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Determining The Best School Using The Concept Generalized Picture Fuzzy Soft Set

Mardiatul Faizah, Admi Nazra*, Nova Noliza Bakar

Department of Mathematics, Andalas University,
Kampus UNAND Limau Manis Padang-25163, INDONESIA
* Corresponding Author: nazra@sci.unand.ac.id

Abstract – Determining the best school in the education system is an essential task. One approach that can be used to determine the best school is using the generalized picture fuzzy soft set (GPFSS) concept. GPFSS is an extension of the picture fuzzy soft set (PFSS) concept in which each parameter is defined a picture fuzzy set (PFS) stating the level of importance of the parameter. This research proposes the GPFSS approach to determine the best schools. This approach is based on consideration of several factors, namely the quality of the school environment, the quality of school facilities, the quality of teachers, the quality of the learning process, and school achievement. The research results show that the GPFSS approach can accurately determine the best schools. The best schools based on the GPFSS approach have a good school environment, facilities, quality teachers, learning processes, and good school performance.

Keywords – Generalized picture fuzzy soft set, Operations, Decision making.

I. INTRODUCTION

In the education system, determining the best school is an important task. This can help students and parents choose a school according to their needs and desires. One approach that can be used to determine the best school is to use the GPFSS concept. GPFSS is a development of the PFSS concept. In this research, the concepts in solving uncertainty problems will be discussed again. L. A. Zadeh [7] in 1965 introduced a theory to overcome this problem, namely fuzzy set (FS), which contains the degree of membership. The concept of fuzzy sets is developed into intuitionistic fuzzy set (IFS) by Atanassov [1] in 1983, which includes degrees membership and non-membership. In 1999, Molodtsov [4] introduced the soft set (SS), which is the set of pairs between parameters and related objects. In 2014, Cuong [2] introduced a new set which is a development of the intuitionistic fuzzy set (IFS) concept which contains positive membership degrees, neutral membership degrees, and negative membership degrees. In 2015, Yang [6] examines the picture fuzzy soft set (PFSS), which is a combination of picture fuzzy sets and soft sets. In 2017, Wei [5] determined a multi-attribute decision making algorithm on PFSS and applied it to decision making. In 2019, Khan, M. J [3] studied generalized picture fuzzy soft set (GPFSS). This study aims to apply the concept of generalized picture fuzzy soft set in the case of determining the best school based on multi attribute decision making.

II. FUZZY SET, INTUITIONISTIC FUZZY SET, SOFT SET, PICTURE FUZZY SET, PICTURE FUZZY SOFT SET, GENERALIZED PICTURE FUZZY SOFT SET

In this section, we will briefly recall the basic concepts of fuzzy sets, intuitionistic fuzzy sets, soft sets, picture fuzzy sets, picture fuzzy soft sets, and generalized picture fuzzy soft sets.

Definition 2.1. [3] *Let U be a universal set. A fuzzy set of M over U is defined as*

$$M = \{(x; \mu_M(x) \mid x \in U)\},$$

where $\mu_M : U \to [0,1]$ is the membership function, and $\mu_M(x)$ is called the degree of membership $x \in U$ in fuzzy set M.

Definition 2.2. [1] *Let U be a universal set. An intuitionistic fuzzy set N over U is defined as*

$$N = \{ (x; \mu_N(x); \gamma_N(x)) \mid x \in U \},$$

where $\mu_N : U \to [0,1]$ is the membership function and $\gamma_N : U \to [0,1]$ is nonmembership function. Then, for each $x \in U$ degree of membership $\mu_N(x)$ and degree of nonmembership $\gamma_N(x)$ satisfies $0 \le \mu_N(x) + \gamma_N(x) \le 1$.

Definition 2.3. [4] *Let U be a universal set and E be a parameter set. A pair (F, E) is called a soft set over U if and only if F is a mapping of E into the set of all subsets of the set U.*

Definition 2.4. [2] *A picture fuzzy set $\widehat{M}$ on a universe set U defined as*

$$\widehat{M} = \{ (x; \xi_{\widehat{M}}(x); \eta_{\widehat{M}}(x); \upsilon_{\widehat{M}}(x)) \mid x \in U \},$$

where $\xi_{\widehat{M}}(x) \in [0,1]$ is called the degree of positive membership of x in $\widehat{M}$, $\eta_{\widehat{M}}(x) \in [0,1]$ is called the degree of neutral membership of x in $\widehat{M}$, and $\upsilon_{\widehat{M}}(x) \in [0,1]$ is called the degree of negative membership of x in $\widehat{M}$. Furthermore, $\xi_{\widehat{M}}, \eta_{\widehat{M}}, \upsilon_{\widehat{M}}$ satisfy the following conditions $0 \le \xi_{\widehat{M}}(x) + \eta_{\widehat{M}}(x) + \upsilon_{\widehat{M}}(x) \le 1, \forall x \in U$. Then, $\pi_{\widehat{M}}(x) = 1 - (\xi_{\widehat{M}}(x) + \eta_{\widehat{M}}(x) + \upsilon_{\widehat{M}}(x))$ is called the degree of rejection of membership of x in $\widehat{M}$.

For convenience, $(\xi_{\widehat{M}}; \eta_{\widehat{M}}; \upsilon_{\widehat{M}})$ is called picture fuzzy number (PFN) of PFS $\widehat{M}$ over U, where $\xi_{\widehat{M}} \in [0,1], \eta_{\widehat{M}} \in [0,1], \upsilon_{\widehat{M}} \in [0,1], \xi_{\widehat{M}} + \eta_{\widehat{M}} + \upsilon_{\widehat{M}} \le 1$.

Definition 2.5. [2] *Let $\widehat{M}$ dan $\widehat{N}$ be two PFS over U. Then the subset, union, intersection and complement are defined as follows:*

1. $\widehat{M} \subseteq \widehat{N}, if\ and\ only\ if\ \xi_{\widehat{M}}(x) \le \xi_{\widehat{M}}(x), \eta_{\widehat{M}}(x) \le \eta_{\widehat{N}}(x), \upsilon_{\widehat{M}}(x) \le \upsilon_{\widehat{N}}(x), \forall x \in U,$
2. $\widehat{M} = \widehat{N}, if\ and\ only\ if\ \widehat{M} \subseteq \widehat{N},$
3. $\widehat{M} \cup \widehat{N} = \{(x;\ maks(\xi_{\widehat{M}}(x), \xi_{\widehat{N}}(x));\ min(\eta_{\widehat{M}}(x), \eta_{\widehat{N}}(x));\ min(\upsilon_{\widehat{M}}(x), \upsilon_{\widehat{N}}(x)) \mid x \in U)\},$
4. $\widehat{M} \cap \widehat{N} = \{(x;\ maks(\xi_{\widehat{M}}(x), \xi_{\widehat{N}}(x));\ min(\eta_{\widehat{M}}(x), \eta_{\widehat{N}}(x));\ min(\upsilon_{\widehat{M}}(x), \upsilon_{\widehat{N}}(x)) \mid x \in U)\},$
5. $\widehat{M}^c = \{ (x; \upsilon_{\widehat{M}}(x); \eta_{\widehat{M}}(x); \xi_{\widehat{M}}(x)) \mid x \in U \}.$

Definition 2.6. [5] *Let $q = (\xi_q;\ \eta_q;\ \upsilon_q)$ a picture fuzzy number (PFN), a score function $\varTheta$ of PFN can be represented as follows*

$$\varTheta(q) = \xi_q - \upsilon_q, \varTheta(q) \in [-1, 1].$$

Definition 2.7. [5] *Let $q = (\xi_q;\ \eta_q;\ \upsilon_q)$ a picture fuzzy number (PFN), an accuracy function ϖ of PFN can be represented as follows*

$$\varpi(q) = \xi_q + \eta_q + \upsilon_q, \varpi(q) \in [0, 1].$$

Definition 2.8. [5] *Let $p = (\xi_p;\ \eta_p; \upsilon_p)$ and $q = (\xi_q; \eta_q; \upsilon_q)$ be two PFN, $\varTheta(p) = \xi_p - \upsilon_p$ and $\varTheta(q) = \xi_q - \upsilon_q$ be the scores of p and q, respectively, and $\varpi(p) = \xi_p + \eta_p + \upsilon_p$ and $\varpi(q) = \xi_q + \eta_q + \upsilon_q$ be the accuracy degrees of p and q, respectively.*

1. *If $\varTheta(p) < \varTheta(q)$, then p is smaller than q, denoted by $p \prec q$.*
2. *For $\varTheta(p) = \varTheta(q)$,*
   a. *If $\varpi(p) = \varpi(q)$, then p and q represent the same information, denoted by $p = q$, and*
   b. *If $\varpi(p) < \varpi(q)$, then p is smaller than q, denoted by $p \prec q$.*

Definition 2.9. [3] *Let $q = (\xi_q; \eta_q; \upsilon_q)$ be PFN. Then the PFDWA operator is a function of $Q^n \to Q$ defined by*

$$PFDWA_{\varpi}(q_1, q_2, \cdots, q_n) = \oplus_{i=1}^{n}\ \omega_i q_i$$

$$= \left(1 - \frac{1}{1 + \left\{ \sum_{i=1}^{n} \omega_i \left(\frac{\xi_i}{1 - \xi_i} \right)^k \right\}^{1/k}}; \frac{1}{1 + \left\{ \sum_{i=1}^{n} \omega_i \left(\frac{1 - \eta_i}{\eta_i} \right)^k \right\}^{1/k}}; \frac{1}{1 + \left\{ \sum_{i=1}^{n} \omega_i \left(\frac{1 - \upsilon_i}{\upsilon_i} \right)^k \right\}^{1/k}} \right).$$

where $k \geq 1$ *and* $\omega = (\omega_1; \omega_2; \cdots; \omega_n)$ *is the weight vektor with each* $\omega_i > 0$ *and* $\sum_{i=1}^{n} \omega_i = 1$.

Definition 2.10. [6] *Let U be a universal set and E a set of parameters. A PFSS over U is a pair* (F, A) *where* $A = \{e_1, e_2, \cdots, e_n\} \subset E$ *and* $F: A \to KPFS(U)$, *with KPFS(U) is the set of all picture fuzzy set over U.*

Definition 2.11. [3] *Let* $L_1 = (F, A)$ *and* $L_2 = (G, B)$ *be two PFSS over U. Then extended intersection of* L_1 *and* L_2 *is defined as PFSS* $(H, C) = (F, A) \cap_\epsilon (G, B)$, *where* $C = A \cup B$ *and for all* $e \in C$,

$$H(e) = \begin{cases} F(e) & if\ e \in A - B, \\ G(e) & if\ e \in B - A, \\ F(e) \cap G(e) & if\ e \in A \cap B. \end{cases}$$

Definition 2.12. [3] *Let U be a universal set and E a parametric set. Set* $A = \{e_1, e_2, \cdots, e_n\} \subset E$ *and* $\Phi(A)$ *the set of all picture fuzzy subsets of A. Generalized picture fuzzy soft set is denoted* (F, A, ρ), *where* (F, A) *is a PFSS over U and* $\rho: A \to \Phi(A)$ *is a PFS in A.*

Definition 2.13. [3] *The two GPFSS* $\Gamma_1 = (F, A, \rho)$ *and* $\Gamma_2 = (G, B, \sigma)$ *are said to be generalized picture soft equal and denoted by* $\Gamma_1 = \Gamma_2$, *if* $A = B, (F, A) = (G, B)$, *and* $\rho = \sigma$.

Definition 2.14. [3] *Let* $\Gamma_1 = (F, A, \rho)$ *and* $\Gamma_2 = (G, B, \sigma)$ *be two GPFSS over U. Then extended intersection is denoted by* $(H, C, \tau) = (F, A, \rho) \sqcap_\epsilon (G, B, \sigma)$ *and defined as* $(H, C) = (F, A) \cap_\epsilon (G, B)$ *where* $C = A \cup B$ *and for all* $e \in C, \tau = \rho \cap \sigma$ *with*

$$\xi_\tau(e) = \begin{cases} \xi_\rho(e) & if\ e \in A - B, \\ \xi_\rho(e) & if\ e \in B - A, \\ min\{\xi_\rho(e), \xi_\sigma(e)\} & if\ e \in A \cap B. \end{cases}$$

$$\eta_\tau(e) = \begin{cases} \eta_\rho(e) & if\ e \in A - B, \\ \eta_\rho(e) & if\ e \in B - A, \\ min\{\eta_\rho(e), \eta_\sigma(e)\} & if\ e \in A \cap B. \end{cases}$$

$$\upsilon_\tau(e) = \begin{cases} \upsilon_\rho(e) & if\ e \in A - B, \\ \upsilon_\rho(e) & if\ e \in B - A, \\ maks\{\upsilon_\rho(e), \upsilon_\sigma(e)\} & if\ e \in A \cap B. \end{cases}$$

Definition 2.15. [3] *Suppose given a GPFSS* (F, A, ρ) *over U. Let* $q_e = (\xi_e; \eta_e; \upsilon_e)$ *where* $e \in A$ *is a PFN at* ρ. *Then defined an expectation function* $\delta(q_e) \in [0,1]$, *where for all* $e \in A$,

$\delta(q_e) = \frac{\xi_e - \upsilon_e + \eta_e + 1}{2}$.

Definition 2.16. [3] *Let* $\Gamma = (F, A, \rho)$ *be a GPFSS over U such that*

$$\sum_{e \in A} \delta(q_e) = b < +\infty,$$

where δ *is an expectation score function calculate by Definition 2.15. Then by using Definition 2.9, the Dombi aggregated picture fuzzy decision value (DAPFDV) of x in U given by*

$$W_\Gamma(x) = \bigoplus_{e \in A} \frac{\delta(q_e)}{b} F(e)(x),$$

for all $x \in U$.

Note: F(e)(x) denotes a PFN over PFS U.

Next will be given the multi attribute decision making (MADM) problem algorithm as the application of the generalized picture fuzzy soft set.

Algorithm:

1. Let $U = \{x, x_2, \ldots, x_n\}$ be a universal set and $E = \{e_1, e_2, \cdots, e_m\}$ be a parameter set. Two experts provides BPFSS (F, A) and (G, B) over U separately. Two PPFS ρ and σ are given by the head or director, so that forms two GPFSS, namely $\Gamma_1 = (F, A, \rho)$ and $\Gamma_2 = (G, B, \sigma)$.
2. Calculate the expanded intersection of Γ_1 and Γ_2 based on Definition 2.14.
3. Calculating Dombi aggregated picture fuzzy decision value (DAPFDV) by using picture fuzzy Dombi weighted average (PFDWA) as follows

$$W_\Gamma(x) = \bigoplus_{e \in A} \frac{\delta(q_e)}{b} F(e)(x),$$

4. Calculating the score function of $W_\Gamma(x_i)$ based on Definition 2.6.
5. Sort $W_\Gamma(x_i)$ using Definition 2.8. Rating x_i $(i = 1, 2, \cdots, n)$ the highest of $W_\Gamma(x_i)$ is the optimal decision is the largest PFN based on Definition 2.8.

III. Result And Discussion

This section will provide a simple case of solving a decision-making problem using the GPFSS concept. The case to be studied is the case of selecting the best school.

Case. An educational institution in city A conducts an assessment against several schools to choose the best school. For example there are seven schools, namely $U = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$ where $x_1, x_2, x_3, x_4, x_5, x_6, x_7$ respectively represent school-1, school-2, school-3, school-4, school-5, school-6, and school-7. The school is assessed based on five parameters, namely $E = \{e_1, e_2, e_3, e_4, e_5\}$ where e_1, e_2, e_3, e_4, e_5 respectively state the quality of the school environment, quality of school facilities, quality of teachers, quality of the learning process, and school achievement. The assessment is carried out by an assessment team consisting of from an institution chairman and 2 experts. Parameter set $A = \{e_2, e_3, e_4, e_5\}$ is given to the first expert and $B = \{e_1, e_2, e_4, e_5\}$ is given to second expert. Both experts assess each school and award PFSS (F, A) and PFSS (G, B) as appropriate. The head of the institution evaluates the assessment carried out by the two experts is general and provides its opinion in a PPFS ρ and σ, thus yielding two GPFSS (F, A, ρ) and (G, B, σ), shown in Tables 3.1 and 3.2.

Step 1. Given two GPFSS (F, A, ρ) and (G, B, σ) by the assessment team individually separated.

Table 3.1: GPFSS (F, A, ρ)

U	e_2	e_3	e_4	e_5
x_1	(0.4; 0.2; 0.3)	(0.5; 0.2; 0.3)	(0.5; 0.1; 0.3)	(0.2; 0.3; 0.4)
x_2	(0.4; 0.2; 0.3)	(0.4; 0.3; 0.2)	(0.1; 0.3; 0.5)	(0.3; 0.2; 0.3)
x_3	(0.3; 0.1; 0.5)	(0.3; 0.3; 0.3)	(0.4; 0.3; 0.3)	(0.4; 0.1; 0.3)
x_4	(0.2; 0.2; 0.5)	(0.1; 0.3; 0.4)	(0.2; 0.4; 0.3)	(0.6; 0.1; 0.2)
x_5	(0.6; 0.1; 0.2)	(0.2; 0.2; 0.4)	(0.6; 0.1; 0.2)	(0.2; 0.5; 0.2)
x_6	(0.5; 0.1; 0.3)	(0.6; 0.1; 0.2)	(0.4; 0.1; 0.1)	(0.3; 0.2; 0.2)
x_7	(0.2; 0.2; 0.5)	(0.5; 0.3; 0.1)	(0.3; 0.3; 0.3)	(0.7; 0.1; 0.2)
ρ	(0.3; 0.4; 0.2)	(0.3; 0.3; 0.4)	(0.5; 0.3; 0.1)	(0.4; 0.1; 0.4)

Table 3.2: GPFSS (G, B, σ)

U	e_1	e_2	e_4	e_5
x_1	$(0.3; 0.2; 0.4)$	$(0.3; 0.1; 0.5)$	$(0.1; 0.5; 0.2)$	$(0.3; 0.1; 0.4)$
x_2	$(0.3; 0.1; 0.4)$	$(0.2; 0.2; 0.4)$	$(0.6; 0.2; 0.1)$	$(0.3; 0.1; 0.4)$
x_3	$(0.5; 0.2; 0.2)$	$(0.4; 0.1; 0.4)$	$(0.3; 0.2; 0.3)$	$(0.2; 0.2; 0.5)$
x_4	$(0.1; 0.7; 0.1)$	$(0.4; 0.2; 0.3)$	$(0.5; 0.1; 0.3)$	$(0.3; 0.2; 0.5)$
x_5	$(0.6; 0.1; 0.2)$	$(0.2; 0.3; 0.4)$	$(0.1; 0.4; 0.3)$	$(0.5; 0.1; 0.3)$
x_6	$(0.4; 0.2; 0.1)$	$(0.5; 0.1; 0.3)$	$(0.1; 0.3; 0.4)$	$(0.6; 0.1; 0.2)$
x_7	$(0.5; 0.3; 0.2)$	$(0.2; 0.2; 0.5)$	$(0.4; 0.3; 0.2)$	$(0.4; 0.2; 0.3)$
σ	$(0.3; 0.2; 0.5)$	$(0.4; 0.1; 0.5)$	$(0.3; 0.4; 0.3)$	$(0.5; 0.2; 0.5)$

Step 2. Calculate the expanded intersection of GPFSS (F, A, ρ) and (G, B, σ) using Definition 2.14.

$$\Gamma = (H, C, \tau) = (F, A, \rho) \sqcap_{\epsilon} (G, B, \sigma).$$

Based on Definition 2.11 it will be calculated $(H, C) = (F, A) \cap_{\epsilon} (G, B)$, where $C = A \cup B$. Furthermore, based on Definition 2.14 for all $e \in C = A \cup B$, is obtained

$$\tau = \{(e_1; 0.3; 0.2; 0.5), (e_2; 0.3; 0.1; 0.5), (e_3; 0.3; 0.3; 0.4), (e_4; 0.3; 0.3; 0.3), (e_5; 0.4; 0.1; 0.5)\}.$$

Thus, the GPFSS (H, C, τ) is obtained which is presented in the table following.

Table 3.3: GPFSS (H, C, τ)

U	e_1	e_2	e_3	e_4	e_5
x_1	$(0.3; 0.2; 0.4)$	$(0.3; 0.1; 0.5)$	$(0.5; 0.2; 0.3)$	$(0.1; 0.1; 0.3)$	$(0.2; 0.1; 0.4)$
x_2	$(0.3; 0.1; 0.4)$	$(0.2; 0.2; 0.4)$	$(0.4; 0.3; 0.2)$	$(0.1; 0.2; 0.5)$	$(0.3; 0.1; 0.4)$
x_3	$(0.5; 0.2; 0.2)$	$(0.3; 0.1; 0.5)$	$(0.3; 0.3; 0.3)$	$(0.3; 0.2; 0.3)$	$(0.2; 0.1; 0.5)$
x_4	$(0.1; 0.7; 0.1)$	$(0.2; 0.2; 0.5)$	$(0.1; 0.3; 0.4)$	$(0.2; 0.1; 0.3)$	$(0.3; 0.1; 0.5)$
x_5	$(0.6; 0.1; 0.2)$	$(0.2; 0.1; 0.3)$	$(0.2; 0.2; 0.4)$	$(0.1; 0.1; 0.3)$	$(0.2; 0.1; 0.3)$
x_6	$(0.4; 0.2; 0.1)$	$(0.5; 0.1; 0.3)$	$(0.6; 0.1; 0.2)$	$(0.1; 0.1; 0.4)$	$(0.3; 0.1; 0.2)$
x_7	$(0.5; 0.3; 0.2)$	$(0.2; 0.2; 0.5)$	$(0.5; 0.3; 0.1)$	$(0.3; 0.3; 0.3)$	$(0.4; 0.1; 0.3)$
τ	$(0.3; 0.2; 0.5)$	$(0.3; 0.1; 0.5)$	$(0.3; 0.3; 0.4)$	$(0.3; 0.3; 0.3)$	$(0.4; 0.1; 0.5)$

Step 3. Calculate DAPFDV based on Definition 2.16 and use PFDWA for $k = 1$. First, the expectation score function will be calculated $\delta\left(q_{e_j}\right) (j = 1,2, \cdots ,5)$ using Definition 2.15, we obtain expectation score function $\delta(q_{e_1}) = 0.50, \delta(q_{e_2}) = 0.45, \delta(q_{e_3}) = 0.60, \delta(q_{e_4}) = 0.65, \delta(q_{e_5}) = 0.50$ and the sum is $b = \sum_{e \in C} \delta\left(q_{e_j}\right) = 2.70$. Next, the weight of PPFS τ will be calculates that is $\omega_j = \frac{\delta(q_{e_j})}{b}$ the weight vector is obtained as follows

$$\omega_j = (0.1852; 0.1667; 0.2222; 0.2407; 0.1852)^T.$$

For more details, the following table is given.

Table 3.4: Calculation of Weights from PPFS τ

A	e_1	e_2	e_3	e_4	e_5
q_e	$(0.3; 0.2; 0.5)$	$(0.3; 0.1; 0.5)$	$(0.3; 0.3; 0.4)$	$(0.3; 0.3; 0.3)$	$(0.4; 0.1; 0.5)$
$\delta\left(q_{e_j}\right)$	0.50	0.45	0.60	0.65	0.50
ω_j	0.1852	0.1667	0.2222	0.2407	0.1852

By using a weight that expresses the level of importance of each parameter, calculate DAPFDV based on Definition 2.16, is obtained

$$W_\Gamma(x_1) = (0.3084; 0.1256; 0.3568),$$

$$W_\Gamma(x_2) = (0.2729; 0.1543; 0.3407),$$

$$W_\Gamma(x_3) = (0.3339; 0.1565; 0.3152),$$

$$W_\Gamma(x_4) = (0.1847; 0.1640; 0.2555),$$

$$W_\Gamma(x_5) = (0.3094; 0.1125; 0.2893),$$

$$W_\Gamma(x_6) = (0.4218; 0.1102; 0.1982),$$

$$W_\Gamma(x_7) = (0.4033; 0.2064; 0.2040).$$

Step 4. Calculating the score function of $W_\Gamma(x_i)$ $(i = 1,2,\cdots,7)$ based on Definition 2.6, obtained

$$\Theta\big(W_\Gamma(x_1)\big) = -0.0484,$$

$$\Theta\big(W_\Gamma(x_2)\big) = -0.0678,$$

$$\Theta\big(W_\Gamma(x_3)\big) = 0.0187,$$

$$\Theta\big(W_\Gamma(x_4)\big) = -0.0708,$$

$$\Theta\big(W_\Gamma(x_5)\big) = 0.0201,$$

$$\Theta\big(W_\Gamma(x_6)\big) = 0.2236,$$

$$\Theta\big(W_\Gamma(x_7)\big) = 0.1993.$$

Step 5. Sorting DAPFDV based on Definition 2.8, is obtained

$$\Theta\big(W_\Gamma(x_4)\big) < \Theta\big(W_\Gamma(x_2)\big) < \Theta\big(W_\Gamma(x_1)\big) < \Theta\big(W_\Gamma(x_3)\big) < \Theta\big(W_\Gamma(x_7)\big) < \Theta\big(W_\Gamma(x_5)\big) < \Theta\big(W_\Gamma(x_6)\big).$$

From the DAPFDV sequence above, the following PFDWA sequence is obtained

$$W_\Gamma(x_4) \prec W_\Gamma(x_2) \prec W_\Gamma(x_1) \prec W_\Gamma(x_3) \prec W_\Gamma(x_7) \prec W_\Gamma(x_5) \prec W_\Gamma(x_6).$$

Based on the sequence in Step 5, x_6 is obtained as a decision optimal, meaning an educational institution that conducts assessments can choose school-6 as the best school. With similar steps, for $k = 2$ and $k = 3$, x_6 is also obtained as the optimal decision.

IV. CONCLUSION

The best school based on the GPFSS approach are schools that have a good school environment, good school facilities, good quality teachers, good learning process, and good school performance. The application of the generalized picture fuzzy soft set concept to multi attribute decision making in determining the best school out of 7 schools, namely $x_1, x_2, x_3, x_4, x_5, x_6, x_7$, obtained x_6 as the optimal decision.

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