Research Article

Multiobjective Reliability-Based Design Optimization of Recycled Aggregates Used in Corrosive Environment Based on Response Surface Modelling

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Received 19 October 2021; Revised 28 January 2022; Accepted 24 February 2022; Published 22 March 2022

Abstract

In this study, durability properties of concrete samples including rapid chloride migration and electrical resistance as corrosion evaluation indicators were tested. The effects of some environmental parameters including humidity percentage, temperature, and chloride concentration were also examined on concrete electrical resistance. Prediction models for mechanical and durability parameters of concrete were obtained using the response surface method. These models were then evaluated using a metaheuristic optimization algorithm coupled with a simple and fast usability new method of reliability evaluation. Eventually, the probabilistic optimal values of using recycled aggregates were calculated for achieving environmentally friendly concrete. Probabilistic multiobjective optimization results revealed that, in an environment with humidity of 70%, temperature of 23°C, and chloride ion concentrations of 3%, 5%, and 8%, use of recycled aggregates for above different chloride ion concentrations was limited to (33.56%, 13.23%), (32.14%, 5.56%), and (13.23%, 2.86%), recycled coarse and fine aggregates, respectively. Furthermore, optimization procedures were performed for the environment or precontaminant recycled aggregate with the chloride concentration of 10%, but the analysis procedure did not converge to an optimum design point.

1. Introduction

Investment growth in sustainable development in the construction industry can be a determining factor in increasing recycling as the community response to the growing environmental problems. Meanwhile, meeting technological requirements, a sustainable solution should seek to maintain a balance between social and economic growth and environmental needs. In addition, green movements emphasize the environmental aspects of sustainable development, which is highly relevant to the developed countries. However, many nearby buildings have reached the end of their useful life, and besides those destroyed by huge natural disasters or war, also many structures have not been well-built according to relevant building specifications or are rendered unsafe for use according to the new building design specifications [1–9]. It can be suggested that the aggregates recycled from construction industry waste can always be reused in such construction activities as buildings, underlay for roads and pavements, and other construction applications. As explained by researchers, the ordinary concrete is not affected by the replacement ratio when the replacement percentage is limited (not more than 20%) [2]. Thus, with an increased replacement ratio, or where a particular performance (such as durability and resistance under harsh environmental conditions) is required, recycled aggregates
may perform poorly in durability and mechanical parameters. The compressive strength of the concrete is considered a significant indicator which is often associated with modes of stress such as tensile and bending strength and modulus of elasticity.

Further, extensive attention has been paid in recent years to the research and development of electrical resistance measurement as a Nondestructive Technique (NDT) for assessing the durability of concrete structures. This method is becoming commonplace, especially in field evaluations (in situ) due to its simplicity, speed, and cost-effectiveness of the test process [2, 3]. Electrical resistance is an inherent property of materials that can be used for different purposes, with determining specifications of fresh concrete in early years being one of them. The electrical resistance of the concrete is affected by several factors such as water to cement ratio, type of cement, mineral additives, age, and environmental conditions. Electrochemical techniques such as conductivity or its inverse (electrical resistance) have been proposed as methods for evaluating ion transfer properties as well as changes in the concrete porosity and microstructure [10, 11]. For a reliable and repeatable electrical resistance measurement in quality control applications, it is recommended that the concrete test specimen should be saturated and has a dry surface. In the bulk electrical resistance method (single-axis method), two electrodes are placed on the concrete surface (often two parallel metal plates) plus a moist sponge between concrete and metal on both sides of the specimen. Generally, only standard cylindrical/pyramidal specimens or cores taken from structures are used in this method [10–13]. To summarize, the main purpose of the present study is to find a reliable optimum value of recycled aggregates (RA) in reinforced concrete structures exposed to a corrosive environment. To reach this goal according to the paper framework, first, durability and mechanical parameter of concrete are obtained in the experimental part. The effects of important parameters of a corrosive environment such as relative humidity, temperature, and concentration of chloride are also tested on the electrical resistance of concrete as the corrosion risk evaluation index. The prediction models for compressive strength (CS) and electrical resistance (ER) of concrete are then developed by applying the response surface method [14–16] based on two parameters of the percentage of recycled coarse aggregate and recycled fine aggregate. In the end, these models are applied as optimization problem constraints to reach reliable values of RA for a green concrete in a probabilistic optimization procedure by coupling two algorithms, namely, weighted simulation method and estimate distribution algorithm (MOEDA – WSM) in a multiobjective mode [17–32]. In short, the results of analyses indicate different ranges of using RA for environmental conditions with different corrosion risk levels (low, medium, and high) and different safety levels or target reliability index ($\beta$). Figure 1 displays the framework designed in this study to extract reliability-based design optimization result for RA mix design.

1.1. Experimental Work

1.1.1. Materials. In studying the effects of replacing natural coarse aggregates with recycled ones, the density of fine and coarse aggregates as well as water absorption of both natural and recycled aggregates was measured (Table 1) following ASTM C29 [34], ASTM C127 [35], and ASTM C128 [36]. Table 2 reports the specifications of Type II Portland cement used in this research.

1.2. Methods. Natural and recycled coarse as well as fine aggregates (Figure 2) were weighed (ASTM C33 [37]). Cement and water were mixed and poured in cylindrical molds (300 mm × 150 mm and 200 mm × 150 mm) and in cubical molds (150 mm × 150 mm and 100 mm × 100 mm), and compressive strengths of 28- and 90-day-old specimens were obtained (ASTM C39 [38]) (Figure 3). Water absorption and porosity tests were performed (ASTM C642 [39]) after 28 days of curing. The electrical resistance test (ASTM C1760-12 [40]) was conducted after 28 and 90 days of curing under saturation conditions with a dry surface (Figure 4). The rapid chloride migration (RCM) test was carried out according to the guideline NT Build 492 [41] (Figure 5).

1.3. Mixing Proportions and Specimens Preparation. The mix design is considered as the model variable, following the requirements of the response surface method, w/c, and the amount of the recycled coarse aggregates (Table 3). In this study, cylindrical and cubical concrete specimens have been prepared with 0, 20, 50, 70, and 100% NA replacement with RA, consistency of RCA, and RFA to create the model as well as to perform compressive strength, electrical resistance, porosity, and water absorption tests.

1.4. Experimental Results. Table 1 outlines the water absorption of waste concrete aggregates versus natural ones. As shown, water absorption of the recycled coarse aggregates is 8.61 times that of natural ones since recycled aggregates are covered with the primary concrete mortar (the main feature of this aggregate type). Similarly, water absorption of the recycled fine aggregates is 12.37 times that of the natural ones meaning the latter absorb more mortar from the old concrete mix. Also, Table 1 indicates a 1% reduction in the specific weight of the recycled coarse aggregates compared to natural ones; for fine aggregates, this reduction is 11%. Considering the bulk density, the reduction for recycled coarse aggregates is 13.13% compared to natural ones. In response to extraction of aggregates from recycled concrete, the adherence of primer mortar to recycled aggregates is known as the major factor in enhancing the porosity (Figure 6) and water absorption (Figure 7) in recycled aggregates concrete. Figures show porosity and water absorption have increased by 215.49% and 210.10% in the maximum percentage of RA (100%), respectively. In response to increasing porosity and volume of pure solution electrical resistance [42,43], Figure 8 reduces by
Table 1: Properties of normal and recycled aggregates.

| Material | Mechanical test | Germany specification [33] |
|----------|-----------------|-----------------------------|
|          | Specific gravity | Bulk density (kg/m³) | Water absorption (%) | Standard water absorption (%) | Standard specific gravity |
| NCA      | 2.73            | 1561                       | 0.73                | ≤15                          | ≥2.0                       |
| NFA      | 2.65            | -                          | 0.79                | ≤15                          | ≥2.0                       |
| RCA      | 2.71            | 1356                       | 6.33                | ≤15                          | ≥2.0                       |
| RFA      | 2.36            | -                          | 9.77                | ≤15                          | ≥2.0                       |

Chemical analysis

| Material | \( C_{CL} \) (%) |
|----------|------------------|
| NA       | 0.05             |
| RA       | 0.05             |

Figure 1: Proposed framework for optimization of RA mix.
Table 2: Portland cement type II chemical and physical properties.

| Chemical analysis          | Result |
|----------------------------|--------|
| Silicon dioxide (SiO₂): %  | 21.05  |
| Aluminum oxide (Al₂O₃): %  | 4.76   |
| Iron oxide (Fe₂O₃): %      | 3.43   |
| Calcium oxide (CaO): %     | 62.86  |
| Magnesium oxide (MgO): %   | 3.46   |
| Physical test              | Result |
| Loss on ignition: %        | 1.21   |
| Blaine finesse: m²/kg      | 312    |

Figure 2: Recycled coarse and fine aggregates. (a) Demolished concrete. (b) Sieved coarse and fine aggregates (19 mm, 12.5 mm, 9.5 mm, 4.75 mm, 2.36 mm, 1.18 mm, 600 μm, 300 μm, 150 μm, respectively).

Figure 3: Compressive strengths specimens test. (a) Prepared samples. (b) Compressive strengths test equipment.

approximately 55.74% at the maximum use of RAs (100%). Figure 9 reveals increased recycled concrete aggregate in the concrete mix adds their surrounding porous region to those already existing there, causing a weak transition zone to develop in concrete due to the coverage of these aggregates with the mortar in the old concrete mix [2, 3]. An increase in RA (100%) would reduce the compressive strength by nearly 28.75%. Figure 10 shows that an increase in RCA (100%) has lowered the electrical resistance by approximately 37.84% and demonstrates that an increase in RFA (100%) has
reduced the electrical resistance by approximately 49.56% which resulted from high-water absorption of recycled aggregates causing more pores concrete with powerful ion conductive channel [42, 43]. Figure 11 indicates that an increase in RCA (100%) has lowered the compressive strength by approximately 19.97% and a rise in RFA (100%) has decreased the compressive strength by approximately 24.32% which is related to weak interfacial transition zone caused by recycled aggregates high-water absorption inherent property.

### 2. RSM to Estimate the RA Concrete Compressive Strength and Electrical Resistance

For a constrained optimization of an objective function, here, concrete with maximum RA, effort should be made to define the required limit functions. In most engineering problems, this is a major challenge since obtaining exact, precise, robust functions that could be applied easily in optimization problems needs enormous computational

![Table 3: Mix proportion, basic parameters of experimental data.](image)

![Figure 4: Electrical resistance specimens test.](image)

![Figure 5: Rapid chloride migration specimens test. (a) Prepared samples. (b) RCM test equipment. (c) Tested samples.](image)
In this research, the response surface model has been utilized to find functions of the concrete compressive strength and electrical resistance. Such models are used in the next section of the research as optimization constraints. The RSM’s main concept is to estimate a real and complex function with a simple and explicit one. Mathematically, any order of the Taylor polynomial expansion on the randomly selected points can be chosen to predict appropriate responses. In general, researchers have proposed the second-order polynomial. Hence, Taylor polynomial expansion is as follows [14–16]:

**Figure 6:** Porosity-RA relationship.

**Figure 7:** Water absorption-RA relationship.

**Figure 8:** Electric resistance-RA relationship.

**Figure 9:** Compressive strength-RA relationship.

**Figure 10:** Electric resistance RCA-RFA relationship.

**Figure 11:** Compressive strength RCA-RFA relationship.
where $g(X)$ is the desired response, $X$ represents a set of the desired random variables, and $\beta$ denotes unknown coefficients for the determination of which function may be converted to a linear regression model. In other words, second-order terms are changed to first-order as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon,$$

where $\epsilon$ is the existing error. The above equation can be rewritten as follows:

$$y = \beta X + \epsilon. \quad (3)$$

Using the least squares method, the matrix of coefficients can be calculated as follows:

$$\beta = (X^T X)^{-1} X^T y. \quad (4)$$

In this research, to estimate the compressive strength and electrical resistance through combinatory terms, (RCA, RFA) and ($\rho, f_c$) are utilized as input and output variables, respectively. Based on the input variables, a second-order polynomial is assigned to the laboratory data and its coefficients are calculated considering the least error between laboratory data and the estimated values [14–16].

2.1. Modelling Results

2.1.1. The Proposed Compressive Strength Estimation Model.

After measuring the 28-day concrete compressive strength ($f_{c28}$) in the laboratory, the following relation is defined between its variables using the collected data and the response surface method (Figure 12 and Figure 13):

$$f_c = f_{c28}(\text{RCA} \%, \text{RFA} \%)$$

$$f_{c28}(x_1, x_2) = 0.0001x_1^2 - 0.08x_1 - 0.001x_2^2 - 0.021x_2 + 39.410, \quad (5)$$

where $f_c$ is the compressive strength of the standard cylindrical specimen in MPa.

2.1.2. The Proposed Electrical Resistance Estimation Model.

The ER of concrete is a key index for evaluating the quality of concrete for various environmental conditions affected by material-related and environmental parameters. Note the same experimental work was performed in this research compared with [42, 43], for example, chloride concentration ($C_{Cl^-}$), ambient temperature (T), and relative ambient humidity ($r_{RH}$) on concrete electrical resistance. In addition, the effect of consuming recycled aggregates in concrete was experimented. The ER of concrete at the ages of 28 and 90 days under the saturated conditions with a dry surface was measured ($\rho_0$). After calculating the coefficients of material and environment, ER was computed using (7):

$$R^2 = 0.86$$

\[ R^2 = 0.86; \text{RMSE} = 1.384 \]
The solution of this model is presented in [45] and yields the following equation for the $D_{RCM}$:

$$D_{RCM} = \frac{RT}{zFE} + \alpha \sqrt{x_d} \frac{1}{t},$$  \hspace{1cm} (8)
where $D_{RCM}$ is the compressive strength of the standard cylindrical specimen in MPa (Figure 19).

2.1.4. The Proposed Chloride Diffusion Coefficient Estimation Model Based on Electrical Resistance. Chloride diffusion coefficient has a close relationship with electric resistance based on electric flux in a magnetic field. The following relation was obtained by doing regression analysis on experimental data:

$$D_{RCM} = D_{RCM}(\rho),$$

where $D_{RCM}$ is the compressive strength of the standard cylindrical specimen in MPa (Figure 20).

3. Reliability-Based Design Optimization

The reliability-based design optimization (RBDO), an important structure optimization area involving uncertainties, is an attempt to search for the best agreement between cost reduction and safety assurance based on probabilistic constraint assessments. In short, it not only finds the construction costs but is also responsible for the reliability level; total cost is the sum of the construction, design, defects, and repairs costs.

The reliability-based structure optimization is generally formulated as follows:

Minimize: $f(X)$,

$$P[G(X_1, X_2) < 0] \leq P_f,$$

Subject to: $X^L \leq X \leq X^U$,

$$X^L_1 \leq X_1 \leq X^U_1,$$

$$X^L_2 \leq X_2 \leq X^U_2,$$

where $f(X)$ is the objective function, $X$ denotes the vector of random variables, and $X^L$ and $X^U$ are the random variables’ lower and upper bounds, respectively. The objective failure probability is simply expressed in terms of the objective reliability index as $P_f = \Phi(-\beta)$ where $\Phi(.)$ is the standard normal cumulative distribution function. An objective reliability index of 2.5 means an objective failure probability of $0.00392 = 0.000014$. Here, the design variables are the values of RCA and the RFA. The reliability-based optimization problem in this study can be expressed as follows:

Maximize: $f(X) = \text{Max}(X_1, X_2)$,

$$P[G(X_1, X_2) < 0] \leq P_f,$$

Subject to:

$$0 \leq X_1, X_2 \leq 100,$$

3.1. Estimation Distribution Algorithm (EDA). Proposed first in 1994 by Balija [17–24], EDAs quickly became an important branch of evolutionary algorithms because of their better mathematical foundations compared to their counterparts. According to the statistical learning theory, EDAs use, in the evolutionary generation process, some selected (the best) population generations to develop a probability model and generate subsequent generations by sampling from this probability model through a probabilistic method.

3.1.1. The MOEDA-WSM Multiobjective Optimization Algorithm. Several domains of science, engineering, and industry have defined its application in the form of a tactic between two or more reciprocal optimal decision-makings which need equilibrium. It is rarely claimed that a single solution can simultaneously optimize each objective function of the multiobjective optimization problems [25–32]. Thus, multi-objective optimization algorithms should be able to
(i) A pseudocode of the algorithmic structure of most EDAs is given below [20].

Algorithm structure of EDAs.

1. Initialization: Initialize population of solutions $X^0_{best}$ and solution distribution model $P^0$
2. Main Loop: while stopping criteria are satisfied do
   3.1.1. $X^t_{parent} = \text{select}(X^t_{best}, f)$ / Selection
   3.1.2. $P^{t+1} = \text{estimate}(X^t_{parent}, P^t)$ / Estimation
   3.1.3. $X^{t+1}_{offspring} = \text{sampling}(P^{t+1})$ / Sampling
   3.1.4. $X^t_{best} = \text{replacement}(X^{t+1}_{offspring}, X^t_{best}, f)$ / Replacement
   $t = t+1$
end while

Step 3. Evaluating the failure probability for each particle. For this objective, each population particle should be considered as a possible average value for the design variables. For instance, if particle $j$ position is considered as the average value for random variables $(\mu_X = [\mu_{X_1}, \ldots, \mu_{X_m}])$, the vector of the specified new weight coefficients ($W^k_j$) will be generated by

$$W^k_j = \prod_{i=1}^{m} \text{PDF}(X_i, \mu_{X_i}, \sigma_{X_i}),$$

where PDF($X_i, \mu_{X_i}, \sigma_{X_i}$) is the vector generated through calculating the PDF for simulated random variable $i$ with mean $\mu_{X_i}$ and standard deviation $\sigma_{X_i}$. The failure probability of each constraint that should have been specified for this particle can be calculated as follows using the new weight coefficients:

$$p^i_j = \frac{\sum_{i=1}^{N} I_i \cdot W^i_j}{\sum_{i=1}^{N} W^i_j}$$

Step 4. Evaluating the cost function for each particle and ordering based on the corresponding value of the cost function.

Step 5. Finding non-dominated solutions.

Step 6. Updating the archives with the resulting non-dominated solutions; in this step, if the archive is full, one particle is eliminated from the populous zone of the archive to allow one non-dominated solution to enter the archive.

Step 7. Obtaining the solution domain and defining the hypercube divided network.

Step 8. Calculating the value of $w$ and $p$ using the following formula:

$$I_i(g_j) = \begin{cases} 1, & \text{if } g_j(X_i) \leq 0, \\ 0, & \text{otherwise}. \end{cases}$$
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\[ w_i = \frac{1}{q k \sqrt{2\pi}} e^{-(i-1)^2/(2(qk)^2)}, \quad k = nPop, \quad i = 1: \frac{k}{2}. \] (17)

\[ p_i = \frac{w_i}{\sum_{i=1}^{k/2} w_i} \]

**Step 9.** Forming the probability model:

\[ \sigma_i = \frac{\sum_{j=1}^{k} |s_j - s_i|}{k - 1}, \] (18)

\[ P_{best} = \text{Truncation (percentage from sorted population based on fitness function)}. \]

\[ P_{i}^{\text{New}}(j) = \text{mutate}(P_{i}^{k}(j), \text{Mutation Rate Mutation Step Size, Varmin, Varmax}). \] (20)

Here, \( P_{i}^{k}(j) \) is the position of the contiguous particle, and \( P_{i}^{\text{New}}(j) \) denotes the position of the new particle in the present iteration. If the new particle is dominated, it will be replaced by the contiguous particle.

**Step 12.** Finding nondominated solutions and updating the archive plus hypercube network.

**Step 13.** Controlling the convergence criterion; if the algorithm does not converge, the optimization process will be iterated from Step 7 to Step 13.

4. Reliability-Based Design Optimization Results

The mean and coefficient variation of random variables, i.e., percentage of replacement of RCA and RFAs ratio, were assumed to be (50, 50) and (0.20, 0.20), respectively, for two random variables with a normal distribution. The failure threshold for the limit state function of CS is \( f_{\text{CS}} = 35 \text{MPa} \), and that for the limit state function of ER is \( \rho_{\text{th}} = 1000 \Omega.m \). The defined objective function is obtaining the maximum use of waste concrete RA in the concrete mixture for corrosive environmental conditions. The classification of corrosive environmental conditions in this study was considered according to Table 4 [46, 47]. Initially, based on the main goal of this study, i.e., the use of maximum RAs to reduce destructive environmental effects, the excessive use of natural aggregates, and a large volume of construction waste, when this was analysed only with the WSM method without coupling it with a metaheuristic algorithm, achieved result of analysis that is unstable and needed more analysis to find optimum design point, but with a metaheuristic optimization algorithm this problem was solved.

4.1. WSM RBDO. As shown in Figure 21(a)–21(d), based on assumed corrosion risk level for steel reinforcement, i.e., medium (\( \rho \leq 100 \Omega.m \)), safety level, or target reliability index \( \beta_i = 3.0 \), and the environment with humidity of 70%, temperature of 23 \( ^\circ \text{C} \), and chloride concentration of 0%, 3%, 5%, and 8%, using of RAs is limited to (33.56%, 13.23%), (32.14%, 5.56%), and (13.23%, 2.86%), RCAs and RFAs, respectively.

**Step 10.** Updating the position of each particle.

\[ P_{i}^{k+1}(j) = P_{i}^{k}(j) + \text{rand}(.) \times \sigma_{i}(j) + (0.50 - \text{rand}(.)) \times \left( G_{\text{best}}^{k}(j) - P_{i}^{k}(j) \right). \] (19)

In this step, running the minimum-maximum of position can prevent the excessive displacement of particles.

**Step 11.** To avoid the local optima, with a new solution using the mutation process in this step, a new particle is produced.

4.2. MOEDA-WSM RBDO. When WSM is coupled with a metaheuristic optimization algorithm, for example, EDA in form of a multiobjective probabilistic optimization problem only in one run of optimization procedure this point was founded; see Figure 22(a)–22(d). As with the previous section on environmental condition and level of safety, it can be observed that the use of RAs is limited to an archive of design points which offers more advice to the designer for selecting one of these as an optimum design point. Further, the optimization procedure for the environment with the chloride concentration of 10% was performed but the analysis procedure did not converge to an optimum design point.

5. Discussion

The hardened concrete aggregates test results, comparison of proposed models with those found from other methods, validation of the proposed models, and the optimization procedure reveal the following:

1. Natural aggregates are extracted from waste concrete, after breaking into recycled ones having mortar on their surfaces. This mortar on the natural aggregate creates a porous area around it and causes it to absorb more water whose amount depends on the volume of the surrounding mortar. Coarse aggregates that are surrounded by less mortar absorb less water (6.33%) compared to fine aggregates with more mortar and then high-water absorption (9.77%).

2. The concrete porosity increases with an increase in RFA; increase in porosity and the volume of pores
results in a stronger ion conduction channel in concrete causing an average reduction of about 49.56% in the concrete electrical resistance if maximum RFA is used.

The concrete porosity grows with an increase in RFA; increase in porosity which weakens the transition zone among concrete components, due to this, obtained an average decrease of about 24.32% in the

| Environment required risk level | Required bulk resistivity (Ω·m) |
|---------------------------------|---------------------------------|
| Low                             | <50                             |
| Moderate                        | 50–100                          |
| High                            | 100–200                         |
| Very high                       | 200–2000                        |
| Negligible                      | >2000                           |

**Table 4:** Classification based on environment risk level.

![Table 4: Classification based on environment risk level.](image)

**Figure 21:** WSM RBDO result for different environment condition. (a) $T = 23\, ^\circ\text{C}$, $\text{rh} = 70\%$, $C_{ci} = 3\%$, $\rho_{thr} = 100\, \Omega\cdot\text{m}$. (b) $T = 23\, ^\circ\text{C}$, $\text{rh} = 70\%$, $C_{ci} = 5\%$, $\rho_{thr} = 100\, \Omega\cdot\text{m}$. (c) $T = 23\, ^\circ\text{C}$, $\text{rh} = 70\%$, $C_{ci} = 8\%$, $\rho_{thr} = 100\, \Omega\cdot\text{m}$. (d) $T = 23\, ^\circ\text{C}$, $\text{rh} = 70\%$, $C_{ci} = 10\%$, $\rho_{thr} = 80\, \Omega\cdot\text{m}$.
concrete compressive strength if maximum RFA is used.

(4) Relative humidity has a significant effect on the electrical resistance and hence on the steel corrosion in concrete; increase in the moisture content reduces the electrical resistance exponentially. Changes in other important parameters (ambient temperature, chloride content, RCA, and RFA content) alter the electrical resistance differently.

(5) Results of the reliability-based optimization accompanied with a probabilistic evaluation and metaheuristic algorithms showed the design variables’ uncertainties could affect the allowable amount of RCA and the maximum RFA in concrete mix. Accordingly, the allowable RCA can vary depending on the reliability design levels; at a failure level $P_f = 1.13 \times 10^{-3}$ maximum RCA and RFA values are 32.58% and 24.89%, respectively.

6. Conclusions

The corrosive environments have high volumes of construction waste and raw materials’ consumption due to their severe conditions causing relatively low service life of engineering structures. This study was performed to determine the probable optimum utilization of recycled aggregates for corrosive environments.

This research results concluded that it is possible to use a considerable volume of recycled coarse and fine aggregates in concrete structures for moderate corrosion level. Depending on environmental conditions, the recycled coarse and fine aggregates replacement ratio was obtained as 32.58 and 24.89%, respectively, which can give companies in the construction industry a good public image, and environmental concerns will fade in the community. Also, the results revealed the restriction for using the recycled aggregates under severe environment conditions as well as by aggregates’ chloride ions precontamination. For further
studies, considering whether using the additive materials can enhance concrete quality made with the recycled aggregates and provide the possibility of their use in the environments with higher corrosive conditions can be valuable.

**Data Availability**

The data used to support the findings of this study are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

**Acknowledgments**

The authors would like to thankfully acknowledge the personnel of the Concrete Laboratory of the University of Sistan and Baluchestan for their help with the required tests.

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