

Corrigendum Notice

Journal: International Journal of Integrated Engineering

Article Title: Multi-Additive Optimization of Fine-grained Soil using Taguchi-Grey Relational Analysis Approach

Author: Amit Kumar and Ashwani Jain

Volume: Vol. 17 No. 5

Original Article ID: 15402

DOI: <https://doi.org/10.30880/ijie.2025.17.05.014>

Reason for Correction:

The authors wish to inform that several important corrections have been made to the previously published article due to technical errors and the need to enhance the accuracy of the data analysis:

1. **Methodological Update:** The analytical methodology has been updated from Taguchi-Grey Relational Analysis (T-GRA) to a more comprehensive approach using the Performance Index (PI) and the Best-Worst Method (BWM). This change was implemented to address the limitations of the T-GRA method in managing multiple decision criteria.
2. **Experimental Data Correction:** A technical error was identified in the column arrangement of the experimental results table (Table 15 in the original version). The values for California Bearing Ratio (CBR) and Mass Loss (ML) were inadvertently interchanged. The accurate data has now been updated in the new version of the article (Table 19).
3. **Title Update:** The article title has been changed to "Multi-Objective Optimization for Stabilized Subgrade Soil through Performance Index and Taguchi Integrated Best-Worst Optimization Technique" to accurately reflect the improved methodology.

Impact on Conclusions:

These corrections do not alter the overall data trends. However, they provide more precise weightage values for each tested soil quality characteristic, thereby strengthening the validity of the final research findings.

The authors apologize for any inconvenience caused by these technical errors.

Multi-Objective Optimization for Stabilized Subgrade Soil through Performance Index and Taguchi Integrated Best-Worst Optimization Technique

Amit Kumar^{1*}, Ashwani Jain¹

¹ National Institute of Technology Kurukshetra,
Kurukshetra, 136119, INDIA

*Corresponding Author: amit_6160040@nitkkr.ac.in

DOI: <https://doi.org/10.30880/ijie.2025.17.05.014>

Article Info

Received: 6 September 2024

Accepted: 23 April 2025

Available online: 30 August 2025

Keywords

Subgrade material, freeze-thaw, multi-objective optimization, Taguchi, best-worst method, performance index

Abstract

The multi-objective optimization of a project involving number of performance characteristics is always a complicated task. Present article demonstrates two different multi-objective optimization approaches to fill the gap of non-availability of multi-objective optimization option in a popular design of experiments-based optimization technique i.e., Taguchi method. Though both approaches use the weightage criteria but have their own pros and cons over each other. First approach namely Performance Index method follows the numeric methods and could perform independently while second is an improvement over traditional Taguchi method and could be coupled with predefined robust Design of Experiments. The analytical results have been found compliance with the attainment of optimal design mixtures accordance to performance characteristics preferences. The demonstration of the techniques has addressed the drawbacks of the traditional Taguchi method over novel Best-Worst method. Results have shown that significant improvement in total quality of stabilized subgrade soil could be achieved by assigning appropriate weightage to factors and quality characteristics.

1. Introduction

Production of quality material satisfying manufacturer preferences and customer needs depends upon the evaluation of the involved components concurrently. The components affect the quality of final product and its performance significantly, and sometimes could be contradictory to each other [1]–[3]. On the other hand, the process of choosing the best alternative from a set of performance criteria considering all factors and limitations simultaneously may be referred to as multi-objective optimization [4], [5]. The Multiple Criteria Decision Making (MCDM) related problems are basically solved through the principle of reduction of alternative sets using standardized or logical mathematical expressions and preferences. Finally, a decision is made complying with the best alternative that suits the various evaluation criteria. MCDM is a modern-day decision-making tool and has its applications in numerous applied disciplines i.e., engineering, economics, logistics, military and administration [6], [7]. For MCDM applications, weights are assigned to criteria to reflect the prioritisation of specific performance characteristics. But, there is no specific or unique division rule available for determining the criteria weightage and therefore, totally depends upon the understanding and need of the decision maker (DM). The decision models could be classified as objective and subjective models. The objective models are based on the criteria weightage coefficient calculations at the initial stage. Some of the objective models are Entropy Method, CRITIC method (CRiteria Importance Through Intercriteria Correlation), and FANMA method. All the methods have their names after their inventors. Subjective models are based on the preferences assigned by the decision-

maker (DM) according to final product specifications; consequently, results may vary depending on the number of participants and the criteria assignment techniques used. Therefore, the subjective models are basically pairwise comparisons. The pairwise comparison was introduced in the late 1920, where the decision-making matrix was represented in a structured manner. In situations, where, it is impractical or illogical to assign ratings to actions based on criteria, pairwise comparisons are employed to indicate the relative importance of 'm' actions.

The Analytic Hierarchy Process (AHP) method is commonly used and reckoned technique among pairwise comparisons [8]–[13]. Recently, a new MCDM technique namely Best-Worst method (BWM) has emerged to overcome the inadequacies of AHP, such as the requirement of large dataset to achieve optimization. BWM implies the optimal weight coefficients obtained with only $2n-3$ comparisons in criteria pairs and therefore is capable to remove the variations in comparison criteria. Consequently, BWM produces more reliable results by undermining the transitivity relations those affect the consistency of the results in a greater way. In BWM technique, only the advantages of the best and worst criterion are considered instead of making more secondary comparison pairs [14]. BWM has already been used in various fields including marketing [15]–[20], quality assessment [21]–[24], IoT, Cloud services [25], [26], resource allocation [27]–[29], recruitment [30], geospatial and energy conservation [31], [32] etc. The performance index is a mathematical tool that can condense multiple data into a single response. This tool could be coupled with the predefined Design of Experiment (DOE) for MCDM. The methodology of using this tool is also based on the weightage and ranking assigned to the performance characteristics [33]–[35]. Present article demonstrates the Performance Index (PI) and Taguchi method integrated Best-Worst Method (BWM) to enable the selection process of the most suitable mixture complying with the required performance criteria. The results of the current study could be utilized in pavement engineering as the research work concentrates on the production of a sustainable subgrade material to withstand against frequent freeze and thaw cycles.

1.1 Scope of the Study

The main contribution of this study is that three different parameters were optimized using two distinct approaches, effectively solving the multi-criteria optimization problem. Both novel optimization techniques were engaged with the Design of Experiments (DOE) to overcome the deficiencies of the Taguchi optimization technique. The proposed Performance Index (PI) and Taguchi integrated Best-Worst Method (BWM) approaches not only simplify the involved tedious calculation processes but also check the limitations of the traditional optimization approaches.

2. Materials and Methods

The stabilized soil is intended for subgrade use in both normal and weathered conditions, specifically under frequent freeze-thaw cycles. Consequently, the additives were selected not only for their performance but also for their economic viability and environmental sustainability.

2.1 Materials

The soil was obtained from a road construction site located at Jammu and Kashmir, a Union Territory of India. Prior to laboratory testing, the soil was thoroughly cleaned by removing foreign matter, such as stones, organic debris, and other impurities, to ensure sample uniformity. Grain size distribution curve and physical properties of the soil have been shown in Fig. 1 and given in Table 1 respectively [36], [37].

Table 1 Soil characterization report

Physical property	Value
Gravel (%)	0
Sand (%)	15
Clay + Silt (%)	85
Specific Gravity at 27°C, G	2.68
Liquid Limit at 27°C, LL (%)	34
Plastic Limit at 27°C, PL (%)	29
Plasticity Index, I _P (%)	05
Indian Standard Classification	ML
Maximum Dry Density at 27°C* (g/cc)	1.72
Optimum Moisture Content at 27°C* (%)	19.33

*Obtained by Standard Proctor Test

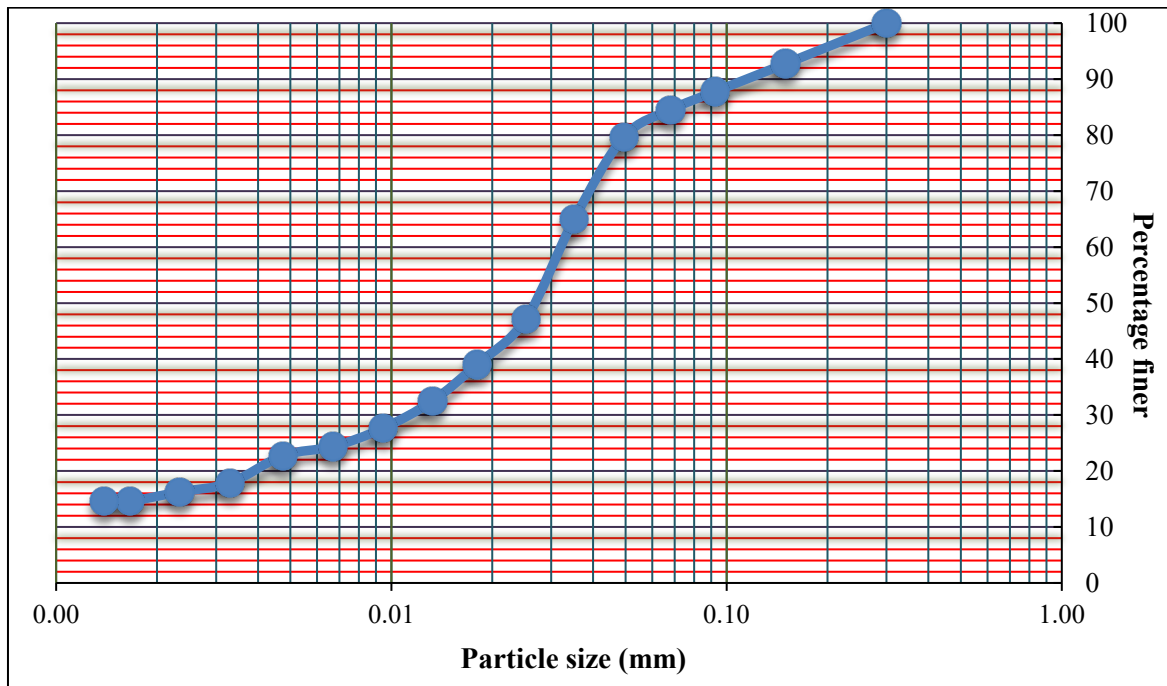


Fig. 1 Grain size distribution curve of the soil

Since the soil was found fine-grained and could be stabilized by using lime and cement but, procurement of both additives has their own demerits such as extraction of natural lime involves the harm to the nature and cement production intensify the carbon emission in the environment [38]. Therefore, minute eggshell powder (ESP) was chosen alternatively, as it contains high lime content in its chemical composition and easily available at no price at all. ESP was sieved through IS grade 425micron sieve to maintain the uniformity of size in preparing the laboratory test specimens. The specific gravity of eggshell powder at 27°C was reported as 1.33. ESP primarily contains a strong base known as CaO and traces of Cl, Al₂O₃, SiO₂, MnO and CuO [39]. The granulometric curve of the finely grounded eggshell powder has been shown in Fig. 2 [40].

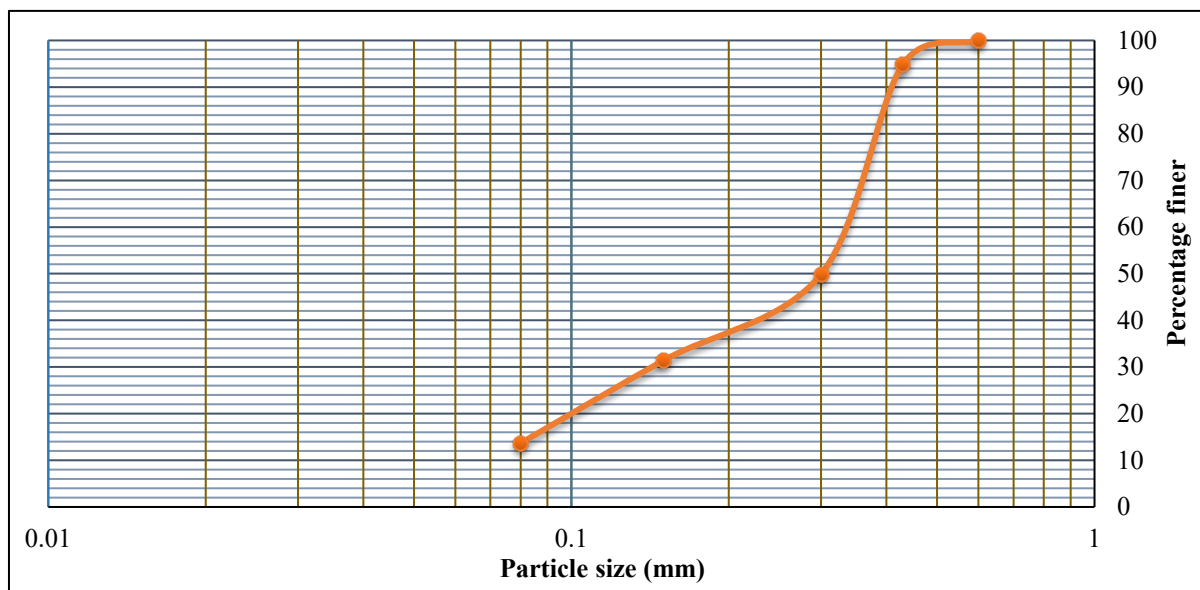


Fig. 2 Granulometric curve of eggshell powder

Though the soil was supposed to be served in cold regions too where frequent freeze-thaw is common so sodium chloride (NaCl) was selected as a deliquescent. Moreover, it can lower the freezing temperature of the

presented water in the soil. Some of the manufacturer provided specifications for the used NaCl have been given in Table 2 [41].

Table 2 Sodium chloride characterization

Property	Description
Chemical composition	Na ⁺ Cl ⁻
Molecular weight	58.44 g/mol
Color	Achromatic
Appearance	Translucent crystals
Density at 0°C (g/cc)	2.165
Melting point (°C)	801
Boiling range (°C)	1413

During thaw, the water gets evaporated that may result into desiccation cracks in the stabilized soil. Therefore, synthetic polypropylene fibers (PPF) were used to check the crack propagation after stabilization. Some typical and manufacturer provided fiber specifications have been provided in Table 3 [42].

Table 3 Physical properties of polypropylene fiber

Property	Description
Appearance	Short length fiber
Color	Pure white
Shape	Trilobal
Effective diameter (μm)	25-40
Length (mm)	12
Specific gravity	0.90-0.91
Melting point (°C)	160-165

2.2 Methodology

2.2.1 Design of Experiments (DoE)

For a robust DOE, the additives; 425μm sieved ESP (3% – 9%), 12 mm length PPF (0.05% – 0.15%) and laboratory NaCl (2% – 6%) have been adopted as parameters and their proportions as levels respectively. Table 4 contains a coded datasheet for the same. An L9 orthogonal array (OA) has been chosen as the proposed standardized DOE and corresponding matrix of structured OA has been shown in Table 5. The columns represent the levels of parameters and each row is a mix proportion for the pilot tests [42].

Table 4 Coded datasheet for parameters and their levels

Parameter	Description	Levels		
		1	2	3
A	Eggshell Powder (%)	3	6	9
B	PPF (%)	0.05	0.10	0.15
C	NaCl (%)	2	4	6

Table 5 Proposed standardized DOE

Experiment No.	Parameter		
	ESP (%)	PPF (%)	NaCl (%)
1	3	0.05	2
2	3	0.10	4
3	3	0.15	6
4	6	0.05	4
5	6	0.10	6
6	6	0.15	2
7	9	0.05	6
8	9	0.10	2
9	9	0.15	4

2.2.2 Testing Procedure

The soil was tested for determining the strength and durability characteristics by performing Unconfined Compression Strength, California Bearing Ratio and Mass Loss tests accordance to Indian Standards of soil testing for civil engineering purposes [37], [40], [42]. The compressive strength tests were performed in both i.e., normal and weathered conditions while the mass loss and CBR tests have their unique procedures of testing the soil in soaked conditions only and; in both soaked and unsoaked conditions, respectively.

a. Unconfined Compressive Strength Test

In the first phase, the samples were tested for unconfined compression under normal conditions, i.e., without subjecting the samples to freeze-thaw cycles, and after subjecting the samples to curing periods 7, 14 and 21 days. In the second phase, the 21-day cure samples were subjected to weathering process induced by freeze-thaw cycles in an open system to simulate field conditions. Water-saturated felt pads were placed between the specimens and specimen carriers for further process. The freeze-thaw cycles were simulated in the laboratory by first placing the specimen in freezing cabinet at -20°C for 6 hours of freezing followed by shifting the specimen to humidity chamber maintained at $+25^{\circ}\text{C}$ for 6 hours of thawing in controlled moisture environment at a relative humidity of 90%. Free potable water was made available to the absorbent pads under the specimens to permit the specimens to absorb water by capillary action during the thawing period. The samples were tested for uniaxial compression after 3, 5 and 10 freeze-thaw cycles.

A series of unconfined compressive strength tests were conducted on cylindrical specimens of size 3.81 cm diameter and 7.62 cm height. The axial strain rate was chosen as 1.0 mm/minute by appropriate setting of turret lever and strain setting lever. The compressive stress taken by the sample is recorded at various strain levels. At failure, peak compressive stress was noted as unconfined compressive strength and failure strain was also recorded as per the recommendations given in IS: 2720 (Part X) (1991).

b. Mass loss Test

Mass loss is the function of loss in bonding of particles under specific conditions. Mass loss tests were conducted to have further assessment of durability of treated soil broadly after the procedure laid down in IS: 4332 (Part IV) (1968). The 21-day cure samples were subjected to weathering process induced by freeze-thaw (FT) cycles. For freezing, the specimens were placed in freezing cabinet at -20°C for 12 hours followed by thawing in a humidity chamber maintained at $+25^{\circ}\text{C}$ for 12 hours at a relative humidity of 90%. The samples were continually tested for mass loss after subjecting it to 3, 5 and 10 freeze-thaw cycles.

c. California Bearing Ratio Test

The method combines a load penetration test performed in the laboratory or in-situ with the empirical design charts to determine the thickness of pavement and of its constituent layers using CBR values. California Bearing Ratio (CBR) tests have been performed on the soil, treated with the chosen stabilizers, following the specifications laid down in IS: 2720 (Part XVI) (1987).

2.2.3 Taguchi Method

Taguchi method was introduced by Genichi Taguchi (Taguchi, 1987) for the optimization of parameters to enhance the product quality. The standardized DOE represented by an OA has been adopted to design the soil mix proportions. The laboratory tests, i.e., strength and durability tests, have been conducted on the untreated and

treated soil specimens for checking the suitability of mix proportions as a qualifying subgrade material. The use of quantity design in the method to optimize a process, with one or multiple performance characteristics, includes the following steps [43].

- a. Identification of performance characteristic and selection of process quantities (factors) to be evaluated.
- b. Determination of number of quantity levels for the process and possible interaction between the process quantities (factors).
- c. Assignment of the process quantities to the selected appropriate standard orthogonal array.
- d. Perform the experiments based on the arrangements of the orthogonal array.
- e. Analyzing the experimental results accordance to the performance characteristic.
- f. Calculation of performance statistics and ANOVA.
- g. Selection of optimal levels of process quantities.
- h. Verification of optimal process quantities through the confirmation tests [44].

Taguchi method solves the complex optimization problems statistically, in which the inputs (experimental results/responses) produce the signal (desirable) to noise (undesirable) ratio, called S/N ratio. Broadly, orthogonal array (OA), S/N ratio, analysis of variance (ANOVA) and response graphs are the essential tools of a solution of optimization problem. In which, OA is a robust matrix and rest are the statistical terms. The Taguchi method employs standard tables known as the Orthogonal Arrays (OA) for constructing a well-defined DOE, in this case, L9, as it is best suited with the taken levels of the parameters. In Taguchi method, S/N ratio has been taken instead of the mean value to interpret the responses into a value for the evaluation characteristics in the optimum setting analysis. S/N ratio expresses a scatter around the target response value. S/N ratio is measured in decibel (dB) and can be classified into three categories namely larger the better (Eq. 1), smaller the better (Eq. 2) and nominal the better (Eq. 3).

$$\frac{S}{N} = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right] \quad (1)$$

$$\frac{S}{N} = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n y_i^2 \right] \quad (2)$$

$$\frac{S}{N} = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n (y_i - y_0)^2 \right] \quad (3)$$

Where, S/N are performance statistics, n is the number of repetitions for an experimental combination and, y_i is a performance value of the i^{th} experiment and y_0 is nominal value desired. In the Taguchi method, the experiment corresponding to optimum working conditions might have not been done during the whole period of the experimentation. In this case, the performance value corresponding to optimum working conditions can be predicted by utilizing the balanced characteristic of the OA [45], [46].

2.2.4 Proposed Multi-objective Optimization Methods

a. Performance Index Method (PI Method)

Previous research by the authors established several optimized conditions for specific soil properties. However, for practical implementation, it is essential to integrate these into a single, unified optimized condition, providing practitioners with a standardized set of dosages for field applications. Weight ranking and numeric index-based performance evaluation of the optimized dosages has been done to convert the multiple responses into a single response [46], which ensures multi-response optimization without affecting Taguchi optimization results. The performance index (PI) method has been adopted to facilitate the selection process of the proportions of ESP, PPF and NaCl to produce the most suitable mix complying with the required performance criteria.

The performance index (PI) is a mathematical tool that allows the integration of multiple information sets into an overall evaluation measure to condense the set of information into just one metric. In first step, a weight ranking (W_i) is calculated for each individual criterion using Eq. 4. The weight ranking is kept in such a way that the mixture achieving the best test response in a certain criterion scores 1.00, and the rest of the test values of the mixtures are proportioned to that best test value, therefore have their weight ranking ≤ 1.00 . The second step towards the execution of PI approach is the computation of a numeric index (R_i) using Eq. 5. The highest R_i value used in this study has been set to 5.00, which could be arbitrarily taken as 10 or 100. Based on the required

performance quality characteristics (n), the related R_i is multiplied to get a mixture score (S_{in}) as given in Eq. 6. The mixture achieving the highest score is designated as the best suitable mixture in terms of the corresponding required multiple criteria [46].

$$W_i = \frac{\text{Measured performance for each mixture}}{\text{Best measured performance}} \tag{4}$$

$$R_i = 5 \times W_i \tag{5}$$

$$S_{in} = R_{i1} \times R_{i2} \times \dots \times R_{in} \tag{6}$$

Performance evaluation of the mixes has been done after calculating the indices of the designed mixes for both i.e., individual performance criterion and multiple performance criteria.

b. Best-Worst Method (BWM)

The BWM determines the weights of various quality characteristics (QC) by evaluating the preference of the most important (Best) and least important (Worst) criteria against all other remaining factors. This is typically measured on a scale of 1-9 or 10-90. The process follows these five structured steps:

- i. **Define the Criteria Set:** Identify and list the quality criteria {QC₁, QC₂, ..., QC_n} that will be used in the MCDM process.
- ii. **Identify Extremes:** Select the single Best (most important) criterion and the single Worst (least important) criterion from the set.
- iii. **Best-to-Others Comparison:** Determine the preference of the "Best" criterion over all other QCs using a scale of 1-9. This results in the Best-to-Others vector.
- iv. **Others-to-Worst Comparison:** Determine the preference of all remaining QCs over the "Worst" criterion using the same 1-9 scale. This results in the Others-to-Worst vector.
- v. **Optimize Weights:** Calculate the optimal weights {w₁, w₂, ..., w_n} by solving for the values that minimize the maximum absolute differences between the weight ratios and their corresponding preferences.

The resulting weights are unique to the specific criteria identified as the Best and Worst. Consequently, only one criterion can be designated as the "Best" and one as the "Worst" for a single iteration of this calculation.

For each duo of W_B/W_j and W_j/W_w ,

$$\frac{W_B}{W_j} = a_{Bj} \tag{7}$$

Similarly,

$$\frac{W_j}{W_w} = a_{jw} \tag{8}$$

Where, $j = 1, \dots, n$

W_B = Weight of best criterion

W_w = Weight of worst criterion

W_j = Weight of other criteria

a_{Bj} = Comparative result of best to other criteria

a_{jw} = Comparative result of other criteria to worst

The optimal weights are considered as the minimum of the absolute value of the maximum differences of the below given linear models:

Therefore, min. ξ subject to

$$\left| \frac{W_B}{W_j} - a_{Bj} \right| \leq \xi, \text{ for all } j$$

$$\left| \frac{W_j}{W_w} - a_{jw} \right| \leq \xi, \text{ for all } j$$

$$\sum_j W_j = 1$$

$$W_j \geq 0, \text{ for all } j$$

$$W_j \geq 0, \text{ for all } j \tag{9}$$

Solving Eq. 9, the optimal weights (w_1, w_2, \dots, w_n) and ξ^* (Consistency ratio) are obtained.

2.2.5 The Proposed Methodology

Generally, optimization results in multiple end conditions that conflict with one another. Taguchi method, itself, is unable to address such types of problems where multiresponses has to be dealt. The present study is also based on the multi-response optimization, where, stabilized soil has different optimization conditions obtained from three laboratory tests namely, Unconfined Compressive Strength Test, Mass-loss Test, California Bearing Ratio Test under normal and weathered conditions. Therefore, an integrated approach has been used to bridge the gap of involved parameters and optimization objectives. Following steps could be taken for the proposed integrated, Taguchi-BWM, approach:

- a. Nominate the control parameters, their valid range and allocate the required quality characteristics (QC).
- b. Assign the preferences to quality characteristics and calculate the weights of each.
- c. Select the appropriate Taguchi robust OA.
- d. Obtain the responses by performing laboratory tests and calculate the relative weights of each response with respect to each quality characteristics.
- e. Calculation of total weight by multiplying the weight calculated in step (b) and step (d).
- f. S/N ratio for larger the better is calculated for all quality characteristics by taking the respective responses obtained from laboratory tests. From where, optimal levels correspond to higher levels of S/N ratio graphs and analysis of variance (ANOVA) is performed to determine the significant factors.

The illustrative model and flow diagram of the BWM and Taguchi integrated method have been given in Fig. 3 and Fig. 4, respectively.

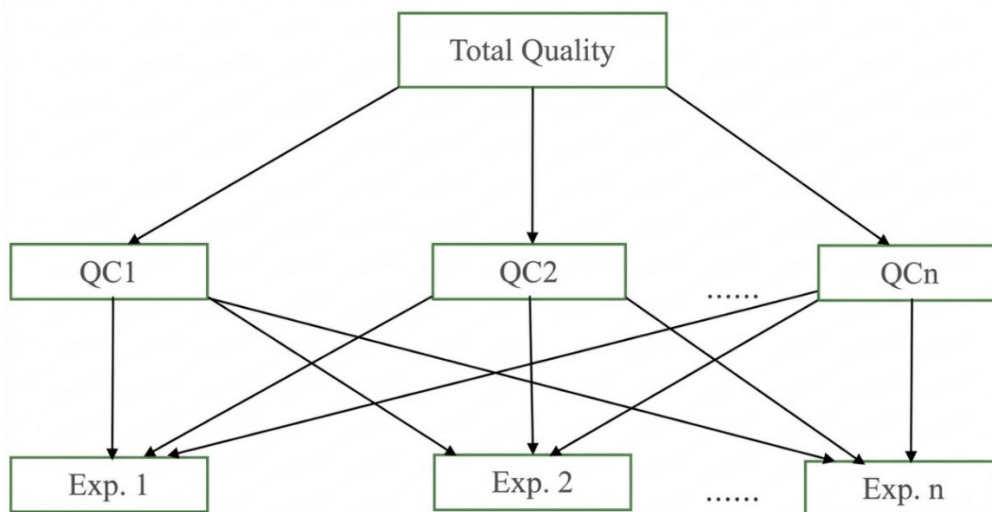


Fig. 3 Proposed BWM model

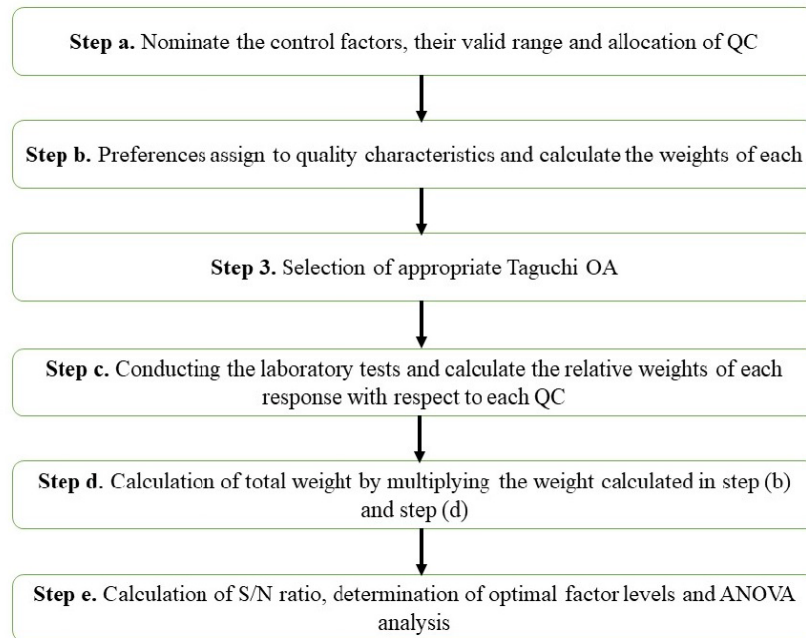


Fig. 4 Taguchi Integrated BWM proposed methodology

2.2.6 Significance of MCDM in Present Study

Evaluating the optimal mix design is the vital issue for the practitioners and decision makers to achieve the robustness without compromising the quality. Basically, the optimization techniques are meant to produce quality product at low cost and for global use. As the stabilized soil was intended to be taken as subgrade material in normal and weathered conditions found in Jammu and Kashmir, India. Therefore, the requisite tests i.e., UCS, ML and CBR have been performed in the laboratory by maintaining the field conditions. For the optimization purpose, MCDM techniques have been adopted. The Unconfined Compressive Strength (UCS) of the soil indicates its shear strength; therefore, it must be high to resist slippage or shear failure. Similarly, UCS following freeze-thaw (FT) cycles must remain high to support structural loads during the thaw period. Furthermore, the durability of the stabilized subgrade must not be compromised; consequently, mass loss must remain minimal, even under severe weathering conditions. Target S/N values have been summarized in Table 6 to facilitate a clearer understanding of the experimental objectives.

Table 6 Proposed orthogonal array

Sr. No.	Notation	Quality Characteristic	Target S/N
1.	QC1	UCS (kg/cm ²)	larger the better
2.	QC2	UCS _{FT} (kg/cm ²)	larger the better
3.	QC3	ML (%)	smaller the better
4.	QC4	CBR (%)	larger the better

In the present study, alphabet P, F and C have been used to represent the optimized levels of the parameters i.e., ESP, PPF and NaCl, respectively. Therefore, P1, F2 and C3 are correspond to 3% ESP, 0.10% PPF and 6% NaCl.

3. Results and discussion

In this section, the results from both MCDM techniques i.e., PI method and BWM have been given and discussed in two parts. First section details the PI method including calculations and second section focuses on the implementation and elaboration of the BWM for MCDM adopted by the decision makers.

3.1 Performance Index (PI) Method

During the study, number of optimized dosage of additives have been found for the specific soil properties. It is necessary to integrate them into a single optimized condition for practitioners at site. The performance index (PI)

method has been adopted to facilitate the selection process for the amount of ESP, PPF and NaCl that produces the most suitable mixture complying with the required quality characteristics.

Table 7 reports the calculated performance indices for individual quality characteristics of treated soil samples in terms of UCS of 21 days cured specimens, UCS and mass loss of 21 days cured specimens subjected to 10 freeze-thaw cycles, and CBR of soaked specimens.

Table 7 Performance indices for individual quality characteristics

Experiment No.	UCS (21 Days)		UCS (10C)		ML (10C)		CBR (Soaked)	
	W _i	R _i	W _i	R _i	W _i	R _i	W _i	R _i
1	1.00	5.00	0.60	2.98	3.74	18.69	0.80	3.99
2	0.32	1.61	0.28	1.38	3.30	16.49	0.27	1.35
3	0.66	3.30	0.50	2.50	1.48	7.42	0.58	2.91
4	0.89	4.43	0.30	1.48	1.94	9.70	0.99	4.93
5	0.65	3.26	0.93	4.64	3.32	16.59	0.75	3.75
6	0.80	4.00	0.60	3.01	1.00	5.00	0.69	3.43
7	0.62	3.09	0.53	2.65	1.94	9.72	0.69	3.47
8	0.97	4.87	0.94	4.69	4.16	20.81	0.55	2.76
9	0.79	3.96	1.00	5.00	3.74	18.71	1.00	5.00

The chosen multiple quality characteristics have been reported in Table 8. The calculated performance indices for multiple quality characteristics have been reported in Table 9.

Table 8 Performance quality characteristics

Performance Index	Performance Criterion
PI-1	UCS (21 days cure) + UCS (10C)
PI-2	UCS (21 days cure) + ML (10C)
PI-3	ML (10C) + CBR (Soaked)
PI-4	UCS (21 days cure) + ML (10C) + CBR (Soaked)

Table 9 Performance indices for multiple quality characteristics

Experiment No.	PI-1	PI-2	PI-3	PI-4
1	14.92	93.43	74.55	372.73
2	2.22	26.53	22.32	35.91
3	8.26	24.53	21.58	71.29
4	6.56	43.00	47.78	211.91
5	15.14	54.10	62.29	203.12
6	12.04	20.00	17.15	68.59
7	8.19	30.01	33.69	104.01
8	22.86	101.33	57.47	279.84
9	19.78	74.03	93.56	370.17

From Table 9, it can be interpreted that the mix proportion assigned to experiment no. 8 (eggshell powder 9%, polypropylene fiber 0.10%, sodium chloride 2% i.e., P3F2C1) has been found best suited for PI-1 and PI-2, while mix proportion assigned to experiment no. 9 (eggshell powder 9%, polypropylene fiber 0.15%, sodium chloride 4% i.e., P3F3C2) and mix proportion assigned to experiment no. 1 (eggshell powder 3%, polypropylene fiber 0.05%, sodium chloride 2% i.e., P1F1C1) have been found best suited for PI-3 and PI-4 respectively.

3.2 Best-Worst Method (BWM)

Following steps have been taken into account to work with the BWM for MCDM for the present study:

1. Selection of factors and their levels followed by the preference assigned to the nominated quality characteristics.

2. Preference comparison from best to others and others to worst is to be done as given in Table 10 and Table 11, respectively.
3. By solving the linear model expressed as Eq. (9), optimal weights (w_1, w_2, \dots, w_n) and ξ^* (consistency ratio) have been obtained and given in Table 12. For a consistent pair-wise comparison Consistency ratio (ξ^*) must be less than 0.1. If the comparisons are not fully consistent, for problems with more than three criteria, multiple optimal solutions might be founded, one of which can be selected by the decision-maker [47].

Table 10 Best to others comparison

Quality Characteristic Comparison	QC1	QC2	QC3	QC4
	6	9	1	3

Table 11 Others to worst comparison

Quality Characteristic Comparison	QC1	QC2	QC3	QC4
	4	1	9	7

Table 12 Quality characteristics weights

Sr. No.	Quality Characteristic	Criteria Weight
1.	QC1	0.1192
2.	QC2	0.0518
3.	QC3	0.5907
4.	QC4	0.2383
Consistency ratio (ξ^*)		0.2083 (Pairwise acceptable)

4. Arrange the responses of all the pilot experiments and compare among best to others and others to worst. The pilot test responses and reference comparisons (best to others and others to worst) of the quality characteristics has been given in Table 13, Table 14 and Table 15, respectively.

Table 13 Pilot test responses

Experiment No.	QC1 kg/cm ²	QC2 kg/cm ²	QC3 %	QC4 %
1	1.15	1.17	7.40	2.21
2	0.37	0.54	6.53	0.75
3	0.76	0.98	2.94	1.61
4	1.02	0.58	3.84	2.73
5	0.75	1.82	6.57	2.08
6	0.92	1.18	1.98	1.90
7	0.71	1.04	3.85	1.92
8	1.12	1.84	8.24	1.53
9	0.91	1.96	7.41	2.77

Table 14 Reference comparison (Best-to-others)

Quality Characteristic	Best Experiment	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Exp. 7	Exp. 8	Exp. 9
QC1	Exp. 1	1	9	5	2	5	3	5	1	3
QC2	Exp. 9	6	9	8	9	2	6	7	2	1
QC3	Exp. 6	7	6	2	3	6	1	3	9	7
QC4	Exp. 9	3	9	7	2	6	5	5	7	1

5. On the basis of the comparison, relative weight of each pilot test result with respect to individual quality characteristic is calculated as given in Table 16.

Table 15 Reference comparison (Others-to-worst)

Quality Characteristic	Worst Experiment	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Exp. 7	Exp. 8	Exp. 9
QC1	Exp. 2	9	1	5	8	5	7	5	9	7
QC2	Exp. 2	4	1	2	1	8	4	3	8	9
QC3	Exp. 8	3	4	8	7	4	9	7	1	3
QC4	Exp. 2	7	1	3	8	4	5	5	3	9

Table 16 Relative weight of each pilot test result w.r.t. quality characteristics

Experiment No.	QC1	QC2	QC3	QC4
1	0.0000	0.3333	0.0000	0.6667
2	0.0000	0.2857	0.4286	0.2857
3	0.0000	0.1628	0.6512	0.1860
4	0.0000	0.1176	0.3529	0.5294
5	0.0000	0.6000	0.2000	0.2000
6	0.0000	0.0000	1.0000	0.0000
7	0.0000	0.2113	0.4930	0.2958
8	0.0000	0.6632	0.1474	0.1895
9	0.0000	0.5000	0.0000	0.5000

6. Calculation of the total weight with respect to each pilot test results (responses) is done for the conversion of the multi-objective problem into a single-objective problem so that the lacuna of using Taguchi method alone could be addressed. Total weight with respect to each pilot test results is a product of weights obtained in step 3 (Table 12) and step 4 (Table 16).

Table 17 Total weight w.r.t. each pilot test result

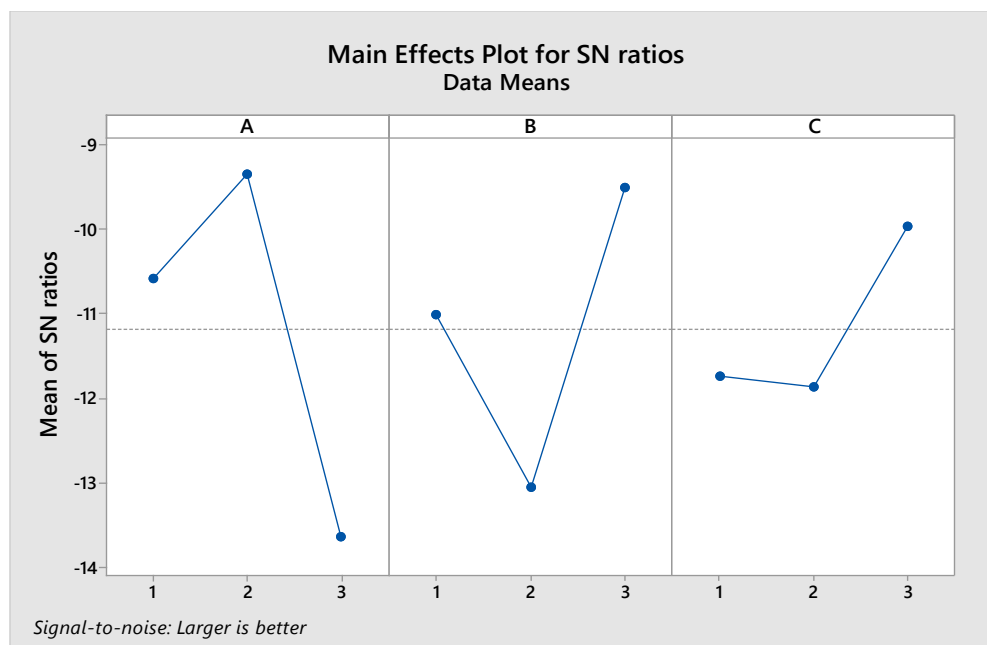
Experiment No.	Total Weight
1	0.1761
2	0.3361
3	0.4374
4	0.3407
5	0.1969
6	0.5907
7	0.3726
8	0.1666
9	0.1451

7. Since maximize the total quality of the product is the prime objective of the proposed Taguchi-BWM; therefore, S/N ratio with respect to each pilot test result has been calculated by using eq. 1 i.e., larger the better. All calculated S/N ratios have been arranged in Table 18.

Table 18 *S/N ratio w.r.t. each pilot test result*

Experiment No.	S/N ratio
1	-15.0848
2	-9.4706
3	-7.1824
4	-9.3526
5	-14.1151
6	-4.5727
7	-8.5751
8	-15.5665
9	-16.7667

Additionally, for the determination of the optimized levels of the factors a S/N ratio graph has also been obtained using MINITAB software and shown in Fig. 5. From where, optimum levels of the factors are corresponded to highest S/N ratio. So, P2F3C3 i.e., ESP 6%, PPF 0.15% and NaCl 6% have been found as the combination to maximize the product quality without compromising the quality characteristics.

**Fig. 5** *S/N ratio graph for Taguchi-BWM*

In order to determine the significant factor a general linear model-based analysis of variance (ANOVA) has also been done and arranged in Table 19. From observing the Table 18, it can be interpreted that ESP contributed more followed by the PPF and NaCl and hence, is a significant factor to affect the quality characteristics to produce a robust material for the subgrade in the cold regions.

Table 19 *Analysis of variance for Taguchi-BWM based S/N ratio*

Factor	DOF	Seq. SS	Adj. MS	Adj. SS	Contribution (%)
ESP	2	29.262	14.631	29.262	19.91
PPF	2	18.986	9.493	18.986	12.92
NaCl	2	6.829	3.414	6.829	4.65

Though PI Method has been employed to demonstrate the MCDM in optimization problems but, it has also been found independent from Taguchi method. For different multi criterion, PI method has identified four different mix proportions (in the present study), that could be a problem for practitioners at field. Whereas,

Taguchi integrated BWM has identified a single mix proportion to obtain maximum good quality in the final product under certain conditions, for instance in this case, normal and weathered conditions. As discussed previously, Taguchi method is incompetent to deal with multi criterion problems so, it is advisable that to conclude the MCDM problems in a single optimized condition Taguchi method may be coupled with other multi criterion optimization techniques (MC-OT) e.g., Artificial Neural Network (ANN), Grey relational analysis (GRA), Teaching-Learning Based Optimization (TLBO) etc.

4. Conclusions

Multiple quality characteristics may cause a problem in achieving the desired product quality by contradicting each other. Taguchi method has been found experimentally incompetent to solve such problems. This study is a demonstration of solving the multi-response problems by using two methods. First is numeric based and independent from Taguchi, named as Performance Index (PI) method. Second is the improved Taguchi integrated Best-Worst method, in which decision maker assigns the weights to the factors and quality characteristics to get the desired product quality. PI method produced three different mix proportions corresponding to four different pavement subgrade quality characteristics while Taguchi integrated BWM provided a single set of mix proportions for different quality characteristics set by the decision maker. Further studies can be done by coupling the Taguchi method with advanced artificial intelligence and machine learning techniques to get better outcomes on robust modelling.

Acknowledgement

The authors gratefully acknowledge the Council of Scientific and Industrial Research, New Delhi (Govt. of India) for the financial support to the project and National Institute of Technology Kurukshetra, Kurukshetra, India (An Institution of National Importance) for experimental work.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: **study conception and design:** Amit Kumar, Ashwani Jain; **data collection:** Amit Kumar; **analysis and interpretation of results:** Amit Kumar; **draft manuscript preparation:** Amit Kumar, Ashwani Jain. All authors reviewed the results and approved the final version of the manuscript.

References

- [1] García, J. L., Rama, M. D. L. C. D. R., Alonso, M., & Brea, J. A. F. (2014). Dependence relationship between the critical quality factors and social impact. *Revista de Administração de Empresas*, 54(6), 692-705, <https://doi.org/10.1590/S0034-759020140609>
- [2] Anusha, C., & Umasankar, V. (2020). Performance Prediction through OEE-Model. *International Journal of Industrial Engineering and Management*, 11(2), 93-103, <https://doi.org/10.24867/IJIEM-2020-2-256>
- [3] Baghernejad, A., & Anvari-Moghaddam, A. (2021). Exergoeconomic and Environmental Analysis and Multi-Objective Optimization of a New Regenerative Gas Turbine Combined Cycle. *Applied Sciences*, 11(23), 11554, <https://doi.org/10.3390/app112311554>
- [4] Stankovic, M., Gladovic, P., & Popovic, V. (2019). Determining the importance of the criteria of traffic accessibility using fuzzy AHP and rough AHP method. *Decis. Mak. Appl. Manag. Eng.*, 2, 86-104, <https://doi.org/10.31181/dmame1901086s>
- [5] Petrovic, G., Mihajlovic, J., Cojbasic, Z., & Madic, M., Marinkovic, D. (2019). Comparison of three fuzzy MCDM methods for solving the supplier selection problem. *Facta Univ. Ser. Mech. Eng.*, 17, 455-469, <https://doi.org/10.22190/FUME190420039P>
- [6] Hassanpour, M. (2019). Evaluation of Iranian Wood and Cellulose Industries. *Decis. Mak. Appl. Manag. Eng.*, 2, 13-34, <https://doi.org/10.31181/dmame1901013h>
- [7] Diyaley, S., & Chakraborty, S. (2019). Optimization of multi-pass face milling parameters using metaheuristic algorithms. *Facta Univ. Ser. Mech. Eng.*, 17, 365-383, <https://doi.org/10.22190/FUME190605043D>
- [8] Thurstone, L. L. (1927). A law of comparative judgment. *Psychol. Rev.*, 34, 273-286, <https://doi.org/10.1037/h0070288>

- [9] Shannon, C. E., & Weaver, W. The Mathematical Theory of Communication; The University of Illinois Press: Urbana, IL, USA, 1947.
- [10] Saaty, T. L. Analytic Hierarchy Process; McGraw-Hill: New York, NY, USA, 1980.
- [11] Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The CRITIC method. *Comput. Oper. Res.*, 22, 763-770, [https://doi.org/10.1016/0305-0548\(94\)00059-H](https://doi.org/10.1016/0305-0548(94)00059-H)
- [12] Tzeng, G. H., Chen, T. Y., & Wang, J. C. (1998). A weight-assessing method with habitual domains. *Eur. J. Oper. Res.*, 110, 342-367.
- [13] Srdjevic, B., Medeiros, Y. D. P., Faria, A. S., & Schaer, M. (2003). Objektivno vrednovanje kriterijuma performanse sistema akumulacija. *Vodoprivreda*, 35, 163-176, (In Serbian)
- [14] Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, 53, 49-57, <https://doi.org/10.1016/j.omega.2014.11.009>
- [15] Gupta, H., & Barua, M. K. (2017). Supplier selection among SMEs on the basis of their green innovation ability using BWM and fuzzy TOPSIS. *J. Clean. Prod.*, 152, 242-258, <https://doi.org/10.1016/j.jclepro.2017.03.125>
- [16] Vahidi, F., Torabi, S. A., & Ramezankhani, M. J. (2018). Sustainable supplier selection and order allocation under operational and disruption risks. *J. Clean. Prod.*, 174, 1351-1365, <https://doi.org/10.1016/j.jclepro.2017.11.012>
- [17] Haeri, S. A. S., & Rezaei, J. (2019). A grey-based green supplier selection model for uncertain environments. *J. Clean. Prod.*, 221, 768-784, <https://doi.org/10.1016/j.jclepro.2019.02.193>
- [18] Bai, C., Kusi-Sarpong, S., Badri Ahmadi, H., & Sarkis, J. (2019). Social sustainable supplier evaluation and selection: a group decision-support approach. *International Journal of Production Research*, 57(22), 7046-7067, <https://doi.org/10.1080/00207543.2019.1574042>
- [19] Jafarzadeh Ghouschi, S., Khazaeili, M., Amini, A., & Osgooei, E. (2019) Multi-criteria sustainable supplier selection using piecewise linear value function and fuzzy best-worst method. *J. Intell. Fuzzy Syst.*, 37, 2309-2325, <https://doi.org/10.3233/jifs-182609>
- [20] Amiri, M., Hashemi-Tabatabaei, M., Ghahremanloo, M., Keshavarz-Ghorabae, M., Zavadskas, E. K., & Banaitis, A. (2020). A new fuzzy BWM approach for evaluating and selecting a sustainable supplier in supply chain management. *International Journal of Sustainable Development & World Ecology*, 28(2), 125-142, <https://doi.org/10.1080/13504509.2020.1793424>
- [21] You, P., Guo, S., Zhao, H., & Zhao, H. (2017). Operation performance evaluation of power grid enterprise using a hybrid BWM-TOPSIS method. *Sustainability*, 9(12), 2329, <https://doi.org/10.3390/su9122329>
- [22] Zhao, H., Guo, S., & Zhao, H. (2018). Comprehensive performance assessment on various battery energy storage systems. *Energies*, 11(10), 2841, <https://doi.org/10.3390/en11102841>
- [23] Zhao, H., Zhao, H., & Guo, S. (2018). Comprehensive Performance Evaluation of Electricity Grid Corporations Employing a Novel MCDM Model. *Sustainability*, 10(7), 2130, <https://doi.org/10.3390/su10072130>
- [24] Kumar, A., Aswin, A., & Gupta, H. (2020). Evaluating green performance of the airports using hybrid BWM and VIKOR methodology. *Tourism Management*, 76, 103941, <https://doi.org/10.1016/j.tourman.2019.06.016>
- [25] Chen, Z., Ming, X., Zhou, T., Chang, Y., & Sun, Z. (2020). A hybrid framework integrating rough-fuzzy best-worst method to identify and evaluate user activity-oriented service requirement for smart product service system. *Journal of Cleaner Production*, 253, 119954, <https://doi.org/10.1016/j.jclepro.2020.119954>
- [26] Hussain, A., Chun, J., & Khan, M. (2020). A novel framework towards viable Cloud Service Selection as a Service (CSSaaS) under a fuzzy environment. *Future Generation Computer Systems*, 104, 74-91, <https://doi.org/10.1016/j.future.2019.09.043>
- [27] Maghsoodi, A. I., Rasoulipannah, H., López, L. M., Liao, H., & Zavadskas, E. K. (2019). Integrating interval-valued multi-granular 2-tuple linguistic BWM-CODAS approach with target-based attributes: Site selection for a construction project. *Computers & Industrial Engineering*, 139, 106147, <https://doi.org/10.1016/j.cie.2019.106147>
- [28] Rahimi, S., Hafezalkotob, A., Monavari, S. M., Hafezalkotob, A., & Rahimi, R. (2020). Sustainable landfill site selection for municipal solid waste based on a hybrid decision-making approach: Fuzzy group BWM-MULTIMOORA-GIS. *Journal of Cleaner Production*, 248, 119186, <https://doi.org/10.1016/j.jclepro.2019.119186>

- [29] Tabatabaei, M. H., Firouzabadi, S. M. A. K., Amiri, M., & Ghahremanloo, M. (2020). A combination of the fuzzy best-worst and VIKOR methods for prioritisation of Lean Six Sigma improvement projects. *International Journal of Business Continuity and Risk Management*, 10(4), 267-277, <https://ideas.repec.org/a/ids/ijbcrm/v10y2020i4p267-277.html>
- [30] Luo, S., & Xing, L. (2019). A hybrid decision-making framework for personnel selection using BWM, MABAC, and PROMETHEE. *International Journal of Fuzzy Systems*, 21(8), 2421-2434, <https://doi.org/10.1007/s40815-019-00745-4>
- [31] Ramezanali, A. K., Feizi, F., Jafarirad, A., & Lotfi, M. (2020). Application of Best-Worst method and Additive Ratio Assessment in mineral prospectivity mapping: A case study of vein-type copper mineralization in the Kuhshah-e-Urmak Area, Iran. *Ore Geology Reviews*, 117, 103268, <https://doi.org/10.1016/j.oregeorev.2019.103268>
- [32] van de Kaa, G., Fens, T., & Rezaei, J. (2018). Residential grid storage technology battles: A multi-criteria analysis using BWM. *Technology Analysis & Strategic Management*, 30(7), 1-13, <https://doi.org/10.1080/09537325.2018.1484441>
- [33] Jordan, G., Prevette, S., & Woodward, S. (2001). Analyzing, reviewing, and reporting performance data. In *The Performance-Based Management Handbook (Vol. 5)*. Performance-Based Management Special Interest Group, US Department of Energy.
- [34] El Dieb, A. S., & Kanaan, D. M. (2018). Ceramic waste powder as an alternative cement replacement: Characterization and evaluation. *Sustainable Materials and Technologies*, 17, e00063, <https://doi.org/10.1016/j.susmat.2018.e00063>
- [35] Alzard, M. H., El-Hassan, H., & El-Maaddawy, T. (2021). Environmental and economic life cycle assessment of recycled aggregates concrete in the United Arab Emirates. *Sustainability*, 13(18), 10348, <https://doi.org/10.3390/su131810348>
- [36] Kumar, A., & Soni, D. K. (2019a). Effect of calcium and chloride-based stabilizer on plastic properties of fine-grained soil. *International Journal of Pavement Research and Technology*, 12(5), 537-545, <https://doi.org/10.1007/s42947-019-0064-6>
- [37] Kumar, A., & Soni, D. K. (2020). Strength and microstructural characterisation of plastic soil under freeze and thaw cycles. *Indian Geotechnical Journal*, 50(3), 359-371, <https://doi.org/10.1007/s40098-019-00372-8>
- [38] Kumar, A., & Jain, A. (2021). Polypropylene fibre: A solution for problematic expansive soil. Elivapress. <https://www.elivapress.com/en/book/book-7842185352/>
- [39] Soundara, B., & Vilasini, P. P. (2015). Effect of egg shell powder on the properties of clay. Proceedings of 50th Indian Geotechnical Conference, Pune, Maharashtra, India. Retrieved from <https://scholar.google.co.in/citations?user=1fjTnkAAAAAJ&hl=en> (Accessed on 26/08/2021)
- [40] Kumar, A., & Soni, D. K. (2019b). Study of the mechanical behaviour of a clayey soil under normal and frozen conditions. *Slovak Journal of Civil Engineering*, 27(1), 29-35, <https://doi.org/10.2478/sjce-2019-0013>
- [41] Kumar, A., & Soni, D. K. (2022). Statistical analysis of fibre reinforced frozen soil. *Acta Scientiarum Polonorum Architectura*, 21(2), 3-9, <https://doi.org/10.22630/aspa.2022.21.2.9>
- [42] Kumar, A., & Jain, A. (2023). Penetration characteristics optimization and design of hilly rural road. *International Journal of Pavement Research and Technology*, 16(2), 1-15, <https://doi.org/10.1007/s42947-023-00284-0>
- [43] Zaimoğlu, A. S., Calik, Y., Akbulut, R. K., & Yetimoglu, T. (2016). A study on freeze-thaw behavior of randomly distributed fiber-reinforced soil. *Periodica Polytechnica Civil Engineering*, 60(1), 3-9, <https://doi.org/10.3311/PPci.7533>
- [44] Bayrak, O. U., Hattatoglu, F., & Hınıslioglu, S. (2010). Determination of modulus of rupture of pavement concrete with silica fume and fly ash using Taguchi technique. *International Journal of Civil and Structural Engineering*, 1(3), 518-533, <https://doi.org/10.6088/ijcser.00202010042>
- [45] Ross, J. P. (1988). Taguchi techniques for quality engineering (2nd ed.). McGraw-Hill. United States.
- [46] Taguchi G (1987) System of Experimental Design. Kraus International Publications, Vol. 1 and 2, White Plains, New York, USA.
- [47] El-Dieb, A. S., & Kanaan, D. M. (2018). Ceramic waste powder as an alternative cement replacement: Characterization and evaluation. *Sustainable Materials and Technologies*, 17, 1-11, <https://doi.org/10.1016/j.susmat.2018.e00063>