



Application of a weighted Grey-Taguchi method for optimizing recycled aggregate concrete mixtures

C.Y. Chang^a, R. Huang^a, P.C. Lee^{b,*}, T.L. Weng^c

^a Institute of Materials Engineering, National Taiwan Ocean University, No. 2, Pei-Ning Road, Keelung 20224, Taiwan, ROC

^b Department of Civil Engineering and Hazard Mitigation Design, China University of Technology, No. 56, Sec. 3, Singlong Rd., Wunshan District, Taipei 116, Taiwan, ROC

^c Physics Division, Tatung University, No. 40, Sec. 3, Jhongshan N. Rd., Jhongshan District, Taipei 104, Taiwan, ROC

ARTICLE INFO

Article history:

Received 15 December 2010

Received in revised form 2 June 2011

Accepted 28 June 2011

Available online 23 July 2011

Keywords:

Design of experiment

Grey relational analysis

Mixture proportions

Recycled aggregate concrete

Taguchi method

ABSTRACT

Assessment of the optimal mixture is an important issue to obtain desired quality. This paper integrates grey relational analysis and an objective weighting technique into the Taguchi method to propose the weighted Grey-Taguchi method. This method can be employed to assess the optimal mixture with multiple responses. In the application of this method, water/cement ratio, volume ratio of recycled coarse aggregate, replacement by river sand, content of crushed brick, and cleanliness of aggregate are selected as control factors with responses of slump, slump-flow, resistivity (7-day, 14-day, 28-day), ultrasonic pulse velocity (7-day, 14-day, 28-day), and compressive strength (7-day, 14-day, 28-day) to assess the optimal mixture of recycled aggregate concrete. Results demonstrate and verify that the optimal mixture has a water/cement ratio of 0.5, a volume fraction of recycled coarse aggregate of 42.0%, 100% replacement of river sand, 0% crushed brick, and water-washed aggregates.

© 2011 Elsevier Ltd. All rights reserved.

1. Introduction

The assessment of an optimal mixture for obtaining desired quality is an important issue in the field of material engineering. The problem of optimal mixture assessment can be described as $y = f(x_1, x_2, \dots, x_n)$, in which y denotes the key response used to represent quality, and x_1 to x_n are the control factors that will mainly affect the performance of the response. If each control factor has three input levels, 3^n mixtures (factor level combinations) are required for a full factorial design to determine the optimal mixture by the traditional design of experiment (DOE) [1].

Since DOE, which can be mainly divided into full factorial design and fractional factorial design (the latter to decrease the number of experiments), was developed, it has been widely employed in various mixture proportion studies, such as mineral aggregates [2], high strength concrete beams [3], and aerostatic bearings [4]. However, two problems, namely large time/cost requirements for experiments and complex calculations resulting from full factorial design and fractional factorial design, respectively, will be encountered in practice. Therefore, a Taguchi method [5] employing an orthogonal array and signal-to-noise ratio (S/N ratio) analysis was proposed to improve the effectiveness and efficiency of DOE by reducing the time/cost of experiments and obtaining robust evaluations. Taguchi methods have been successfully employed to solve

mixture proportion problems of epoxy-TiO₂ particulate filled functionally graded composites [6], pulsed current gas tungsten arc welding [7], and laser welding [8].

Both conventional DOE and Taguchi methods can only consider a single response at a time. But, in practice, the presentation of quality ought to be considered in various responses, i.e., the problem of optimal mixture assessment ought to be described as $(y_1, y_2, \dots, y_m) = f(x_1, x_2, \dots, x_n)$ where y_1 to y_m are different responses used to represent quality. To solve the optimal mixture problems with multiple responses by DOE and Taguchi methods, the optimal mixture for each response is frequently assessed individually, and then the overall optimal mixture is determined by engineering experience or cross analysis. This approach still cannot deal with too many responses at the same time, because of the increasing complexity of the calculations and the possibility of erroneous judgments.

Therefore, a Grey-Taguchi method employing grey relational analysis in the Taguchi method [5] has been proposed to effectively solve the optimal mixture problem with multiple responses. The technique of grey relational analysis can provide a comprehensive index, i.e., grey relational grade (GRG), to represent the complete performance of all responses (y_1, y_2, \dots, y_m) . Recently, this Grey-Taguchi method has been utilized to solve optimal mixture problems with multiple responses in various fields, such as thin-film sputtering processes [9], submerged arc welding process parameters in hardfacing [10], and laser butt welding parameters [11].

* Corresponding author. Tel.: +886 2 29305384; fax: +886 2 29304694.

E-mail address: D9205102@mail.ntust.edu.tw (P.C. Lee).

To enhance the reasonability of the comprehensive index produced by grey relational analysis, this paper proposes a weighting technique for determining appropriate weights on responses. Generally, weighting techniques can be established in subjective or objective ways. Subjective weighting techniques are based on engineering judgments, and two common subjective techniques are the analytic hierarchy process (AHP) and the analytic network process (ANP) [12]. However, this paper proposes an objective weighting technique based on the maximum deviation, i.e., larger weights are assigned to responses which can distinguish the differences between mixtures more effectively. Such an objective technique can not only provide weights on responses but also detect inefficient responses to further reduce time/cost of experiments.

Finally, this paper merges the proposed weighting technique into the Grey-Taguchi method to establish a weighted Grey-Taguchi method to solve optimal mixture problems with multiple responses. In the application of the weighted Grey-Taguchi method, this paper utilizes a set of experimental data on concrete made with recycled aggregates (recycled aggregate concrete) to assess the optimal mixture. In the experimental data, water/cement ratio, volume ratio of recycled coarse aggregate, replacement by river sand, content of crushed brick, and cleanliness of aggregate are selected as control factors on the eleven responses of slump, slump flow, resistivity (at 7, 14, and 28 days), ultrasonic pulse velocity (at 7, 14, and 28 days), and compressive strength (at 7, 14, and 28 days) of recycled aggregate concrete. Full response design and reduced response design (resulting from the weighting technique) are compared to demonstrate the effectiveness of the weighting technique. A verification experiment is also performed to determine the applicability and correctness of the weighted Grey-Taguchi method for recycled aggregate concrete with multiple responses.

1.1. Orthogonal array and S/N ratio

Orthogonal arrays and S/N ratios are two main components of the Taguchi method. An orthogonal array is used to reduce testing time/cost. If an experiment has 15 control factors with two levels, all possible $n = 2^{15} = 32,768$ mixtures are required to test for assessing the optimal mixture by using a full factorial design of experiment. By using the orthogonal array $L_{16}2^{15}$, only 16 mixtures are required to estimate the optimal mixture versus the optimal determination via the full factorial design of experiment. To drastically reduce the number of tests while still gaining significant insight on important factors and optimal settings, Taguchi recommended the use of eighteen basic orthogonal fractional factorial arrays known as the standard orthogonal arrays [5].

On the analysis side, Taguchi advocated the S/N ratio as a single indicator that jointly and simultaneously considers the average value and standard deviation of test results to determine the relative importance of the factors under study. The S/N ratio can be categorized into three types as follows. Selection of the appropriate S/N ratio depends on the features of responses.

1. The smaller-the-better (STB) type

$$SN_{STB} = -10 \log_{10} \left(\frac{1}{t} \sum_{i=1}^m y^2(i) \right). \quad (1)$$

2. The larger-the-better (LTB) type

$$SN_{LTB} = -10 \log_{10} \left(\frac{1}{t} \sum_{i=1}^m \frac{1}{y^2(i)} \right). \quad (2)$$

3. The nominal-the-better (NTB) type

$$SN_{NTB} = 10 \log_{10} \left(\frac{1}{t} \sum_{i=1}^m (y(i) - v)^2 \right). \quad (3)$$

In the above-mentioned equations, m , $y(i)$, and v are the number of mixtures, the testing result of the i th test, and the target value of the response, respectively.

1.2. Grey relational analysis

Grey relational analysis can be used to consider multiple responses at the same time and then to provide a comprehensive index to represent the evaluation of responses. Grey relational analysis has been widely employed in various fields and has thus demonstrated its applicability [13–15].

Pre-processing of the raw data matrix is required to satisfy the comparability (non-dimension, scaling, and polarization) among responses before conducting grey relational analysis. The raw data matrix, D , is illustrated as follows.

$$D = \begin{bmatrix} x_0(1) & x_0(2) & \dots & x_0(m) \\ x_1(1) & x_1(2) & \dots & x_1(m) \\ x_2(1) & x_2(2) & \dots & x_2(m) \\ \dots & \dots & \dots & \dots \\ x_n(1) & x_n(2) & \dots & x_n(m) \end{bmatrix}.$$

in which x_0 is the reference set, and x_1 to x_n are the comparison set. Each set is composed of m responses, and $x_i(j)$ represents the evaluation of the i th series on the j th response. The reference series can be composed of measured data or assumed data based on the requirements of evaluation. The raw data matrix can be pre-processed by Eq. (4) (the smaller-the-better type) or Eq. (5) (the larger-the-better type) depending on the feature of response [16] (Eq. (5) is used in the present study)

$$r_i(j) = -\frac{x_i(j)}{OB} + 2. \quad (4)$$

$$r_i(j) = \frac{x_i(j)}{OB}. \quad (5)$$

OB indicates the object value of responses. In the smaller-the-better type of response, such as cost, OB can be defined as the minimum value of the response. In the larger-the-better type of response, such as benefit, OB can be defined as the maximum value of the response. $r_0(j)$ and $r_i(j)$ are the pre-processed values of $x_0(j)$ and $x_i(j)$, respectively. The difference between $r_0(j)$ and $r_i(j)$ can be calculated as $\Delta_{0i}(j) = |r_0(j) - r_i(j)|$ and then the difference matrix, Δ , is constructed as follows.

$$\Delta = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \dots & \Delta_{01}(m) \\ \Delta_{02}(1) & \Delta_{02}(2) & \dots & \Delta_{02}(m) \\ \dots & \dots & \dots & \dots \\ \Delta_{0n}(1) & \Delta_{0n}(2) & \dots & \Delta_{0n}(m) \end{bmatrix},$$

The grey relational coefficient, $\varepsilon_{0i}(j)$, between $r_0(j)$ and $r_i(j)$ is defined as

$$\varepsilon_{0i}(j) = \frac{\Delta_{min} + \rho \Delta_{max}}{\Delta_{0i}(j) + \rho \Delta_{max}}, \quad (6)$$

in which ρ is the identification coefficient ($\rho \in (0,1]$ and usually set as 0.5). $\Delta_{min} = \min_{vi} \min_{vj} \Delta_{0i}(j)$ and $\Delta_{max} = \max_{vi} \max_{vj} \Delta_{0i}(j)$. The grey relational coefficient is used to measure the closeness between $r_0(j)$ and $r_i(j)$ in the space of pre-processed data. Thus, the grey relational coefficient matrix, ε , is constructed as follows.

$$\varepsilon = \begin{bmatrix} \varepsilon_{01}(1) & \varepsilon_{01}(2) & \dots & \varepsilon_{01}(m) \\ \varepsilon_{02}(1) & \varepsilon_{02}(2) & \dots & \varepsilon_{02}(m) \\ \dots & \dots & \dots & \dots \\ \varepsilon_{0n}(1) & \varepsilon_{0n}(2) & \dots & \varepsilon_{0n}(m) \end{bmatrix},$$

Finally, the grey relational grade, g_{0i} , between r_0 and r_i can be obtained by using Eq. (7)

$$g_{0i} = \sum_{j=1}^m w'(j) \varepsilon_{0i}(j) \quad (7)$$

in which $w'(j)$ represents the normalized non-negative weight assigned to the j th response and $\sum_{j=1}^m w'(j)$ is equal to 1. Grey relational grade is regarded as the sum of weighted grey relational coefficients and can be then used to determine the priority of comparison series.

1.3. Weighting technique

As shown in Eq. (7), $w(j)$ is an important component to obtain reasonable grey relational grades. The following weighting technique proposed in this paper is constructed by the concept of maximum deviation. Note that the definition of deviation in this paper is used to measure the degree of dispersion, which is different from the standard deviation used in statistics and probability theory.

The weight vector, w , is assumed as $w = [w(1), w(2), \dots, w(m)]$, in which $w(j) \geq 0$ and $\sum_{j=1}^m w(j)^2 = 1$. For a specific response j , the unit deviation, $D_i(j)$, can be defined as

$$D_i(j) = \sum_{k=1}^n d_i(k) \sum_{k=1}^n \sqrt{[r_i(j) - r_k(j)]^2}, \quad (8)$$

in which $r_i(j)$ is the normalized value of $x_i(j)$ and $d_i(k)$ is the distance between $r_i(j)$ and $r_k(j)$. Then, the weighted deviation of the j th response, $D(j)$, can be calculated as $D(j) = \sum_{i=1}^n \sum_{k=1}^n w(j) d_i(k)$. The total weighted deviation of all responses can be also calculated as $D = \sum_{j=1}^m D(j)$. The aim of this weighting technique is to assign larger weights to responses which can distinguish the differences between mixtures more effectively. For this reason, this paper utilizes the following optimization equation to identify the weight vector which can maximize the total deviations.

$$\begin{cases} \max D = \sum_{j=1}^m \sum_{i=1}^n \sum_{k=1}^n w(j) d_i(k) \\ \text{s.t. } w(j) \geq 0, \sum_{j=1}^m w(j)^2 = 1 \end{cases} \quad (9)$$

A Lagrange function is employed to solve Eq. (9) as

$$L(w, \lambda) = \sum_{j=1}^m \sum_{i=1}^n \sum_{k=1}^n w(j) d_i(k) + \lambda \left[\sum_{j=1}^m w(j)^2 - 1 \right]. \quad (10)$$

Calculating the gradients of Eq. (10) as,

$$\begin{cases} \frac{\partial L}{\partial w(j)} = \sum_{i=1}^n \sum_{k=1}^n d_i(k) + 2\lambda \sum_{j=1}^m w(j) = 0 \\ \frac{\partial L}{\partial \lambda} = \sum_{j=1}^m w(j)^2 - 1 = 0 \end{cases} \quad (11)$$

then, $w(j)$ can be calculated as

$$w(j) = \frac{\sum_{i=1}^n \sum_{k=1}^n d_i(k)}{\sqrt{\sum_{j=1}^m \left[\sum_{i=1}^n \sum_{k=1}^n d_i(k) \right]^2}}. \quad (12)$$

$w(j)$ ought to be further transformed into $w'(j)$ to satisfy the requirement of normalization, i.e., $w'(j) = \frac{w(j)}{\sum_{j=1}^m w(j)}$. Hence, the weight of the

j th response, $w'(j)$, can be defined as

$$w'(j) = \frac{\sum_{i=1}^n \sum_{k=1}^n d_i(k)}{\sum_{j=1}^m \sum_{i=1}^n \sum_{k=1}^n d_i(k)}. \quad (13)$$

2. Recycled aggregate concrete

Due to the flourish of urban construction caused by the fast development of industry, many old or degraded buildings need to be demolished or reconstructed according to urban renewal plans. Thus, large amounts of construction waste or demolition waste are produced, with concrete waste accounting for the highest proportion. Traditionally, most concrete waste was sent to a landfill. However, owing to the limitations of available urban landfill areas, the conservation of natural resources, and the prevention of environmental pollution, use of recycled concrete aggregate whenever possible has become an important issue, especially with the urgent requirements of sustainability. In related studies, recycled concrete aggregate has been widely employed as construction materials, such as base or sub-base materials [17–20]. Furthermore, the properties of concrete made with recycled aggregates have also been studied to assess their flexibility and applicability [21–23].

The constituents of the concrete used in this study included the ASTM C 150 Type I Portland cement, crushed recycled coarse and fine concrete aggregates, river sand, and crushed recycled brick. The crushed recycled coarse and fine concrete aggregates were generated through the demolition of Portland cement concrete elements of reinforced concrete buildings collected from different construction sites in Taiwan. These concrete rubbles were crushed by a 3/4-in. jaw crusher and then screened to the desired gradation for both coarse and fine aggregates using the conventional sieve analysis process.

Three tests were run on each mixture and their responses were recorded. The size of each cylindrical concrete specimen is $\phi 100 \times 200$ mm, and the mixing of concrete satisfies the requirements of the ACI 211.1 specification.

3. The weighted Grey-Taguchi procedure

The weighted Grey-Taguchi method is employed in this paper to assess the optimal mixture with multiple responses for recycled aggregate concrete. The procedure of the weighted Grey-Taguchi method is illustrated as Fig. 1 and stated as follows.

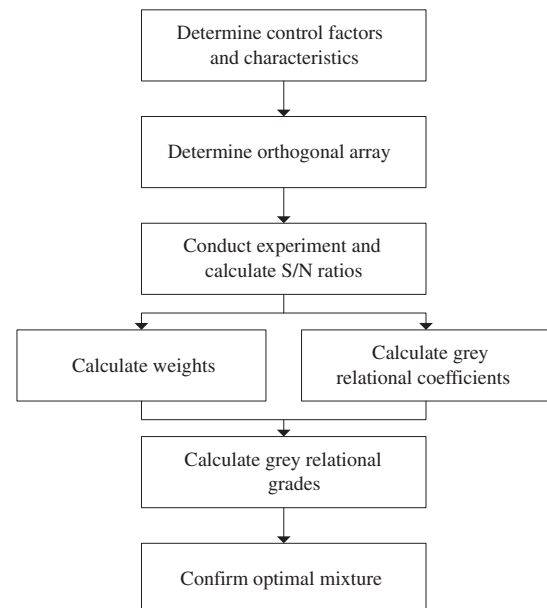


Fig. 1. Flow chart of the weighted Grey-Taguchi method.

Table 1

Designation of control factors and factor levels.

Designation	Control factors	Level 1	Level 2
A	Water/cement ratio	0.5	0.7
B	Volume ratio of recycled coarse aggregate	42.00%	40.40%
C	Replacement of river sand	0%	100%
D	Content of crushed brick	5%	0%
E	Cleanliness of aggregate	as-is	water-washed

Table 2

Response variables.

Designation	Responses
y_1	Slump (cm)
y_2	Slump-flow (cm)
y_{31}	7-day resistivity ($K\Omega$ cm)
y_{32}	14-day resistivity ($K\Omega$ cm)
y_{33}	28-day resistivity ($K\Omega$ cm)
y_{41}	7-day ultrasonic pulse velocity (m/s)
y_{42}	14-day ultrasonic pulse velocity (m/s)
y_{43}	28-day ultrasonic pulse velocity (m/s)
y_{51}	7-day compressive strength (MPa)
y_{52}	14-day compressive strength (MPa)
y_{53}	28-day compressive strength (MPa)

Step 1. Determine control factors and responses.

Five two-level control factors including (1) water/cement ratio, (2) volume ratio of recycled coarse aggregate, (3) replacement of river sand, (4) content of crushed brick, and (5) cleanliness of aggregate which are labelled by A, B, C, D, and E, respectively, are considered in this paper, as shown in Table 1. On the other hand, eleven responses of slump, slump-flow, resistivity (7-day, 14-day, 28-day), ultrasonic pulse velocity (7-day, 14-day, 28-day), and compressive strength (7-day, 14-day, 28-day) are considered as the quality responses of recycled aggregate concrete, as shown in Table 2.

Step 2. Determine orthogonal array.

In addition to the specified five control factors, ten interaction factors ($A \times B$, $A \times C$, $A \times D$, $A \times E$, $B \times C$, $B \times D$, $B \times E$, $C \times D$, $C \times E$, $D \times E$) were also considered in this paper. The total degrees of freedom required are $5 \times (2-1) + 10 \times (2-1) \times (2-1) = 15$. Hence, the $L_{16}2^{15}$ orthogonal array was utilized, as shown in Table 3. In classical design of experiment, this would be equivalent to a 2^{5-1} fractional factorial design [1]. These sixteen mixtures of recycled aggregate concrete can be used to identify the optimal mixture. The arrangement of these sixteen mixtures is shown in Table 4.

Table 4.

Step 3. Conduct experiment and calculate S/N ratios.

After Step 2, the experiment can be conducted. Three testing results of each mixture on each response are collected. Then, the S/N ratio of the three testing results can be calculated. Because the specified eleven responses are all assumed to be the larger-the-better type, Eq. (2) is adopted to calculate the S/N ratios. In the following steps, $sn_i(j)$ represents the S/N ratio of i th mixture on the j th response.

Step 4. Calculate the weights of responses.

All the computed S/N ratios can be collected as $SN = \{sn_i(j)\}_{n \times m}$, where SN is composed of n mixtures and m responses and illustrated as follows.

$$SN = \begin{bmatrix} sn_1(1) & sn_1(2) & \dots & sn_1(m) \\ sn_2(1) & sn_2(2) & \dots & sn_2(m) \\ \dots & \dots & \dots & \dots \\ sn_n(1) & sn_n(2) & \dots & sn_n(m) \end{bmatrix}, \quad (14)$$

An ideal series of S/N ratios, denoted as sn_0 , can be assumed at the same time, in which for fixed response j , $sn_0(j)$ is the maximum value among $sn_i(j)$, i.e., $sn_0(j) = \max_i sn_i(j)$. Each column of SN has to be normalized to provide comparability. Eq. (5) is adopted, because all S/N ratios are of the larger the better type, to transform $sn_i(j)$ into $r_i(j)$, where $OB = sn_0(j)$; thus, the weight $w(j)$ of response j can be determined by Eqs. (8) and (13).

Step 5. Calculate grey relational coefficients.

The calculations of grey relational coefficients are based on the difference between $r_0(j)$ and $r_i(j)$, where $r_0(j)$ is the normalized value of $sn_0(j)$ and is equal to 1. Grey relational coefficients can be calculated by Eq. (6).

Step 6. Calculated grey relational grades.

By inputting the calculated weights of responses and grey relational coefficients into Eq. (7), the grey relational grade of each mixture can be obtained. Afterward, the priority of the selected mixtures can be sorted via their grey relational grades. A larger grey relational grade means better comprehensive performance.

Table 3Orthogonal array $L_{16}2^{15}$ with factor assignment for the experiment.

No.	A	B	$A \times B$	C	$A \times C$	$B \times C$	$D \times E$	D	$A \times D$	$B \times D$	$C \times E$	$C \times D$	$B \times E$	$A \times E$	E	Designation of mixture
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	A1B1C1D1E1
2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	A1B1C1D2E2
3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	A1B1C2D1E2
4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	A1B1C2D2E1
5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	A1B2C1D1E2
6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	A1B2C1D2E1
7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	A1B2C2D1E1
8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	A1B2C2D2E2
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	A2B1C1D1E2
10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	A2B1C1D2E1
11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	A2B1C2D1E1
12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	A2B1C2D2E2
13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	A2B2C1D1E1
14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	A2B2C1D2E2
15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	A2B2C2D1E2
16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	A2B2C2D2E1

Table 4

Sixteen sets of mixture of recycled aggregate concrete.

No.	Designation of mixture	Water/cement ratio	Volume ratio of recycled coarse aggregate (%)	Replacement of river sand (%)	Content of crushed brick (%)	Cleanliness of aggregate
1	A1B1C1D1E1	0.5	42.00	0	5	as-is
2	A1B1C1D2E2	0.5	42.00	0	0	water-washed
3	A1B1C2D1E2	0.5	42.00	100	5	water-washed
4	A1B1C2D2E1	0.5	42.00	100	0	as-is
5	A1B2C1D1E2	0.5	40.40	0	5	water-washed
6	A1B2C1D2E1	0.5	40.40	0	0	as-is
7	A1B2C2D1E1	0.5	40.40	100	5	as-is
8	A1B2C2D2E2	0.5	40.40	100	0	water-washed
9	A2B1C1D1E2	0.7	42.00	0	5	water-washed
10	A2B1C1D2E1	0.7	42.00	0	0	as-is
11	A2B1C2D1E1	0.7	42.00	100	5	as-is
12	A2B1C2D2E2	0.7	42.00	100	0	water-washed
13	A2B2C1D1E1	0.7	40.40	0	5	as-is
14	A2B2C1D2E2	0.7	40.40	0	0	water-washed
15	A2B2C2D1E2	0.7	40.40	100	5	water-washed
16	A2B2C2D2E1	0.7	40.40	100	0	as-is

Step 7. Confirm optimal mixture.

The result of Step 6 indicates the best mixture among the selected sixteen mixtures in the orthogonal array. However, the overall optimal mixture ought to be confirmed by main effects table, main effects plot, analysis of variance (ANOVA), and contribution

ratio. Both main effects table and main effects plot are used to represent the effects of each control factor on the grey relational grade at different levels. The calculation of effect is an absolute value in the Taguchi method, which is used to measure the impact of changes in factor levels. The overall optimal mixture can be then identified. The purpose of ANOVA is to investigate which control

Table 5

Average values of responses for the sixteen mixtures.

No.	Designation of mixture	Slump (cm)	Slump flow (cm)	Resistivity (K Ω cm)			Ultrasonic pulse velocity (m/s)			Compressive strength (MPa)		
				7-day	14-day	28-day	7-day	14-day	28-day	7-day	14-day	28-day
1	A1B1C1D1E1	17.50	37.00	7.57	7.97	7.93	2837	2893	2723	17.79	20.94	22.91
2	A1B1C1D2E2	15.50	40.00	6.50	9.43	9.00	2753	3253	3013	17.54	24.89	25.24
3	A1B1C2D1E2	18.00	35.00	7.73	9.55	9.30	2817	3347	3193	18.35	22.04	28.88
4	A1B1C2D2E1	18.00	32.00	7.43	9.17	9.20	2910	3130	2873	23.16	25.94	30.17
5	A1B2C1D1E2	9.50	20.00	7.23	8.07	8.53	3040	3155	3057	21.96	26.22	29.91
6	A1B2C1D2E1	14.00	26.00	6.50	7.20	7.43	2843	3120	2893	17.02	18.92	20.26
7	A1B2C2D1E1	10.50	20.00	7.07	7.10	7.80	3047	2933	2837	23.64	29.35	33.59
8	A1B2C2D2E2	5.00	20.00	9.03	8.63	10.13	2750	3277	3007	28.36	33.79	36.16
9	A2B1C1D1E2	10.00	23.00	7.47	9.03	9.10	2573	3003	2707	13.22	17.17	18.48
10	A2B1C1D2E1	20.00	56.00	6.40	8.47	8.67	2550	2620	2840	5.85	7.57	9.74
11	A2B1C2D1E1	15.00	60.00	7.83	8.20	8.33	2383	3015	3043	10.54	13.88	17.64
12	A2B1C2D2E2	9.00	20.00	9.20	10.33	9.53	2747	3050	2910	21.55	23.98	27.67
13	A2B2C1D1E1	16.00	35.00	6.67	6.77	7.70	2677	2556	2937	7.88	9.98	12.91
14	A2B2C1D2E2	19.00	43.00	5.70	6.93	7.93	2567	2783	2863	8.76	11.92	14.32
15	A2B2C2D1E2	11.50	36.00	7.07	7.37	7.80	2907	3000	2723	11.87	14.63	19.86
16	A2B2C2D2E1	16.00	33.00	6.63	7.03	7.43	2750	3103	2800	11.81	16.22	20.42

Table 6

Computed S/N ratios of recycled aggregate concrete mixtures.

No.	Designation of mixture	Slump	Slump flow	Resistivity			Ultrasonic pulse velocity			Compressive strength		
				7-day	14-day	28-day	7-day	14-day	28-day	7-day	14-day	28-day
1	A1B1C1D1E1	24.82	31.36	17.53	18.02	17.98	69.01	69.20	68.53	25.00	26.40	27.18
2	A1B1C1D2E2	23.80	32.04	16.14	19.39	19.05	68.49	70.24	69.54	24.88	27.79	28.00
3	A1B1C2D1E2	25.11	30.87	17.73	20.71	19.33	68.76	70.48	70.05	24.96	26.84	29.21
4	A1B1C2D2E1	25.11	30.09	17.42	19.24	19.27	69.05	69.87	68.79	27.28	28.27	29.59
5	A1B2C1D1E2	19.53	26.00	17.18	18.13	18.62	69.65	69.94	69.69	26.83	28.37	29.51
6	A1B2C1D2E1	22.88	28.29	16.26	17.14	17.32	69.05	69.88	69.23	24.61	25.45	26.08
7	A1B2C2D1E1	20.40	25.93	16.95	17.01	17.82	69.64	69.14	69.05	27.47	29.35	30.52
8	A1B2C2D2E2	13.61	25.93	19.11	18.46	20.07	68.64	70.29	69.56	29.05	30.57	31.16
9	A2B1C1D1E2	19.99	27.18	17.43	19.12	19.16	68.13	69.53	68.49	22.41	24.68	25.16
10	A2B1C1D2E1	26.00	34.96	16.00	18.54	18.75	68.08	68.30	69.05	15.33	17.57	19.76
11	A2B1C2D1E1	23.48	35.55	17.87	18.24	18.41	67.46	69.55	69.66	20.45	22.84	24.91
12	A2B1C2D2E2	18.89	26.00	19.26	20.26	19.58	68.54	69.65	68.95	26.67	27.60	28.82
13	A2B2C1D1E1	24.07	30.87	16.35	16.60	17.69	68.55	68.02	69.35	17.90	19.96	22.22
14	A2B2C1D2E2	25.57	32.66	15.05	16.80	17.94	68.09	68.85	69.13	18.80	21.51	23.11
15	A2B2C2D1E2	21.17	31.12	16.98	17.34	17.76	69.27	69.52	68.53	21.49	23.28	25.96
16	A2B2C2D2E1	24.07	30.36	16.28	16.93	17.38	68.60	69.82	68.93	21.42	24.19	26.18

factors significantly affect the responses. ANOVA is accomplished by separating the total variability of the grey relational grades, which is measured by the sum of the squared deviations from the total mean of the grey relational grades, into contributions by each control factor and the error. The contribution ratio by each control factor in the total sum of the squared deviations can be used to evaluate the importance of a control factor change on the performance of all responses.

Table 7

Pre-processed values of S/N ratios on full responses.

No.	y_1	y_2	y_{31}	y_{32}	y_{33}	y_{41}	y_{42}	y_{43}	y_{51}	y_{52}	y_{53}
r_0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	0.95	0.88	0.91	0.87	0.90	0.99	0.98	0.98	0.86	0.86	0.87
2	0.92	0.90	0.84	0.94	0.95	0.98	0.99	0.99	0.86	0.91	0.90
3	0.97	0.87	0.92	1.00	0.96	0.99	1.00	1.00	0.86	0.88	0.94
4	0.97	0.85	0.90	0.93	0.96	0.99	0.99	0.98	0.94	0.92	0.95
5	0.75	0.73	0.89	0.88	0.93	1.00	0.99	0.99	0.92	0.93	0.95
6	0.88	0.80	0.84	0.83	0.86	0.99	0.99	0.99	0.85	0.83	0.84
7	0.78	0.73	0.88	0.82	0.89	0.99	0.98	0.99	0.95	0.96	0.98
8	0.52	0.73	0.99	0.89	1.00	0.99	0.99	0.99	1.00	1.00	1.00
9	0.77	0.76	0.91	0.92	0.95	0.98	0.99	0.98	0.77	0.81	0.81
10	1.00	0.98	0.83	0.89	0.93	0.98	0.97	0.99	0.53	0.57	0.63
11	0.90	1.00	0.93	0.88	0.92	0.97	0.99	0.99	0.70	0.75	0.80
12	0.73	0.73	1.00	0.98	0.98	0.98	0.99	0.98	0.92	0.90	0.93
13	0.93	0.87	0.85	0.80	0.88	0.98	0.97	0.99	0.62	0.65	0.71
14	0.98	0.92	0.78	0.81	0.89	0.98	0.98	0.99	0.65	0.70	0.74
15	0.81	0.88	0.88	0.84	0.89	0.99	0.99	0.98	0.74	0.76	0.83
16	0.93	0.85	0.85	0.82	0.87	0.98	0.99	0.98	0.74	0.79	0.84

Table 8

Deviations of mixtures on full responses.

No.	y_1	y_2	y_{31}	y_{32}	y_{33}	y_{41}	y_{42}	y_{43}	y_{51}	y_{52}	y_{53}
1	1.68	1.18	0.76	0.78	0.62	0.12	0.14	0.14	1.72	1.5	1.3
2	1.48	1.34	0.92	1.09	0.65	0.11	0.17	0.11	1.71	1.66	1.36
3	1.77	1.12	0.84	1.91	0.75	0.11	0.22	0.2	1.72	1.52	1.54
4	1.77	1.13	0.73	1.02	0.72	0.12	0.12	0.11	2.27	1.79	1.64
5	2.28	1.79	0.70	0.77	0.57	0.22	0.13	0.13	2.11	1.82	1.61
6	1.53	1.33	0.86	0.97	0.94	0.12	0.12	0.09	1.71	1.50	1.31
7	1.97	1.81	0.70	1.02	0.66	0.22	0.15	0.08	2.35	2.20	2.00
8	5.42	1.81	1.69	0.79	1.24	0.10	0.18	0.11	3.11	2.76	2.28
9	2.10	1.52	0.73	0.97	0.68	0.15	0.12	0.15	1.86	1.55	1.48
10	2.21	2.29	1.01	0.81	0.59	0.16	0.29	0.08	4.45	4.04	3.57
11	1.48	2.52	0.91	0.77	0.57	0.28	0.11	0.13	2.27	1.90	1.54
12	2.57	1.79	1.79	1.60	0.90	0.10	0.11	0.09	2.07	1.62	1.46
13	1.51	1.12	0.83	1.27	0.72	0.10	0.34	0.09	3.21	2.95	2.46
14	1.98	1.51	1.70	1.14	0.62	0.16	0.19	0.08	2.84	2.34	2.12
15	1.79	1.14	0.70	0.91	0.68	0.15	0.12	0.14	1.99	1.79	1.33
16	1.51	1.12	0.85	1.06	0.90	0.10	0.12	0.09	2.01	1.61	1.30
Sum	33.03	24.50	15.74	16.88	11.83	2.34	2.63	1.85	37.39	32.55	28.30

Table 9Differences between $r_0(j)$ and $r_i(j)$ on full responses.

No.	y_1	y_2	y_{31}	y_{32}	y_{33}	y_{41}	y_{42}	y_{43}	y_{51}	y_{52}	y_{53}
1	0.05	0.12	0.09	0.13	0.10	0.01	0.02	0.02	0.14	0.14	0.13
2	0.08	0.10	0.16	0.06	0.05	0.02	0.01	0.01	0.14	0.09	0.10
3	0.03	0.13	0.08	0.00	0.04	0.01	0.00	0.00	0.14	0.12	0.06
4	0.03	0.15	0.10	0.07	0.04	0.01	0.01	0.02	0.06	0.08	0.05
5	0.25	0.27	0.11	0.12	0.07	0.00	0.01	0.01	0.08	0.07	0.05
6	0.12	0.2	0.16	0.17	0.14	0.01	0.01	0.01	0.15	0.17	0.16
7	0.22	0.27	0.12	0.18	0.11	0.01	0.02	0.01	0.05	0.04	0.02
8	0.48	0.27	0.01	0.11	0.00	0.01	0.01	0.01	0.00	0.00	0.00
9	0.23	0.24	0.09	0.08	0.05	0.02	0.01	0.02	0.23	0.19	0.19
10	0.00	0.02	0.17	0.11	0.07	0.02	0.03	0.01	0.47	0.43	0.37
11	0.10	0.00	0.07	0.12	0.08	0.03	0.01	0.01	0.30	0.25	0.20
12	0.27	0.27	0.00	0.02	0.02	0.02	0.01	0.02	0.08	0.10	0.07
13	0.07	0.13	0.15	0.20	0.12	0.02	0.03	0.01	0.38	0.35	0.29
14	0.02	0.08	0.22	0.19	0.11	0.02	0.02	0.01	0.35	0.30	0.26
15	0.19	0.12	0.12	0.16	0.11	0.01	0.01	0.02	0.26	0.24	0.17
16	0.07	0.15	0.15	0.18	0.13	0.02	0.01	0.02	0.26	0.21	0.16

4. Results and discussion

4.1. Full responses design

Table 5 shows the average values of the specified eleven responses for the selected sixteen mixtures while Table 6 contains their corresponding S/N ratios. Scanning Table 6 for the largest value (shaded) in each of the 11 columns, it is seen that the reference/

Table 10

Grey relational coefficients of mixtures on full responses.

No.	y_1	y_2	y_{31}	y_{32}	y_{33}	y_{41}	y_{42}	y_{43}	y_{51}	y_{52}	y_{53}
1	0.84	0.67	0.73	0.65	0.7	0.96	0.93	0.92	0.63	0.64	0.65
2	0.74	0.71	0.6	0.79	0.82	0.93	0.99	0.97	0.62	0.72	0.70
3	0.87	0.64	0.75	1.00	0.87	0.95	1.00	1.00	0.63	0.66	0.79
4	0.87	0.61	0.71	0.77	0.86	0.96	0.96	0.93	0.8	0.76	0.83
5	0.49	0.47	0.69	0.66	0.77	1.00	0.97	0.98	0.76	0.77	0.82
6	0.67	0.54	0.60	0.58	0.64	0.96	0.97	0.95	0.61	0.59	0.59
7	0.53	0.47	0.67	0.57	0.68	1.00	0.93	0.94	0.81	0.86	0.92
8	0.33	0.47	0.97	0.69	1.00	0.94	0.99	0.97	1.00	1.00	1.00
9	0.51	0.50	0.72	0.76	0.84	0.92	0.95	0.91	0.51	0.55	0.55
10	1.00	0.93	0.58	0.69	0.78	0.91	0.88	0.94	0.34	0.36	0.39
11	0.71	1.00	0.77	0.67	0.74	0.88	0.95	0.98	0.45	0.49	0.54
12	0.47	0.47	1.00	0.92	0.91	0.94	0.95	0.94	0.74	0.71	0.76
13	0.76	0.64	0.61	0.55	0.67	0.94	0.87	0.96	0.38	0.41	0.45
14	0.94	0.75	0.52	0.56	0.69	0.91	0.91	0.95	0.40	0.45	0.48
15	0.56	0.66	0.67	0.59	0.67	0.98	0.95	0.92	0.48	0.50	0.59
16	0.76	0.62	0.61	0.57	0.64	0.94	0.96	0.94	0.48	0.53	0.60

ideal set of S/N ratios is $sn_0 = (26.00, 35.55, 19.26, 20.71, 20.07, 69.65, 70.48, 70.05, 29.05, 30.57, 31.16)$. The normalized values of S/N ratios are shown in Table 7, in which $r_0(j)$ is the normalized value of $sn_0(j)$ and is identically 1.

To calculate the weights of the responses, the deviation of each mixture for each response is determined as shown in Table 8. Then, the deviation sums of responses are calculated as $D(j) = (33.03, 24.50, 15.74, 16.88, 11.83, 2.34, 2.63, 1.85, 37.39, 32.55, 28.30)$, in which $D(j)$ is computed by $\sum_{i=1}^{16} D_i(j)$. The total deviation sum is also calculated as $\sum_{j=1}^{11} D(j) = 207.05$. Finally, the weights of responses can be calculated by Eq. (13) as $w'(j) = (0.16, 0.12, 0.08, 0.08, 0.06, 0.01, 0.01, 0.01, 0.18, 0.16, 0.14)$.

To calculate the grey relational coefficients, the differences between $r_0(j)$ and $r_i(j)$ are computed in Table 9. As shown in Table 9, Δ_{max} and Δ_{min} are assessed as 0.48 and 0.00, respectively. Grey relational coefficients are calculated by Eq. (6), based on Table 9 and $\rho = 0.5$, and are shown in Table 10.

Finally, by inputting the weights of the responses and the grey relational coefficients, the grey relational grades of the sixteen mixtures can be calculated via Eq. (7) and are shown in Table 11. From Table 11, the best of the sixteen mixtures is A1B2C2D2E2 (GRG of 0.80), which means water cement ratio of 0.5, volume ratio of recycled coarse aggregate of 40.4%, 100% replacement of river sand, 0% crushed brick, and water-washed aggregate.

Although the mixture of A1B2C2D2E2 is the best of the sixteen mixtures identified by grey relational analysis, it is not guaranteed to be the optimal one of all possible mixtures. The overall optimal mixture has to be determined by main effects table, main effects plot, and ANOVA. When adopting DOE or the Taguchi methods,

every main effects plot on each response has to be produced. Figs. 2 and 3 are the main effects plots for average value (Table 5) on each response and S/N ratio (Table 6) on each response, respectively. The effects of each control factor at different levels on every response can be observed in these main effects plots. As shown in Figs. 2 and 3, different performances of the mixtures are obtained depending on the response of interest. Thus, the comprehensive main effects plot can be further obtained by the weighted Grey-Taguchi method.

Table 12 shows the effects of each control factor on grey relational grade at different levels, and can be further drawn as the main effects plot, as shown in Fig. 4. The dashed line in Fig. 4 is the total mean value of the grey relational grades and is equal to 0.668. According to the computed effects in Table 12 and Fig. 4, the priority of control factors for affecting the multiple performance responses is sequentially A (water/cement ratio), C (replacement of river sand), B (volume ratio of recycled coarse aggregate), D (content of crushed brick), and E (cleanliness of aggregate).

Further confirmation can be conducted by ANOVA of the control factors on the grey relational grades, as shown in Table 13. An *F*-test is also adopted to determine which control factors have significant effects on the performance responses [24]. Results of ANOVA indicate that A (water/cement ratio), B (volume ratio of recycled coarse aggregate), and C (replacement of river sand) are indeed the significant control factors for affecting the multiple responses, and that A (water/cement ratio) is the most significant control factor due to its highest contribution ratio (50.591%) among the control factors.

Finally, according to this analysis, the optimal mixture with multiple responses for recycled aggregate concrete assessed in this paper is A1B1C2D2E2, meaning water cement ratio of 0.5, volume ratio of recycled coarse aggregate of 42.0%, 100% replacement of river sand, 0% crushed brick, and water-washed aggregate.

4.2. Reduced responses design

The proposed weighting technique can not only determine the weights of responses but also detect inefficient responses to reduce time/cost of experiments. As shown in their computed weights, the weights of ultrasonic pulse velocity (at 7, 14, and 28 days) are rather small relative to other responses, meaning ultrasonic pulse velocity cannot distinguish the differences among mixtures of recycled aggregate concrete and can be ignored in the experiment. Hence, a set of reduced responses including slump, slump flow, resistivity (7-day, 14-day, 28-day) and compressive strength (7-day, 14-day, 28-day) can obtain the same results as the set of full responses.

Table 11

Grey relational grades for mixtures on full responses.

No.	Designation	Grey relational grade
1	A1B1C1D1E1	0.69
2	A1B1C1D2E2	0.71
3	A1B1C2D1E2	0.76
4	A1B1C2D2E1	0.79
5	A1B2C1D1E2	0.69
6	A1B2C1D2E1	0.61
7	A1B2C2D1E1	0.71
8	A1B2C2D2E2	0.80
9	A2B1C1D1E2	0.59
10	A2B1C1D2E1	0.62
11	A2B1C2D1E1	0.65
12	A2B1C2D2E2	0.71
13	A2B2C1D1E1	0.55
14	A2B2C1D2E2	0.60
15	A2B2C2D1E2	0.58
16	A2B2C2D2E1	0.61

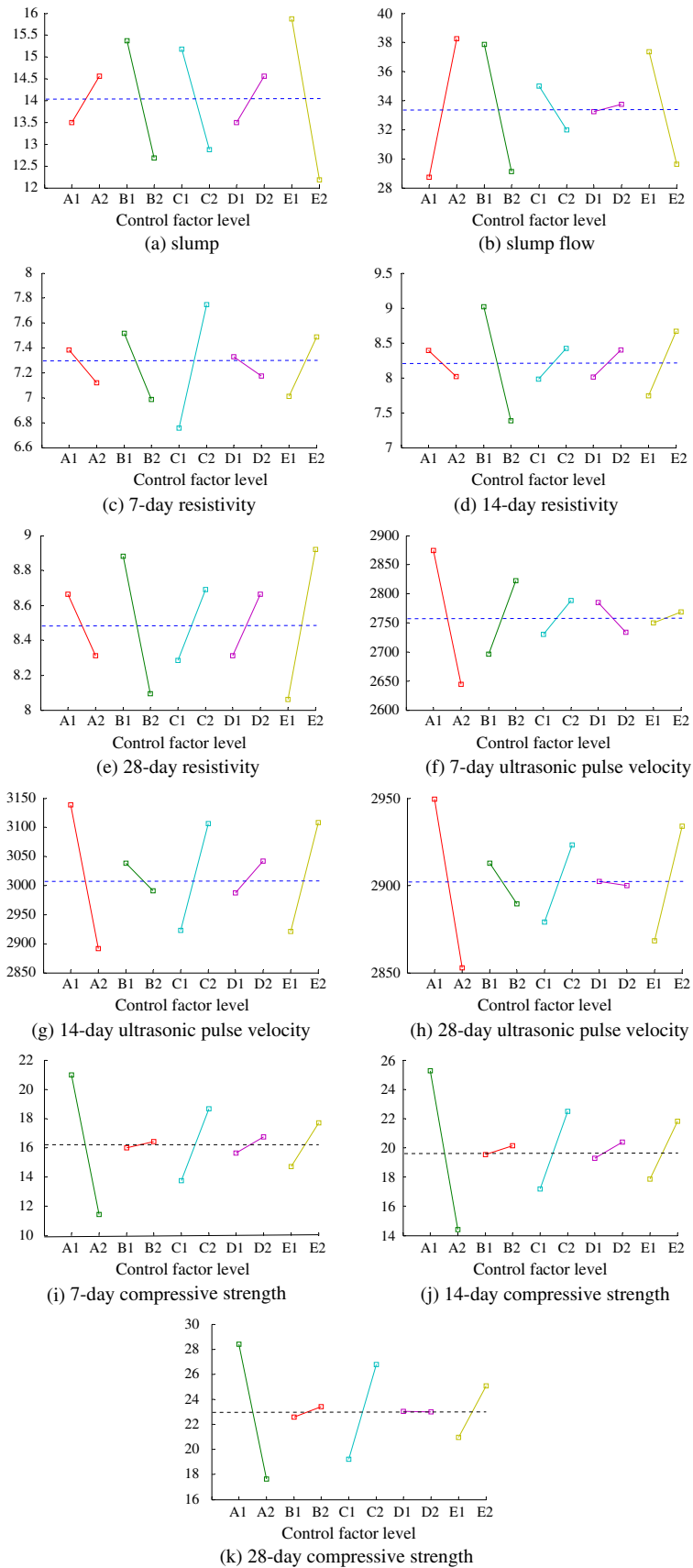


Fig. 2. Main effects plot for average value for each response.

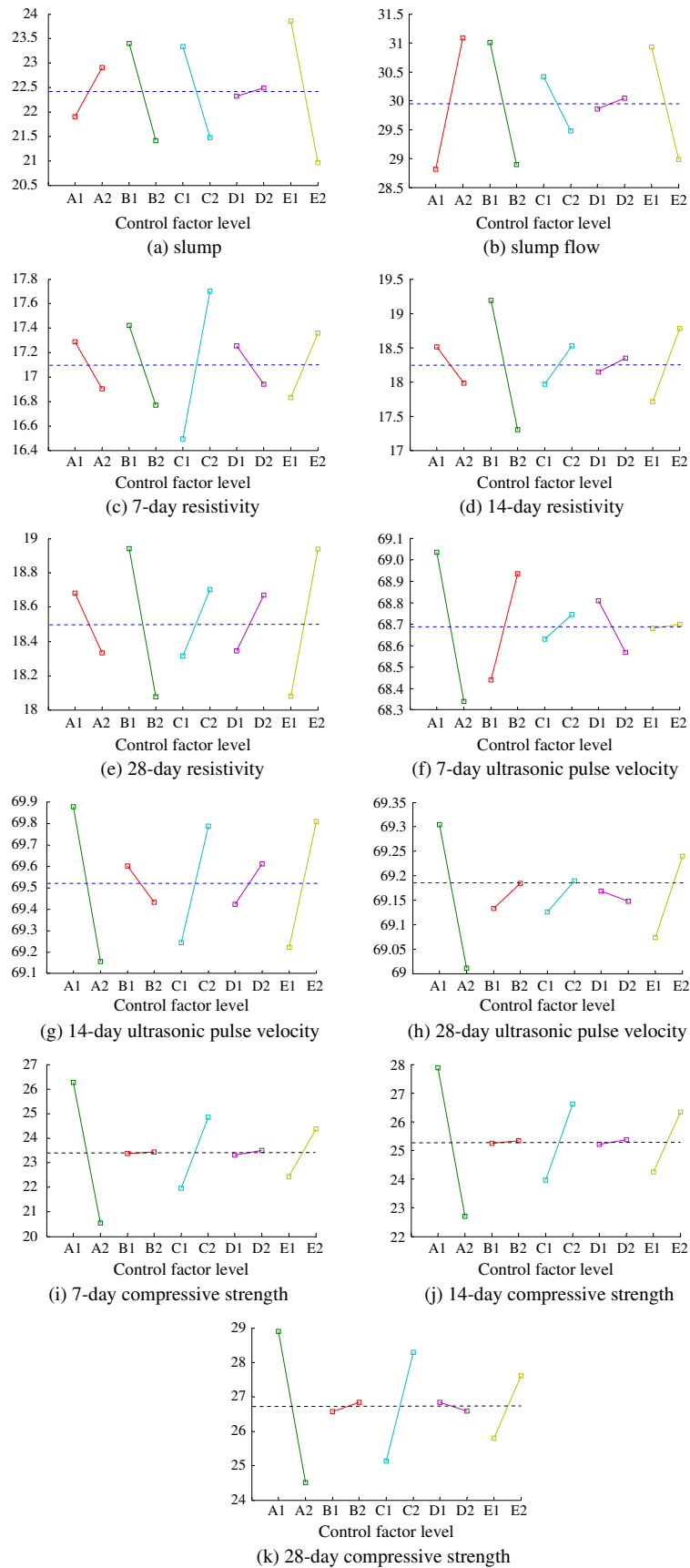
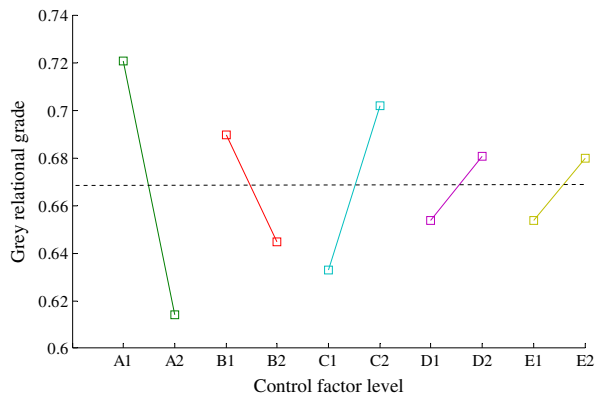
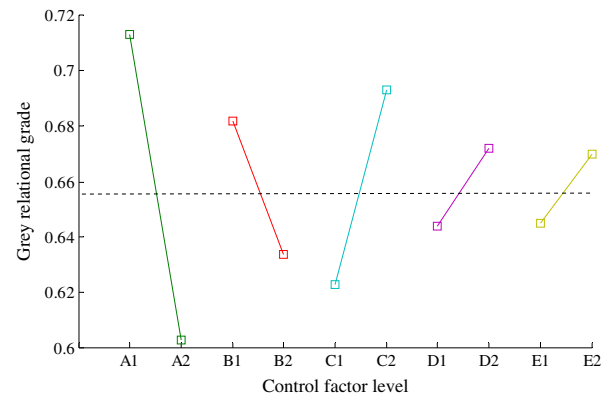


Fig. 3. Main effects plot for S/N ratio for each response.

Table 12

Main effects table for the grey relational grade on full responses.

Designation	Control factors	Grey relational grade		
		Level 1	Level 2	Effect
A	Water/cement ratio	0.72	0.61	0.11
B	Volume ratio of recycled coarse aggregate	0.69	0.64	0.05
C	Replacement of river sand	0.63	0.70	0.07
D	Content of crushed brick	0.65	0.68	0.03
E	Cleanliness of aggregate	0.65	0.68	0.03

**Fig. 4.** Main effects plot for grey relational grade for full responses.**Fig. 5.** Main effects plot for grey relational grade for reduced responses.

The experimental data of reduced responses were also subjected to the same steps of the weighted Grey-Taguchi method including pre-processing, calculation of weights, computation of grey relational coefficients, and determination of grey relational grades. After calculating the deviations of mixtures using reduced responses, the deviation sums of reduced responses are obtained as $D(j) = (33.03, 24.50, 15.74, 16.88, 11.83, 37.39, 32.55, 28.30)$ and the total deviation sum is also calculated as $\sum_{j=1}^{11} D(j) = 200.23$. Thus, the weights of reduced responses can be calculated as $w(j) = (0.16, 0.12, 0.08, 0.08, 0.06, 0.19, 0.16, 0.14)$. The weights of these reduced responses are more similar to each other.

Differences between $r_0(j)$ and $r_i(j)$ for reduced responses can be also calculated. Then, Δ_{max} and Δ_{min} are assessed as 0.48 and 0.00, respectively. Grey relational coefficients can be further calculated to obtain the grey relational grades of the mixtures. The best of the sixteen mixtures is identified as A1B2C2D2E2 (GRG of 0.80).

A main effects plot (or table) and ANOVA are also conducted to confirm the optimal mixture. Fig. 5 (dashed line of 0.658) illustrates the main effects plot and shows the priority of control factors for affecting the reduced responses is sequentially A (water/cement ratio), C (replacement of river sand), B (volume ratio of recycled coarse aggregate), D (content of crushed brick), and E (cleanliness of aggregate), which is the same as the full response design.

The results of ANOVA also indicate that A (water/cement ratio), B (volume ratio of recycled coarse aggregate), and C (replacement of river sand) are indeed the significant control factors for affecting the reduced responses. A (water/cement ratio) is also the most significant control factor due to its highest contribution ratio (50.208%) among the control factors.

Finally, the optimal mixture based on reduced responses is also identified as A1B1C2D2E2 by the proposed weighted Grey-Taguchi

Table 13

ANOVA of control factors on grey relational grades on full responses.

Designation	Degrees of freedom	Sum of squares	Mean square	F	Contribution ratio
A	1	0.0461	0.046	140.64	50.591%
B	1	0.0083	0.008	25.388	8.836%
A × B	1	0.0005	0.000	1.502	–
C	1	0.0187	0.019	56.976	20.280%
A × C	1	0.0017	0.002	5.258	1.543%
B × C	1	0.0001	0.000	0.377	–
D × E	1	0.0024	0.002	7.393	2.316%
D	1	0.0031	0.003	9.435	3.056%
A × D	1	0.0007	0.001	2.214	–
B × D	1	0.0001	0.000	0.337	–
C × E	1	0.000	0.000	0.005	–
C × D	1	0.002	0.002	6.023	1.820%
B × E	1	0.0014	0.001	4.249	1.177%
A × E	1	0.0005	0.001	1.565	–
E	1	0.0028	0.003	8.656	2.774%
Pooled	6	0.0020	0.0003	1.000	–

Table 14
Results of verification experiment.

Designation	S/N ratios											GRG
	Y ₁	Y ₂	Y ₃₁	Y ₃₂	Y ₃₃	Y ₄₁	Y ₄₂	Y ₄₃	Y ₅₁	Y ₅₂	Y ₅₃	
A1B1C1D1E1	23.747	30.999	17.612	17.832	18.004	68.952	69.212	68.711	24.897	27.937	28.088	0.753
A1B1C1D2E1	24.823	31.922	16.244	19.498	19.019	68.761	70.197	69.536	25.042	27.104	27.160	0.816
A1B2C2D2E2	14.114	27.602	19.121	18.612	20.072	68.927	70.356	69.540	29.114	30.591	31.173	0.795
A1B1C2D2E2	23.591	30.874	17.490	19.256	19.321	69.307	70.101	69.245	29.071	30.515	31.169	0.899

method. These results demonstrate the effectiveness of the proposed weighting technique.

4.3. Verification experiment

A confirmation experiment has also been conducted to compare the performance among mixtures of A1B1C1D1E1, A1B1C1D2E1, A1B2C2D2E2, and A1B1C2D2E2. A1B1C1D1E1 is considered as the initial mixture. A1B1C1D2E1 and A1B2C2D2E2 are the optimal mixtures based on slump and 28-day compressive strength, respectively, proposed in a previous study [25]. Besides, A1B2C2D2E2 is also the mixture based on the largest grey relational grade, and A1B1C2D2E2 is the optimal mixture proposed in this paper. Table 14 shows the results of the verification experiment and demonstrates that A1B1C2D2E2 (GRG of 0.899) is still the best among the compared mixtures.

5. Conclusion

Based on the results of this study, the following five conclusions can be drawn:

1. This paper has proposed the weighted Grey-Taguchi method to assess the optimal mixture with multiple responses for recycled aggregate concrete. Water/cement ratio, volume ratio of recycled coarse aggregate, replacement by river sand, content of crushed brick, and cleanliness of aggregate were selected as control factors with responses of slump, slump-flow, resistivity (at 7, 14, and 28 days), ultrasonic pulse velocity (at 7, 14, and 28 days), and compressive strength (at 7, 14, and 28 days). Results show that the optimal mixture of recycled aggregate concrete is water cement ratio of 0.5, volume ratio of recycled coarse aggregate of 42.0%, 100% replacement of river sand, 0% crushed brick, and water-washed aggregate.
2. The algorithm of the weighted Grey-Taguchi method is described by a step-by-step procedure in this paper. The weighted Grey-Taguchi method takes the Taguchi method as its basic structure and adopts grey relational analysis to deal with multiple responses as well as using the proposed weighting technique to enhance the distinguishing ability of grey relational analysis. The proposed weighting technique can not only provide reasonable weights on responses but also detect inefficient responses to reduce time/cost of experiments.
3. In the full responses design, the priority of control factors for affecting the full eleven responses has been identified by the weighted Grey-Taguchi method as water/cement ratio (effect of 0.11), replacement of river sand (effect of 0.07), volume ratio of recycled coarse aggregate (effect of 0.05), content of crushed brick (effect of 0.03), and cleanliness of aggregate (effect of 0.03), sequentially. Besides, based on the results of ANOVA, water/cement ratio ($F = 140.639$), volume ratio of recycled coarse aggregate ($F = 25.388$), and replacement of river sand ($F = 56.976$) are further identified as the significant control factors for affecting the multiple responses. The water/cement ratio is considered as the most significant control factor due to its highest contribution ratio (50.591%) among the control factors.

4. Owing to ultrasonic pulse velocities (7-day, 14-day, 28-day) being identified as inefficient responses by the proposed weighting technique, reduced responses of slump, slump flow, resistivity (7-day, 14-day, 28-day), and compressive strength (7-day, 14-day, 28-day) are discussed in this paper and compared with the results of the full responses design. Results show that the mixture assessed from the reduced responses design is the same as that of the full responses design, and also demonstrate the effectiveness of the proposed weighting technique.
5. The practicability of the weighted Grey-Taguchi method has been demonstrated in the application of recycled aggregate concrete. This method can be easily applied to related mixture problems.

References

- [1] Box GEP, Hunter WG, Hunter JS. Statistics for experimenters. New York: Wiley; 1978.
- [2] Muthukumar M, Mohan D, Rajendran M. Optimization of mix proportions of mineral aggregates using Box Behnken design of experiment. *Cem Concr Compos* 2003;25:751–8.
- [3] Sullivan PJE. A probabilistic method of testing for the assessment of deterioration and explosive spalling of high strength concrete beams in flexure at high temperature. *Cem Concr Compos* 2004;26:155–62.
- [4] Panzera TH, Rubio JC, Bowen CR, Walker PJ. Microstructural design of materials for aerostatic bearings. *Cem Concr Compos* 2008;30:649–60.
- [5] Phadke MS. Quality engineering using robust design. Prentice Hall; 1989.
- [6] Siddhartha, Patnaik A, Bhatt AD. Mechanical and dry sliding wear characterization of epoxy-TiO₂ particulate filled functionally graded composites materials using Taguchi design of experiment. *Mater Des* 2011;32(2):615–27.
- [7] Yousefieh M, Shamanian M, Saatchi A. Optimization of the pulsed current gas tungsten arc welding (PCGTAW) parameters for corrosion resistance of super duplex stainless steel (UNS S32760) welds using the Taguchi method. *J Alloys Compd* 2011;509(3):782–8.
- [8] Chan CW, Man HC. Laser welding of thin foil nickel–titanium shape memory alloy. *Opt Lasers Eng* 2011;49(1):121–6.
- [9] Chiang YM, Hsieh HH. The use of the Taguchi method with grey relational analysis to optimize the thin-film sputtering process with multiple quality characteristic in color filter manufacturing. *Comput Ind Eng* 2009;56:648–61.
- [10] Datta S, Sankar Mahapatra S. Use of desirability function and principal component analysis in Grey-Taguchi approach to solve correlated multi-response optimization in submerged arc welding. *J Adv Manuf Syst* 2010;9(2):117–28.
- [11] Sathiya P, Abdul Jaleel MY, Katherasan D, Shanmugarajan B. Optimization of laser butt welding parameters with multiple performance characteristics. *Opt Laser Technol* 2011;43(3):660–73.
- [12] Saaty TL. Decision making for leaders: the analytic hierarchy process for decisions in a complex world. Pittsburgh: RWS Publications; 2008.
- [13] Wong WG, He G. Grey evaluation method of concrete pavement comprehensive condition. *J Transport Eng* 1999;125:547–51.
- [14] Yen JF, Cheng SP. Hazard risk analysis of typhoon damage by applying grey system theory. *J Grey Syst* 2005;8:51–8.
- [15] Shen DH, Du JC. Application of grey relational analysis to evaluation HMA with reclaimed building materials. *J Mater Civil Eng* 2005;17:400–6.
- [16] Lin YH, Lee PC, Chang TP. Practical expert diagnosis model based on the grey relational analysis technique. *Expert Syst Appl* 2008;36:1523–8.
- [17] Benert T. Utilization of construction and demolition debris under traffic-type loading in base and subbase applications. *Transport Res Rec* 2000;1714:33–9.
- [18] Poon CS, Kou SC, Lam L. Use of recycled aggregate in molded concrete bricks and blocks. *Constr Build Mater* 2002;16:281–9.
- [19] Ajdukiewicz A. Influence of recycled aggregate on mechanical properties of HS/HPC. *Cem Concr Compos* 2002;24:269–79.
- [20] Zhang W, Ingham JM. Using recycled concrete aggregates in New Zealand ready-mix concrete production. *J Mater Civil Eng* 2010;22:443–50.
- [21] Sagoe-Crentsil KK, Brown T, Taylor AH. Performance of concrete made with commercially produced coarse recycled concrete aggregate. *Cem Concr Res* 2001;31:707–12.

- [22] Xiao J, Li J, Zhang C. Mechanical properties of recycled aggregate concrete under uniaxial loading. *Cem Concr Res* 2005;35:1187–94.
- [23] Etxeberria M, Vázquez E, Marí A, Barr M. Influence of amount of recycled coarse aggregates and production process on properties of recycled aggregate concrete. *Cem Concr Res* 2007;37:735–42.
- [24] Fisher RA. Statistical methods for research workers. London: Oliver & Boyd; 1925.
- [25] Lin YH, Tyan YY, Chang TP, Chang CY. An assessment of optimal mixture for concrete made with recycled concrete aggregates. *Cem Concr Res* 2004;34:1373–80.