Expert Systems With Applications 272 (2025) 126732

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

An improved framework for multi-objective optimization of cementitious composites using Taguchi-TOPSIS approach

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ARTICLE INFO

Keywords:
Cementitious composites
Multi-objective optimization
Normalization
Taguchi method
TOPSIS

ABSTRACT

The traditional Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodology is commonly used for the multi-objective optimization of cementitious composites, allowing the simultaneous optimization of various mechanical and physical properties. Due to the significant scale differences among these properties, such as target strength (ranging from tens to hundreds) and strain (typically 0–1%), normalization is essential for accurate comparison. However, current civil engineering practices often employ fixed normalization methods, which may not always lead to optimal performance. This study addresses this limitation by proposing a novel framework for evaluating normalization methods within the TOPSIS process. The framework integrates metrics such as the Ranking Consistency Index (RCI), Spearman Correlation (SC), Rank Variance (RV), plurality voting, and Pareto dominance sorting to identify and exclude unsuitable normalization techniques. It was validated using three experimental datasets: hybrid fibre engineered cementitious composites, recycled aggregate concrete, and geopolymer concrete. The results showed considerable variation in optimization outcomes depending on the normalization method. For the tested datasets, the framework identified the Linear max–min and Lai and Hwang methods as superior due to their higher RCI, SC and lower RV, and these methods also resulted in optimal properties, thereby confirming the effectiveness of the framework. Overall, the study highlights the critical role of selecting suitable normalization methods in multi-response optimization and demonstrates how the proposed framework improves optimization accuracy.

1. Introduction

The design process of cementitious composites, such as engineered cementitious composites (ECC) considers multiple control factors (e.g., binder proportions, fibre geometry and dosage, water-binder ratio) and diverse response parameters (e.g., peak compressive stress, ultimate tensile strength, strain capacity) (Rawat et al., 2022). Traditionally, optimal mix proportions are determined through extensive laboratory testing using methods like full factorial design (Ozbay et al., 2009). However, limited modelling capacity of this method and extensive experimental cost has driven the development of alternative approaches, including fractional factorial design (Bhaskar et al., 2023) and response surface methodology (Li et al., 2021). Moreover, multi-response optimization studies have increasingly utilized advanced techniques, including evolutionary multi-objective optimization algorithms such as Non-dominated Sorting Genetic Algorithm II (NSGA-II), as well as reinforcement learning approaches, to optimize mechanical properties and minimize the cost (Chen et al., 2022; Wang et al., 2023; Zheng et al., 2023).

Taguchi method is another powerful framework that allows the identification of optimal mix design with limited experiments on selective control factors and control levels. When applied to cementitious composites with a single response parameter, Taguchi method has proven to be effective in reducing experimental trials (Ravathi and Chithra, 2022; Zhu et al., 2022). Building on this, recent studies have successfully integrated Taguchi method with other multi-response

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https://doi.org/10.1016/j.eswa.2025.126732
Received 13 February 2024; Received in revised form 11 January 2025; Accepted 30 January 2025
Available online 3 February 2025

analysis approaches, such as Grey relational analysis (Cui et al., 2017), Utility concept (Rahim et al., 2013), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Al Ghafri et al., 2024; Swathi & Vidjeapriya, 2024; Şimşek et al., 2022) to provide the ideal mix design by simultaneously considering multiple objectives. Compared to reinforcement learning, Taguchi method offers advantages in terms of computational efficiency, ease of implementation, and lower experimental cost—especially due to the use of orthogonal arrays to minimize the number of required experiments. Therefore, the integrated Taguchi framework offers a promising approach for optimizing cementitious composite mix designs while keeping costs and complexity manageable.

However, it is important to note that experiments designed within the Taguchi framework for cementitious composites often result in response data that may be incomparable due to differences in dimensions, scaling, and polarization (Rawat et al., 2022). For example, peak compressive strain typically ranges from 0 to 1 %, as it represents deformation and is constrained by material behaviour, while compressive stress, which quantifies resistance to applied loads, can exceed this range. This variation is not contradictory but rather indicative of the distinct physical characteristics of these performance metrics and is an inherent feature of concrete datasets. Therefore, normalization is required to convert the raw data into numerically comparable data on a common scale (Corrente & Tasiou, 2023).

Existing researchers tend to adopt the normalization methods from the other previous studies neglecting the significant impact the choice may have. Moreover, there is no clear guideline on what normalization method should be adopted for multi-response optimization. For instance, Singh et al. (2023) used linear normalization for previous concrete mixtures, Warda et al. (2022) used Fuzzy weighted normalization technique for fibre reinforced concrete, Şimşek et al. (2013) used vector normalization method for self-compacting concrete, whereas Rawat et al. (2022) used linear max–min normalization method for ECC. This issue is particularly important in light of recent studies on Multi-Criteria Decision-Making (MCDM) problems, which have shown that the choice of normalization technique can alter the resultant optimal design and may neglect the best decision solution (Corrente & Tasiou, 2023; Vafaei et al., 2018). It is therefore likely that a similar bias could occur in the optimization of cementitious composite mixes if an unsuitable normalization method is applied. Vafaei et al. (2018) proposed an assessment process for MCDM incorporating various statistical assessment methods to elect the better suited normalization method. However, its applicability to concrete or cementitious composite mix design optimization remains uncertain.

The current study addresses this gap by focusing on the analysis of the impact of normalization methods on the optimization of cementitious composite mix designs using the Taguchi-TOPSIS framework. To achieve this, the approach suggested by Vafaei et al. (2018) was adopted and a new evaluation process for normalization methods is proposed to provide more robust evaluation procedure applicable to the optimization of cementitious composites. The new process consists of i) *Ranking consistency index* (RCI) to show similarity between different normalization methods; ii) *Spearman correlation (SC)* to identify the consistency of normalization methods, iii) *Rank Variance (RV)* analysis to show the relative amount of error for each normalization methods; and iv) *plurality voting and Pareto dominance sorting* to identify the best normalization method. Three data sets were used to validate the new overarching framework including a variety of mix designs namely for recycled aggregate concrete (Chang et al., 2011), geopolymer concrete (Chokkalingam et al., 2022) and hybrid fibre ECC (Rawat et al., 2022) and demonstrate the universal applicability of the proposed framework. This new evaluation system will allow a rigorous selection of the normalization method, which can be integrated with Taguchi method and multi-response analysis approaches (TOPSIS for the current case) to comprise an overarching framework for material optimization.

2. Methodology

2.1. Proposed overarching framework

TOPSIS is a widely acknowledged multi-response analysis approach and has been successfully used in various fields including engineering (Golui et al., 2024; Wang et al., 2024; Zhang et al., 2025). The combination of TOPSIS and Taguchi method gained popularity in concrete mix design optimization recently (Şimşek et al., 2013; Warda et al., 2022) but has not been sufficiently tested for ECC. Therefore, the framework has been specifically designed for integrated Taguchi-TOPSIS method and the applicability of the framework has been demonstrated with the ECC data set collected recently by the authors (Rawat et al., 2022). The detailed process outlining the improved framework integrating Taguchi-TOPSIS method is shown in Fig. 1.

The suggested approach introduces a normalization assessment framework within the analysis process. The primary goal is to identify and evaluate potential normalization methods from the available options. Jahan and Edwards (2015) provided a comprehensive review of normalization techniques, serving as a foundational reference for selecting suitable methods. Table 1 shows some of the available methods which may be applicable to the mix design of cementitious materials. The advantages and disadvantages of these methods are also presented alongside.

The first step involves identifying a subset of normalization methods appropriate for the dataset under consideration. Once these methods have been shortlisted, the framework can be employed to determine the most effective normalization technique for the specific dataset. The selected normalization method is then integrated with the TOPSIS approach to evaluate and optimize the mix proportions. Each step of the framework has been described in detail in the following section.

2.1.1. Taguchi method

2.1.1.1. Determination of control factors, control levels and response parameters. The framework begins with determination of control factors, levels, and response parameters to implement the Taguchi orthogonal array. In the present study, the control factors and control levels have been directly adopted from Rawat et al. (2022) where they optimized the mix design of ECC using Taguchi-Grey relational analysis and Taguchi-Utility concept. These parameters were then utilized to design Taguchi L16 array and implement the proposed framework with TOPSIS. Five governing control factors were chosen as:

(i) Total cement replacement (TCR) by supplementary cementing materials (SCM) – This factor was varied from 50 % to 80 % of the weight of binder and was adopted to ensure that the total cement consumption could be minimized.

(ii) Dolomite to binder ratio – Dolomite was selected as one of the SCM to minimize the waste resulting from stone quarries (Rawat et al., 2022) and its potential to use in ECC was assessed by varying its content from 10 % to 30 % of binder.

(iii) Slag to fly ash (FA) ratio – Recognizing the positive effect of ternary or quaternary blends in ECC for enhancing hydration and particle packing, the effectiveness of blends comprising slag and fly ash was further examined by varying this ratio from 1:0 to 1:0.6.

(iv) Fibre content – Combination of high modulus steel and low modulus polyethylene (PE) fibres was employed to achieve an optimal balance between compressive and tensile performance. Dosage of PE fibre was varied from 1.25 % to 1.75 % of the total volume and dosage of steel fibre was varied from 0.75 % to 1.0 % of the total volume.

(v) Water-binder ratio (WBR) – This factor was chosen to understand the effect of how water-binder ratio could affect hydration process and thereby, the performance of a quaternary blended mix. The ratio was varied from 0.20 to 0.30 to systematically capture its effect and estimate the strength range.

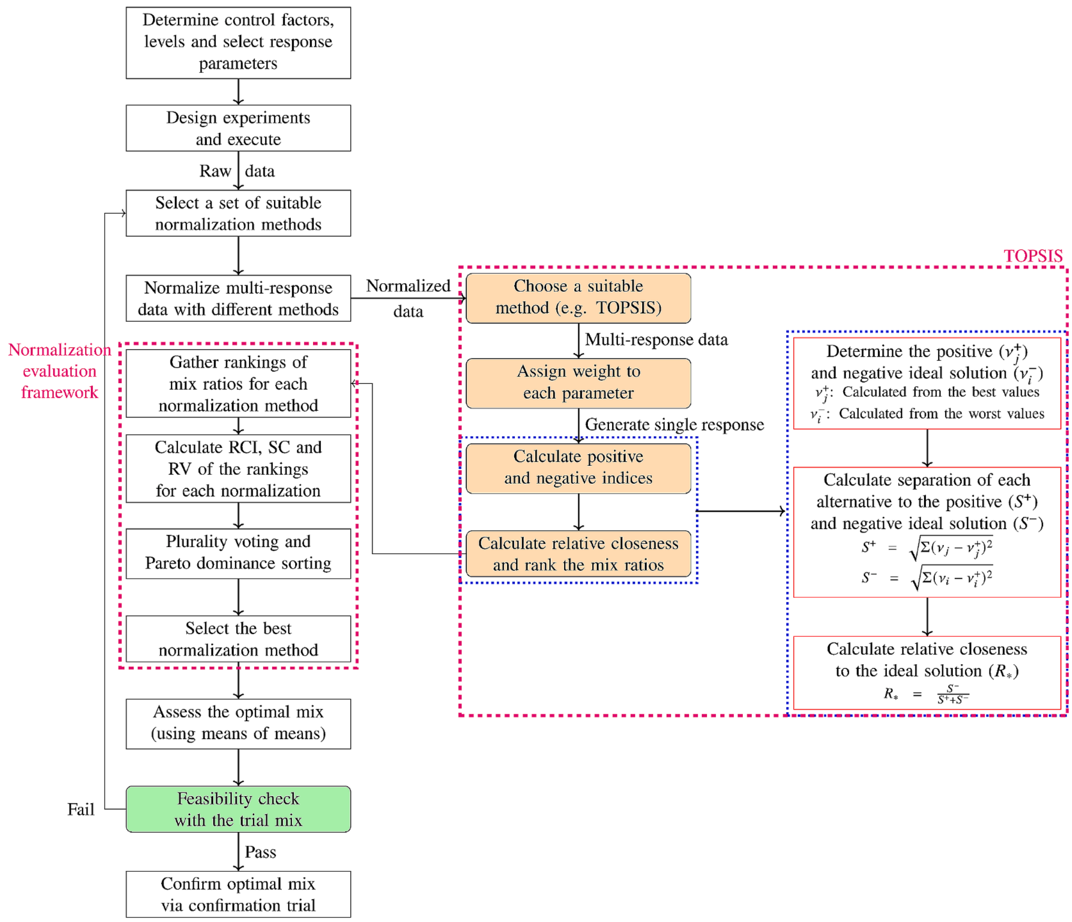

Fig. 1. Proposed Taguchi-TOPSIS based overarching framework for optimization of mix proportion of cementitious composites.

Table 1
Some of the available normalization methods for raw data conversion (benefit criteria).

Normalization method	Formula	Pros	Cons
Vector	$\frac{r_{ij}}{\sqrt{\sum r_{ij}^2}}$	Retains proportionality; ideal for datasets with similar scales.	Sensitive to outliers; may not work if comparing disparate ranges (like stress and strain).
Linear (max–min)	$\frac{r_{ij} - r_j^{min}}{r_j^{max} - r_j^{min}}$	Scales data to [0, 1]; applicable for most of the concrete mechanical properties datasets.	May not be suitable for non-linear data or data with outliers.
Linear	$\frac{r_{ij}}{r_j^{max}}$	Useful when the maximum value matters (e.g. strength).	May misinterpret if maximum value is an outlier.
z transformation	$\frac{r_{ij} - \mu_j}{\sigma_j}$	Centers data around the mean and handles outliers; useful for normally distributed data.	May not work well for all concrete data, as it doesn't preserve scale and could complicate interpretation.
Lai and Hwang normalization	$\frac{r_{ij}}{r_j^{max} - r_j^{min}}$	Useful for datasets where the difference between max and min matters.	Sensitive to outliers that may stretch the range.
Enhanced accuracy	$1 - \frac{r_j^{max} - r_{ij}}{\sum(r_j^{max} - r_{ij})}$	Balances normalization by considering global dataset properties.	Computationally intensive for large datasets.
Linear (sum based)	$\frac{r_{ij}}{\sum r_{ij}}$	Simple to interpret; easy to apply	Sensitive to large values and may overshadow smaller values which may be critical in concrete materials context.
Non-linear	$\left(\frac{r_{ij}}{r_j^{max}}\right)^2$	Useful for applications requiring non-linear scaling.	Distorts relationship between smaller values as squaring the ratios can magnify the differences.
Logarithmic	$\frac{\ln r_{ij}}{\ln \prod r_{ij}}$	Useful for datasets spanning several orders of magnitude.	Can not handle zero or negative values; may not work for values close to zero (e.g. peak comprssive or tensile strain).
Tzeng and Huang Normalization	$\frac{r_j^{max}}{r_{ij}}$	Highlights differences relative to the maximum value.	May overemphasize the smaller but less significant values.
Zavadskas and Turskis normalization	$1 - \left\lvert\frac{r_j^{max} - r_{ij}}{r_j^{max}}\right\rvert$	Balances normalization around the maximum value.	Struggles with wide-range datasets and outliers, especially if the maximum value is an outlier.

Note: Here, r_{ij}= the rating of alternative i to performance attribute j, r_j^{max}=the maximum value of the performance attribute j, r_j^{min}=the minimum value of the performance attribute j, μ_j=the mean value of performance attribute j, and σ_j = standard deviation of performance attribute j.

The integration of optimization method was mainly aimed at maximizing five fundamental performance attributes, which consist of compressive strength (P1), peak compressive strain (P2), elastic modulus (P3), tensile strength (P4) and ultimate tensile strain (P5). These performance attributes represent the fundamental mechanical properties of any cementitious composite and can be used to identify its suitability for structural applications. It is further important to note that these performance attributes (P1-P5) are not absolute indicators for a given mix design; they can vary depending on external factors such as curing conditions and age of the material.

2.1.1.2. Design of the experiment and execution. For the considered case, the full factorial design would demand 1024 experimental testings to cover all the variation in the 5 control factors and 4 control levels. The orthogonal array (OA) principle proposed by Taguchi was therefore applied to reduce the number of experimentations. Taguchi recommended the use of L16 array for five four-level factors to sufficiently represent all control factors as well as allowing the extraction of the maximum amount of information (Roy, 2010). The detailed mix proportion of each trial is shown in Appendix A, Table A1. Each of the 16 trials was mixed separately and cast in 100 mm diameter × 200 mm height cylinder for compression testing and 368 × 80 × 20 mm dogbone specimens (with a reduced section of 100 × 35 × 20 mm) for tensile testing. These specimens were demolded 24 h after casting and cured in the fog room maintained at 23 °C and 95.5 % relative humidity for 28 days. Three specimens were prepared for each mix proportion to minimize the bias in the results of response parameters. Subsequently, cylinder specimens were tested at a displacement-controlled loading rate of 0.05 mm/minute to obtain uniaxial compressive stress–strain behaviour and load controlled rate of 0.25 MPa/sec to obtain elastic modulus. The uniaxial tensile stress–strain curve tests were performed at a loading rate of 0.1 mm/minute and collectively, a decision matrix was obtained, which lists the test results of five performance attribute (P1-P5) for all 16 mix trials (R1 – A1B1C1D1E1 to R16 – A4B4C1D3E2, Table A2). Note that the current study mainly focuses on implementation of TOPSIS on the previous dataset and application of the existing normalization framework. A detailed mix design procedure, specimen setup and testing procedure can be found in the original work (Rawat et al., 2022).

2.1.2. Normalization

In multi-response studies, the test results usually present varying dimensions and units across all response parameters, which requires data normalization to pre-process the data to comparable and non-dimensional, and scaled values. Normalization also helps to avoid erroneous results resulting from disparate goals and directions of the factors (Chang et al., 2011). For the ECC data set, the raw data was obtained for compressive strength, peak compressive strain, elastic modulus, tensile strength, and ultimate tensile strain, which had different dimensions (MPa vs %) and scales (MPa vs GPa). A detailed analysis of this raw data is available in the authors' earlier work (Rawat et al., 2022) and it is further collated in Appendix Table A2.

In the context of the TOPSIS method, normalization is a foundational step to ensure the data is suitable for multi-response analysis. While vector normalization is commonly used, there is no universal consensus on the best method, as the choice often depends on the characteristics of the dataset and the desired solution. For this study, six normalization methods were selected from the 11 listed in Table 1—Vector (M1), Linear max–min (M2), Linear (M3), Z transformation (M4), Lai and Hwang method (M5), and Enhanced Accuracy (M6). These methods were chosen not only for their suitability to the dataset but also to demonstrate the flexibility and applicability of the proposed framework. If the outcomes from these methods were unsatisfactory, alternative approaches could be explored accordingly. It should further be noted that the normalization step also facilitates identifying the ideal solution, which represents the best possible value for each response parameter. In this study, benefit criteria were applied, where the ideal solution corresponds to the maximum value for performance attributes.

2.1.3. Multi-response analysis with TOPSIS

2.1.3.1. Weighting matrix. The normalized results of all response parameters need to be weighted before conducting the TOPSIS analysis. This can be done through various available techniques such as analytic hierarchy process, entropy method, deviation maximization method etc. (Chen, 2021). Rawat et al. (2022) recognized the importance of selecting appropriate weighting techniques where weighting method based on maximum deviation was found to be more appropriate for ECC. Therefore, the same method was adopted in the current study as the dataset being used is the same.

2.1.3.2. Generating single response. TOPSIS is an effective data analysis approach for multi-response problems that generates ranking of the alternative solutions based on the shortest distance from the positive ideal solution and the farthest from the negative ideal solution (Vafaei et al., 2018). A step-by-step calculation procedure is also shown in Fig. 1.

Firstly, the positive and negative ideal solutions are identified from the normalized and weighted multi-response results. The positive ideal solution is calculated from all the best value and the negative ideal solution is calculated from all worst values at the responses in the weighted normalized decision matrix. For each alternative, the separation to the positive ideal solution in each attribute sums up to the positive index (S^{+}), which is expressed in eq. 1 (Xie & Zhang, 2023):

$$S^{+} = \sqrt{\sum \left(\nu_j - \nu_j^{+}\right)^2} \tag{1}$$

where ν_j is the normalized and weighted value of attribute j of the alternative, and ν_j^{+} is the value of positive ideal solution for the attribute j across all alternatives.

Similarly, the negative index of a mix ratio (S^{-}) is the summation of the distance in all response parameters between normalized and weighted values of the alternatives to the values in the negative ideal solution (eq. 2).

$$S^{-} = \sqrt{\sum \left(\nu_i - \nu_i^{-}\right)^2} \tag{2}$$

where ν_i^{-} is the value of attribute i of the negative ideal solution across all alternatives.

With the computation of S^{+} and S^{-}, each decision matrix can be reduced from 16 (mix ratios) × 5 (performance attributes) to 16 × 2 (S^{+} and S^{-}). Finally, the relative closeness of a mix ratio (R_{*}) needs to be calculated using eq. 3:

$$R_{*} = \frac{S^{-}}{S^{+} + S^{-}} \tag{3}$$

Note higher value of the relative closeness represents better performance (Vafaei et al., 2018), which can be ranked from the highest value to the lowest to determine the optimal mix ratio. Herein, ranking of the mix ratios is denoted as R. Thereafter, normalized multi-response decision matrices are reduced to a 16 × 1 (rank of the mix ratio) vector.

2.1.4. Normalization evaluation framework

Since different normalization methods can significantly influence MCDM outcomes, each method may produce a unique ranking, potentially leading to different optimal mixes after the TOPSIS analysis. To address this, the current study introduces a novel evaluation process for selecting the most appropriate normalization method for cementitious composites based on the work by Vafaei et al. (2018). Before implementing the evaluation process, normalization methods are chosen based on the characteristics of the dataset under consideration. If after the application of framework, none of the selected normalization methods lead to satisfactory optimized results or if the outcomes appear unreliable, the user may need to revisit and select alternative normalization methods. In the present case, the six single response vectors are gathered to form a compilation of 16 (from Taguchi L16 orthogonal array) × 6 (rankings in each normalization method) matrices. Using this 16 × 6 matrix, the proposed evaluation criteria are then applied as described below.

(a) The new evaluation process starts with the calculation of RCI, which indicates the probability of a certain normalization method generating same optimal mix as the other normalization methods. Out of the total number of tests, the number of scenarios when a normalization method produced the same optimal mix with others were counted and weighted according to the extents of the consistency. RCI of a normalization method is then computed as the ratio of the sum of the weighted counts to the total number of tests. Detailed computation procedure can be found in Yeo et al. (2007) and Chakraborty & Yeh (2009).

(b) The second part is the application of SC which shows the closeness of the ranking of mix proportions between alternative normalization methods (Vafaei et al., 2018; Wang and Luo, 2010) and is expressed as (eq. 4):

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{4}$$

where r_s represents the Spearman correlation for a normalization method, d_i is the difference in the rankings of an alternative between two normalization methods, and n is the total number of comparisons. The difference in ranking d_i is calculated as (eq. 5):

$$d_i = Rank_{method\alpha}(x_i) - Rank_{method\beta}(x_i) \tag{5}$$

here $Rank_{method\alpha}(x_i)$ and $Rank_{method\beta}(x_i)$ denote the ranks of the i-th alternative under the two selected normalization methods, α and β, respectively.

Intuitively, the more comparable a normalization method is to others, the smaller the difference in the ranking of the mix ratios exists, the higher SC is reported.

(c) The next step in the evaluation process is to assess the variance of each normalization method with RV, which can be described through eq. 5:

$$RV = \frac{1}{n}\sum_{1}^{n}\left(R_{iM} - R_{i,avg}\right)^2 \tag{5}$$

where n is total number of mix proportions, R_{iM} is the ranking of the i-th mix proportion resulted by normalization method M and $R_{i,avg}$ is the arithmetic average of the rankings of the i-th mix proportion across all normalization methods. Unlike RCI and SC, a lower RV is preferred, as it indicates greater consistency across different normalization methods and stable rankings across trials. This is particularly important for the practical application of new cementitious construction materials, where high variability could lead to unreliable or less repeatable performance parameters. Therefore, the inclusion of RV ensures that the selected optimal mix is not overly influenced by the choice of normalization methods, promoting better consistency for the practitioners.

(d) Finally, the normalization methods are ranked based on their statistical performance in three criteria: the highest RCI, the highest SC, and the lowest RV, respectively. Two approaches were employed to identify the most suitable normalization method by integrating performance across these criteria: *Plurality Voting and Pareto Dominance Sorting*. In the Plurality Voting approach, the rankings for RCI, SC, and RV were combined into an index by summing their individual rankings. The normalization method with the highest index value was considered the best overall performer, indicating the most statistically suitable method. In contrast, Pareto Dominance Sorting involved pairwise comparisons of normalization methods to identify non-dominated solutions. A method was considered non-dominated if no other method outperformed it across all three criteria while being strictly better in at least one (Dosantos et al., 2024). This process identified the Pareto front, representing the set of optimal trade-offs among the objectives. Both approaches were compared, and the optimal mix design consistently predicted by both methods was selected as the best representative mix.

2.2. Data sets

In this work, a total of 48 trials from three studies were collated, showing relevant information on the mix proportions. The dataset on ECC is originally sourced from Rawat et al. (2022) and the application of framework is shown after reconducting the confirmation trial in this study using Taguchi-TOPSIS approach. Additionally, two other case studies are included, one on recycled aggregate concrete (Chang et al., 2011) and another on geopolymer concrete (Chokkalingam et al., 2022). All three studies were analysed with Taguchi-TOPSIS method integrated with the new framework. A summary of the mix proportions and the resulting datasets is presented in Appendix A, Tables A1–A.6. The mix proportions (Tables A1, A3, and A5) were tested according to their respective methodologies, and the corresponding data matrices were generated (Tables A2, A4, and A6) for use in this study.

3. Results

This section presents a detailed implementation of the framework outlined in Fig. 1. It includes a tabulated decision matrix and results matrix, along with normalized and plotted data to illustrate how the choice of normalization method can impact the mix design results. The tabulated results for normalization rankings, as well as the mechanical properties of the optimal mix formula, have also been described.

3.1. Normalized results and TOPSIS analysis

According to the framework in Fig. 1, the five performance attributes were normalized using six normalization methods. As described earlier, the normalization method was first applied to the raw data of the five performance attributes (P1-P5), and for each normalization method, the value of R was reported. For instance, when vector normalization (M1) was applied to the mix, the results for R1 – A1B1B1D1E1 (Table A2) in terms of the five performance attributes were converted to [P1, P2, P3, P4, P5] = [0.313, 0.232, 0.288, 0.240, 0.147]. This normalized data was then weighted, and TOPSIS analysis was performed to reduce the multi-response raw data to S^+ and S^-, R_* and ranking R. Similarly, other normalization methods were applied to the dataset. The ranking of the first alternative – R1 among the total 16 tested mixtures is shown in Table 2. It can be observed that ranking of R1 is different for different normalization methods M1-M6 confirming that change in normalization method may lead to variation in processed data.

Tables 3 and 4 further demonstrates the collated results of the positive and negative ideal solution (S^+ and S^-), Relative closeness (R_*) and TOPSIS ranking (R) for all 16 tested mix trials (R1-R16, Table A2) with

Table 2
Calculation results of R1 after normalization with M1-M6 methods.

	M1	M2	M3	M4	M5	M6
Normalized decision matrix of R1						
P1	0.313	0.946	0.976	1.642	2.179	0.993
P2	0.232	0.295	0.750	−0.654	2.115	0.920
P3	0.288	1.000	1.000	1.362	3.084	1.000
P4	0.240	0.300	0.717	−0.264	1.774	0.932
P5	0.147	0.051	0.344	−1.065	0.497	0.908
Relative closeness						
R_*	0.217	0.540	0.331	0.499	0.540	0.683
Ranking of R1 in different normalization methods						
R	13	4	12	4	4	2

Table 3
Positive and negative ideal solution (S^+ and S^-) for each mix computed using six normalization methods.

Mix No.	M1		M2		M3		M4		M5		M6	
	S^+	S^-	S^+	S^-	S^+	S^-	S^+	S^-	S^+	S^-	S^+	S^-
R1	0.110	0.030	0.264	0.310	0.216	0.107	1.013	1.008	0.264	0.310	0.023	0.050
R2	0.115	0.038	0.217	0.374	0.220	0.131	0.792	1.290	0.217	0.374	0.018	0.054
R3	0.103	0.025	0.264	0.227	0.205	0.077	0.933	0.847	0.264	0.227	0.027	0.034
R4	0.075	0.049	0.335	0.201	0.170	0.104	1.106	0.906	0.335	0.201	0.049	0.021
R5	0.019	0.117	0.205	0.286	0.065	0.231	0.763	1.006	0.205	0.286	0.029	0.032
R6	0.091	0.035	0.244	0.247	0.181	0.098	0.930	0.832	0.244	0.247	0.024	0.038
R7	0.086	0.036	0.267	0.193	0.176	0.087	0.979	0.676	0.267	0.193	0.031	0.028
R8	0.114	0.020	0.293	0.241	0.227	0.074	1.115	0.763	0.293	0.241	0.027	0.041
R9	0.101	0.025	0.313	0.183	0.207	0.071	1.157	0.623	0.313	0.183	0.033	0.029
R10	0.084	0.040	0.269	0.237	0.172	0.101	1.055	0.766	0.269	0.237	0.027	0.038
R11	0.073	0.050	0.316	0.155	0.163	0.101	1.106	0.611	0.316	0.155	0.041	0.019
R12	0.064	0.058	0.258	0.195	0.140	0.119	0.928	0.706	0.258	0.195	0.033	0.026
R13	0.061	0.062	0.287	0.194	0.142	0.125	0.979	0.791	0.287	0.194	0.038	0.023
R14	0.043	0.093	0.361	0.192	0.133	0.180	1.223	0.743	0.361	0.192	0.053	0.017
R15	0.049	0.074	0.210	0.262	0.111	0.154	0.790	0.919	0.210	0.262	0.027	0.033
R16	0.090	0.035	0.283	0.268	0.187	0.093	1.143	0.846	0.283	0.268	0.030	0.043

Table 4
The relative closeness (R_*) and the TOPSIS ranking (R) for each mix computed using six normalization methods.

Mix No.	M1		M2		M3		M4		M5		M6	
	R_*	R	R_*	R	R_*	R	R_*	R	R_*	R	R_*	R
R1	0.217	13	0.540	4	0.331	12	0.499	4	0.540	4	0.683	2
R2	0.250	12	0.633	1	0.373	8	0.620	1	0.633	1	0.745	1
R3	0.193	15	0.463	8	0.273	14	0.476	5	0.463	8	0.556	7
R4	0.393	7	0.375	13	0.378	7	0.450	7	0.375	13	0.302	15
R5	0.862	1	0.582	2	0.780	1	0.569	2	0.582	2	0.519	9
R6	0.280	11	0.504	5	0.352	10	0.472	6	0.504	5	0.608	3
R7	0.296	9	0.419	11	0.329	13	0.409	12	0.419	11	0.478	10
R8	0.150	16	0.451	9	0.245	16	0.406	13	0.451	9	0.601	4
R9	0.196	14	0.369	14	0.254	15	0.350	16	0.369	14	0.466	11
R10	0.325	8	0.469	7	0.370	9	0.421	11	0.469	7	0.588	5
R11	0.407	6	0.329	16	0.384	6	0.356	15	0.329	16	0.320	14
R12	0.475	5	0.430	10	0.460	5	0.432	9	0.430	10	0.441	12
R13	0.501	4	0.403	12	0.468	4	0.447	8	0.403	12	0.373	13
R14	0.686	2	0.348	15	0.575	3	0.378	14	0.348	15	0.245	16
R15	0.600	3	0.556	3	0.580	2	0.538	3	0.556	3	0.546	8
R16	0.281	10	0.486	6	0.332	11	0.425	10	0.486	6	0.588	6

all 6 normalization methods. As shown in Table 4, the rankings for the 16 alternatives vary depending on the normalization method applied, with no clear trend in the rankings of the different trials. Though normalization methods M2, M4, M5, and M6 suggest that trial 2 is closer to the optimum, vector normalization (the most preferred method in TOPSIS) places it as the 6th ranked trial. Moreover, the ranking of other trials is also not consistent even among M2, M4, M5 and M6. Since the final optimal outcome depends on the combined effect of the ranking system, significant variations in the TOPSIS ranking imply that the choice of normalization method could notably influence the determination of optimal mix design.

The effect of normalization methods on the observed trend could further be understood using Fig. 2 which depicts the variation of the mean value of the average normalized data with changing control levels in five control factors. It can be observed that different normalization methods lead to different optimal mix design. For example, despite the variation in the mutual rankings of different trials for Linear max – min (M2), Z transformation (M4), Lai and Hwang method (M5) and Enhanced accuracy (M6) normalization methods, the best mix design remained the same i.e. TCR 50 %-dolomite 15 %-slag: FA (1:0.2) –fibre content (PE + Steel = 1.50 + 0.75)-water/binder ratio 0.2. However, with Vector (M1) and Linear (M3) methods, the optimal mix design prediction differed. Method M1 indicated a TCR 80 %-dolomite 10 %-slag: FA (1:0.2)-fibre content (PE + Steel = 1.25 + 0.75)-water/binder ratio 0.3 as optimum, whereas M3 predicted the optimum ratio as TCR 80 % – dolomite 10 % – Slag: FA (1:0.2) – fibre content (PE + Steel = 1.50 + 0.75) – water/binder ratio 0.3.

Notably, the optimum levels of dolomite content, slag to FA ratio and fibre content from all six normalization methods fall in similar range as identified previously (Rawat et al., 2022). However, methods M1 and M3 predict 80 % total cement replacement and a water-binder ratio of 0.3 as the optimal mix, which is in clear contradiction of the outcome from the L16 trials in the authors' earlier work (Rawat et al., 2022). In that study, the elastic modulus was found to have the highest weight among all the factors, and its values at 80 % total cement replacement and a 0.3 water-binder ratio were clearly the least, as shown in Fig. 3. This is because such high replacement percentages or water content are not likely to fully contribute to hydration and hence will lead to a reduced compressive performance. Consequently, any approach (in this case M1 and M3) resulting in this outcome may not accurately represent the true optimum scenario. Therefore, the evaluation and selection of suitable normalization method is crucial to the Taguchi based multi-response optimal analysis.

3.2. Evaluation of the most suitable normalization method

Table 4 and Fig. 2 indicate that multiple optimal mixes can be deduced by applying different normalization methods. To search for the most desirable optimal mix, the evaluation framework as in Fig. 1 was implemented, which allows the identification of the best normalization method and sequentially the most appropriate optimal formula.

The evaluation process was operated using the TOPSIS ranking of the

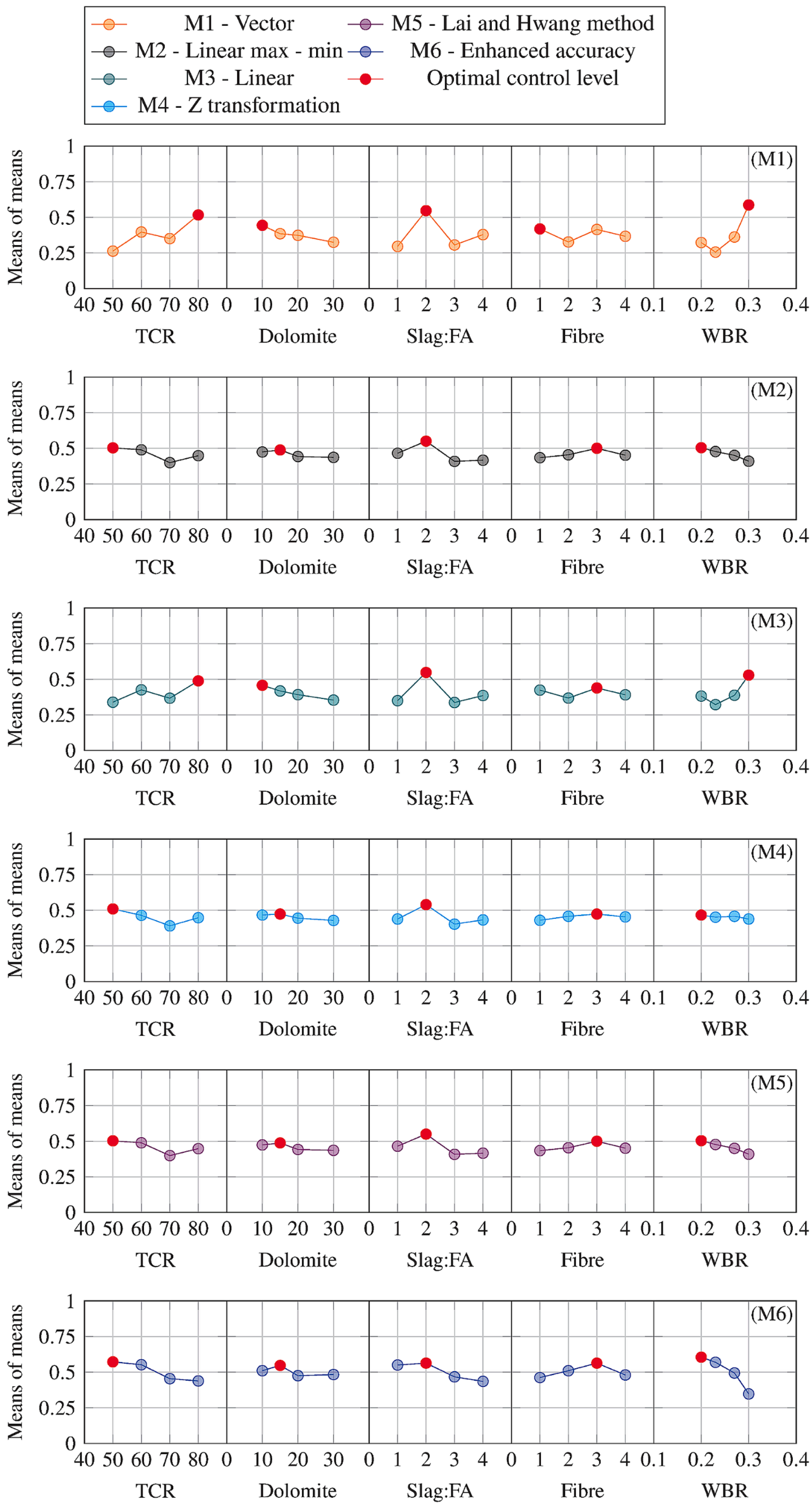

Fig. 2. Comparison of the optimization results with different normalization methods for ECC data sets (Note: Levels 1,2,3, and 4 of Slag:FA represent 1:0, 1:0.2, 1:0.4 and 1:0.6 respectively. Levels 1,2,3, and 4 of Fibre represent 1.25 %PE + 0.75 %steel, 1.25 % PE + 1 % Steel, 1.5 % PE + 0.75 % Steel, and 1.75 % PE + 0.75 % Steel respectively).

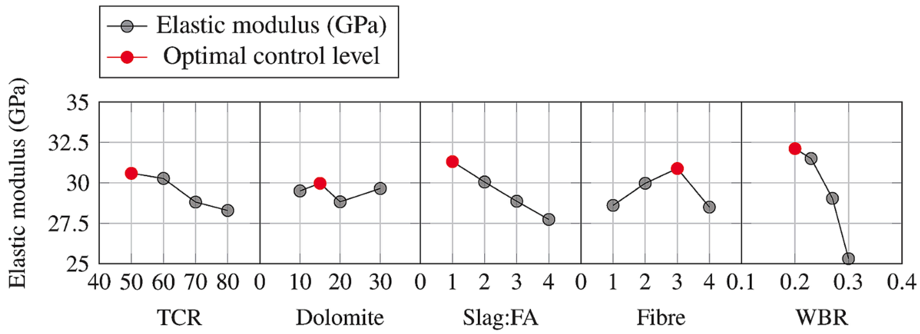

Fig.3. Mean effect of different control factors and levels on elastic modulus (Rawat et al., 2022).

Table 5
Evaluation of the normalisation methods for ECC data sets of Rawat et al. (2022).

Normalization methods	Values		
	RCI	**SC**	**RV**
Vector	5.2	0.04	40.7
Linear max–min	10.0	0.52	20.4
Linear	1.8	0.19	34.3
Z transformation	7.4	0.51	20.9
Lai and Hwang method	10.0	0.52	20.4
Enhanced accuracy	3.2	0.20	33.8

16 tested mix ratios (*R*) in Table 4. RCI, SC and RV were calculated for each normalization method as per the method described in section 2.1.4 and the deduced values are listed in Table 5. Thereafter, plurality voting and Pareto dominance sorting were employed to rank the normalization methods by combining the statistical performance across all three criteria (RCI, SC, and RV), as shown in in Table 6.

As shown in the Table 4, the Linear max–min (M2) and Lai and Hwang (M5) methods emerge as the best performers, each receiving the highest voting score and being non-dominated in the Pareto analysis, indicating they offer the most consistent and reliable rankings across the evaluation criteria, and should be prioritized for selecting the optimal mix design. The corresponding TOPSIS analysis results are shown in Table 7, note that the S^{+}, S^{-}, R_{*}, and R for M2 and M5 are the same.

3.3. Optimal mix and confirmation test

According to Table 7, R2 is the best ranked mix in the 16 tested formulae. However, it is encouraged to check with the plotted full response result in Fig. 2 to deduce the most optimal formula (Rawat et al. 2022). For the ECC dataset, the full response results in Fig. 2 indicate a slightly different optimal mix, which was not covered by the orthogonal array. By applying the M2 normalization method, the optimal mix design was identified as A1B2C2D3E1, with the factors corresponding to the following: TCR of 50 % – dolomite 15 % – Slag: FA (1:0.2) – Fiber content (PE + Steel = 1.50 + 0.75) – WBR as 0.2. In A1B2C2D3E1, the letter A, B, C, D, E represents the five factors (in order) as shown in Fig. 2 and number 1, 2 and 3 denote the first, second, and third control level, respectively. This emphasizes the importance of using a mean of means analysis, as it allows for identifying the optimal mix even outside the range of the trial matrix. The confirmation test was further conducted to verify the prediction in terms of the performance attributes (P1-P5) of the optimal mix ratio.

Table 7
TOPSIS results of Rawat et al. (2022) using the best M2/M5 normalization method.

Mix No.	S^{+}	S^{-}	R_{*}	R
R1	0.264	0.310	0.540	4
R2	0.217	0.374	0.633	1
R3	0.264	0.227	0.463	8
R4	0.335	0.201	0.375	13
R5	0.205	0.286	0.582	2
R6	0.244	0.247	0.504	5
R7	0.267	0.193	0.419	11
R8	0.293	0.241	0.451	9
R9	0.313	0.183	0.369	14
R10	0.269	0.237	0.469	7
R11	0.316	0.155	0.329	16
R12	0.258	0.195	0.430	10
R13	0.287	0.194	0.403	12
R14	0.361	0.192	0.348	15
R15	0.210	0.262	0.556	3
R16	0.283	0.268	0.486	6

Table 8 and Fig. 4 show test values of the five performance attributes namely compressive strength, peak compressive strain, elastic modulus, tensile strength, and ultimate tensile strain. As shown in the Table 8, the optimal mix demonstrates high strength 90.8 MPa of compressive strength and 10.3 MPa of tensile strength, as well as high ductility with the peak compressive strain of 0.52 % and ultimate tensile strain of 1.22 %. Unlike the results of the L16 trials which failed to optimize all parameters at once, these response parameters using the predicted optimal

Table 8
Mechanical properties of optimum mix obtained using TOPSIS.

Mix design	P1 (MPa)	P2 (%)	P3 (GPa)	P4 (MPa)	P5 (%)
A1B2C2D3E1	90.8	0.52	28.5	10.3	1.22

Table 6
Plurality voting and Pareto Dominance sorting for data sets of Rawat et al. (2022).

Normalization methods	Plurality voting				Pareto Dominance	
	RCI	**SC**	**RV**	**Plurality voting**	**Dominated by Any Other?**	**Pareto front (Yes = 1, No = 0)**
Vector	3	5	5	0	Yes	0
Linear max–min	1	1	1	3	No	1
Linear	5	4	4	0	Yes	0
Z transformation	2	2	2	0	Yes	0
Lai and Hwang method	1	1	1	3	No	1
Enhanced accuracy	4	3	3	0	Yes	0

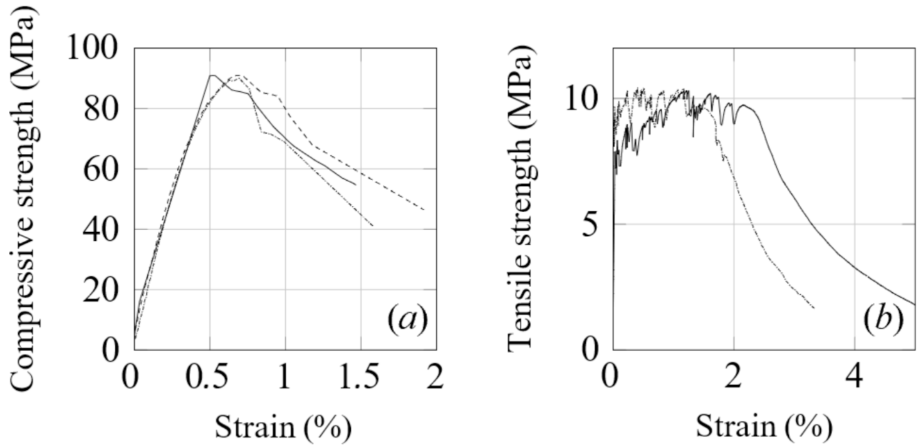

Fig. 4. Mechanical properties of the optimal mix – A1B2C2D3E1 of ECC (a) Compressive strength; (b) Tensile strength.

mix were found to be higher for each factor. For instance, not only does this mix has higher ultimate tensile strain (>1%) but also shows high value of peak compressive strain (>0.5 %) deeming it suitable for structural applications. Moreover, the mean value of the relative closeness value of the confirmation trial was found to be 0.567 which is within 95 % confidence interval of the predicted optimum (0.653).

These results further validate the suitability of TOPSIS method and the developed framework in achieving a mix design with excellent mechanical properties. However, it is important to note that the proposed Taguchi-TOPSIS framework focuses on single-point optimization by identifying the closest alternative to the ideal solution. While this approach is generally straightforward and computationally efficient, making it practical for implementation, it may overlook other optimal solutions that represent trade-offs between objectives. For instance, when durability of ECC is weighted higher than the strength, the proposed method may emphasize solutions that maximize durability, potentially excluding some better alternatives that offer acceptable durability but superior strength. In cases where flexibility is required or trade-offs are highly context-dependent, other methods such as non-dominated sorting methods (e.g., NSGA-II) could be considered, which may provide an advantage by offering a broader range of solutions (Chen et al., 2022).

4. The application of the proposed framework in other types of concrete

The previous section demonstrates that the proposed framework, utilizing TOPSIS and the normalization method evaluation framework, can effectively solve the MCDM problem for the optimization of ECC mix design. To further highlight the versatility and broad applicability of this framework, two additional research examples—recycled aggregate concrete and ceramic waste geopolymer concrete—are discussed in this section.

4.1. Recycled aggregate concrete

For the recycled aggregate concrete, the Taguchi orthogonal array and the average responses presented in the study by Chang et al. (2011) were adopted. The original mix proportions and data set from this study are also collated in Appendix A, Table A3-A.4, which shows five control factors and two levels for each control factor. In this case, there are eleven responses as the assessment criteria, and all of them are considered to be positive factors. To simplify the calculation, all the eleven responses are assumed to be equally important and therefore, the weighting of each attributes followed the equal weight method with (*j*) = 0.09. By applying the framework, the evaluation results of the six normalization methods were obtained and has been demonstrated in

Table 9
Evaluation of the normalization methods for recycled aggregate concrete data sets of Chang et al. (2011).

Normalization methods	Values		
	RCI	**SC**	**RV**
Vector	32.6	0.945	2.33
Linear max–min	42.4	0.961	1.65
Linear	28.2	0.945	2.33
Z transformation	41.0	0.961	1.68
Lai and Hwang method	42.4	0.961	1.65
Enhanced accuracy	26.2	0.957	1.83

Table 9. The best normalization method is determined based on highest values for RCI and SC, along with lowest value for RV. Table 10 indicates that the Linear max–min and Lai and Hwang methods are the most suitable normalization techniques for this case. These methods were ranked highest in the plurality voting (both with 3 votes) and dominate the Pareto front, confirming their effectiveness in optimizing the mix design of recycled aggregate concrete.

The ranking analysis revealed that C3 (A1B1C2D1E2) was the most optimal mix among the tested alternatives, as shown in Table 11. Further analysis, using the means of the means normalized with the Linear max–min method, was plotted in Fig. 5. This plot indicated that a mix ratio similar to C4 (A1B1C2D2E2) emerged as the overall most optimal mix design. These findings showed agreement with the original literature, demonstrating the applicability of the current framework in recycled concrete design.

4.2. Geopolymer concrete

Another numerical example involves the optimization of geopolymer concrete made from ceramic waste, as explored by Chokkalingam et al. (2022). Five control factors with four levels were considered in their experimental design (Table A5), and the developed Taguchi orthogonal array is shown in Appendix A, Table A6. The signal to noise (S/N) ratio obtained from the raw test results from the original literature showed some discrepancies. However, since the focus of the current study was to compare the normalization methods, the S/N matrix was directly adopted to showcase the application of proposed framework.

With the application of the proposed framework, six normalization methods were applied to normalize the raw data, and the data obtained after the application of framework is listed in Tables 12 and 13. It is interesting to note that the two best normalization methods for ceramic waste geopolymer concrete are same as the above-mentioned two study cases, which are Linear max–min and Lai and Hwang. In addition, the Z transformation method also showed suitability to predict the optimum

Table 10
Plurality voting and Pareto Dominance sorting for data sets of Chang et al. (2011).

Normalization methods	Plurality voting				Pareto Dominance	
	RCI	**SC**	**RV**	**Plurality voting**	**Dominated by Any Other?**	**Pareto front (Yes = 1, No = 0)**
Vector	3	4	4	0	Yes	0
Linear max–min	1	1	1	3	No	1
Linear	4	4	4	0	Yes	0
Z transformation	2	2	2	0	Yes	0
Lai and Hwang method	1	1	1	3	No	1
Enhanced accuracy	5	3	3	0	Yes	0

Table 11
TOPSIS results of Chang et al. (2011).

Mix No.	S^+	S^-	R_*	R
C1	0.176	0.151	0.461	9
C2	0.130	0.187	0.590	4
C3	0.105	0.221	0.678	1
C4	0.120	0.202	0.628	2
C5	0.155	0.188	0.547	6
C6	0.198	0.134	0.404	10
C7	0.187	0.176	0.485	7
C8	0.146	0.235	0.617	3
C9	0.200	0.126	0.386	11
C10	0.226	0.142	0.386	12
C11	0.183	0.160	0.467	8
C12	0.147	0.201	0.578	5
C13	0.237	0.100	0.297	16
C14	0.230	0.114	0.332	15
C15	0.206	0.121	0.371	14
C16	0.208	0.125	0.375	13

response for the adopted dataset. All the three methods ranked the highest in the plurality voting and were not dominated by any other method, making them the most suitable choices for the dataset.

The result of Taguchi-TOPSIS with the most suitable normalization methods (Linear max–min) are presented in Table 14 and the mean of means plot has been further shown in Fig. 5. Notably, the optimized case using the proposed framework, A2B3C1D2E2, matched with the findings reported in the study, despite their use of a vector normalization approach. This underscores the applicability of the current framework for this type of dataset. However, it should be noted that the ranking of the resultant matrix obtained through the use of framework slightly differed from that reported in original literature. This may be crucial in case of dataset involving wide range of performance attributes as shown for the case of ECC. Consequently, in such instances, relying solely on vector normalization might not be suitable. Instead, the utilization of the proposed framework is recommended for achieving accurate results. Moreover, though linear max–min and Lai and Hwang method were found suitable for the dataset considered in the present study, these methods may not be universally applicable, and the framework needs to be applied to each dataset individually to ensure accurate prediction of optimal mix proportions.

5. Conclusion

Taguchi method is typically integrated with multi-response analysis methods such as TOPSIS to simultaneously optimize more than one

Table 12
Evaluation of the normalization methods for geopolymer concrete data sets of Chokkalingam et al. (2022).

Normalization methods	Values		
	RCI	**SC**	**RV**
Vector	168.8	0.984	0.700
Linear max–min	190.4	0.996	0.175
Linear	181.6	0.993	0.300
Z transformation	190.4	0.996	0.175
Lai and Hwang method	190.4	0.996	0.175
Enhanced accuracy	185.6	0.992	0.325

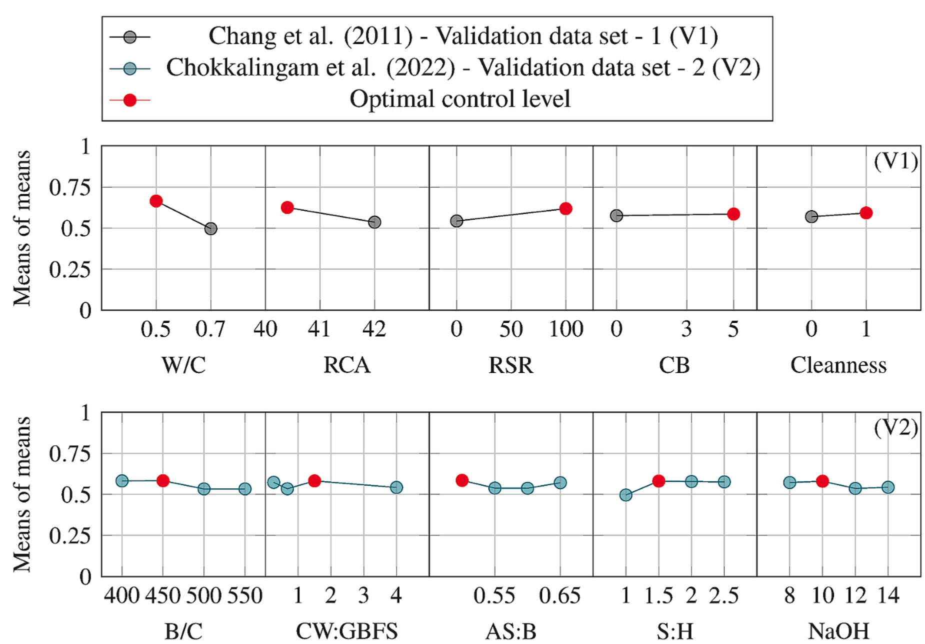

Fig. 5. Normalized results of Recycled concrete and geopolymer concrete data sets with Linear max – min method.

Table 13
Plurality voting and Pareto Dominance sorting for data sets of Chokkalingam et al. (2022).

Normalization methods	Plurality voting				Pareto Dominance	
	RCI	**SC**	**RV**	**Plurality voting**	**Dominated by Any Other?**	**Pareto front (Yes = 1, No = 0)**
Vector	4	4	4	0	Yes	0
Linear max–min	1	1	1	3	No	1
Linear	3	3	2	0	Yes	0
Z transformation	1	1	1	3	No	1
Lai and Hwang method	1	1	1	3	No	1
Enhanced accuracy	2	2	3	0	Yes	0

Table 14
TOPSIS results of Chokkalingam et al. (2022).

Mix No.	S^+	S^-	R_*	R
Ch1	0.231	0.314	0.576	10
Ch2	0.235	0.330	0.584	3
Ch3	0.231	0.324	0.583	7
Ch4	0.231	0.324	0.583	8
Ch5	0.233	0.328	0.584	4
Ch6	0.232	0.326	0.584	6
Ch7	0.234	0.325	0.581	9
Ch8	0.234	0.329	0.584	5
Ch9	0.232	0.305	0.569	12
Ch10	0.233	0.292	0.557	14
Ch11	0.236	0.343	0.592	1
Ch12	0.342	0.241	0.413	15
Ch13	0.233	0.299	0.563	13
Ch14	0.342	0.241	0.413	16
Ch15	0.233	0.309	0.571	11
Ch16	0.235	0.333	0.586	2

performance attributes. Normalization is of the essence in such analysis, as the data with multi-scale and diverse dimensions need to be transformed to dimensionless and comparable to obtain the best results for the attributes. The present study showed that choice of normalization method can significantly influence the final optimization outcomes. A novel framework was introduced, combining Taguchi and TOPSIS with a robust evaluation process for normalization techniques. The framework assesses various metrics, including the RCI, SC and RV, followed by plurality voting and Pareto dominance sorting to select the most suitable normalization method for a given dataset.

The suitability of this framework was demonstrated on three published research cases consisting of ECC, recycled aggregate concrete, and ceramic waste geopolymer concrete. For these datasets, the framework identified the Linear max–min and Lai and Hwang methods as consistently outperforming other normalization techniques. For instance, these two methods achieved the highest RCI (10.0), SC (0.52), and lowest RV (20.4) for ECC dataset, whereas, the commonly used vector normalization method produced inferior results, with an RCI of 5.2, SC of 0.04, and RV of 40.7. The identified normalization methods also produced the best-optimized mix proportions, which were consistent with the results from existing literature, further demonstrating the effectiveness of the framework.

Overall, the proposed approach is both feasible and widely applicable for optimizing mix proportions for a wide range of concrete. Therefore, it is strongly recommended that this framework be integrated into future research on mix design optimization to improve the accuracy and reliability of outcomes. A meaningful extension of the current study could involve assessing the applicability of the framework for other multi-response analysis methods, such as grey relational analysis and the utility concept. Moreover, since the current method focuses on a single optimal solution, it may overlook other feasible alternatives that could better suit different weighting schemes or priorities. Future research could explore the use of evolutionary optimization algorithms (e.g., NSGA-II) and reinforcement learning techniques to assess their comparative accuracy with the integrated Taguchi method. Especially in scenarios where flexibility and complex trade-offs between different objectives are essential, this extension could offer valuable insights and help identify the most suitable approach for cementitious composite optimization.

CRediT authorship contribution statement

Sanket Rawat: Conceptualization, Methodology, Investigation, Data curation, Writing – review & editing, Visualization. **Hanwen Cui:** Methodology, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Yuekai Xie:** Data curation, Writing – review & editing. **Yingying Guo:** Conceptualization, Data curation, Writing – review & editing. **Chi King Lee:** Conceptualization, Supervision, Resources, Writing – review & editing. **Yixia Zhang:** Supervision, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Commonwealth's support for this research received through Australian Government RTP and UNSW Canberra's support through UIPA Scholarship are gratefully acknowledged. The authors would also like to acknowledge Dr N. Vafaei from UNINOVA and Faculty of Sciences and Technology, Portugal, for providing initial advice on the framework verification method.

Appendix A. Data sets

Details of all datasets utilized in this study are summarized in Tables A1–A6, which expand upon the datasets collected from Rawat et al. (2022), Chang et al. (2011), and Chokkalingam et al. (2022). Table A1 outlines the mix proportions from the authors' previous study (Rawat et al., 2022), where cement, slag, fly ash (FA), dolomite, sand, water, and high-range water reducer (HRWR) are expressed as volumetric ratios to cement. Additionally, polyethylene (PE) and steel fibers are expressed as volumetric percentages of the mix. These mixes were designed based on the methodology reported in the original article, and the corresponding performance attributes are presented in Table A2. Similarly, Table A3 provides a summary of mix proportions from Chang et al. (2011), where W/C is the water-to-cement ratio, RCA represents recycled coarse aggregate (%), RSR denotes river sand replacement (%), and CB refers to crushed bricks (%). The resulting performance attributes from this dataset are listed in Table A4.

Table A5 contains the dataset from Chokkalingam et al. (2022), where B/C represents the binder-to-cement ratio (kg/m^3), CW is ceramic waste, GBFS is ground granulated blast furnace slag, AS refers to the alkaline solution, B stands for binder, S:H is the sodium silicate-to-sodium hydroxide ratio, and NaOH is the sodium hydroxide concentration expressed in moles (M). The quality performance criteria (QPC) derived from this study are further compiled in Table A6. Across all datasets (Tables A1–A6), the letters A–E represent the five control factors, while the numbers 1–4 denote the four control levels.

Table A1
Mix proportions from Rawat et al. (2022).

Mix. No.	Cement	Slag	FA	Dolomite	Sand	Water	HRWR	PE fibre (%)	Steel fibre (%)
R1 – A1B1B1D1E1	1.00	0.80	0.00	0.20	0.73	0.40	0.042	1.25	0.75
R2 – A1B2C2D2E2	1.00	0.58	0.12	0.30	0.73	0.46	0.022	1.25	1.00
R3 – A1B3C2D2E3	1.00	0.43	0.17	0.40	0.73	0.54	0.012	1.50	0.75
R4 – A1B4C4D4E4	1.00	0.25	0.15	0.60	0.73	0.60	0.008	1.75	0.75
R5 – A2B1C2D3E4	1.00	1.04	0.21	0.25	0.91	0.75	0.010	1.50	0.75
R6 – A2B2C1D4E3	1.00	1.13	0.00	0.38	0.91	0.68	0.014	1.75	0.75
R7 – A2B3C4D1E2	1.00	0.63	0.38	0.50	0.91	0.58	0.028	1.25	0.75
R8 – A2B4C3D2E1	1.00	0.54	0.21	0.75	0.91	0.50	0.052	1.25	1.00
R9 – A3B1C3D4E2	1.00	1.43	0.57	0.33	1.21	0.77	0.018	1.75	0.75
R10 – A3B2C4D3E1	1.00	1.15	0.69	0.50	1.21	0.67	0.070	1.50	0.75
R11 – A3B3C1D2E4	1.00	1.67	0.00	0.67	1.21	1.00	0.011	1.25	1.00
R12 – A3B4C2D1E3	1.00	1.11	0.22	1.00	1.21	0.90	0.031	1.25	0.75
R13 – A4B1C4D2E3	1.00	2.19	1.31	0.50	1.82	1.35	0.055	1.25	1.00
R14 – A4B2C3D1E4	1.00	2.32	0.93	0.75	1.82	1.50	0.021	1.25	0.75
R15 – A4B3C2D4E1	1.00	2.50	0.50	1.00	1.82	1.00	0.097	1.75	0.75
R16 – A4B4C1D3E2	1.00	2.50	0.00	1.50	1.82	1.15	0.029	1.50	0.75

Table A2
Average value of performance attributes corresponding to mix R1-R16 (Rawat et al., 2022).

Mix. No.	Compressive Strength (MPa)	Peak compressive Strain (%)	Elastic Modulus (GPa)	Tensile Strength (MPa)	Ultimate tensile Strain (%)
R1 – A1B1B1D1E1	99.66	0.43	34.16	4.91	0.98
R2 – A1B2C2D2E2	102.13	0.49	34.12	6.85	0.88
R3 – A1B3C2D2E3	80.68	0.51	30.25	4.82	1.13
R4 – A1B4C4D4E4	60.36	0.57	23.82	4.96	1.68
R5 – A2B1C2D3E4	84.09	0.45	28.04	5.50	2.86
R6 – A2B2C1D4E3	90.58	0.44	31.13	5.05	1.33
R7 – A2B3C4D1E2	79.42	0.45	28.99	4.93	1.43
R8 – A2B4C3D2E1	81.86	0.42	32.92	4.70	0.93
R9 – A3B1C3D4E2	82.19	0.44	29.23	4.08	1.18
R10 – A3B2C4D3E1	87.88	0.41	31.55	4.55	1.47
R11 – A3B3C1D2E4	69.72	0.48	26.27	4.25	1.72
R12 – A3B4C2D1E3	73.58	0.47	28.21	5.03	1.85
R13 – A4B1C4D2E3	68.24	0.52	26.59	4.63	1.92
R14 – A4B2C3D1E4	56.41	0.49	23.08	4.39	2.49
R15 – A4B3C2D4E1	72.15	0.45	29.83	6.33	2.09
R16 – A4B4C1D3E2	67.80	0.37	33.67	6.08	1.37

Table A3
Mix proportions from Chang et al. (2011).

Mix. No.	W/C	RCA (%)	RSR (%)	CB (%)	Washed
C1 – A1B1C1D1E1	0.50	42.00	0	5.00	No
C2 – A1B1C2D2E2	0.50	42.00	0	0.00	Yes
C3 – A1B1C2D1E2	0.50	42.00	100	5.00	Yes
C4 – A1B1C2D2E1	0.50	42.00	100	0.00	No
C5 – A1B2C1D1E2	0.50	40.40	0	5.00	Yes
C6 – A1B2C1D2E1	0.50	40.40	0	0.00	No
C7 – A1B2C2D1E1	0.50	40.40	100	5.00	No
C8 – A1B2C2D2E2	0.50	40.40	100	0.00	Yes
C9 – A2B1C1D1E2	0.70	42.00	0	5.00	Yes
C10 – A2B1C1D2E1	0.70	42.00	0	0.00	No
C11 – A2B1C2D1E1	0.70	42.00	100	5.00	No
C12 – A2B1C2D2E2	0.70	42.00	100	0.00	Yes
C13 – A2B2C1D1E1	0.70	40.40	0	5.00	No
C14 – A2B2C1D2E2	0.70	40.40	0	0.00	Yes
C15 – A2B2C2D1E2	0.70	40.40	100	5.00	Yes
C16 – A2B2C2D2E1	0.70	40.40	100	0.00	No

Table A4
Average value of performance attributes corresponding to mix C1-C16 (Chang et al., 2011).

Mix. No.	Slump (cm)	Slump flow (cm)	Resistivity (KΩ 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
C1 – A1B1C1D1E1	17.50	37.00	7.57	7.97	7.93	2837	2893	2723	17.79	20.94	22.91
C2 – A1B1C2D2E2	15.50	40.00	6.50	9.43	9.00	2753	3253	3013	17.54	24.89	25.24
C3 – A1B1C2D1E2	18.00	35.00	7.73	9.55	9.30	2817	3347	3193	18.35	22.04	28.88
C4 – A1B1C2D2E1	18.00	32.00	7.43	9.17	9.20	2910	3130	2873	23.16	25.94	30.17
C5 – A1B2C1D1E2	9.50	20.00	7.23	8.07	8.53	3040	3155	3057	21.96	26.22	29.91
C6 – A1B2C1D2E1	14.00	26.00	6.50	7.20	7.43	2843	3120	2893	17.02	18.92	20.26
C7 – A1B2C2D1E1	10.50	20.00	7.07	7.10	7.80	3047	2933	2837	23.64	29.35	33.59
C8 – A1B2C2D2E2	5.00	20.00	9.03	8.63	10.13	2750	3277	3007	28.36	33.79	36.16
C9 – A2B1C1D1E2	10.00	23.00	7.47	9.03	9.10	2573	3003	2707	13.22	17.17	18.48
C10 – A2B1C1D2E1	20.00	56.00	6.40	8.47	8.67	2550	2620	2840	5.85	7.57	9.74
C11 – A2B1C2D1E1	15.00	60.00	7.83	8.20	8.33	2383	3015	3043	10.54	13.88	17.64
C12 – A2B1C2D2E2	9.00	20.00	9.20	10.33	9.53	2747	3050	2910	21.55	23.98	27.67
C13 – A2B2C1D1E1	16.00	35.00	6.67	6.77	7.70	2677	2556	2937	7.88	9.98	12.91
C14 – A2B2C1D2E2	19.00	43.00	5.70	6.93	7.93	2567	2783	2863	8.76	11.92	14.32
C15 – A2B2C2D1E2	11.50	36.00	7.07	7.37	7.80	2907	3000	2723	11.87	14.63	19.86
C16 – A2B2C2D2E1	16.00	33.00	6.63	7.03	7.43	2750	3103	2800	11.81	16.22	20.42

Table A5
Mix proportions from Chokkalingam et al. (2022).

Mix. No.	B/C (kg/m^3)	CW:GBFS	AS:B	S:H	NaOH (M)
Ch1 – A1B1C1D1E1	400	4:1	0.50	1.0	8
Ch2 – A1B2C2D2E2	400	3:2	0.55	1.5	10
Ch3 – A1B3C3D3E3	400	2:3	0.60	2.0	12
Ch4 – A1B4C4D4E4	400	1:4	0.65	2.5	14
Ch5 – A2B1C2D3E4	450	4:1	0.55	2.0	14
Ch6 – A2B2C1D4E3	450	3:2	0.50	2.5	12
Ch7 – A2B3C4D1E2	450	2:3	0.65	1.0	10
Ch8 – A2B4C3D2E1	450	1:4	0.60	1.5	8
Ch9 – A3B1C3D4E2	500	4:1	0.60	2.5	10
Ch10 – A3B2C4D3E1	500	3:2	0.65	2.0	8
Ch11 – A3B3C1D2E4	500	2:3	0.50	1.5	14
Ch12 – A3B4C2D1E3	500	1:4	0.55	1.0	12
Ch13 – A4B1C4D2E3	550	4:1	0.65	1.5	12
Ch14 – A4B2C3D1E4	550	3:2	0.60	1.0	14
Ch15 – A4B3C2D4E1	550	2:3	0.55	2.5	8
Ch16 – A4B4C1D3E2	550	1:4	0.50	2.0	10

Table A6
S/N value of QPC corresponding to mix Ch1-Ch16 (Chokkalingam et al., 2022).

Mix. No.	QPC-1	QPC-2	QPC-3	QPC-4	QPC-5	QPC-6	QPC-7	QPC-8	QPC-9
Ch1 – A1B1C1D1E1	26.7	16.0	28.4	30.7	12.2	4.7	19.2	58.8	70.5
Ch2 – A1B2C2D2E2	31.7	12.8	31.1	23.6	10.6	9.2	24.4	65.2	72.6
Ch3 – A1B3C3D3E3	29.8	15.2	28.4	30.6	10.6	7.6	20.5	60.5	72.5
Ch4 – A1B4C4D4E4	29.8	15.1	28.6	30.1	10.2	7.6	20.2	60.2	72.6
Ch5 – A2B1C2D3E4	30.8	13.5	31.4	24.8	12.0	8.8	21.7	62.5	73.0
Ch6 – A2B2C1D4E3	30.3	13.8	31.4	26.0	11.4	7.7	21.4	62.5	72.3
Ch7 – A2B3C4D1E2	30.1	13.9	28.6	27.0	10.1	8.3	20.5	62.1	72.0
Ch8 – A2B4C3D2E1	31.4	13.1	30.8	24.3	9.3	9.0	23.6	64.8	71.9
Ch9 – A3B1C3D4E2	24.1	16.4	26.9	36.4	9.0	4.1	16.8	58.0	69.7
Ch10 – A3B2C4D3E1	20.5	16.9	26.6	40.0	4.3	0.8	11.4	57.7	69.2
Ch11 – A3B3C1D2E4	35.1	12.4	31.4	19.3	13.8	9.8	28.3	72.6	76.2
Ch12 – A3B4C2D1E3	−60.0	100.0	100.0	100.0	−60.0	−60.0	−60.0	−60.0	−60.0
Ch13 – A4B1C4D2E3	22.5	16.7	26.0	37.6	5.9	3.9	15.6	57.3	69.2
Ch14 – A4B2C3D1E4	−60.0	100.0	100.0	100.0	−60.0	−60.0	−60.0	−60.0	−60.0
Ch15 – A4B3C2D4E1	25.6	15.7	26.6	35.2	7.6	4.2	17.2	58.2	70.2
Ch16 – A4B4C1D3E2	32.2	12.7	31.1	23.1	13.0	9.3	25.9	66.9	73.6

Data availability

Data will be made available on request.

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