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IndetermSoft Set for Talent Training Quality Assessment in University Engineering Management under the Background of "Dual Carbon"

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Abstract: With the global push towards carbon neutrality, the need for sustainable engineering talent has never been greater. University engineering management programs must adapt to meet the evolving demands of the "Dual Carbon" strategy, which aims to achieve peak carbon emissions and carbon neutrality. This paper explores a comprehensive framework for assessing the quality of talent training in university engineering management under the "Dual Carbon" background. Key evaluation criteria include curriculum relevance, integration of sustainable technologies, interdisciplinary knowledge development, faculty expertise, industry collaboration, and student engagement in green initiatives. By utilizing Multi-Criteria Decision-Making (MCDM) methods, this study provides an objective assessment of various training models and their effectiveness in preparing graduates for the sustainable engineering sector. We use the IndetermSoft Set to deal with indeterminacy values in the criteria of this study. The IndetermSoft set is used with the SWARA method to obtain the criteria weights and the CoCoSo method to rank the alternatives.

Keywords: IndetermSoft Set; Dual Carbon; Talent Training; University Engineering Management; MCDM Methods.

1. Introduction

The transition to a low-carbon economy is reshaping industries, requiring a workforce with expertise in sustainable engineering, green technologies, and carbon-neutral solutions. Universities play a pivotal role in preparing future engineers who can integrate environmental considerations into engineering practices. Traditional engineering education, however, often lacks a dedicated focus on sustainability and carbon reduction strategies[1], [2]. The quality assessment of talent training programs in engineering management must evolve to ensure graduates are equipped with the necessary competencies to support the "Dual Carbon" initiative.

Engineering management bridges technical expertise with strategic decision-making, making it a critical discipline in driving sustainable development. Programs that integrate carbon neutrality principles provide students with the ability to manage projects with an emphasis on energy efficiency, environmental impact, and sustainable innovation[3], [4]. Evaluating these programs requires a structured approach that considers both academic and practical training dimensions, ensuring that students receive a holistic education aligned with industry demands.

To assess the effectiveness of talent training in engineering management under the "Dual Carbon" background, multiple factors must be considered. These include curriculum relevance to carbon neutrality, integration of green technologies, faculty expertise, research and innovation in sustainability, and student participation in industry-led green projects[5], [6]. A well-rounded evaluation framework can provide universities with insights into areas requiring enhancement to produce graduates who meet the needs of the evolving job market.

One of the most significant indicators of a successful talent training program is its connection with industry partners. Universities that collaborate with green energy companies, governmental organizations, and research institutions provide students with real-world exposure to sustainable engineering challenges[7], [8]. Practical training opportunities, such as internships and industry projects, enable students to apply theoretical knowledge to real sustainability problems, enhancing their employability and contribution to the carbon-neutral economy.

Advancements in digital tools, such as artificial intelligence, big data, and smart grid systems, are revolutionizing engineering education. Universities must integrate these technologies into their curriculum to provide students with the analytical skills needed for data-driven decision-making in carbon reduction strategies[9], [10]. Digital learning platforms, virtual labs, and AI-assisted simulations can enhance the effectiveness of engineering management training, making it more adaptable to sustainability challenges.

Multi-Criteria Decision-Making (MCDM) methods offer a systematic approach to evaluating the effectiveness of engineering management education under the "Dual Carbon" framework[11], [12]. MCDM methods can be employed to assess various training programs based on predefined criteria. The application of MCDM enables objective decision-making, providing universities with actionable insights for curriculum development and policy formulation[13], [14].

As the global commitment to carbon neutrality strengthens, universities must continuously adapt their engineering management programs to remain relevant. Future talent training must emphasize interdisciplinary collaboration, integrating knowledge from environmental science, policy, economics, and engineering. The growing importance of sustainability in engineering education calls for an ongoing reassessment of training methodologies to ensure that graduates possess the competencies required for the carbon-neutral future.

The main contributions of this study are organized as follows:

We use the IndetermSoft Set to deal with indeterminacy values in the main criteria values. This study has one indeterminacy values in the first criterion.

The proposed approach is applied three times to show the results of the indeterminacy values in the application.

The SWARA method is used to obtain the criteria weights based on the opinions of the experts and decision makers.

The CoCoSo method is used to rank the alternatives based on the criteria weights in the SWARA method.

2. MCDM Methodology with IndetermSoft Set

This part shows the steps of the MCDM methodology with the IndetermSoft set to compute the criteria weights and ranking the alternatives.

H is a non-empty subset of U, U is a discourse universe, and P(H) is the powerset of H. Suppose that A is a set of its values and that and is an attribute. A function F: A → (H) pertaining to the values of one or more attributes is known as an IndetermSoft Set (Function); set A contains some ambiguity[15], [16].
P(H) has some indeterminacy. Alternatively, if at least one attribute value $v \in A, then\ F(v) =$ indeterminate (uncertain, ambiguous, or not unique). or any mix of those three situations. An IndetermSoft Set, according to Smarandache, is a soft set that contains a given quantity of indeterminate (ambiguous, uncertain, alternate, conflicting) data or methodology.

Then we apply the steps of the SWARA methodology such as[17], [18]:

Ordering the criteria based on the opinion of the experts and decision makers.

Compute the coefficient values such as:

$$X_j = \begin{cases} 1 & if\ j = 1 \\ y_j + 1 & if\ j > 1 \end{cases} \tag{1}$$

Calculate the initial weights.

$$Z_j = \begin{cases} 1 & if\ j = 1 \\ \frac{Z_j}{X_j} & if\ j > 1 \end{cases} \tag{2}$$

The relative weights are computed such as:

$$w_j = \frac{Z_j}{\sum_{j=1}^{n} Z_j} \tag{3}$$

Then we show the steps of the CoCoSo method to rank the alternatives[19], [20].

The decision matrix is created based on the opinions of experts and decision makers.

The decision matrix is normalized such as:

$$r_{ij} = \frac{y_{ij} - \min_i y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \tag{4}$$

$$r_{ij} = \frac{\max_i y_{ij} - y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \tag{5}$$

The sum and product of the weighted decision matrix is computed such as:

$$A_i = \sum_{j=1}^{n} w_j r_{ij} \tag{6}$$

$$B_i = \sum_{j=1}^{n} \left(r_{ij}\right)^{w_j} \tag{7}$$

The relative weights of each alternatives is computed such as:

$$V_{i1} = \frac{A_i + B_i}{\sum_{i=1}^{m} (A_i + B_i)} \tag{8}$$

$$V_{i2} = \frac{A_i}{\min_i A_i} + \frac{B_i}{\min_i B_i} \tag{9}$$

$$V_{i3} = \frac{h(A_i) + (1-h)(B_i)}{\left(h \max_i A_i + (1-h) \max_i B_i\right)} \; 0 \le h \le 1 \tag{10}$$

The alternatives are ranked such as:

$$V_i = (V_{i1} V_{i2} V_{i3})^{\frac{1}{3}} + \frac{1}{3}(V_{i1} + V_{i2} + V_{i3}) \tag{11}$$

3. Application

This section shows the results of the application of the proposed approach to compute the criteria weights and ranking the alternatives.

The criteria of this study are organized as follows: Curriculum Relevance to Dual Carbon Goals: {Highly Relevant, Slightly Relevant}, Integration of Green and Low-Carbon Technologies: {Strongly Integrated}, Practical Training and Industry Collaboration {Extensive Collaboration}, Innovation and Research in Sustainable Engineering: {Highly Innovative}, Interdisciplinary Knowledge and Skill Development: {Comprehensive}, Faculty Expertise in Sustainable Development: {Expert Level}, Student Engagement in Green Engineering Projects: {Highly Engaged}, Employment Rate in Green Energy and Low-Carbon Industries {Very High}. The alternatives of this study are organized as follows: Traditional Engineering Management Program, Engineering Management with Focus on Green Technologies, Dual Carbon-Oriented Sustainable Engineering Program, Industry-Integrated Engineering Training Model, Research-Driven Engineering Management Education, Interdisciplinary Carbon-Neutral Engineering Program, International Collaboration-Based Green Engineering Program, Digital and Smart Engineering Management with a Sustainability Focus.

We show the results of the SWARA method. Experts are ranking the eight criteria based on the importance of these criteria.

We compute coefficient values using Eq. (1).

We calculate the initial weights using eq. (2).

The relative weights are computed using eq. (3) as shown in Table 1.

Table 1. The importance of the criteria.

	Importance
C_1	0.390795
C_2	0.302986
C_3	0.169799
C_4	0.084247
C_5	0.034217
C_6	0.01246
C_7	0.004177
C_8	0.00132

Then we show the results of the CoCoSo method. This study uses the IndetermSoft Set to deal with the indeterminacy in the values of the criteria. The first criterion has indeterminacy so, we apply the IndetermSoft Set with each value.

Highly Relevant

We created the decision matrix based on the opinions of three experts. Then we normalize the decision matrix using eq. (4 and 5) as shown in Table 2.

Then we show the weighted decision matrix and product weighted decision matrix as shown in tables 3 and 4. Then we compute the A_i and B_i values using eqs. (6 and 7).

The relative weight of each alternative is computed using eq. (8-10).

Then we rank the alternatives as shown in table 5.

Table 2. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.099303	0.009968	0.369299	1	1	0	0.938348	0.823847
A_2	0.212544	0.859457	0	0.003382	0.292104	1	1	0
A_3	0.408412	0.538998	0.369299	1	0.656165	0.351742	0.515083	0.850589
A_4	1	0	0.448259	0.077978	0	0.004076	0	1

A_5	0.67994	0.527785	1	0.643931	0.435823	0.253108	0.161011	0.250736
A_6	0	1	0.128494	0.086434	0.189615	0.373548	0.938348	0.009323
A_7	0.212544	0.250187	0.43845	0	0.104629	0.377624	0.07862	0.11212
A_8	0.403932	0.130077	0.417116	0.508268	0.53345	0.115549	0.090875	0.411923

Table 3. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.038807	0.00302	0.062707	0.084247	0.034217	0	0.00392	0.001087
A_2	0.083061	0.260403	0	0.000285	0.009995	0.01246	0.004177	0
A_3	0.159605	0.163309	0.062707	0.084247	0.022452	0.004383	0.002152	0.001123
A_4	0.390795	0	0.076114	0.006569	0	5.08E-05	0	0.00132
A_5	0.265717	0.159911	0.169799	0.054249	0.014913	0.003154	0.000673	0.000331
A_6	0	0.302986	0.021818	0.007282	0.006488	0.004654	0.00392	1.23E-05
A_7	0.083061	0.075803	0.074449	0	0.00358	0.004705	0.000328	0.000148
A_8	0.157855	0.039412	0.070826	0.04282	0.018253	0.00144	0.00038	0.000544

Table 4. The product weighed the decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.405526	0.247515	0.844386	1	1	0	0.999734	0.999744
A_2	0.545972	0.955148	0	0.619217	0.958765	1	1	0
A_3	0.704725	0.82923	0.844386	1	0.985686	0.987066	0.997233	0.999786
A_4	1	0	0.872629	0.806589	0	0.933736	0	1
A_5	0.860063	0.823964	1	0.963597	0.971982	0.983027	0.9924	0.998176
A_6	0	1	0.705812	0.813615	0.944693	0.987806	0.999734	0.993848
A_7	0.545972	0.657178	0.869357	0	0.925668	0.987939	0.989433	0.997116
A_8	0.701694	0.539034	0.862025	0.944581	0.978728	0.97347	0.990032	0.99883

Table 5. The rank of the alternatives.

	Ranks
A_1	6
A_2	4
A_3	8
A_4	1
A_5	7

A_6	3
A_7	2
A_8	5

Slightly Relevant

Then we normalize the decision matrix using eq. (4 and 5) as shown in Table 6.

Then we show the weighted decision matrix and product weighted decision matrix as shown in tables 7 and 8. Then we compute the A_i and B_i values using eqs. (6 and 7).

The relative weight of each alternative is computed using eq. (8-10).

Then we rank the alternatives as shown in table 9.

Table 6. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.198864	0.009968	0.369299	1	1	0	0.938348	0.823847
A_2	0.198864	0.859457	0	0.003382	0.292104	1	1	0
A_3	0	0.538998	0.369299	1	0.656165	0.351742	0.515083	0.850589
A_4	0.227273	0	0.448259	0.077978	0	0.004076	0	1
A_5	0.56993	0.527785	1	0.643931	0.435823	0.253108	0.161011	0.250736
A_6	1	1	0.128494	0.086434	0.189615	0.373548	0.938348	0.009323
A_7	0.207605	0.250187	0.43845	0	0.104629	0.377624	0.07862	0.11212
A_8	0.562937	0.130077	0.417116	0.508268	0.53345	0.115549	0.090875	0.411923

Table 7. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.077715	0.00302	0.062707	0.084247	0.034217	0	0.00392	0.001087
A_2	0.077715	0.260403	0	0.000285	0.009995	0.01246	0.004177	0
A_3	0	0.163309	0.062707	0.084247	0.022452	0.004383	0.002152	0.001123
A_4	0.088817	0	0.076114	0.006569	0	5.08E-05	0	0.00132
A_5	0.222726	0.159911	0.169799	0.054249	0.014913	0.003154	0.000673	0.000331
A_6	0.390795	0.302986	0.021818	0.007282	0.006488	0.004654	0.00392	1.23E-05
A_7	0.081131	0.075803	0.074449	0	0.00358	0.004705	0.000328	0.000148
A_8	0.219993	0.039412	0.070826	0.04282	0.018253	0.00144	0.00038	0.000544

Table 8. The product weighed the decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.53196	0.247515	0.844386	1	1	0	0.999734	0.999744
A_2	0.53196	0.955148	0	0.619217	0.958765	1	1	0
A_3	0	0.82923	0.844386	1	0.985686	0.987066	0.997233	0.999786
A_4	0.560457	0	0.872629	0.806589	0	0.933736	0	1
A_5	0.802743	0.823964	1	0.963597	0.971982	0.983027	0.9924	0.998176
A_6	1	1	0.705812	0.813615	0.944693	0.987806	0.999734	0.993848
A_7	0.540979	0.657178	0.869357	0	0.925668	0.987939	0.989433	0.997116
A_8	0.798879	0.539034	0.862025	0.944581	0.978728	0.97347	0.990032	0.99883

Table 9. The rank of the alternatives.

	Ranks
A_1	6
A_2	4
A_3	8
A_4	1
A_5	7
A_6	3
A_7	2
A_8	5

Highly Relevant and Slightly Relevant

Then we normalize the decision matrix using eq. (4 and 5) as shown in Table 10.

Then we show the weighted decision matrix and product weighted decision matrix as shown in tables 11 and 12. Then we compute the A_i *and* B_i values using eqs. (6 and 7).

The relative weight of each alternative is computed using eq. (8-10).

Then we rank the alternatives as shown in table 13.

Table 10. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.369299	0.009968	0.369299	1	1	0	0.938348	0.823847
A_2	0	0.859457	0	0.003382	0.292104	1	1	0
A_3	0.369299	0.538998	0.369299	1	0.656165	0.351742	0.515083	0.850589
A_4	0.251103	0	0.448259	0.077978	0	0.004076	0	1

A_5	0.43845	0.527785	1	0.643931	0.435823	0.253108	0.161011	0.250736
A_6	0.369299	1	0.128494	0.086434	0.189615	0.373548	0.938348	0.009323
A_7	0.009809	0.250187	0.43845	0	0.104629	0.377624	0.07862	0.11212
A_8	1	0.130077	0.417116	0.508268	0.53345	0.115549	0.090875	0.411923

Table 11. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.14432	0.00302	0.062707	0.084247	0.034217	0	0.00392	0.001087
A_2	0	0.260403	0	0.000285	0.009995	0.01246	0.004177	0
A_3	0.14432	0.163309	0.062707	0.084247	0.022452	0.004383	0.002152	0.001123
A_4	0.09813	0	0.076114	0.006569	0	5.08E-05	0	0.00132
A_5	0.171344	0.159911	0.169799	0.054249	0.014913	0.003154	0.000673	0.000331
A_6	0.14432	0.302986	0.021818	0.007282	0.006488	0.004654	0.00392	1.23E-05
A_7	0.003833	0.075803	0.074449	0	0.00358	0.004705	0.000328	0.000148
A_8	0.390795	0.039412	0.070826	0.04282	0.018253	0.00144	0.00038	0.000544

Table 12. The product weighed the decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.677538	0.247515	0.844386	1	1	0	0.999734	0.999744
A_2	0	0.955148	0	0.619217	0.958765	1	1	0
A_3	0.677538	0.82923	0.844386	1	0.985686	0.987066	0.997233	0.999786
A_4	0.582728	0	0.872629	0.806589	0	0.933736	0	1
A_5	0.724543	0.823964	1	0.963597	0.971982	0.983027	0.9924	0.998176
A_6	0.677538	1	0.705812	0.813615	0.944693	0.987806	0.999734	0.993848
A_7	0.164109	0.657178	0.869357	0	0.925668	0.987939	0.989433	0.997116
A_8	1	0.539034	0.862025	0.944581	0.978728	0.97347	0.990032	0.99883

Table 13. The rank of the alternatives.

	Ranks
A_1	6
A_2	4
A_3	8
A_4	1
A_5	7

A_6	3
A_7	2
A_8	5

5. Conclusions

The effectiveness of engineering management talent training under the "Dual Carbon" background is essential for equipping future professionals with the skills needed to drive sustainable innovation. A comprehensive assessment framework that evaluates curriculum relevance, industry collaboration, faculty expertise, and student engagement in green initiatives is necessary for continuous improvement in educational programs. Universities must adopt modern teaching strategies, integrate digital technologies, and foster partnerships with industries committed to carbon neutrality. By leveraging advanced assessment methodologies such as MCDM, institutions can refine their programs to align with the sustainability goals of the global economy. The IndetermSoft set is used to deal with indeterminacy values in the sub criteria values. This study used the SWARA method to obtain the criteria weights and the CoCoSo method to rank the alternatives. Eight criteria and eight alternatives are used in this study. The results show alternative 3 is the best and alternative 4 is the worst.

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