

The Novel Harmonic Soft Decision Algorithm for Suitable Institutions and Programme Selection in Higher Studies for Students

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Abstract

Choosing a suitable college or university with respect to different parameters and uncertainty is quite tough. Traditional methods usually apply weightage, ranking, fuzzy membership function, or prediction methods that consume a lot of data. The present research paper tackles the problem with the development of a novel algorithm known as Harmonic Soft Decision Algorithm (HS-DA). The proposed methodological scheme of HS-DA creates a soft set at first, creates a soft univalent set next, introduces a harmonic univalent function, creates a soft harmonic univalent set, and calculates decision states in order to select the best alternative. A characteristic matrix is created using five students and five grade related parameters, and the Python code is written in order to show how the algorithm works. The decision state of each alternative is calculated by adding up the values of its binary parameter relationships, while the harmonic function gives function values. As per the above-mentioned experimental example, the decision states of the five available options are 1, 3, 2, 2, and 1. In other words, the decision state of the second option reaches the maximum decision state of 3, while the minimum decision state is 1. With respect to the harmonic scoring function, it yielded the following values: 1, 9, 7, 5, and 5, which shows how the evaluation of the characteristic vectors is made using this technique. The HS-DA presented here gives an analytical mathematical basis for the decision analysis using soft sets, with easy computation of the method. The primary importance of the algorithm is that it can be interpreted easily and the harmonic univalent functions can be incorporated in the decision-making process. It would be good to verify the results of the algorithm by using some practical decision-making data from higher education selections.

Keywords: Harmonic Soft Set, Univalent Function, Decision Algorithm, Soft Set Theory, Higher Education, Decision Making.

Introduction

The choice of an appropriate institution for higher education and the right programme requires complex decisions on different aspects. This is further complicated by the variety of institutions and programmes available and the consequent need for proper decision support systems (Yan & Liu, 2020; Alsabhan, 2023). Prior research has examined the use of multi-criteria decision making as well as recommenders for education selection (Wang & Luo, 2026; Kumar et al., 2021). AHP and fuzzy-AHP techniques have been applied for graduate admission recommendations taking into consideration several decision criteria while recommender systems have been employed for making subject selection decisions at the higher education level (Wongvilaisakul et al., 2023; Fernández-García et al., 2020). Furthermore, there have been some attempts using hybrid classification techniques as well as neural network for student selection (Chakraborty et al., 2018; Bandhu et al., 2024; Shoaib et al., 2026). Hybrid AHP-TOPSIS as well as machine learning algorithms have been employed for graduate employability predictions (Nouib et al., 2025; Ujwal & Malik, 2023; Agarwal & Tayal, 2022).

Educational decision-making systems based on machine learning have become more concerned with issues related to academic progression, institutional ranking, employability of students, career counseling, vocation transition, admission-success categorization, and student performance prediction (Zub & Gregus, 2025; Huynh-Cam et al., 2022; Angeioplastis et al., 2025).

In addition to the above research topics, there are also other research papers which are concerned with decision-making under various circumstances using fuzzy multi-criteria approaches, admission decision fairness and transparency, federated learning for educational predictions, feature selection and voting-based prediction, and data mining-based e-learning (Farooq et al., 2024; Sánchez et al., 2023).

While all the approaches listed above are quite successful in finding computational solutions, they are largely based on some form of weighting, ranking, fuzzy membership value, machine learning model, or data requirements (Babaei et al., 2018; Raftopoulos et al., 2024; Malik & Jothimani, 2024).

Soft set theory provides an alternative framework for modeling uncertainty in absence of membership functions. In line with this idea, the current paper presents the development of a novel algorithm referred to as Harmonic Soft Decision Algorithm (HS-DA), which combines soft set representation and harmonic univalent functions in decision making. The relevance of the current paper involves the creation of a simple and interpretable mathematical decision tool for higher education selection decisions under uncertainty.

The primary contribution of this research includes the development of the HS-DA algorithm along with its stepwise decision-making procedure, mathematical formulation, example, and Python code for implementing soft harmonic univalent decision making for higher education selection.

The paper is arranged in the following manner. In Section 1, the higher education decision-making problem is introduced. The literature review is also included in this section along with the significance and contribution of HS-DA. Section 2 talks about the basic concepts of soft sets, bijection soft sets, harmonic functions, and soft complex sets. In Section 3, the concept of soft univalent and soft harmonic univalent sets is established. The HS-DA is presented in Section 4. Section 5 concludes the paper.

Preliminaries

The fundamental ideas of soft sets are covered in this section along with examples.

Definition 2.1

If M is a factor set associated with a universe set K , then $P(K)$ is the collection of subsets of K and $L \subseteq M$. A soft set is defined as an ordered 2-tuple (Ω, L) that has the transformation $\Omega: L \rightarrow P(K)$ (Chakraborty et al., 2018; Nouib et al., 2025).

Conversely, a system of factorized subsets of K is referred to as a soft set (Ω, L) over K . The set of u -related elements of a soft set (Chakraborty et al., 2018; Nouib et al., 2025) (Ω, L) , $\forall u \in L$ is denoted as $\Omega(u)$.

Example 2.1 Consider that the set of houses is $K = \{h_1, h_2, h_3, h_4, h_5, h_6\}$ and that the factor set for purchasing the house is L , which has the following definition (Nouib et al., 2025, Sánchez et al., 2023).

$L = \{e_5 = \text{in good repair}, e_4 = \text{in the green surroundings}, e_3 = \text{cheap}, e_2 = \text{wooden}, e_1 = \text{beautiful}\}$.

Suppose that,

$$\Omega(e_5) = \{h_1\}, \Omega(e_4) = \{h_1, h_3, h_5\}, \Omega(e_3) = \{h_3, h_4, h_5\}, \Omega(e_2) = \{h_1, h_3\}, \Omega(e_1) = \{h_2, h_4\},$$

then the soft set

$$(\Omega, L) = \{\text{wooden houses} = \{h_1, h_3\}; \text{beautiful houses} = \{h_2, h_4\}; \text{cheap houses} = \{h_3, h_4, h_5\}; \text{in good repair houses} = \{h_1\}; \text{in the green surroundings houses} = \{h_1, h_3, h_5\}\}.$$

Definition 2.2 Let M be a factor set associated with a universe set K and $L \subseteq M$. The set of subsets of K is denoted as $P(K)$. A relative whole soft set (Nouib et al., 2025; Yan & Liu, 2020) is the soft set (Ω, L) that corresponds to a factor set L if $\forall u \in L, \Omega(u) = K$ and is referred as $\widetilde{K}_L$.

Definition 2.3 If a soft set (Ω, L) over K meets the following two requirements, it is referred to as a bijective soft set (Nouib et al., 2025; Yan & Liu, 2020):

$$\bigcup_{u \in L} \Omega(u) = K$$

The set of u -related items for each different factor u_i, u_j in L has an empty intersection.

(i. e); if $u_i \neq u_j, u_i, u_j \in L$, such that $\Omega(u_i) \cap \Omega(u_j) = \emptyset$. (Nouib et al., 2025; Yan & Liu, 2020)

Example 2.2 Considering a soft set (Ω, E) over K , where $E = \{e_1, e_2, e_3, e_4\}$ and $K = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$. The mapping of (Ω, E) is explained as,

$\Omega(e_4) = \{x_4, x_5, x_6, x_7\}, \Omega(e_3) = \{x_7\}, \Omega(e_2) = \{x_4, x_5, x_6\}, \Omega(e_1) = \{x_1, x_2, x_3\}$. According to the definition 2.3 $(\Omega, \{e_1, e_4\})$ and $(\Omega, \{e_1, e_2, e_3\})$ are bijective soft sets (Nouib et al., 2025; Yan & Liu, 2020).

Definition 2.4: Based on Laplace's equation, a real-valued function $u(z)$ or $u(x, y)$ that is defined and single-valued in a region D is considered harmonic (Ujwal & Malik, 2023) in D or a potential function if it is continuous along with its partial derivatives of the first two orders.

$$\Delta u = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = 0.$$

If both u and v are real harmonic in a complex domain C , then the continuous function $f = u + iv$ is a complex-valued harmonic function in that domain. It is known in a connected domain D (Ujwal & Malik, 2023).

$f = \underline{g} + h$ where g and h are analytic in D . In a connected domain D , it is commonly referred as a necessary and sufficient condition for f to be sense-preserving and locally univalent is that $|h'(z)| > |g'(z)|$ in D .

Definition 2.5: Consider $\hat{C}$ to be the complex number set and $P(\hat{C})$ to be the set of nonempty bounded subsets of the complex numbers. Let $\check{E}$ be a collection of parameters. A soft complex set is then defined as a mapping $\underline{U}: \check{E} \rightarrow P(\hat{C})$ (Agarwal & Tayal, 2022).

Definition 2.6: Consider the soft complex set $(\underline{U}, \check{E})$. If $\underline{z}$ is the complex conjugate of a complex number z , then the complex conjugate of $(\underline{U}, \check{E})$ (Agarwal & Tayal, 2022) is represented by $(\underline{U}, \check{E})$ and is referred as $\underline{U}(\lambda) = \{\underline{z}: z \in U(\lambda)\}, \forall \lambda \in \check{E}$.

Definition 2.7: Consider $f: X \rightarrow Y$ be a function where X, Y are complex numbers. Replace Y by the soft complex sets $\underline{Y}$ then $\underline{f}: X \rightarrow \underline{Y}$ is referred as a soft function (Agarwal & Tayal, 2022) of soft complex sets.

Methodology

Definition 3.1: A pair $(F, \check{G})$ is defined as a *soft univalent set over S*, then there exists a univalent function $\psi: D \rightarrow \hat{C}$ that satisfies $F(g_i)(s_j) = \psi_{ij}(d_j)$, were

$$\psi_{ij}(d_j) = \{1; \text{if } s_j \in F(g_i) 0; \text{otherwise } \forall d_j \in D, i \& j.$$

Example 3.1: Consider $\check{G} = \{g_1, g_2, g_3, g_4, g_5\}$ is the set of grades and $S = \{s_1, s_2, s_3, s_4, s_5\}$ is the set of students were,

$$g_1 = 30 \text{ marks obtained and pass,}$$

$$g_2 = \text{above 50 marks obtained and pass,}$$

$$\begin{aligned}g_3 &= \text{between 50 and 80 marks obtained and pass,} \\g_4 &= \text{exactly 75 marks obtained and pass,} \\g_5 &= \text{100 marks obtained.}\end{aligned}$$

Then soft set $(F, \check{G}) = \{F(g_5) = \{s_5\}, F(g_4) = \{s_2, s_3\}, F(g_3) = \{s_2, s_3, s_4\}, F(g_2) = \{s_2, s_4\}, F(g_1) = \{s_1\}\}$.

Here,

$$\psi_{54}(d_4) = \psi_{53}(d_3) = \psi_{52}(d_2) = \psi_{51}(d_1) = 0, \psi_{55}(d_5) = 1.$$

$$\begin{aligned}\psi_{43}(d_3) &= \psi_{42}(d_2) = 1, \psi_{45}(d_5) = \psi_{44}(d_4) = \psi_{41}(d_1) = 0, \\ \psi_{35}(d_5) &= \psi_{31}(d_1) = 0, \psi_{34}(d_4) = \psi_{33}(d_3) = \psi_{32}(d_2) = 1, \\ \psi_{25}(d_5) &= \psi_{23}(d_3) = \psi_{21}(d_1) = 0, \psi_{24}(d_4) = \psi_{22}(d_2) = 1, \\ \psi_{11}(d_1) &= 1, \psi_{15}(d_5) = \psi_{14}(d_4) = \psi_{13}(d_3) = \psi_{12}(d_2) = 0,\end{aligned}$$

Hence, $(F, \check{G})$ satisfies the univalent condition through the function ψ .

Therefore, $(F, \check{G})$ is a soft univalent set over S .

Example 3.2: Let $J = \{\check{j}_1, \check{j}_2, \check{j}_3, \check{j}_4, \check{j}_5\}$ is the set of jobs and $W = \{w_1, w_2, w_3, w_4, w_5, w_6\}$ is the set of workers where,

$\check{j}_1 = \text{house keeping jobs}, \check{j}_2 = \text{teaching related jobs}, \check{j}_3 = \text{service related jobs},$

$\check{j}_4 = \text{administration related jobs}, \check{j}_5 = \text{computer related jobs}.$

Then soft set $(F, J) = \{F(\check{j}_5) = \{w_5, w_6\}, F(\check{j}_4) = \{w_2, w_3\}, F(\check{j}_3) = \{w_2, w_3, w_4\}, F(\check{j}_2) = \{w_2, w_4\}, F(\check{j}_1) = \{w_1, w_6\}\}$.

Here,

$$\begin{aligned}\psi_{54}(d_4) &= \psi_{53}(d_3) = \psi_{52}(d_2) = \psi_{51}(d_1) = 0, \psi_{56}(d_6) = \psi_{55}(d_5) = 1, \\ \psi_{43}(d_3) &= \psi_{42}(d_2) = 1, \psi_{46}(d_6) = \psi_{45}(d_5) = \psi_{44}(d_4) = \psi_{41}(d_1) = 0, \\ \psi_{36}(d_6) &= \psi_{35}(d_5) = \psi_{31}(d_1) = 0, \psi_{34}(d_4) = \psi_{33}(d_3) = \psi_{32}(d_2) = 1, \\ \psi_{26}(d_6) &= \psi_{25}(d_5) = \psi_{23}(d_3) = \psi_{21}(d_1) = 0, \psi_{22}(d_2) = \psi_{24}(d_4) = 1, \\ \psi_{16}(d_6) &= \psi_{11}(d_1) = 1, \psi_{15}(d_5) = \psi_{14}(d_4) = \psi_{13}(d_3) = \psi_{12}(d_2) = 0,\end{aligned}$$

Hence, (F, J) satisfies the univalent condition through the function ψ .

Therefore, (F, J) is a soft univalent set over W .

Example 3.3: Consider $H = \{\check{h}_1, \check{h}_2, \check{h}_3, \check{h}_4, \check{h}_5\}$ is the set of hospitals and $P = \{p_1, p_2, p_3, p_4, p_5, p_6\}$ is the set of patients where,

$\check{h}_1 = \text{government hospital},$

$\check{h}_2 = \text{private hospital},$

$\check{h}_3 = \text{clinic},$

$\check{h}_4 = \text{hospital with pharmacy},$

$\check{h}_5 = \text{hospital without pharmacy}.$

Then soft set $(F, H) = \{F(\check{h}_5) = \{p_3\}, F(\check{h}_4) = \{p_2, p_3\}, F(\check{h}_3) = \{p_1, p_5\}, F(\check{h}_2) = \{p_3, p_4\}, F(\check{h}_1) = \{p_2\}\}$.

Table 1. Tabular representation of ψ_{ij}

P D	$\check{h}_1$	$\check{h}_2$	$\check{h}_3$	$\check{h}_4$	$\check{h}_5$
d_1	0	0	1	0	0
d_2	1	0	0	1	0
d_3	0	1	0	1	1
d_4	0	1	0	0	0
d_5	0	0	1	0	0

From table 1 and by Definition 3.1, (F, H) not satisfy the univalent condition. Therefore (F, H) not a soft univalent set over P .

Definition 3.2: A soft univalent set $(F, \check{G})$ over S is soft harmonic univalent, if there exists a harmonic univalent function $h: \{0,1\}^{|\check{G}|} \rightarrow R$ such that every $u_i, u_j \in S$,

$$\alpha_k(u_i) \neq \alpha_k(u_j) \text{ implies } h(\alpha_k(u_i)) \neq h(\alpha_k(u_j)), \text{ where } \alpha_k(u_i) = \chi_{F(g_k)}(u_i).$$

Definition 3.3: The decision state of $u_i \in S$ is the sum of all $\alpha_k(u_i)$ is more than

$$\sum_{k=1}^n \alpha_k(u_i) = \sum_{k=1}^n \chi_{F(g_k)}(u_i) \geq 1, \quad k = 1, 2, \dots, n$$

Definition 3.4: The optimal decision state of $u_i^* \in S$ is the maximum of the decision states of each $u_i \in S$.

Applications of Harmonic Soft Decision Algorithm

Harmonic Soft (HS-DA) Decision Algorithm 1

Step 1. Define an initial soft set (Ω, E) over the universe K .

Step 2. From the initial soft set, construct a soft univalent set $(F, \check{G})$ over S .

Step 3. Define a harmonic univalent function

Step 4. Generate the soft harmonic univalent set $(F, \check{G})$ over S .

Step 5. Find the decision states

Step 6. Calculate an optimal decision state $u_i^* \in S$.

Step 7. Define a threshold.

Step 8. Identify the optimal decision.

The HS-DA algorithm (Algorithm 1) takes the initial soft set as an input to obtain the decision states by using soft univalence and harmonic univalence. After that, it finds the maximum decision state, considers the pre-defined threshold value, and selects the best decision.

Illustration 4.1: Consider $S = \{s_1, s_2, s_3, s_4, s_5\}$ is the set of students and $\check{G} = \{\check{g}_1, \check{g}_2, \check{g}_3, \check{g}_4, \check{g}_5\}$ is the set of grades were,

$$\check{g}_1 = 30 \text{ marks obtained and pass,}$$

$$\check{g}_2 = \text{above 50 marks obtained and pass,}$$

$$\check{g}_3 = \text{between 50 and 80 marks obtained and pass,}$$

$$\check{g}_4 = \text{exactly 75 marks obtained and pass,}$$

$$\check{g}_5 = 100 \text{ marks obtained.}$$

$$\text{Then soft set } (F, \check{G}) = \{F(\check{g}_5) = \{s_5\}, F(\check{g}_4) = \{s_2, s_3\}, F(\check{g}_3) = \{s_2, s_3, s_4\}, F(\check{g}_2) = \{s_2, s_4\}, F(\check{g}_1) = \{s_1\}\}.$$

Here,

$$\psi_{11}(d_1) = 1, \psi_{15}(d_5) = \psi_{14}(d_4) = \psi_{13}(d_3) = \psi_{12}(d_2) = 0,$$

$$\psi_{25}(d_5) = \psi_{23}(d_3) = \psi_{21}(d_1) = 0, \psi_{24}(d_4) = \psi_{22}(d_2) = 1,$$

$$\psi_{31}(d_1) = \psi_{35}(d_5) = 0, \psi_{32}(d_2) = \psi_{33}(d_3) = \psi_{34}(d_4) = 1,$$

$$\psi_{43}(d_3) = \psi_{42}(d_2) = 1, \psi_{41}(d_1) = \psi_{44}(d_4) = \psi_{45}(d_5) = 0,$$

$$\psi_{54}(d_4) = \psi_{53}(d_3) = \psi_{52}(d_2) = \psi_{51}(d_1) = 0, \psi_{55}(d_5) = 1.$$

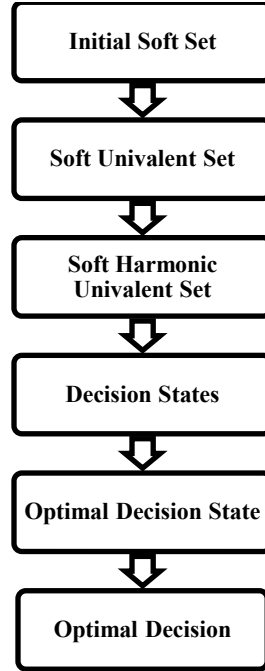


Fig. 1: Flow Chart of Harmonic Soft Decision Algorithm

As depicted in fig.1, HS-DA follows the stepwise decision-making approach in which the decision-making process starts from the soft set and proceeds toward the soft univalence and harmonic univalence until the optimal decision state is arrived at.

Table 2: Tabular Representation of ψ_{ij}

$\begin{matrix} S \\ \mathcal{D} \end{matrix}$	s_1	s_2	s_3	s_4	s_5
d_1	1	0	0	0	0
d_2	0	1	0	0	0
d_3	0	1	1	1	0
d_4	0	1	1	0	0
d_5	0	0	0	0	1

Define a harmonic function $h(z) = z^2 + z^4 + z \quad \forall z \in \hat{\mathcal{C}}$

According to definition 3.2, $\alpha_1(s_1) = 4, \alpha_1(s_2) = 1, \alpha_2(s_2) = 4, \alpha_3(s_2) = \frac{2}{3}, \alpha_3(s_1) = \frac{3}{2},$

$$\alpha_4(s_2) = \frac{3}{2}, \alpha_4(s_1) = \frac{2}{3}, \alpha_4(s_1) = \frac{2}{3}, \alpha_5(s_5) = 4.$$

From the above table 2 $\alpha_i(s_j)$ and definition 3.3, the decision states are s_2 and s_3 . Optimal decision functional values and decision state are $|\dot{o}(s_2/h(3))| = 15.5, |\dot{o}(s_3/h(2))| = 3.6.$

Define threshold limit

$$\rho(s_j) = \left| \dot{o}(s_j/h(z)) \right| \leq \left| \sum \psi_{ij}(s_j) \right| \frac{|S|}{\max \alpha_i(s_j)} \quad (1)$$

From equation (1), the optimal decision state was obtained, which is $s_j^* = s_3.$

Python Code for Harmonic Soft Decision Algorithm

Harmonic Soft Decision Algorithm (HS-DA)

Step 1: Universe (students) and parameters (grades)

students = ["s1", "s2", "s3", "s4", "s5"]

grades = ["g1", "g2", "g3", "g4", "g5"]

```
# Step 2: Initial soft set F(g)
F = {
    "g1": ["s1"],
    "g2": ["s2", "s4"],s
    "g3": ["s2", "s3", "s4"],
    "g4": ["s2", "s3"],
    "g5": ["s5"]
}
# Step 3: Construct characteristic table 2  $\alpha_k(ui)$ 
alpha = [] # matrix
for s in students:
    row = []
    for g in grades:
        if s in F[g]:
            row.append(1)
        else:
            row.append(0)
    alpha.append(row)
print("Characteristic matrix  $\alpha$ :")
for r in alpha:
    print(r)
# Step 4: Harmonic-univalent function h(x)
# (simple injective harmonic mapping)
weights = [1, 2, 3, 4, 5]
def h(vector):
    value = 0
    for i in range(len(vector)):
        value += vector[i] * weights[i]
    return value
# Check harmonic-univalent condition
values = []
is_univalent = True
for r in alpha:
    hv = h(r)
    if hv in values:
        is_univalent = False
    values.append(hv)
print("\nSoft harmonic-univalent:", is_univalent)
# Step 5: Decision states  $d(ui) = \sum \alpha_k(ui)$ 
decision_states = []
for r in alpha:
    s = 0
    for x in r:
        s += x
```

```
decision_states.append(s)
print("\nDecision states:")
for i in range(len(students)):
    print(students[i], ":", decision_states[i])
# Step 6: Optimal decision state
max_state = decision_states[0]
for d in decision_states:
    if d > max_state:
        max_state = d
# Step 7: Optimal decision
optimal = []
for i in range(len(students)):
    if decision_states[i] == max_state:
        optimal.append(students[i])
print("\n decision state =", max_state)
```

Illustration of the HS-DA approach in the Python language is carried out using the characteristic matrix construction based on the initial soft set, univalent harmonized scoring function, univalence testing, decision states evaluation, and finding the maximum decision state.

Fig 2 shows the output of HS-DA decision algorithm.



The screenshot displays a Python IDE with a file named 'main.py'. The code implements the HS-DA algorithm. It starts by defining a universe of students ('s1' to 's5') and a set of grades ('g1' to 'g5'). A soft set F is defined as a dictionary mapping students to their grades. The algorithm then constructs a characteristic matrix alpha based on the soft set. It evaluates the decision states for each student and identifies the optimal decision state. The output shows the characteristic matrix alpha, the soft harmonic-univalent status (False), the decision states for each student, and the final decision state (3).

```
1 # Harmonic Soft Decision Algorithm (HS-DA)
2 # Step 1: Universe (students) and parameters (grades)
3 students = ["s1", "s2", "s3", "s4", "s5"]
4 grades = ["g1", "g2", "g3", "g4", "g5"]
5 # Step 2: Initial soft set F(g)
6 F = {
7     "g1": ["s1"],
8     "g2": ["s2", "s4"],
9     "g3": ["s2", "s3", "s4"],
10    "g4": ["s2", "s3"],
11    "g5": ["s5"]
12 }
13
14 # Step 3: Construct characteristic table a_h(vi)
15
16 alpha = [] # matrix
17
18 for s in students:
19     row = []
20     for g in grades:
21         if s in F[g]:
22             row.append(1)
23         else:
24             row.append(0)
25     alpha.append(row)
26
27 print("Characteristic matrix a:")
28 for r in alpha:
29     print(r)
30
31 # Step 4: Harmonic-univalent function h(x)
32 # (simple injective harmonic mapping)
33
34 weights = [1, 2, 3, 4, 5]
35
36 def h(vector):
37     value = 0
```

Output:

Characteristic matrix a:

```
[1, 0, 0, 0, 0]
[0, 1, 1, 1, 0]
[0, 0, 1, 1, 0]
[0, 1, 1, 0, 0]
[0, 0, 0, 0, 1]
```

Soft harmonic-univalent: False

Decision states:

```
s1 : 1
s2 : 3
s3 : 2
s4 : 2
s5 : 1
```

decision state = 3

Fig. 2: Output of Decision State in HS-DA

Conclusion

The following research has suggested an approach called the Harmonic Soft Decision Algorithm (HS-DA) to solve decision making problems under uncertain conditions, especially those related to selection of appropriate choices in the case of higher education institutions. This approach is based on soft sets along with soft univalent and harmonic univalent concepts. First of all, there is the transformation of soft sets into characteristic matrices; after that, it is necessary to evaluate the harmonic univalent functions' values and determine the decision states to choose the optimal

decision state. In the example, the decision-making process is represented by quantitative arguments for its implementation. Five alternatives were analyzed based on five criteria. The resulting decision states were 1, 3, 2, 2, and 1, respectively. Therefore, the maximum decision state was 3 in relation to the second alternative. The harmonic scoring function generated unique functional values (1, 9, 7, 5, and 5) of the corresponding characteristic vectors, thus representing the application of the proposed injective scoring mechanism in the example. In this way, it is possible to claim that the HS-DA method is able to differentiate between alternatives based on the parameters associated with them while maintaining simplicity of the model. Nevertheless, the present study mainly relies on the use of an illustration and not on the use of empirical data to support its arguments. Future studies may need to validate the use of HS-DA through the analysis of actual datasets related to higher education institutions and program selection while making a comparison of its results with the existing techniques such as AHP, TOPSIS, fuzzy decision making, and recommendation systems.

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