_i(Y) \tag{3}$$

$$(x <_p y) \;=\; (\forall\, i)(x_i < y_i) \wedge (\exists\, i)(x_i < y_i) \tag{4}$$

If there is no dominating solution, the solutions are "non-dominated (non-inferior)" to each other and treated as equally good. The most ideal solution of a MOP is one that dominates the others. However, it is impossible to find a single dominating solution due to the conflicting relation between objectives. Thus, a practical solution of a MOP is to find a set of mutually non-dominated solutions (non-dominated set) that approximates the set of efficient solutions (Pareto optimal set). Each solution in the non-dominated set corresponds to a different tradeoff among multiple objectives. At the final step, therefore, a decision maker is necessary to select a recommended solution among the trade-off solutions (Shin 2006).

According to Pareto optimum definition, if there is a point that is not less than any other by all criteria, only the best point will get a better evaluation. If there is no such a point, a set of non-dominated points will be evaluated. Therefore, the proportioning problem for RAC with GA can be applied to MOP (Maruyama 2001). The concept of Pareto-optimal solution is illustrated in Fig. 2.

3. Genetic algorithm

Genetic algorithm (GA) is inspired by Darwin's theory about evolution. Solution to a problem solved by genetic algorithms is evolved. GA is started with a set of individuals (represented by chromosomes) called population. Individuals from one old population are taken and used to generate a new population by genetic operators. The general form of GA is composed of three major genetic operators, i.e., selection, crossover and mutation. And the new population will be better than the old one by those evolutionary processes as described in the book by Goldberg (1989).

3.1 Selection

Basically, the fundamental principle of GA is based on Darwin`s natural selection. The initial individuals (chromosomes) are selected by this operator. The selection operator of GA has three selection methods, i.e., roulette wheel selection (proportional selection), ranking selection and tournament selection. In these methods, this study adapts roulette wheel selection that is the best-known selecting method for its simplicity. The basic idea of roulette selection is to determine selection probability for each chromosome to be survived to the fitness value (Lim 2004, Eduardo 2004, Adil 2009). The selecting probability for chromosome with fitness values is calculated as follows Eqs. (5)-(7)

$$F = \sum_{i=1}^{N} f_i \tag{5}$$

$$p_i = f_i / F \quad (\text{i}=1, 2, 3, \ldots, N) \tag{6}$$

$$q_i = \sum_{j=1}^{i} p_j = \frac{1}{F} \sum_{j=1}^{i} f_i \quad (\text{i}=1, 2, 3, \ldots, N) \tag{7}$$

where P_i is the selection probability of a chromosome from population N, f_k is the size of population N, F is the size of whole population and q_i is accumulation probability. Therefore, a wheel can be operated according to these probabilities. The selecting operation is based on spinning the roulette wheel population size times. A single chromosome is selected for the new population as described in the last selection each time (Shin 2006).

3.2 Crossover

Crossover is one basic operators of GA. And its type and implementation depends on both encoding and problem property. In general, binary encoding, permutation encoding, value encoding, and tree encoding are representative. Mix problem for concrete can be approached by binary encoding. In binary encoding, crossover simulates the child generation (offspring) from two parents (1, 2). Also crossover is performed by taking parts of the bit string of the parents 1 and the other parts from the parent 2 and by combining both in the child according to crossover rate. This crossover rate is defined as the rate of the number of offspring produced in each generation to the population size. To undergo the crossover operation, this ratio controls the expected number (Crossover rate*Population size) of chromosomes (Lim 2004). The crossover operator of GA has three methods, i.e., single-point, two-point and uniform crossover. In these methods, this study adapts uniform crossover which has been shown to be superior to traditional crossover strategies for combinatorial problem. In uniform crossover, bits in binary encoding are randomly copied from the first or from the second parent and then exchanges relative genes between parents according to the bits with the same size of chromosome. The uniform crossover is illustrated in Fig. 3.

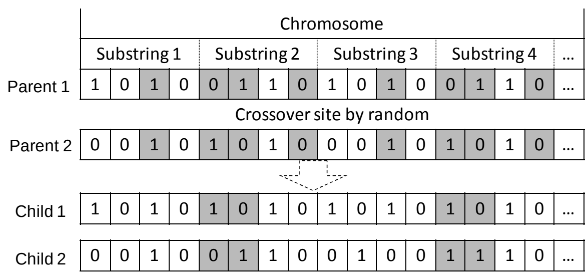


Fig. 3 Uniform crossover

3.3 Mutation

Boundary mutation changes one of the parameters of the parent. While the GA proceeds to generate new genotypes, it is always possible to lose the last copy of an allele value. Because the crossover operator is able to generate all possible values in case that the population contains only copy of a specific allele value. Mutation operator prevents the population of genotypes from losing a specific value of an allele. Mutation is performed with a given probability called mutation rate which is defined as the percentages of new genes to the total number of genes in the population. When mutation rate is too low, many genes that would have been useful are never tried out. Meanwhile, when it is too high, there will be as a random perturbation, the next generation will start losing their resemblance to the parents. In this study, bit inversion method is used as a mutation operator. Bit inversion is that selected bits are inverted according mutation rate. And the range of mutation rate is from 1% to 5% in general. In this study adapts 5% mutation rate for case study. The mutation operator is illustrated in Fig. 4.

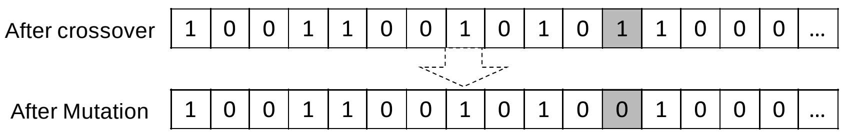


Fig. 4 Mutation

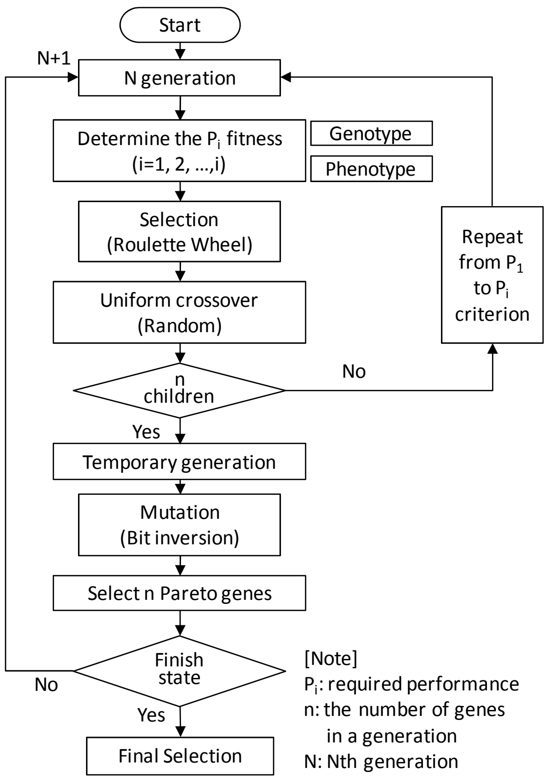


Fig. 5 Genetic algorithm process

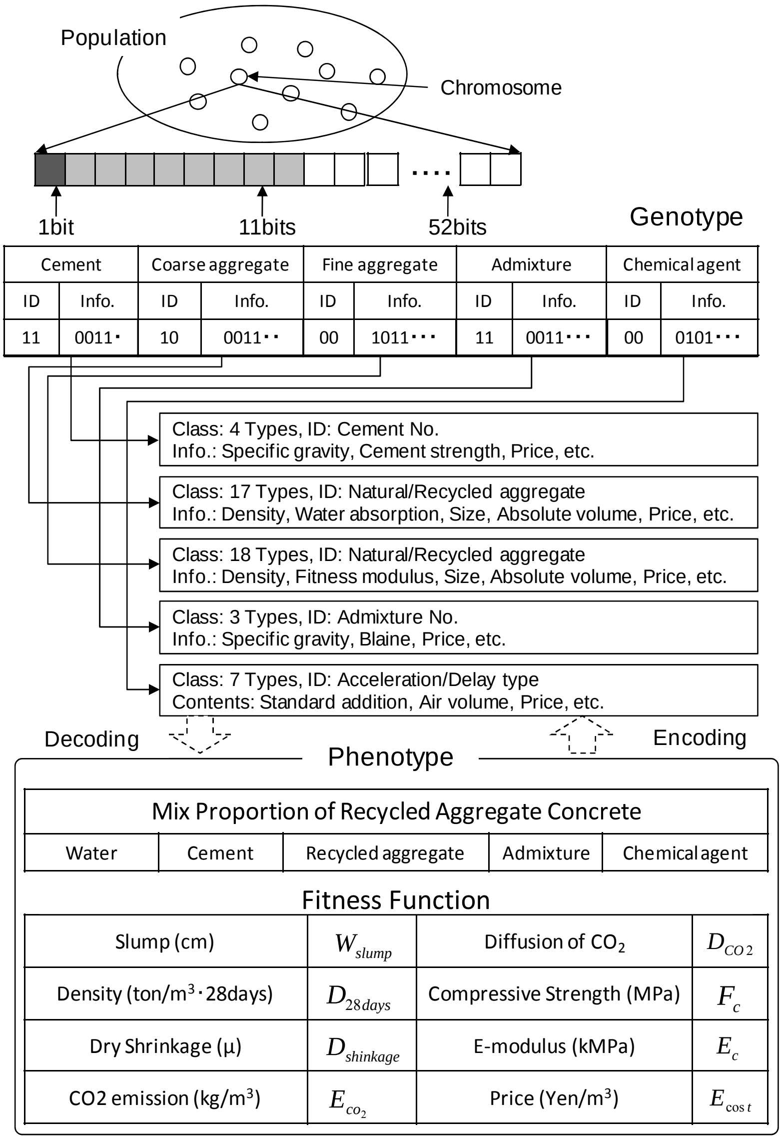
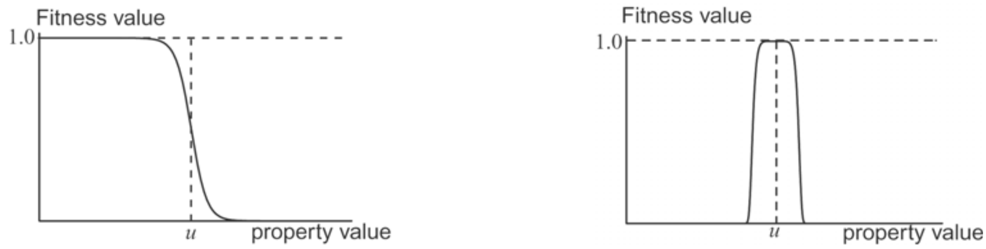


Fig. 6 Schematic of GA applied for mix proportion of RAC

3.4 Process of genetic algorithm

The total procedure of evolutionary optimization using GA is shown as follow. After generating random population of n chromosomes substituting solutions for mix proportion problem for concrete, evaluation on the fitness (P_i) of each chromosome x in the population is conducted by the repeating process of selection, crossover, and mutation. Mutate genes by reversing arbitrary loci with a constant probability of 5%. Select Pareto individual genes from the temporary generation and make the next generation that consists of N individuals. When fitness is satisfied, the repeating process is terminated and optimal solution is approached. Process of GA



(a) Type 1 (b) Type 2
Fig. 7 Fitness value and its shapes

for mix design in this study is shown in Fig. 5 (Maruyama 2002, Eduardo 2004, Yeh 2007 and 2009).

4. GA application to mix proportion design for RAC

To apply GA to a mix proportion design, genotype and phenotype is used as it can be seen in Fig. 1. Genotype is to represent various components and various mixture proportions of each chromosome. And each designed genotype has its phenotype which means the properties and performances of RAC that are estimated from mixture proportions coded information in the genotype. Schematic of GA applied for mix proportion of RAC is shown in Fig. 6 (Maruyama 2002 and Noguchi 2003).

The algorithm makes a phenotype (characteristic form and quality in the designed system) from each genotype and calculates fitness value from the phenotype in the designed system. Fitness value gives the numerical evaluation of both individual and phenotype. According to the fitness values, which can be plural in Pareto optimality problem, an individual in the population representing the set of individuals will be reproduced with crossover and mutation from generation to generation. Thus, when fitness is satisfied, the individuals approach the optimal solution. To derive this process, fitness functions are designed as shown in Eqs. (8) and (9), and Fig. 7. (Noguchi 2003, Maruyama 2001).

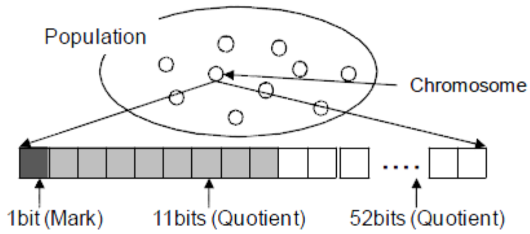
$$f_1(x) = \frac{1.0}{1.0 + e^{-(x-u_1)^n / T_1}} \tag{8}$$

$$f_2(x) = \frac{2.0}{1.0 + e^{-(x-u_2)^{2n} / T_2}} \tag{9}$$

where *f(x)*, *x*, *u* and *T* presents fitness value, fitness function, the parameter representing the required performance of concrete mix and *T* presents the parameter determining fitness function. Using this notion of Pareto optimal set of GA developed for MOP is applied to the problem of concrete mix proportioning.

4.1 Encoding of genotype

Encoding of chromosomes depends on the problem. To solve multi-objective problem such a mix proportion, every chromosome is adjusted to binary encoding method that is the most general



$$2.225074 \times 10^{-308} < Range < 1.797693 \times 10^{308}$$

Fig. 8 Binary encoding and range of data expression

Table 1 Correction factor according to aggregate, cement and admixture

r_1	0.7	Crushed limestone	r_2	0.9	Fly-ash cement
	1.0	Natural aggregate			Early strength cement
	1.2	Lightweight aggregate		1.0	Ordinary Portland cement
	1.4	Recycled aggregate			Portland blast-furnace slag cement
r_3	0.7	Shrinkage reducing agent	r_3	1.0	None
	0.8	Silica fume			Granulated blast-furnace slag
	0.9	Fly-ash			

because of a string of bits (represented by the digits 0 and 1) to encode information for each chromosome even with a small number of alleles. Binary encoding and range of data expression is illustrated in Fig. 8.

4.2 Fitness function for phenotype

When a specific mix proportion for RAC needs to be determined, performances of RAC, i.e., compressive strength, slump, price etc. are very important characteristics in the process of mix design. The fitness functions of various required performance for RAC are essential for GA program. In this study, mainly slump, strength, elastic modulus, carbonation resistance, and price are determined and these are explained in the following sections (Park 2011).

4.2.1 Slump

Slump of RAC can be determined by the relation between the relative thickness of excess paste and the rheological parameters of fresh concrete as follows Eqs. (10) and (11) by Maruyama (2002) and Noguchi (2003).

$$W_{slump} = a \times Log(\tau_c) \times \frac{1}{1 + W/B} + b \tag{10}$$

$$\tau_c = \tau_p \times (1 + 0.075 \cdot \Gamma^{-2.22}) \tag{11}$$

where W/B, S, τ_c, τ_p and Γ are water to binder ratio, slump, yield value of fresh concrete, yield value of cement paste and relative thickness of excess paste. a and b are material parameters.

4.2.2 Dry shrinkage strain

Dry shrinkage strain of RAC can be calculated by formula proposed by AIJ (2006) as follows Eqs. (12) and (13), and Table 1.

$$D_{shrinkage}(t,t_0) = k \cdot t_0^{-0.08} \cdot \left(1-\left(\frac{h}{100}\right)^3\right) \cdot \left(\frac{(t-t_0)}{0.16 \cdot (V/S)^{1.8} + (t-t_0)}\right)^{1.4(V/S)-0.18} \tag{12}$$

$$k = (11 \cdot W - 1.0 \cdot C - 0.82 \cdot G + 404) \cdot \gamma_1 \cdot \gamma_2 \cdot \gamma_3 \tag{13}$$

with the notation

$D_{shrinkage}$` (t, t_0): : dry shrinkage strain when curing age is (t_0) ($\times 10^{-6}$)
W: unit water content (kg/m^3)
C: cement content per unit volume of concrete (kg/m^3)
G: weight of coarse aggregate per unit volume of concrete (kg/m^3)
h: relative humidity (%) (40%≦h≦100%)
V/S: volume to exposed surface-area ratio (mm) (V/S≦300mm)

4.2.3 Compressive strength

The factors affecting compressive strength (F_c) are mortar strength (F_m), impact factors of coarse aggregates (R_{CA}) and fine aggregate (R_{FA}), impact factor of admixture (R_{ad}) and impact factor of air content (R_{air}). In this study, basic fitness function of compressive strength can be formulated as shown in Eq. (14).

$$F_c = F_m \times R_{CA} \times R_{FA} \times R_{ad} \times R_{air} \tag{14}$$

Impact factors of mortar strength (F_m):

when discussing effect of W/B on compressive strength, mortar strength can be calculated by formula proposed by Duff (1910) as follow Eq. (15).

$$F_m = (a(B/W) + b) \cdot K \tag{15}$$

where B/W is binder to water ratio, and a, b and K are material constants depending on cement.

Impact factors of coarse aggregate (R_{CA}) by Maruyama (2002) and Noguchi (2003)

$$R_{CA} = \left(1-\left(c\left(\frac{1}{W/B+1}\right) \cdot \frac{V}{1000}\right)\right) \times (1-(d \cdot B/W + e) \cdot (\log C - \log A) \tag{16}$$

where V, C and A are volume of coarse aggregate per unit weight, maximum size of aggregate and minimum size affecting strength of aggregate. And c, d and e are material constants.

Impact factors of fine aggregate (R_{FA}) in Eq. (17)

$$R_{FA} = k_1 \tag{17}$$

where k_1 denotes the material parameter of fine aggregate type. 1.0 (silicate aggregate) and 0.89 (others) are used respectively (Jones 1957).

Impact factors (R_{FA}), when use recycled aggregate in Eq. (18)

$$\left.\begin{matrix} R_{CA} \\ R_{FA} \end{matrix}\right\} = -0.0242 \times W_{RA} + 1 \tag{18}$$

where W_{RA} is surface water content per unit weight;
Impact factors of admixture (R_{ad}) in Eq. (19)
when use ground granulated blast-furnace slag

$$C_3 < 0.3: \; R_{ad} = 1 + \left(\left(f \cdot (C_2 - g)^{\frac{3}{2}} \right) \cdot \left(\frac{1}{C_1 + 1} \right) + (h \cdot C_2 + i) \right) \cdot \frac{C_3}{0.3} \tag{19}$$

$$C_3 \geq 0.3: \; R_{ad} = R_{0.3} \times (j \cdot C_2 + k) \times \frac{C_3 - 0.3}{0.4} \tag{20}$$

where *f*, g, *h*, *i*, *j* and *k* represent the material parameter, C_1 is water to binder ratio, C_2 is specific surface area of slag, C_3 is the replacement ratio and *R*0.3 denotes the value calculated by Eq. (6) with C_3 of 0.3 by Maruyama (2002) and Noguchi (2003).
when use fly-ash;

$$C_3 < 0.45: \; R_{ad} = 1 - (l \cdot C_1 - m) \times C_3 \tag{21}$$

$$C_3 \geq 0.45: \; R_{ad} = 1 \tag{22}$$

where *l* and *m* represent the material parameter, C_3 is the replacement ratio.
when use silica fume

$$C_3 < 0.2: \; R_{ad1} = 1 + C_3 \tag{23}$$

$$0.2 \leq C_3 < 0.3: \; R_{ad2} = 1.25 \tag{24}$$

$$C_3 \geq 0.3: \; R_{ad3} = 1 \tag{25}$$

where C_3 is the replacement ratio.
Impact factors of air content (R_{air}) Eq. (26)

$$R_{air} = 1 - k2 \times V_{air} \tag{26}$$

where *k2* represents the parameter depending on water to binder ratio and type of coarse aggregate, and *Vair* indicates air content per unit volume of concrete.

4.2.4 Modulus of elasticity

The estimation of the modulus of elasticity of concrete is possible by utilization of formulas used for composite materials (Ilker 2007). Those formulas are expressed as a function of characteristics of concrete components, mainly mortar and aggregates (Paulo 1991). This study used one of those formulas, Hashin's (1962) model which relates the modulus of elasticity of concrete to the modulus as a composite models of the two phases (aggregate and mortar matrix).

$$E_m = \left[\frac{(1-V_{fa})E_p + (1+V_{fa})E_{fa}}{(1+V_{fa})E_p + (1-V_{fa})E_{fa}} \right] E_p \tag{27}$$

$$E_c = \left[\frac{(1-V_{ca})E_m + (1+V_{ca})E_{ca}}{(1+V_{ca})E_m + (1-V_{ca})E_{ca}} \right] E_m \tag{28}$$

$$E_{concrete} = r_{ad} \times E_c \tag{29}$$

with the notation
E_c, E_m, E_p: modulus of elasticity of concrete, mortar and paste
$E_{concrete}$: modulus of elasticity of concrete using admixture
E_{ca}, E_{fa}: modulus of elasticity of coarse aggregate and fine aggregate
V_{ca}, V_{fa}: volume of coarse aggregate and fine aggregate
r_{ad}: correction factor according to admixture

The modulus of elasticity of paste can be estimated by water to cement ratio (W/C) proposed by Kawakami (1994).

when W/C is in the range of 25~45% in Eq. (30),

$$E_p = 3.133 + 43.697 \cdot \log\left(\frac{1.0}{W/C}\right) \tag{30}$$

when W/C is in the range of 45~65% in Eq. (31)

$$E_p = 4.1 + 16.553 \ln\left(\frac{1.0}{W/C}\right) \tag{31}$$

And predicting elastic modulus of aggregate can be estimated by equations suggested by Kiyohara (2004) based on the theory composite material.

$$\left.\begin{matrix} E_{fa} \\ E_{ca} \end{matrix}\right\} = \frac{5.89}{A_a^{0.22}} \times 10^4 \tag{32}$$

where A_a is the water absorption ratio of aggregates

Impact factors of admixture (r_{ad}) in Eq. (32)

when use ground granulated blast-furnace slag;

$$W/B \geq 0.4 \text{ and } C_3 \geq 0.3: \; r_{ad} = 1 - 0.2C_3 \tag{33}$$

$$W/B < 0.4 \text{ and } C_3 \geq 0.3: \; r_{ad} = 1.06 - 0.4(C_3 - 0.3) \tag{34}$$

$$W/B \geq 0.4 \text{ and } C_3 < 0.3: \; r_{ad} = 1 - 0.2C_3 \tag{35}$$

$$W/B < 0.4 \text{ and } C_3 < 0.3: \; r_{ad} = 1 + 0.2C_3 \tag{36}$$

where W/B is water to binder ratio, C_3 is the replacement ratio.

when use fly-ash

$$W/B < 0.4: \; r_{ad} = 1 - 1.6D \tag{37}$$

Table 2 R_3 and R_4

R_4	Natural aggregate			
	Plain	Air entraining agent	Air entraining and high-range water reducing agent	Air entrain and water reducing agent
R_3	1	0.6	0.36	0.4
R_4	Recycled aggregate			
	Plain	Air entraining agent	Air entraining and high-range water reducing agent	Air entrain and water reducing agent
R_3	1.0	1.0	1.0	1.0

when use silica fume

$$r_{ad} = 1 - 1.6D \tag{38}$$

4.2.5 Carbonation speed coefficient

The factors affecting carbonation depth (D_{CO2}) are cement (R_1), admixture (R_2), chemical agent (R_3) and aggregate type (R_4). The estimation of carbonation speed coefficient can be calculated by utilization of formula proposed by Izumi (1984).

$$D_{CO2} = 0.354 \cdot R_1 \cdot R_2 \cdot R_3 \cdot R_4 \cdot \sqrt{t} \tag{39}$$

And correction factor (R_1) in Eq. (39) can be estimated by equation with relationship between water to binder ratio and material constants as shown in Izumi (1984).

$$R_1 = e^{ax-b} \tag{40}$$

when use ordinary Portland cement or Portland blast-furnace slag cement,

$$R_1 = e^{3.34x-2.004} \tag{41}$$

when use early strength cement,

$$R_1 = 0.977e^{3.39x-2.004} \tag{42}$$

when use granulated blast-furnace slag, R_2 in Eq. (43) is as follow while fly-ash and silica fume are R_2=1.

$$R_2 = 1 + 0.3D \tag{43}$$

where D is replacement ratio of admixture.

R_3 and R_4 in Eq. (43) are presented as below Table 2.

4.2.6 Cost for 1 m^3 recycled aggregate concrete

When various mixtures of RAC are derived on GA, cost is one of important required performances at the same time. The function of cost (E_{cost}) is simply the summation of material cost for producing 1 m^3 concrete is calculated by combination of each material in RAC mix proportion (Eduardo 2004).

$$E_{\cos t} = C_c \times W_c + C_{ca} \times W_{ca} + C_{fa} \times W_{fa} + C_{Ad} \times W_{Ad} + C_{ad} \times W_{ad} \tag{44}$$

where C_c, C_{ca}, C_{fa}, C_{Ad} and C_{ad} are prices (Yen) of cement, coarse aggregate, fine aggregate, admixture and chemical agent per unit weight. And W_c, W_{ca}, W_{fa}, W_{Ad} and W_{ad} are weight of cement, coarse aggregate, fine aggregate, admixture and chemical agent in RAC mix proportion derived from GA.

4.2.7 CO_2 emission for 1 m^3 recycled aggregate concrete

RAC has become more important for sustainable building material due to reducing carbon dioxide (CO2) emission. In this study, CO_2 emission is also one of important required performances at the same time. The function of CO_2 emission cost (E_{CO2}) is simply the summation of the amount of CO_2 emission for producing 1 m^3 concrete in RAC mix proportion derived from GA as follow Eq. (45).

$$E_{co_2} = C_{CO_2\_C} \times W_c + C_{CO_2\_CA} \times W_{ca} + C_{CO_2\_FA} \times W_{fa} + C_{CO_2\_Ad} \times W_{Ad} + C_{CO_2\_ad} \times W_{ad} \tag{45}$$

where $C_{CO2\text{-}C}$, $C_{CO2\text{-}CA}$, $C_{CO2\text{-}FA}$, $C_{CO2\text{-}Ad}$ and $C_{CO2\text{-}ad}$ are carbon dioxide (CO_2) emission for producing cement, coarse aggregate, fine aggregate, admixture and chemical agent per unit weight referring to JSCE (2004) and JCI (2010). And W_c, W_{ca}, W_{fa}, W_{Ad} and W_{ad} are weight of cement,

Table 3 Set of case study

	Target aggregate*	Use of RAC	Required performances for RAC
Case 1	H, M, L class	Structural concrete	Workability, strength, durability, cost
Case 2	M, L class	Concrete block	Strength, durability, cost, Low CO_2
Case 3	M, L class	Cast- in-place concrete pile Road, under-bed concrete	Workability, strength, durability, cost, Low CO_2

* H, M and L class are recycled aggregates determined by JIS A 5021, 5022 and 5023.

Table 4 Physical property of recycled aggregate

Classification		Class H	Class M	Class L
Absolute dry density (*t*/m3)	RFA	More than 2.5	More than 2.2	-
	RCA	More than 2.5	More than 2.3	-
Absorption rate (%)	RFA	Less than 3.5	Less than 7.0	Less than 13.0
	RCA	Less than 3.0	Less than 5.0	Less than 7.0
Standard Code		JIS A5021	JIS A5022	JIS A5023
No. JIS		A5021	A5022	A5023

Table 5 Required properties and performances

Property or Performance	Unit	Case 1	Case 2
Slump	cm	15	15
Dry shrinkage strain	μ	500	500
Specific gravity	t/m^3	2.3	2.25
Strength	MPa	36	30
Modulus of elasticity	GPa	24	22
Carbonation speed coefficient	cm/√Year	0.27	0.27
Cost*	Yen/m^3	13000	11000
CO_2 emission	kg/m^3	330	300

*Cost is assumed comparing with the data about ready-mixed concrete (1 m^3) in Japan (2010) coarse aggregate, fine aggregate, admixture and chemical agent in mix proportion.

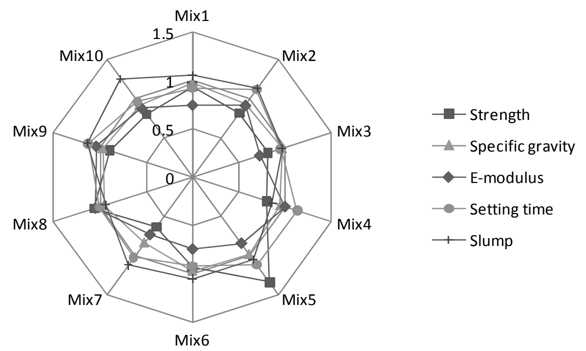
5. Case study and result

5.1 Introduction

Case study is assumed considering various utilization of RAC as it can be seen in Table 3. Table 4 presents the physical properties of recycled aggregate.
Following are three cases optimizing the mix proportion of RAC under its use and required performances by GA system as shown in Table 5.

5.2 Results

After operating the mix design system using GA with 200 individuals, 200 generations and 2% mutation rate, various mix proportions can be derived regarding with each case. Then, selection of individuals which meet required performances in Table 5, is conducted. As a result, several mix proportions in each case were listed in Tables 6 and 7. Also the comparison of expected properties



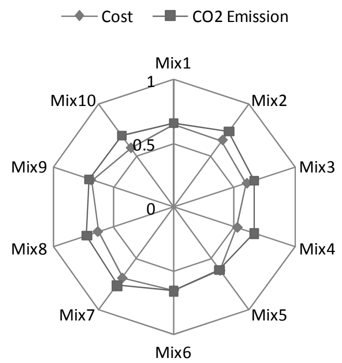


Fig. 9 Ratio between expected property and required property of RAC (Case 1)

Table 6 Pareto optimal mix proportions derived by GA (Case 1)

	W/C	Water	Air	*S/A*	Unit weight (kg)				
					Cement	Sand	Aggregate	Additive	Admixture 1(%/C)
1	59.20	167.70	2.00	0.48	283.2(EC)	901.2(N)	931.1(M)	0.00	0.42(AE)
2	59.88	190.97	2.17	0.42	318.9(LC)	658.8(M)	1047.2(N)	3.13(SF)	0.03(SP)
3	59.19	169.96	2.09	0.41	287.1(OC)	768.4(N)	1051.2(M)	0.00	0.18
4	58.99	170.62	2.00	0.44	289.2(MC)	713.4(M)	1065.1(N)	0.00	0.44(AE)
5	58.76	154.36	2.08	0.55	262.6(LC)	1039.9(N)	794.7(M)	50.64(GS)	0.09
6	59.20	167.70	2.00	0.48	283.2(EC)	901.2(N)	931.1(M)	0.00	0.42(SP)
7	60.45	199.29	2.21	0.85	329.7(EC)	1264.0(L)	270.6(N)	14.77(FA)	0.41(SP)
8	48.49	151.62	2.06	0.54	312.7(MC)	878.3(L)	909.4(N)	7.60(GS)	0.13(SP)
9	58.54	178.58	2.09	0.36	305.0(MC)	573.0(M)	1209.7(N)	14.84(SF)	0.18(SP)
10	58.99	178.10	2.39	0.53	301.9(LC)	845.1(M)	876.4(N)	0.00	0.02(AE)

Table 7 Pareto optimal mix proportions derived by GA (Case 2)

	W/C	Water	Air	*S/A*	Unit weight (kg)				
					Cement	Sand	Aggregate	Additive	Admixture 1(%/C)
1	62.09	157.36	2.08	0.43	253.4(OC)	814.6(N)	1011.2(M)	28.31(SF)	0.01(AE)
2	60.92	164.43	2.00	0.38	269.9(EC)	707.2(N)	1075.2(M)	31.57(FA)	0.05
3	57.86	160.24	2.00	0.46	276.9(LC)	874.8(N)	962.5(M)	23.31(SF)	0
4	64.35	178.30	2.00	0.52	277.0(LC)	965.6(N)	836.4(M)	0	0.20
5	60.92	164.00	2.00	0.38	269.2(EC)	623.0(L)	1155.9(N)	36.41(SF)	0
6	61.42	171.11	2.00	0.52	278.5(MC)	961.0(M)	728.4(M)	89.18(SF)	0.29
7	64.03	154.32	2.29	0.51	240.9(EC)	854.3(L)	961.8(N)	33.88(FA)	0.05(AE)
8	56.40	183.71	2.00	0.56	325.6(EC)	998.1(N)	736.8(L)	22.60(SF)	0
9	60.87	162.44	2.86	0.38	266.8(EC)	722.0(N)	1068.0(M)	19.01(SF)	0.17(AE)

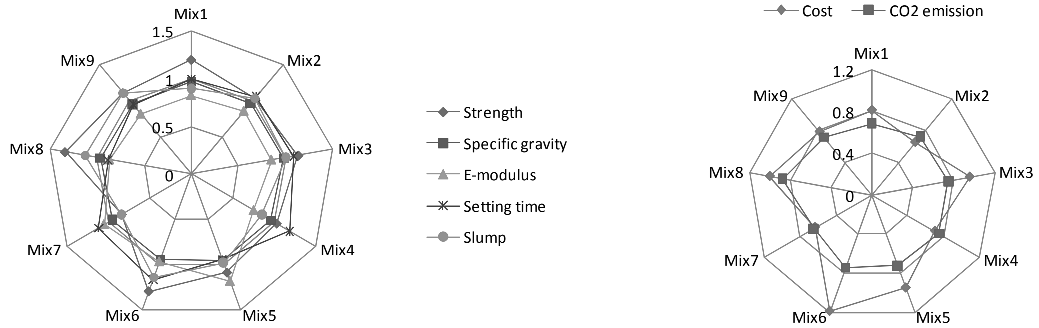


Fig. 10 Ratio between expected property and required property of RAC (Case 2)

of each case is shown in Figs. 9 and 10. As shown in the examples presented in Tables and Figures, it is found that the mix design method for RAC using GA program can derive the appropriate mix proportions.

where EC, LC, OC and MC represent early strength cement, low heat cement, ordinary Portland cement and moderate heat cement, *N* is natural aggregate, *H*, *M* and *L* represent recycled aggregate classes, SF, FA and GA indicate silica fume, fly-ash and blast-furnace slag and AE and SP are air entrain agent and superplasticizer.

6. Conclusions

This paper proposes a new design method for the mix proportion of recycled aggregate concrete to reduce the number of trial mixes. The results of this paper can be summarized as follows:

1. In this paper, GA system using the concept of Pareto optimality was newly developed for solving the MOP of mix proportion for RAC.
2. With the concept of Pareto optimality, various fitness functions for the required properties of concrete such as slump, density, strength, elastic modulus, carbonation resistance, price and CO_2 emission were adapted based on statistical analysis on conventional and various early studies.

3. From the GA system for RAC, several optimum mix proportions for RAC that meets required performances could be obtained. The utility of GA system to expand use of RAC was confirmed comparing with case studies considering various utilization of RAC.
4. It is thought that a new design method for RAC mixtures can minimize the number of trial mixes and provides a reasonable mix proportion. It is indicated that this method is expected to be a new and alternative method for new concrete material design such a RAC.

Acknowledgement

This research was supported by a grant (11CHUD-C060439-01-000000) from High-tech urban development projects Program funded by Ministry of Land, Transport and Maritime Affairs of Korean government.

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