



Measuring the Efficiency of Competitive Sports Talent Cultivation in Universities through the Synergy of Sports and Education using SuperHyperSoft Set

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Abstract: This work suggests the decision-making process for evaluating the cultivating competitive sports talent in universities under the integration of sports and education. We used the neutrosophic sets to deal with the uncertain and vague information. Two methods are used under the neutrosophic sets such as MEREC and TOPSIS. We used the MEREC method to compute the criteria weights and the TOPSIS method to rank the alternatives. These methods are used with the SuperHyperSoft set to treat the various criteria and sub criteria. We proposed nine groups of the SuperHyperSoft set to rank the alternatives. The ranks of alternatives of these groups are stable. We used seven criteria and seven alternatives.

Keywords: Neutrosophic Set; SuperHyperSoft Set; HyperSoft Set; Sports Talent; Education.

1. Introduction and Related Works

The cultivation of competitive sports talent in universities has become a crucial aspect of higher education, particularly under the integration of sports and education policies. These policies aim to strike a balance between academic success and athletic excellence, ensuring that student-athletes receive structured training while also achieving educational milestones[1], [2]. However, evaluating the efficiency of such programs requires a multi-criteria decision-making (MCDM) approach to account for the diverse and complex factors influencing sports talent development.

Universities implement various sports talent development models, ranging from elite sports academies to comprehensive universities with strong sports programs. The success of these models depends on multiple interrelated factors, including training facilities, coaching expertise, financial support, academic flexibility, competition exposure, athlete development programs, and sports science investments[3], [4]. Traditional evaluation methods often fail to provide an objective and quantifiable assessment of these factors. Therefore, MCDM methodologies are essential to systematically analyze, and rank university programs based on multiple conflicting criteria.

Fuzzy sets (FS) were popular when Zadeh [5] introduced the idea. However, the FS only uses the membership degree to indicate the uncertainty of decision information. By adding a non-membership degree, Atanassov [6] introduced intuitionistic fuzzy sets (IFS), which may successfully address issues that FS is unable to resolve. Interval IFS (IIFS) was proposed by Atanassov[7], who expanded the IFS to interval numbers. Hesitant fuzzy sets (HFS), as defined by Torra [8], are a good way to handle the ambiguity brought on by the decision maker's hesitancy. Generalized HFS and double HFS were defined by Qian et al[9].

Information that is inconsistent and discontinuous cannot be handled by FS and its extension sets. This shortcoming is simply compensated for by the rise of the Neutrosophic sets (NS). Smarandache [10] introduced the idea of the NS, which represents fuzzy information using the truth-membership function, the indeterminacy-membership function, and the falsity-membership function—all of which are independent of one another.

In real-world applications, the NS is very inconvenient, even though it broadens the representation of ambiguous information. Ye [11] introduced the idea of simplified Neutrosophic sets (SNS) to streamline the NS, pointing out that SNS include both interval Neutrosophic sets (INS) and single-valued Neutrosophic sets (SVNS). Ye [12] suggested cosine similarity assessment of SNS and aggregation operators.

SNS operations were enhanced in the literature by Peng, Wang et al. [13] introduced single-valued triangular Neutrosophic sets (SVTNS) by combining triangular fuzzy numbers with SVNS. Wang et al. [14] considered the competing criteria, expanded the VIKOR model to SVTNS, and provided the precise procedures for using the approach.

The single-valued triangular Neutrosophic number (SVTNN), which is an extension of the single-valued Neutrosophic number, can successfully manage the enormous quantity of erroneous, partial, and inconsistent information involved in choosing green suppliers. To address the issue of MCDM, Fan et al. [15] suggested a novel aggregate operator that considers the benefits of the single-valued triangular Neutrosophic number.

The criteria's interrelationships and priority connection are taken into consideration by the new aggregate operator. Their presented the Dombi operations to increase the flexibility of the new aggregate operator. The SVTN Dombi prioritized normalized Bonferroni mean operator is proposed by combining the Dombi operations with the prioritized average operator and the Bonferroni mean operator.

The remainder of the document is organized as follows: The second portion provides a detailed introduction to the SVTNS, the suggested approach to computing the criteria weights and ranks the alternatives are suggested in the third part. A model for choosing appropriate alternatives is constructed in the fourth segment. The conclusion is the final section.

2. Single-Valued Triangular Neutrosophic Sets (SVNSs)

The SVTNS is used to deal with uncertainties and vague information in the decision-making process. This section shows the definitions of SVTNSs[15].

Definition 1

We can define the SVNNSs by three functions such as truth, indeterminacy, and falsity.

$$A = \{(x, T_A(x), I_A(x), F_A(x)) | x \in X\} \tag{1}$$

$$T_A(x) = (T_A^1(x), T_A^2(x), T_A^3(x)) \tag{2}$$

$$I_A(x) = (I_A^1(x), I_A^2(x), I_A^3(x)) \tag{3}$$

$$F_A(x) = (F_A^1(x), F_A^2(x), F_A^3(x)) \tag{4}$$

$$0 \leq T_A^3(x) + I_A^3(x) + F_A^3(x) \leq 3 \tag{5}$$

We can define the SVTN number as:

$$A = \left((T_A^1(x), T_A^2(x), T_A^3(x)), (I_A^1(x), I_A^2(x), I_A^3(x)), (F_A^1(x), F_A^2(x), F_A^3(x)) \right)$$

Definition 2

Let two SVTNNs as:

$$A_1 = \left((T_{A_1}^1(x), T_{A_1}^2(x), T_{A_1}^3(x)), (I_{A_1}^1(x), I_{A_1}^2(x), I_{A_1}^3(x)), (F_{A_1}^1(x), F_{A_1}^2(x), F_{A_1}^3(x)) \right)$$

$$A_2 = \left((T_{A_2}^1(x), T_{A_2}^2(x), T_{A_2}^3(x)), (I_{A_2}^1(x), I_{A_2}^2(x), I_{A_2}^3(x)), (F_{A_2}^1(x), F_{A_2}^2(x), F_{A_2}^3(x)) \right)$$

and their operations can be defined as:

$$A_1 \oplus A_2 = \left(\begin{matrix} \left(T_{A_1}^1(x) + T_{A_2}^1(x) - T_{A_1}^1(x)T_{A_2}^1(x), \right. \\ \left. T_{A_1}^2(x) + T_{A_2}^2(x) - T_{A_1}^2(x)T_{A_2}^2(x), \right. \\ \left. T_{A_1}^3(x) + T_{A_2}^3(x) - T_{A_1}^3(x)T_{A_2}^3(x) \right) \\ \left(I_{A_1}^1(x)I_{A_2}^1(x), I_{A_1}^2(x)I_{A_2}^2(x), I_{A_1}^3(x)I_{A_2}^3(x) \right) \\ \left(F_{A_1}^1(x)F_{A_2}^1(x), F_{A_1}^2(x)F_{A_2}^2(x), F_{A_1}^3(x)F_{A_2}^3(x) \right) \end{matrix} \right) \tag{6}$$

$$A_1 \otimes A_2 = \left(\begin{matrix} \left(T_{A_1}^1(x)T_{A_2}^1(x), T_{A_1}^2(x)T_{A_2}^2(x), T_{A_1}^3(x)T_{A_2}^3(x) \right) \\ \left(I_{A_1}^1(x) + I_{A_2}^1(x) - I_{A_1}^1(x)I_{A_2}^1(x), \right. \\ \left. I_{A_1}^2(x) + I_{A_2}^2(x) - I_{A_1}^2(x)I_{A_2}^2(x), \right. \\ \left. I_{A_1}^3(x) + I_{A_2}^3(x) - I_{A_1}^3(x)I_{A_2}^3(x) \right) \\ \left(F_{A_1}^1(x) + F_{A_2}^1(x) - F_{A_1}^1(x)F_{A_2}^1(x), \right. \\ \left. F_{A_1}^2(x) + F_{A_2}^2(x) - F_{A_1}^2(x)F_{A_2}^2(x), \right. \\ \left. F_{A_1}^3(x) + F_{A_2}^3(x) - F_{A_1}^3(x)F_{A_2}^3(x) \right) \end{matrix} \right) \tag{7}$$

$$\nabla_{A_1} = \left(\begin{array}{c} \left(\left(1 - \left(1 - T_{A_1}^1(x) \right)^\nabla, 1 - \left(1 - T_{A_1}^2(x) \right)^\nabla, 1 - \left(1 - T_{A_1}^3(x) \right)^\nabla \right), \right. \\ \left. \left(\left(I_{A_1}^1(x) \right)^\nabla, \left(I_{A_1}^2(x) \right)^\nabla, \left(I_{A_1}^3(x) \right)^\nabla \right), \right. \\ \left. \left(\left(F_{A_1}^1(x) \right)^\nabla, \left(F_{A_1}^2(x) \right)^\nabla, \left(F_{A_1}^3(x) \right)^\nabla \right) \right) \quad (8)$$

$$A_1^\nabla = \left(\begin{array}{c} \left(\left(T_{A_1}^1(x) \right)^\nabla, \left(T_{A_1}^2(x) \right)^\nabla, \left(T_{A_1}^3(x) \right)^\nabla \right), \\ \left(1 - \left(1 - I_{A_1}^1(x) \right)^\nabla, 1 - \left(1 - I_{A_1}^2(x) \right)^\nabla, 1 - \left(1 - I_{A_1}^3(x) \right)^\nabla \right), \\ \left(1 - \left(1 - F_{A_1}^1(x) \right)^\nabla, 1 - \left(1 - F_{A_1}^2(x) \right)^\nabla, 1 - \left(1 - F_{A_1}^3(x) \right)^\nabla \right) \end{array} \right) \quad (9)$$

Definition 3

The score function can be defined as:

$$S(A) = \frac{1}{12} \left[\begin{array}{c} 8 + \left(T_{A_1}^1(x) + 2T_{A_1}^2(x) + T_{A_1}^3(x) \right) - \\ \left(I_{A_1}^1(x) + 2I_{A_1}^2(x) + I_{A_1}^3(x) \right) - \\ \left(F_{A_1}^1(x) + 2F_{A_1}^2(x) + F_{A_1}^3(x) \right) \end{array} \right] \quad (10)$$

3. Suggested Approach

This section shows the steps of the suggested approach. We used the MEREC method to compute the criteria weights and the TOPSIS method to rank the alternatives. These methods are used under the SVTNSs to deal with uncertainty information.

SuperHyperSoft Set (SHSS)

SHSS is an extension of the hyper soft set. It is used to obtain the relations between the criteria and sub criteria[16], [17]. Let the universe set $U = \{A_1, A_2, \dots, A_n\}$. The power set of U is a $P(U)$ and R_1, R_2, R_3 are select as a criteria. $P(R_1) \times P(R_2)$ and $P(R_3)$ are powersets of R_1, R_2, R_3

Let $F: P(R_1) \times P(R_2) \times P(R_3) \rightarrow P(R)$ where \times refers to cartesian product, and this called SHSS over R .

$$P(R_1) \times P(R_2) \times P(R_3) = \left\{ \begin{array}{c} \{R_{11}\}, \{R_{12}\}, \{R_{11}, R_{12}\} \times \\ \{R_{21}\}, \{R_{22}\}, \{R_{21}, R_{22}\} \times \\ \{R_{31}\}, \{R_{32}\}, \{R_{33}\}, \{R_{31}, R_{32}\}, \{R_{31}, R_{33}\}, \\ \{R_{32}, R_{33}\}, \{R_{31}, R_{32}, R_{33}\} \end{array} \right\}$$

1. Build the decision matrix.
2. Normalize the decision matrix.

$$y_{ij} = \begin{cases} \frac{\min x_{ij}}{x_{ij}} & \text{if } j \in B \\ \frac{x_{ij}}{\max x_{ij}} & \text{if } j \in C \end{cases} \quad (11)$$

3. Compute the overall performance of the alternatives.

$$R_i = \ln \left(1 + \left(\frac{1}{m} \sum_j |\ln(y_{ij})| \right) \right) \quad (12)$$

4. Compute the performance of the alternatives by deleting each criterion.

$$R_{ij} = \ln \left(1 + \left(\frac{1}{m} \sum_{k, k \neq j} |\ln(y_{ik})| \right) \right) \quad (13)$$

5. Obtain the summation of absolute deviations.

$$G_j = \sum_i |R_{ij} - R_i| \quad (14)$$

6. Compute the criteria weights.

$$w_j = \frac{G_j}{\sum_j G_j} \quad (15)$$

TOPSIS Method

This part applies the steps of the TOPIS method to rank the alternatives.

1. Compute the normalization matrix

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^i x_{ij}^2} \quad (16)$$

2. Compute the weighted normalized matrix

$$v_{ij} = w_j r_{ij} \quad (17)$$

3. Compute the ideal and non-ideal solution

$$A^+ = \left\{ \begin{array}{l} (\max v_{ij} \text{ for positive criterion} , \\ (\min v_{ij} \text{ for cost criterion}) \end{array} \right\} \quad (18)$$

$$A^- = \left\{ \begin{array}{l} (\min v_{ij} \text{ for positive criterion} , \\ (\max v_{ij} \text{ for cost criterion}) \end{array} \right\} \quad (19)$$

4. Compute the separation measures

$$Q_i^+ = \sum_{j=1}^n (v_{ij} - v_i^+)^2 \quad (20)$$

$$Q_i^- = \sum_{j=1}^n (v_{ij} - v_i^-)^2$$

5. Compute the relative closeness values

$$F_i = \frac{Q_i^-}{Q_i^- + Q_i^+} \quad (21)$$

4. Results and Discussion

This section shows the results of the proposed approach to compute the criteria and ranks the alternatives. We invited three experts to evaluate the criteria and alternatives. We gathered seven criteria and seven alternatives.

The criteria: Financial & Scholarship Support {Low, Medium, High}

Coaching Quality & Expertise {less than 0.5, between 0.5 and 0.7, more than 0.7}

Competition Exposure & Performance {medals are less than 2, between 2 and 6, more than 6}

Athlete Development Programs {adjustable, non-adjustable}

Sports Science & Injury Prevention {sufficient and in sufficient}

Academic-Sports Balance {optimal, non-optimal}

Training Facilities & Infrastructure {low quality and high quality}

The alternatives: Private Universities with Sports Excellence Programs, Public Universities with Government Support, Specialized Sports Academies, Comprehensive Universities with Strong Sports Programs, Community-Based Sports Talent Development Programs, International University Exchange Sports Programs, Elite Sports Universities

1. We build the decision matrix between the criteria and the alternatives as shown in Table 1 using the SVTNNs. Then we obtain crisp values by score function. Then we combine these values into one matrix.
2. Eq. (11) is used to normalize the decision matrix as shown in Table 2.
3. Eq. (12) is used to compute the overall performance of the alternatives.
4. Eq. (13) is used to compute the performance of the alternatives by deleting each criterion.
5. Eq. (14) is used to obtain the summation of absolute deviations.
6. Eq. (15) is used to compute the criteria weights as shown in Table 3.

Table 1. The decision matrix.

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇
A ₁	<(0.42,0.53,0.71), (0.38,0.45,0.53), (0.21,0.34,0.46)>	<(0.50,0.55,0.64), (0.25,0.37,0.42), (0.20,0.29,0.31)>	<(0.75,0.84,0.91), (0.54,0.62,0.67), (0.47,0.57,0.61)>	<(0.85,0.89,0.94), (0.65,0.67,0.75), (0.61,0.69,0.76)>	<(0.42,0.52,0.81), (0.41,0.45,0.58), (0.34,0.42,0.61)>	<(0.64,0.69,0.85), (0.34,0.45,0.52), (0.21,0.29,0.38)>	<(0.54,0.68,0.72), (0.45,0.48,0.51), (0.35,0.39,0.42)>
A ₂	<(0.42,0.53,0.71), (0.38,0.45,0.53), (0.21,0.34,0.46)>	<(0.54,0.68,0.72), (0.45,0.48,0.51), (0.35,0.39,0.42)>	<(0.64,0.69,0.85), (0.34,0.45,0.52), (0.21,0.29,0.38)>	<(0.42,0.52,0.81), (0.41,0.45,0.58), (0.34,0.42,0.61)>	<(0.85,0.89,0.94), (0.65,0.67,0.75), (0.61,0.69,0.76)>	<(0.75,0.84,0.91), (0.54,0.62,0.67), (0.47,0.57,0.61)>	<(0.42,0.53,0.71), (0.38,0.45,0.53), (0.21,0.34,0.46)>
A ₃	<(0.50,0.55,0.64), (0.25,0.37,0.42), (0.20,0.29,0.31)>	<(0.75,0.84,0.91), (0.54,0.62,0.67), (0.47,0.57,0.61)>	<(0.85,0.89,0.94), (0.65,0.67,0.75), (0.61,0.69,0.76)>	<(0.42,0.52,0.81), (0.41,0.45,0.58), (0.34,0.42,0.61)>	<(0.64,0.69,0.85), (0.34,0.45,0.52), (0.21,0.29,0.38)>	<(0.50,0.55,0.64), (0.25,0.37,0.42), (0.20,0.29,0.31)>	<(0.50,0.55,0.64), (0.25,0.37,0.42), (0.20,0.29,0.31)>
A ₄	<(0.85,0.89,0.94), (0.65,0.67,0.75), (0.61,0.69,0.76)>	<(0.75,0.84,0.91), (0.54,0.62,0.67), (0.47,0.57,0.61)>	<(0.50,0.55,0.64), (0.25,0.37,0.42), (0.20,0.29,0.31)>	<(0.42,0.53,0.71), (0.38,0.45,0.53), (0.21,0.34,0.46)>	<(0.54,0.68,0.72), (0.45,0.48,0.51), (0.35,0.39,0.42)>	<(0.42,0.53,0.71), (0.38,0.45,0.53), (0.21,0.34,0.46)>	<(0.75,0.84,0.91), (0.54,0.62,0.67), (0.47,0.57,0.61)>

A ₆	1	1	1.101974	1.145285	1.212719	1.057971	1.006091
A ₇	1.155636	1.074247	1.092654	1.305921	1.129934	1.05947	1.14467

Table 3. The criteria weights.

Criteria	Weights
C ₁	0.062754
C ₂	0.068514
C ₃	0.048278
C ₄	0.047335
C ₅	0.047185
C ₆	0.06656
C ₇	0.659374

TOPSIS Method

In this part, we rank the alternatives by 8 groups of the SHSS. We proposed 8 groups of SHSS values to rank the alternatives as:

{Low, Medium, High}

{less than 0.5, between 0.5 and 0.7, more than 0.7}

{medals are less than 2, between 2 and 6, more than 6}

{adjustable, non-adjustable}

{suffice and in sufficient}

{optimal, non-optimal}

{low quality and high quality}

Group 1: {Low}, {less than 0.5}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 2: {Medium}, {less than 0.5}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 3: {High}, {less than 0.5}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 4: {Low}, {between 0.5 and 0.7}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 5: {Medium}, {between 0.5 and 0.7}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 6: {High}, {between 0.5 and 0.7}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 7: {Low}, {more than 0.7}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 8: {Medium}, {more than 0.7}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 9: {High}, {more than 0.7}, {medals are more than 6}, {adjustable}, {sufficient}, {optimal}, {high quality}

Group 1

1. Eq. (16) is used to compute the normalization matrix as in Fig 1.
2. Eq. (17) is used to compute the weighted normalized matrix as in Fig 2.
3. Eqs. (18 and 19) are used to compute the ideal and non-ideal solution
4. Eq. (20) is used to compute the separation measures
5. Eq. (21) is used to compute the relative closeness values

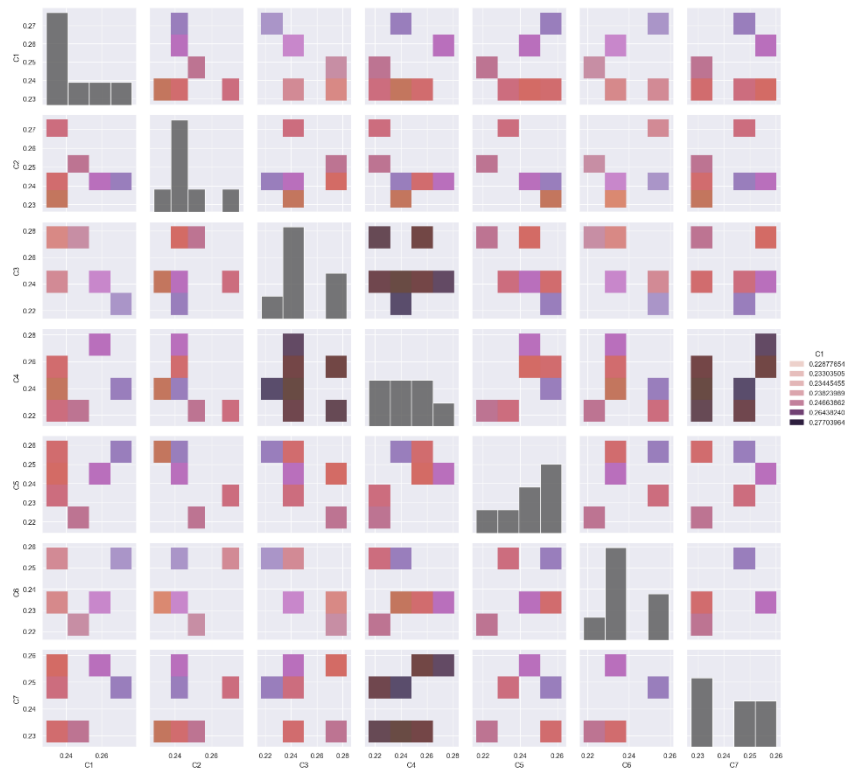


Fig 1. The normalization matrix.

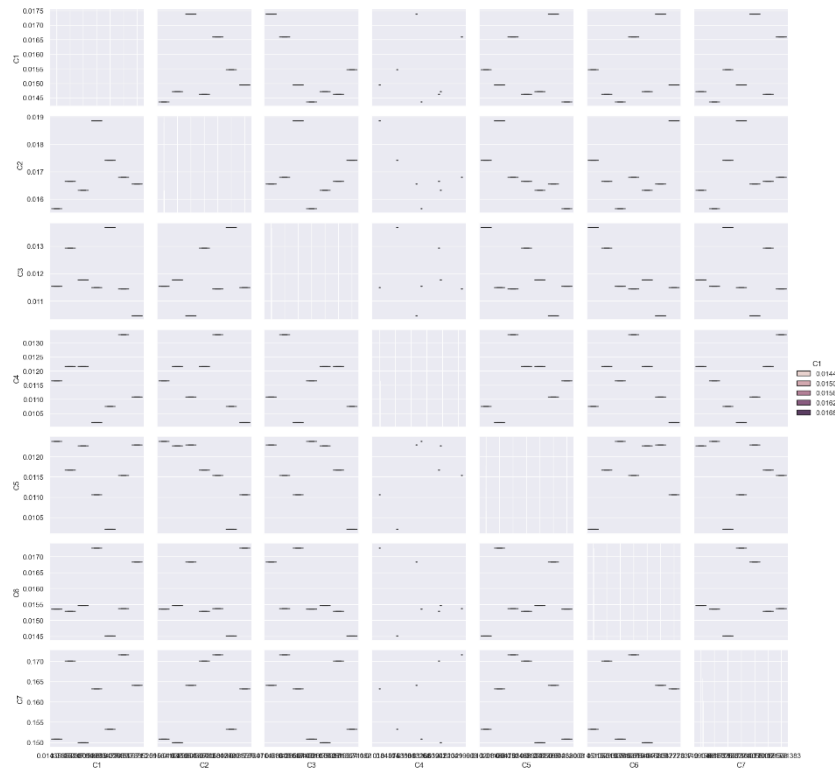


Fig 2. The weighted normalization matrix.

Group 2

The normalization matrix as shown in Fig 3.

The weighted normalized matrix as shown in Fig 4.

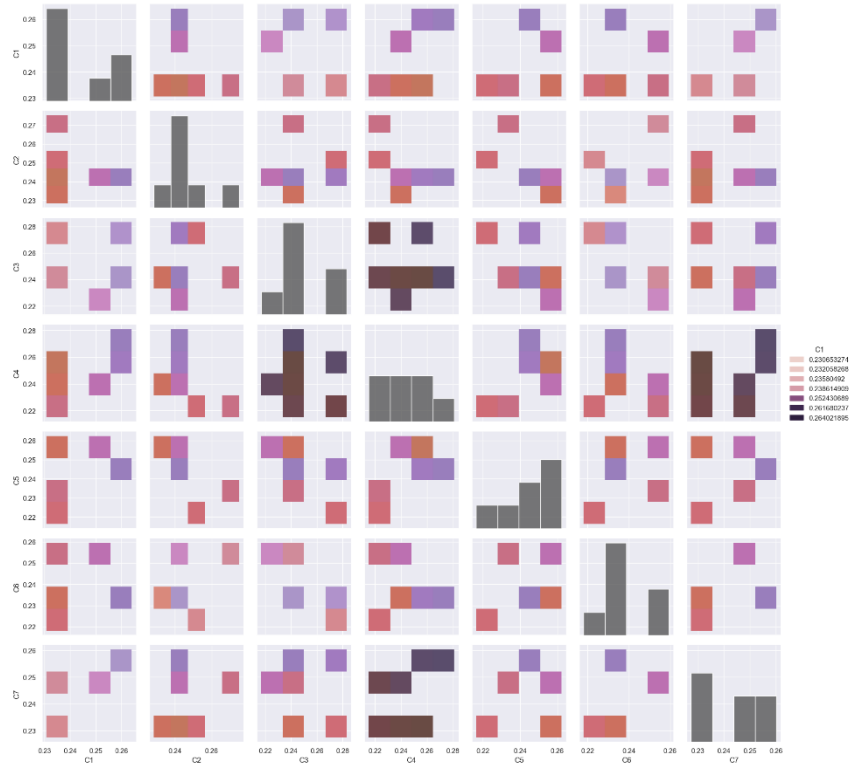


Fig 3. The normalization matrix.

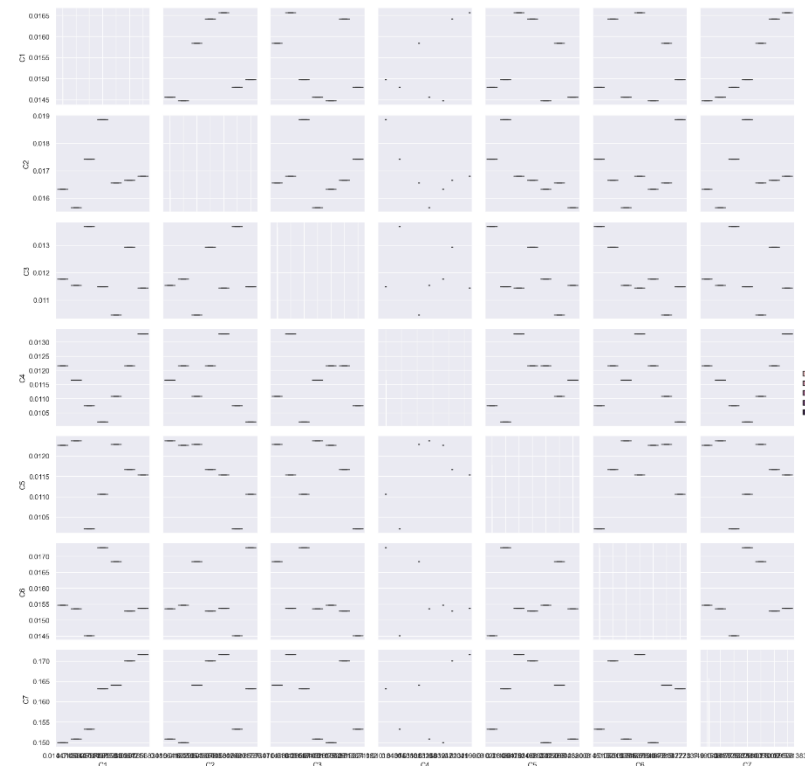


Fig 4. The weighted normalization matrix.

Group 3

The normalization matrix as shown in Fig 5.

The weighted normalized matrix as shown in Fig 6.

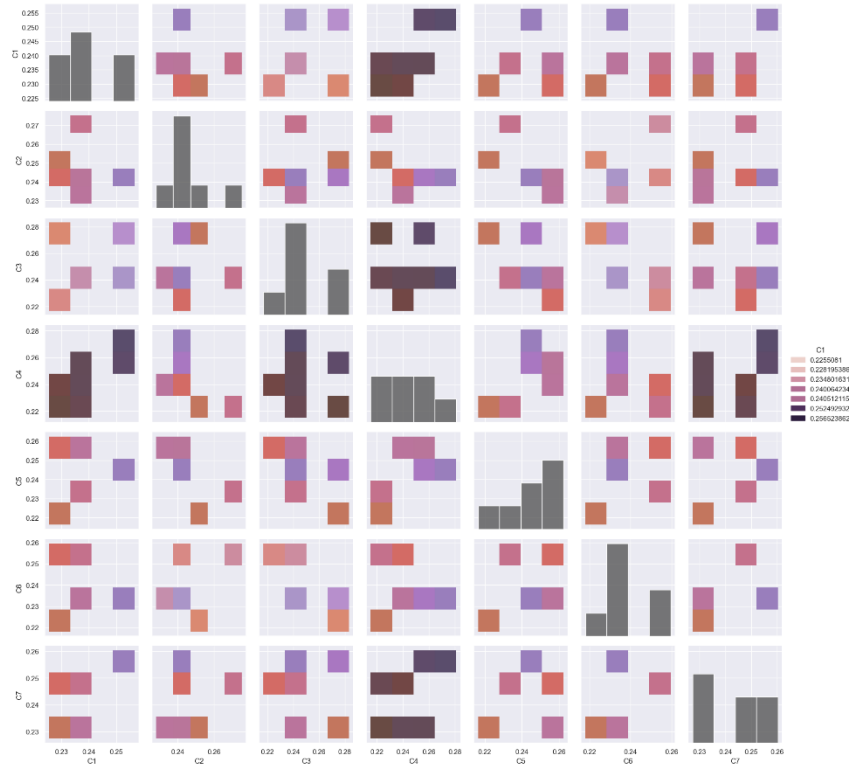


Fig 5. The normalization matrix.

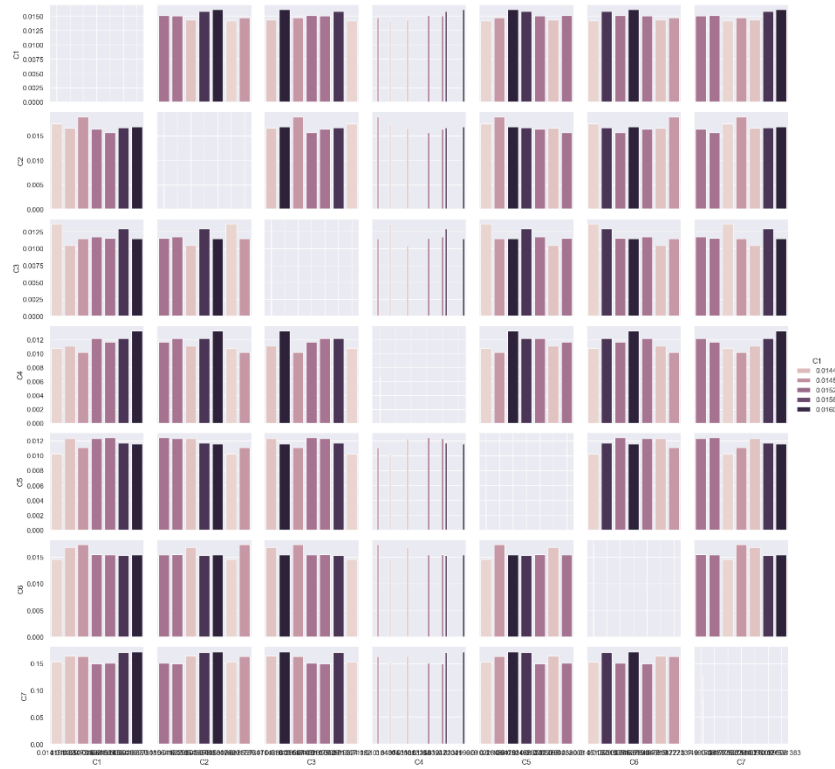


Fig 6. The weighted normalization matrix.

Group 4

The normalization matrix as shown in Fig 7.

The weighted normalized matrix as shown in Fig 8.

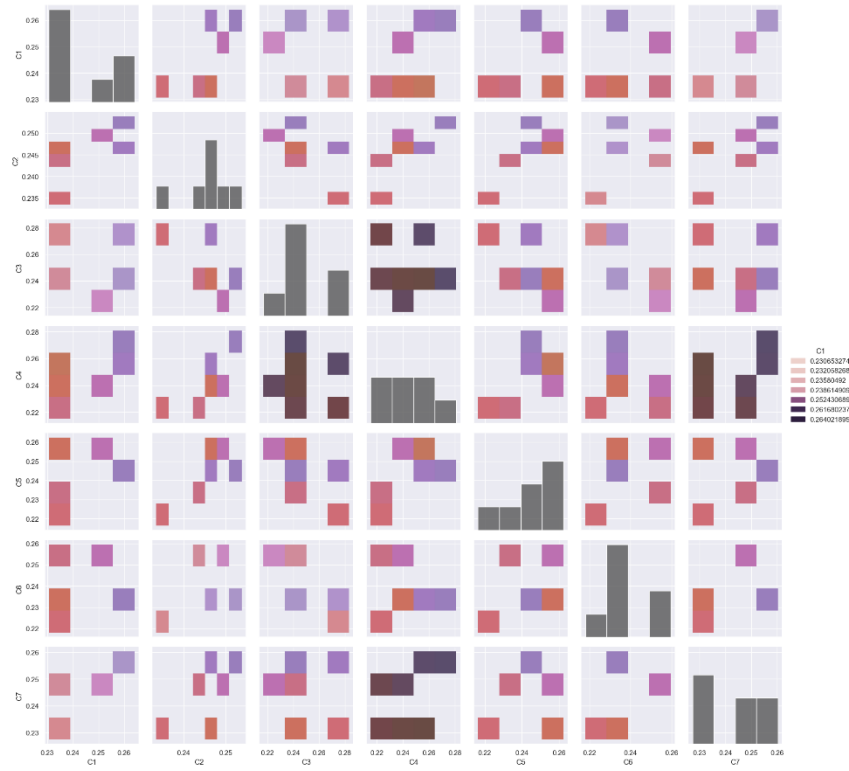


Fig 7. The normalization matrix.

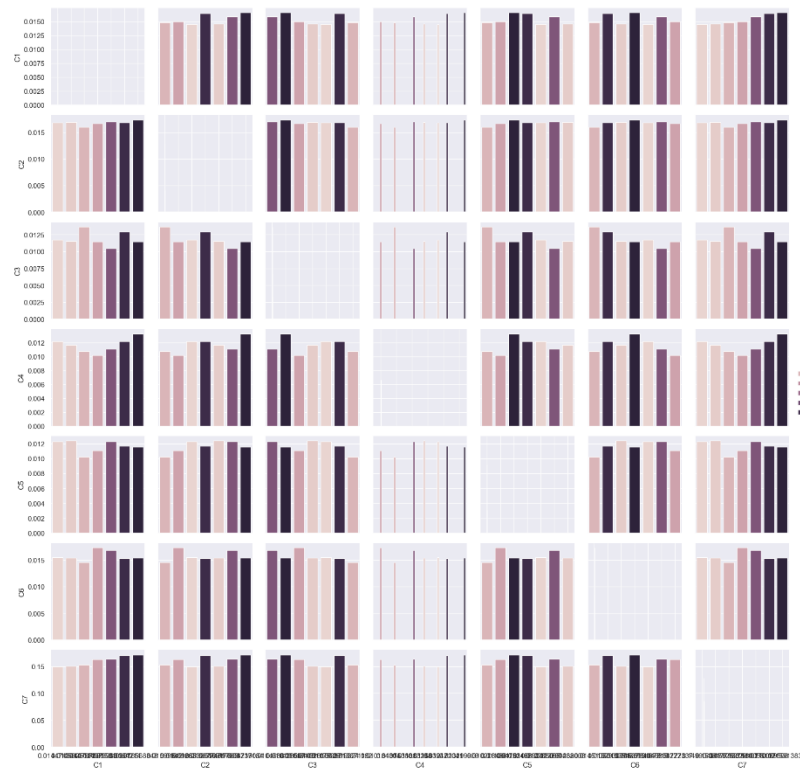


Fig 8. The weighted normalization matrix.

Group 5

The normalization matrix as shown in Fig 9.

The weighted normalized matrix as shown in Fig 10.

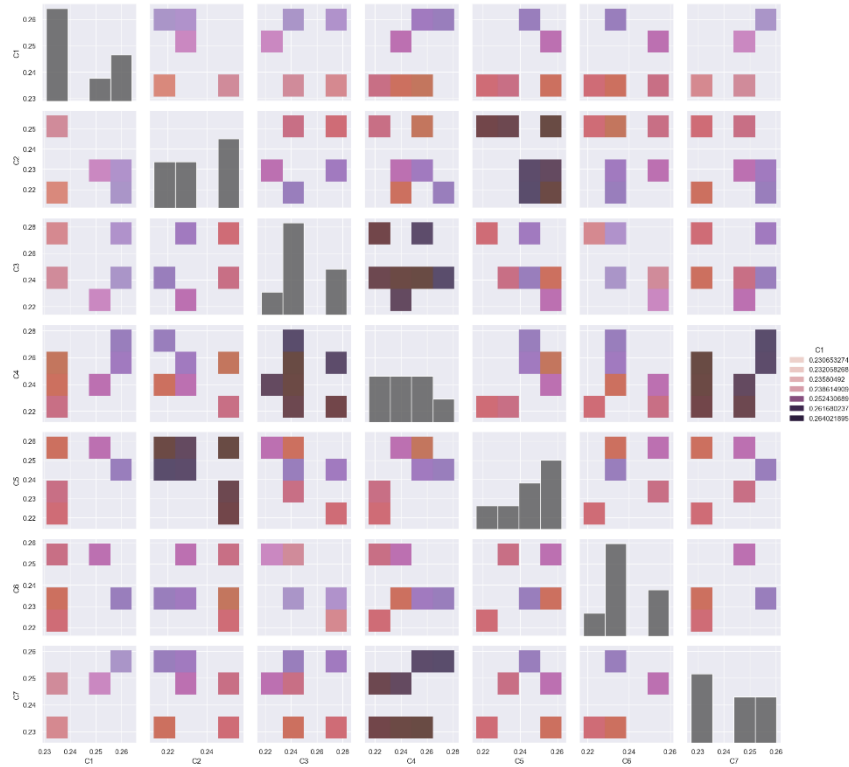


Fig 9. The normalization matrix.

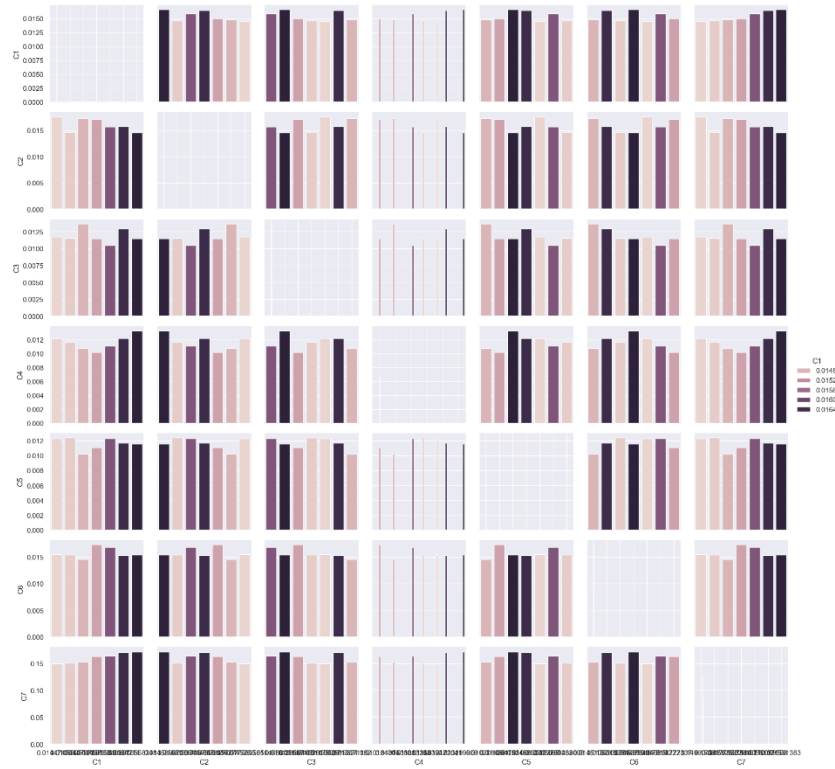


Fig 10. The weighted normalization matrix.

Group 6

The normalization matrix as shown in Fig 11.

The weighted normalized matrix as shown in Fig 12.

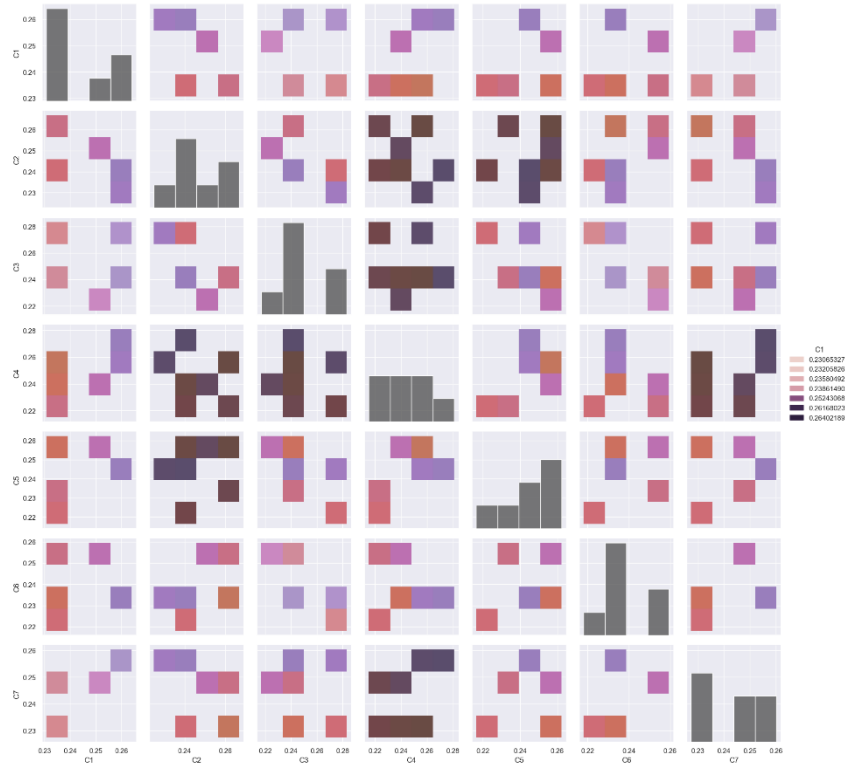


Fig 11. The normalization matrix.

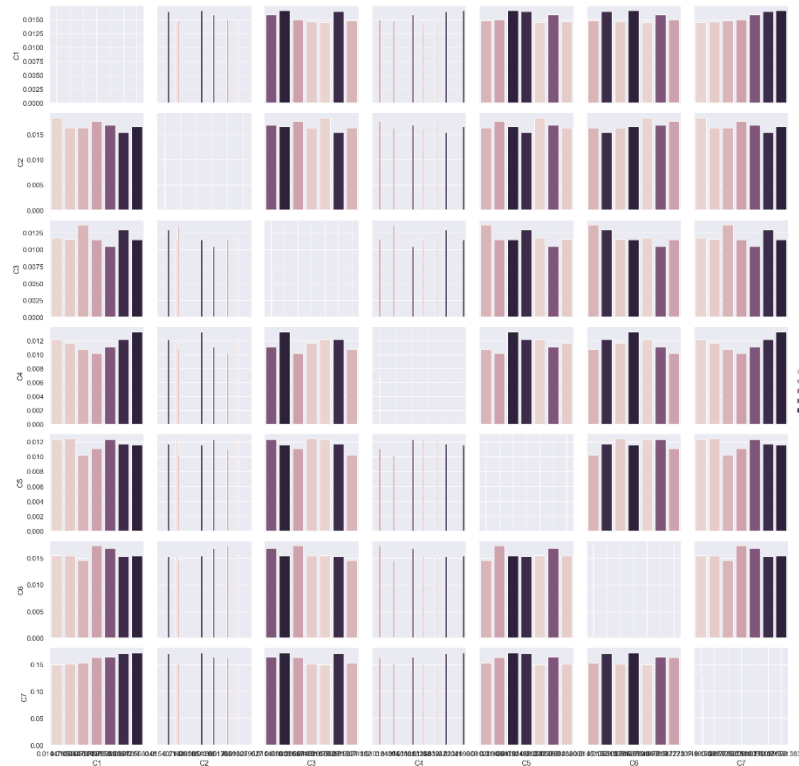


Fig 12. The weighted normalization matrix.

Group 7

The normalization matrix as shown in Fig 13.

The weighted normalized matrix as shown in Fig 14.

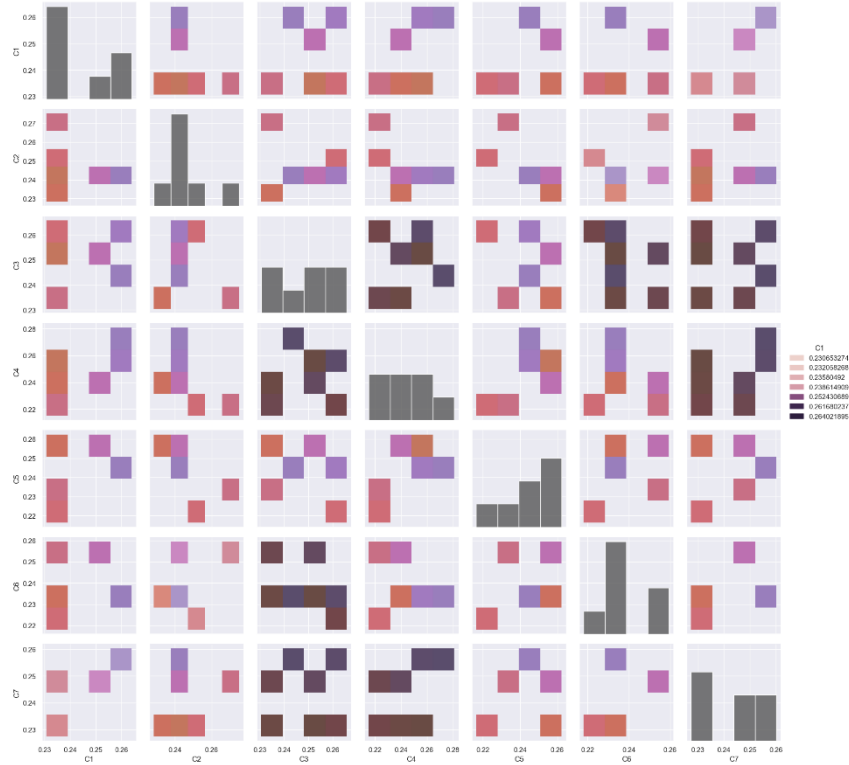


Fig 13. The normalization matrix.

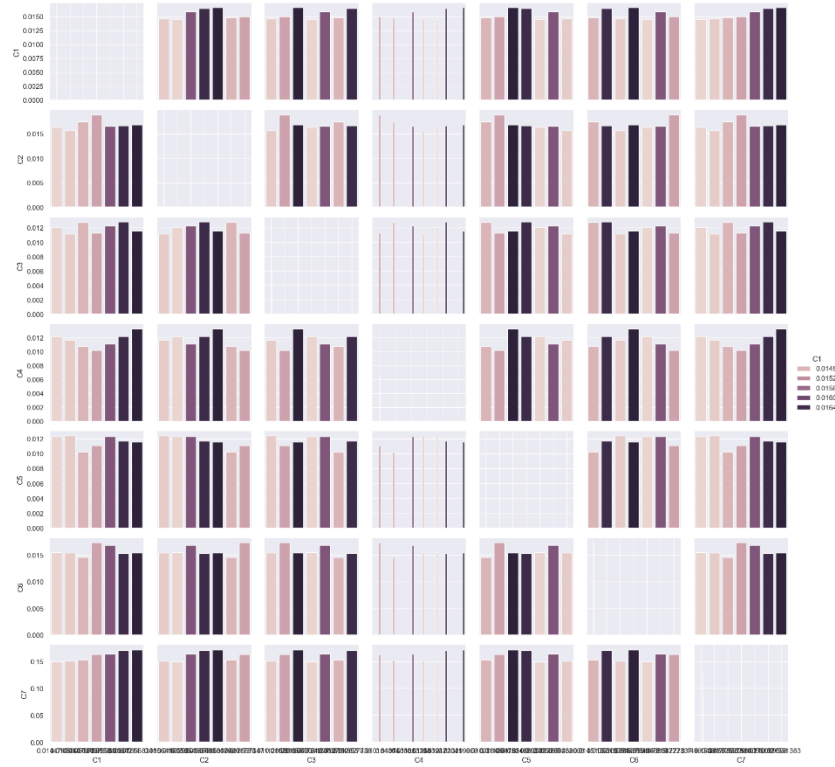


Fig 14. The weighted normalization matrix.

Group 8

The normalization matrix as shown in Fig 15.

The weighted normalized matrix as shown in Fig 16.

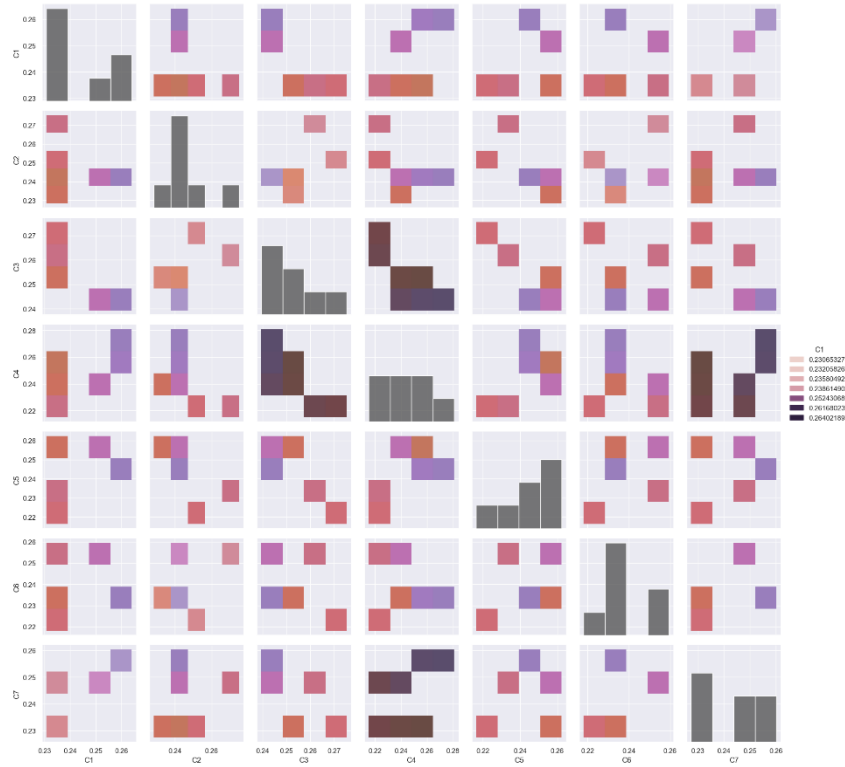


Fig 15. The normalization matrix.

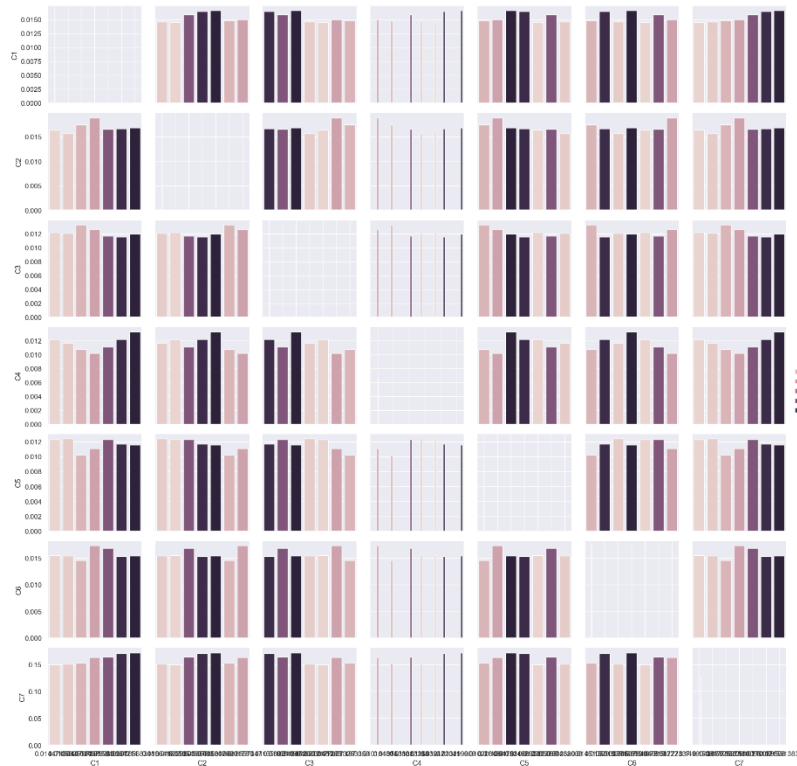


Fig 16. The weighted normalization matrix.

Group 9

The normalization matrix as shown in Fig 17.

The weighted normalized matrix as shown in Fig 18.

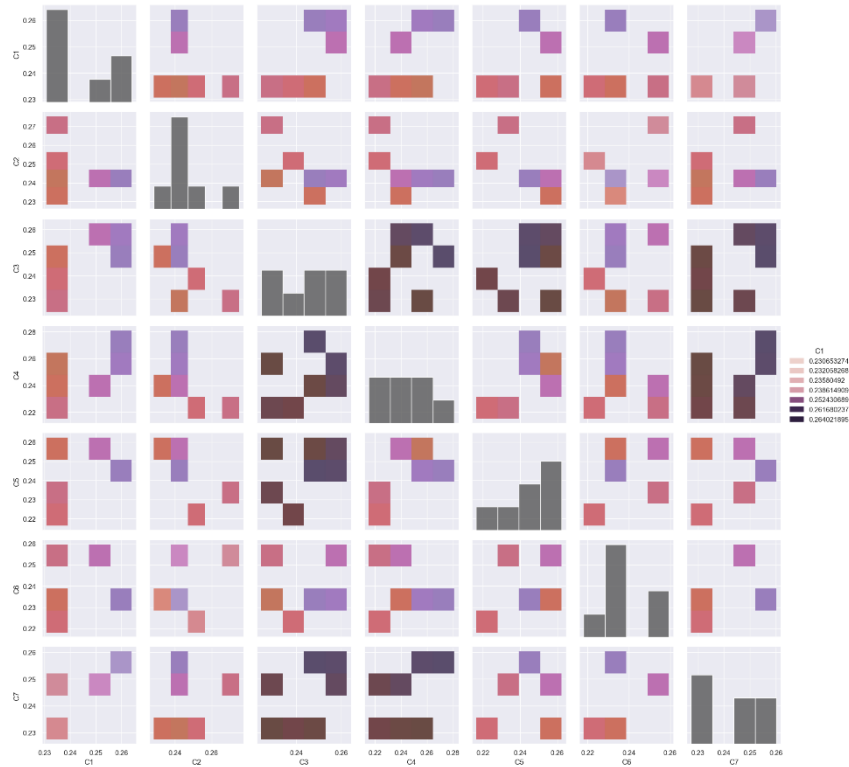


Fig 17. The normalization matrix.

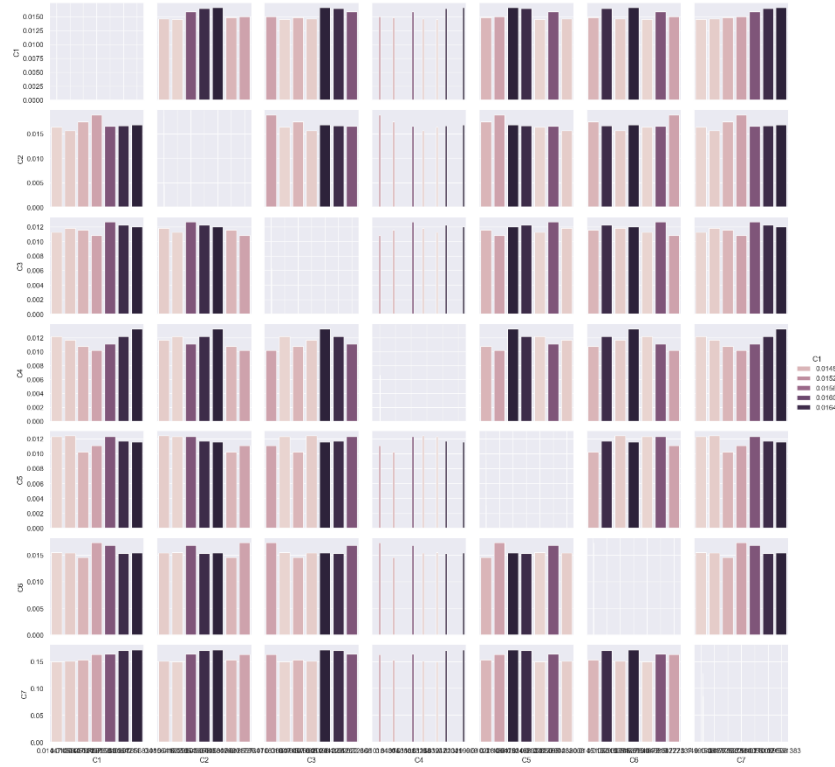


Fig 18. The weighted normalization matrix.

Then we show the final ranks of alternatives as shown in Fig 19. We show alternative 7 is the best and alternative 6 is the worst.

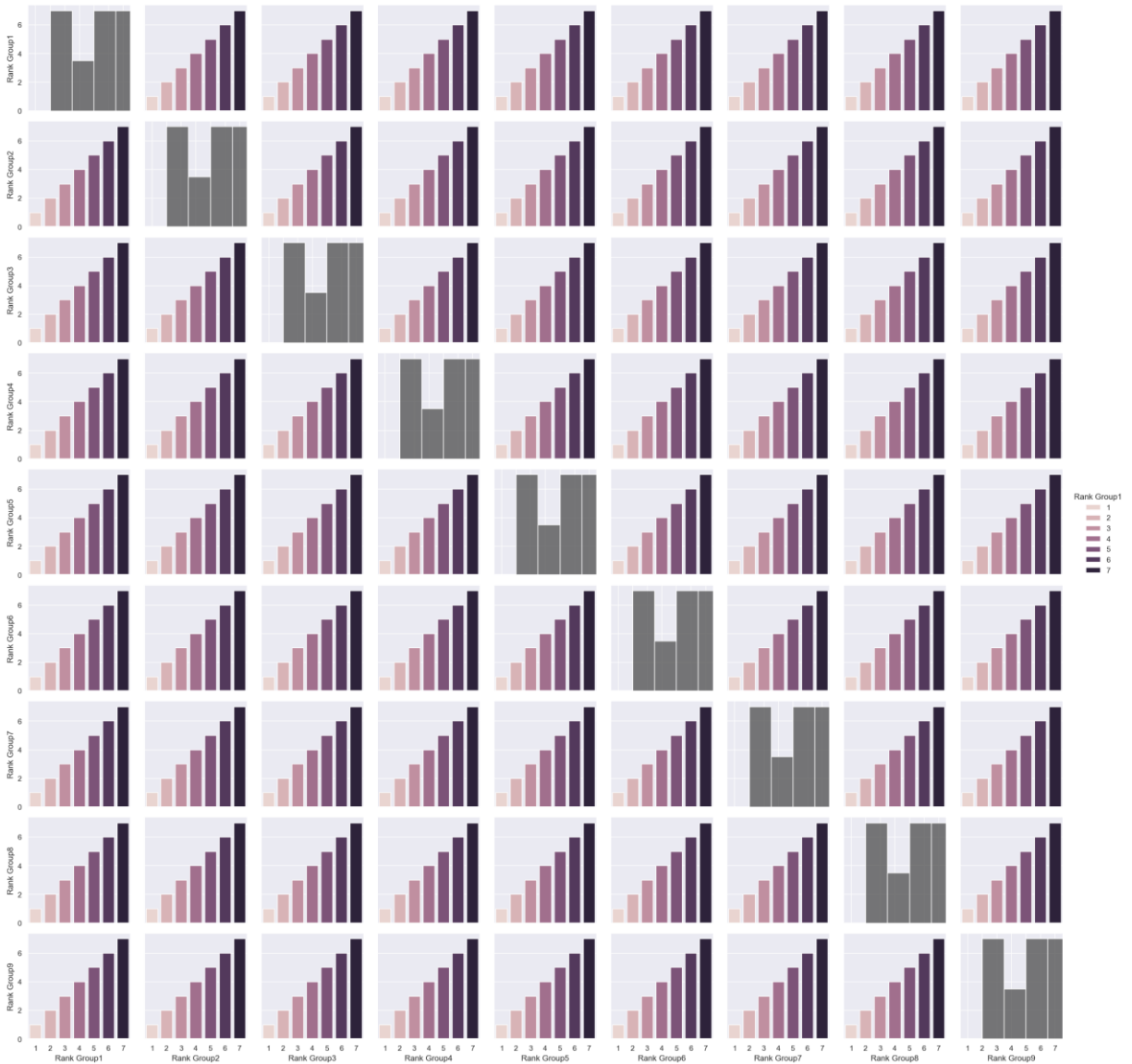


Fig 19. The final ranks of alternatives.

5. Conclusions

This study proposed a uncertainty model to evaluate the criteria and alternatives. Two methods are used in this study named MEREC methodology to compute the criteria weights and the TOPSIS methodology to rank the alternatives. These methods are used under the single valued triangular neutrosophic set to deal with uncertainty and vague information. We used the SuperHyperSoft set to treat the criteria and sub criteria. We proposed 8 groups in the SuperHyperSoft set, then ranked the alternatives under these groups. The ranks of alternatives are stable under these groups.

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