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Single-Valued Neutrosophic Graph with Heptapartitioend Structure

Hanaa fathi[1], M. Myvizhi[2], Ahmed Abdelhafeez[3*,4], Mohamed Refaat Abdellah[5], Mohamed Eassa [3,4], Mohamed S. Sawah[6], Hussam Elbehiery[3]

[1]College of Information Technology, Amman Arab University, Amman, Jordan.

[2]Assistant Professor, KPR Institute of Engineering and Technology, Coimbatore, Tamilnadu, India.

[3]Computer Science Department, Faculty of Information System and Computer Science, October 6 University, Giza, 12585, Egypt

[4]Applied Science Research Center. Applied Science Private University, Amman, Jordan

[5]The Department of Computer Science, College of Information Technology, Misr University for Science and Technology, Cairo, Egypt

[6]Department of Computer Science, Faculty of Information Technology, Ajloun National University P.O.43, Ajloun-26810, JORDAN

*Correspondence: aahafeez.scis@o6u.edu.eg

Abstract

This study applies single-valued neutrosophic sets, which extend the frameworks of fuzzy and intuitionistic fuzzy sets, to graph theory. We introduce a new category of graphs called Single-Valued Heptapartitioned Neutrosophic Graphs (SVHNG) and investigate their characteristics through comprehensive proofs and illustrative examples.

Keywords: Neutrosophic Sets, Heptapartitioend Neutrosophic Set, Neutrosophic Graph, SVHN-Graph.

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1. Introduction

Graph theory is a fundamental branch of mathematics that studies the relationships between objects, represented as vertices or nodes, and the connections between them represented as edges (West, 2001; Bondy & Murty, 2008 [1,2]). It provides a powerful tool for modeling and analyzing complex systems, networks, and relationships in various fields, including computer science, physics, biology, and social sciences (Newman, 2010; Barabási, 2016 [3,4]). By representing systems as graphs, researchers and practitioners can gain insights into their structure, behavior, and evolution, and develop efficient algorithms and techniques for solving complex problems.

For every solution, classical MCDM requires exact accurate numbers as decision data. Nevertheless, as decision theory develops and is used more often, we see that: (1) Most choice problems are ambiguous by nature, which prevents decision-makers (DMs) from providing evaluation values in a binary fashion. Examples include ranking universities' overall strength or evaluating urban modernization. (2) Cognitive elements and personal thought patterns frequently cause ambiguity and confusion in practical decision-making. As a result, it gets harder and harder to apply traditional MCDM theory and techniques to real-world decision issues.

In 1965, Zadeh presented FS theory to address this hazy phenomenon. Uncertain membership in sets results from what we try to represent lacking distinct and well-defined bounds, as the FS theory acknowledges. The unit interval [0,1] defines the thesis range, or the domain of study, thereby expressing this association as a fuzzy set. Such phenomena can be examined and dealt with by defining suitable affiliation functions and applying operations and transformations to fuzzy sets. This theory has wide-ranging applicability in many socioeconomic fields and offers a convincing explanation for the ubiquity of fuzzy occurrences in the objective world.

When assessing things or phenomena, the DMs frequently come across a neutral state distinct from an affirmative or negative position. This condition, the DM's hesitate degree, represents the unpredictability of decision-making processes and may be impacted by several DM-specific characteristics. Several academics have examined and improved traditional FS theory to deal with this ambiguity, suggesting novel FS expansions.

First, the interval fuzzy set, created by researcher Turksen in 1986, expresses the degree of connectivity using interval numbers. The concept of a hesitant fuzzy set was also made by Torra in 2010, which permits the degree of attachment to exist as multiple possible values within a fuzzy set. Interestingly, the degree of reluctance of the decision subject is not directly represented by either interval fuzzy sets or hesitate fuzzy sets. Rather, they statistically characterize uncertainty in decision events by broadening the range of potential values for the degree of attachment.

Second, unlike standard fuzzy sets, the IFSs, developed by scholar Atanassov in 1986, integrate affiliation and unaffiliated degree information. For the first time, they provide a hesitate degree, considering the total affiliation, unaffiliated, and hesitate degrees. IFSs somewhat describe uncertainty in decision events. For example, the intuitionistic fuzzy set can represent a company's vote on whether to invest in a project when a panel of ten DMs is composed of seven in favor, two against, and one abstaining.

It is crucial to remember that the reluctance of decision subjects cannot be fully captured by interval fuzzy sets, IFSs, or hesitate fuzzy sets. Each cannot adequately capture the unpredictability of choice occurrences. One or more of the previously stated classical fuzzy extension sets are the foundation for most of the following fuzzy extension sets. These additional sets improve the capacity to describe fuzziness and uncertainty created by superposing and fusing the original classical fuzzy extension sets. Nevertheless, their internal systems have grown more intricate, which has decreased their usefulness and application.

Neutrosophic sets, introduced by Smarandache in 1998, are a mathematical framework that extends the concept of fuzzy sets to manage indeterminate and inconsistent information (Smarandache, 1998 [5]). Neutrosophic sets are characterized by three membership functions: truth (T), indeterminacy (I), and falsehood (F), which satisfy the condition $T + I + F \leq 3$ (Wang et al., 2010 [6]). This framework provides a powerful tool for modeling and analyzing complex systems, particularly when data is uncertain, imprecise, or incomplete.

Fuzzy graphs are a mathematical framework that combines graph theory with fuzzy set theory, introduced by Zadeh in 1965 [7]. Fuzzy graphs model complex systems where object relationships are uncertain or imprecise (Rosenfeld, 1975 [8]). In a fuzzy graph, each edge is assigned a membership value between 0 and 1, representing the degree of connection or relationship between the vertices (Yeh & Bang, 1975 [9]). This framework provides a powerful tool for modeling and analyzing complex networks, particularly when data is uncertain or incomplete.

Intuitionistic fuzzy graphs are a mathematical framework that combines graph theory with intuitionistic fuzzy set theory, introduced by Atanassov in 1986 [10]. Intuitionistic fuzzy graphs are used to model complex systems where relationships between objects are uncertain, imprecise, or incomplete (Atanassov, 1999 [11]). In an intuitionistic fuzzy graph, each edge is assigned two membership values: a membership value and a non-membership value, which satisfy the condition that the sum of the two values is less than or equal to 1 (Sharma, 2014 [12]). This framework provides a powerful tool for modeling and analyzing complex networks, particularly when data is uncertain or incomplete.

Introduced by Smarandache in 1998, neutrosophic graphs are a mathematical paradigm that blends neutrosophic set theory and graph theory. Complex systems with ambiguous, imperfect, or incomplete interactions between items are modeled using neutrophilic graphs (Smarandache, 2010 [13]). The degree of truth, indeterminacy, and untruth of the link between the vertices is represented by the neutrosophic number allocated to each edge in a neutrosophic network (Broumi et al., 2016 [14]). This paradigm offers a potent tool for modeling and analyzing complicated networks, especially when data is ambiguous or lacking.

Further research on neutrophilic graphs has been done in [15–18]. Interval NGs were first introduced by Broumi et al. [19] and have since been further examined in [20–21]. In a variety of hybrid environments, including neutrosophic soft graphs [22], bipolar SVN graphs [23], rough neutrosophic diagraphs [24], neutrosophic soft, rough graphs [25], and others, NGs have been further investigated. In several settings, recent developments in graph theory have been illustrated in [26].

The concept of heptapartitioned neutrosophic sets was introduced by Florentin Smarandache [27]. A single-valued heptapartitioned neutrosophic set (SVHNS) is a mathematical framework that extends the concept of neutrosophic sets to manage more complex and uncertain information. In an SVHNS, each element is assigned seven membership values: truth (T), indeterminacy (I), falsehood (F), unknown truth (UT), unknown indeterminacy (UI), unknown falsehood (UF), and unknown (U), which satisfy certain conditions (Broumi et al., 2016 [28]). This framework provides a powerful tool for modeling and analyzing complex systems, particularly when data is uncertain, imprecise, or incomplete.

The Single Valued Heptapartitioned Neutrosophic (SVHN) graph is obtained for this study, and its fundamental characteristics are established.

2. Preliminaries

This section offers a few current definitions pertinent to the article's primary findings.

Definition 2.1 [29] Neutrosophic Set A on Y is defined as follows:

$\boldsymbol{B = \{< y, \alpha_B(y), \gamma_B(y), \delta_B(y) >, y \in Y\}}$ where $\boldsymbol{\alpha_B,\ \beta_B,\ \gamma_B : B \to [0,1]}$ and $\boldsymbol{0 \le \alpha_B(x) + \beta_B(y) + \gamma_B(y) \le 3}$.Here, $\boldsymbol{\alpha_B(y)}$ is the degree of membership, $\boldsymbol{\beta_B(y)}$is the degree of indeterminacy and $\boldsymbol{\gamma_B(y)}$ is the degree of non-membership. Here, $\boldsymbol{\alpha_B(x)}$ and $\boldsymbol{\gamma_B(y)}$ are dependent on neutrosophic elements and $\boldsymbol{\beta_B(y)}$ is an independent neutrosophic element.

Definition 2.2 [30] Assume that Y is a universe. A QNS, B on Y with separate neutrosophic components is an example of an object of this sort.

$$\boldsymbol{B = \{< y, \alpha_B(y), C_B(y), U_B(y), \gamma_B(y) >, y \in Y\}}$$

and $\boldsymbol{0 \le \alpha_B(y) + C_B(y) + U_B(y) + \gamma_B(y) \le 4}$ Here, $\boldsymbol{\alpha_B(y)}$ is the truth membership, $\boldsymbol{C_B(y)}$ is contradiction membership, $\boldsymbol{U_B(y)}$ is ignorance membership and $\boldsymbol{\gamma_B(y)}$ is a false membership.

Definition 2.3 [32,33] The set P must not be empty. Every element of P has a PNS over P defined by a truth-membership function $\boldsymbol{\alpha_B(y)}$, a contradiction membership function $\boldsymbol{C_B(y)}$ an ignorance membership function $\boldsymbol{G_B(y)}$ unknown membership function $\boldsymbol{U_B(y)}$ and a falsity membership function $\boldsymbol{\gamma_B(y)}$ such that for each $\boldsymbol{p \in P}$, $\boldsymbol{0 \le \alpha_B(y) + C_B(y) + G_B(y) + U_B(y) + \gamma_B(y) \le 5}$.

Definition 2.4 [31] Let the universe R be non-empty. In the neutrosophic set Heptapartitioned (HNS) every element has a B over R. Here an absolute truth-membership function. $\boldsymbol{0 \le \alpha_B}$, a relative truth membership function M_B, a contradiction membership function C_A, an ignorance membership function I_A, an unknown membership function U_A, an absolute falsity membership function F_A and a relative falsity membership function K_A such that for each $p \in R$, $T_A, M_A, C_A, I_A, U_A, F_A, K_A \in [0,1]$ and

$$\boldsymbol{B = [\,p, \alpha_B(p), M_B(p), C_B(p), \beta_B(p), U_B(p), \gamma_B(p), K_B(p) : p \in R\,]\ 0 \le \alpha_B(p) + M_B(p) + C_B(p) + I_B(p) + U_B(p) + \gamma_B(p) + K_B(p) \le 7}.$$

3. Single valued Heptapartitioned Neutrosophic Graphs

Definition 3.1. Let $\mathfrak{V} = \{v_i, i = 1,2 \dots . n\}$ Be an unchanging collection of vertices and $\mathcal{E} = \{(v_i, v_j), i, j = 1,2 \dots . n\}$ Be the collection of vertices' edges of $\mathfrak{V}$. A Single Valued Heptapartitioned Neutrosophic Graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is defined by $\mathcal{G} = (H_1, H_2)$, where (i) $T_{H_1}: \mathfrak{V} \to [0,1], M_{H_1}: \mathfrak{V} \to [0,1], C_{H_1}: \mathfrak{V} \to [0,1], I_{H_1}: \mathfrak{V} \to [0,1], U_{H_1}: \mathfrak{V} \to [0,1], F_{H_1}: \mathfrak{V} \to [0,1]$, $K_{H_1}: \mathfrak{V} \to [0,1]$ represents the absolute truth, relative truth, contradiction, ignorance, unknown, absolute falsity, relative falsity membership functions of the vertices $v_i \in \mathfrak{V}$ accordingly, such that $0 \leq T_{H_1}(v_i) + M_{H_1}(v_i) + C_{H_1}(v_i) + I_{H_1}(v_i) + U_{H_1}(v_i) + F_{H_1}(v_i) + K_{H_1}(v_i) \leq 7$,for every $v_i \in \mathfrak{V}(i = 1,2 \dots . n)$;

(ii) $T_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1], M_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1], C_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1], I_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1], U_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1], F_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1], K_{H_2}: \mathcal{E} \subseteq \mathfrak{V} \times \mathfrak{V} \to [0,1]$ specified by $T_{H_2}(v_i, v_j) \leq \min\{T_{H_1}(v_i), T_{H_1}(v_j)\}, M_{H_2}(v_i, v_j) \leq \min\{M_{H_1}(v_i), M_{H_1}(v_j)\}, C_{H_2}(v_i, v_j) \leq \min\{C_{H_1}(v_i), C_{H_1}(v_j)\}, I_{H_2}(v_i, v_j) \geq \max\{I_{H_1}(v_i), I_{H_1}(v_j)\}, U_{H_2}(v_i, v_j) \geq \max\{U_{H_1}(v_i), U_{H_1}(v_j)\}, F_{H_2}(v_i, v_j) \geq \max\{F_{H_1}(v_i), F_{H_1}(v_j)\}, K_{H_2}(v_i, v_j) \geq \max\{K_{H_1}(v_i), K_{H_1}(v_j)\}$.

We know that both H_1 and H_2 is the SVHN set over $\mathfrak{V}$ and $\mathcal{E}$ Accordingly.

Example 3.1. Let $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is a graph, where $\mathfrak{V} = \{v_1, v_2, v_3, v_4\}$ and $\mathcal{E} = \{(v_1, v_2), (v_2, v_3), (v_3, v_4), (v_4, v_1)\}$. Here H_1 is an SVHN vertex set of $\mathfrak{V}$ and H_2 is an SVHN edge set of $\mathcal{E}$ specified by the following table values.

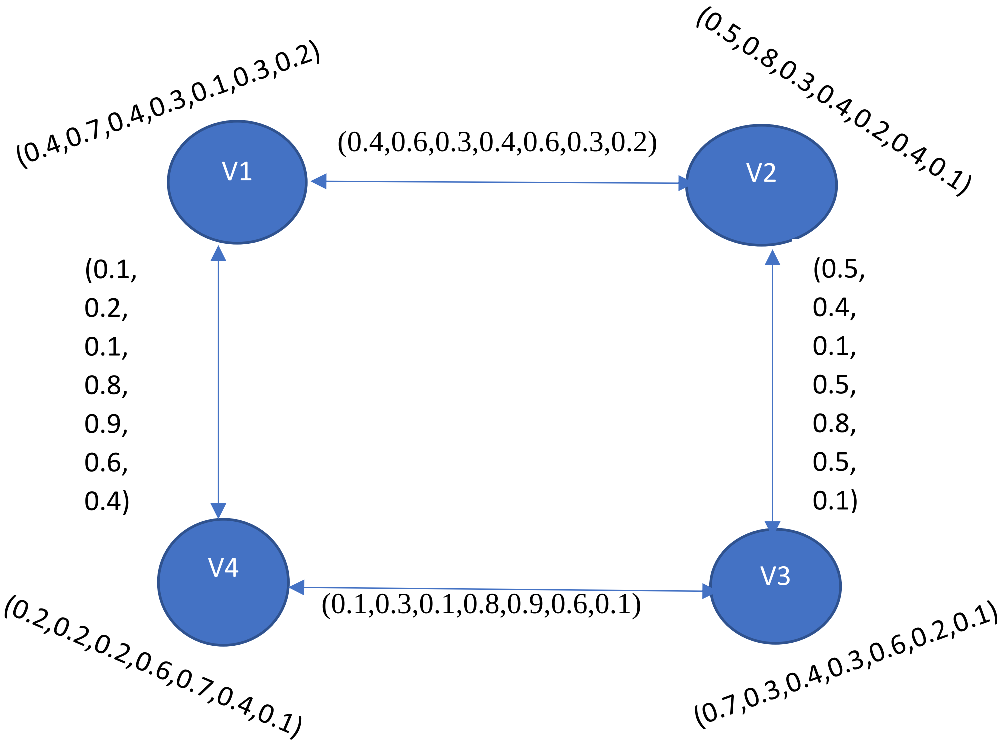
Table 1

	v_1	v_2	v_3	v_4
T_{H_1}	0.4	0.5	0.7	0.2
M_{H_1}	0.7	0.8	0.3	0.2
C_{H_1}	0.4	0.3	0.4	0.2
I_{H_1}	0.3	0.4	0.3	0.6
U_{H_1}	0.1	0.2	0.6	0.7
F_{H_1}	0.3	0.4	0.2	0.4
K_{H_1}	0.2	0.1	0.1	0.1

Table 2

	(v_1, v_2)	(v_2, v_3)	(v_3, v_4)	$(v_4, v_{1,})$
T_{H_2}	0.4	0.5	0.1	0.1
M_{H_2}	0.6	0.4	0.3	0.2
C_{H_2}	0.3	0.1	0.1	0.1
I_{H_2}	0.4	0.5	0.8	0.8
U_{H_2}	0.6	0.8	0.9	0.9
F_{H_2}	0.3	0.5	0.6	0.6
K_{H_2}	0.2	0.1	0.1	0.4

The above table is shown in the following diagram.



Remark 3.1. Let $\mathcal{G} = (H_1, H_2)$ Is an SVHN graph. Afterward, the edge (v_i, v_j) is said to be an incident at v_i and v_j.

Definition 3.2. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph. Subsequently,

(i) $(v_i, T_{H_1}(v_i), M_{H_1}(v_i), C_{H_1}(v_i), I_{H_1}(v_i), U_{H_1}(v_i), F_{H_1}(v_i), K_{H_1}(v_i))$ is called a single-valued heptapartitioned neutrosophic (SVHN) vertex.

(ii) $((v_i, v_j), T_{H_2}(v_i, v_j), M_{H_2}(v_i, v_j), C_{H_2}(v_i, v_j), I_{H_2}(v_i, v_j), U_{H_2}(v_i, v_j), F_{H_2}(v_i, v_j),$

$K_{H_2}(v_i, v_j))$ is called a single-valued heptapartitioned neutrosophic (SVHN) edge.

Definition 3.3. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph. Afterwards, $H = (H_1{}', H_2{}')$ is called an SVHN sub-graph of $\mathcal{G} = (H_1, H_2)$ if $H = (H_1{}', H_2{}')$ is also an SVHN-graph such that:

(i) $H_1{}' \subseteq H_1$ i.e., $T'_{H_{1i}} \le T_{H_{1i}}, M'_{H_{1i}} \le M_{H_{1i}}, C'_{H_{1i}} \le C_{H_{1i}}, I'_{H_{1i}} \ge I_{H_{1i}}, U'_{H_{1i}} \ge U_{H_{1i}}, F'_{H_{1i}} \ge F_{H_{1i}}, K'_{H_{1i}} \ge K_{H_{1i}}$, for every $v_i \in \mathfrak{V}$;

(ii) $H_2{}' \subseteq H_2$ i.e., $T'_{H_{2i}} \le T_{H_{2i}}, M'_{H_{2i}} \le M_{H_{2i}}, C'_{H_{2i}} \le C_{H_{2i}}, I'_{H_{2i}} \ge I_{H_{2i}}, U'_{H_{2i}} \ge U_{H_{2i}}, F'_{H_{2i}} \ge F_{H_{2i}}, K'_{H_{2i}} \ge K_{H_{2i}}$, for every $(v_i, v_j) \in \mathcal{E}$.

Example 3.2. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph as shown in the previous example. Afterwards, $H = (H_1{}', H_2{}')$ where $\mathfrak{V}' = \{\mathcal{v}_1, \mathcal{v}_3, \mathcal{v}_4\}$; $\mathcal{E}' = \{(\mathcal{v}_{1,}\mathcal{v}_3), (\mathcal{v}_{3,}\mathcal{v}_4)\}$ specified by the following table values.

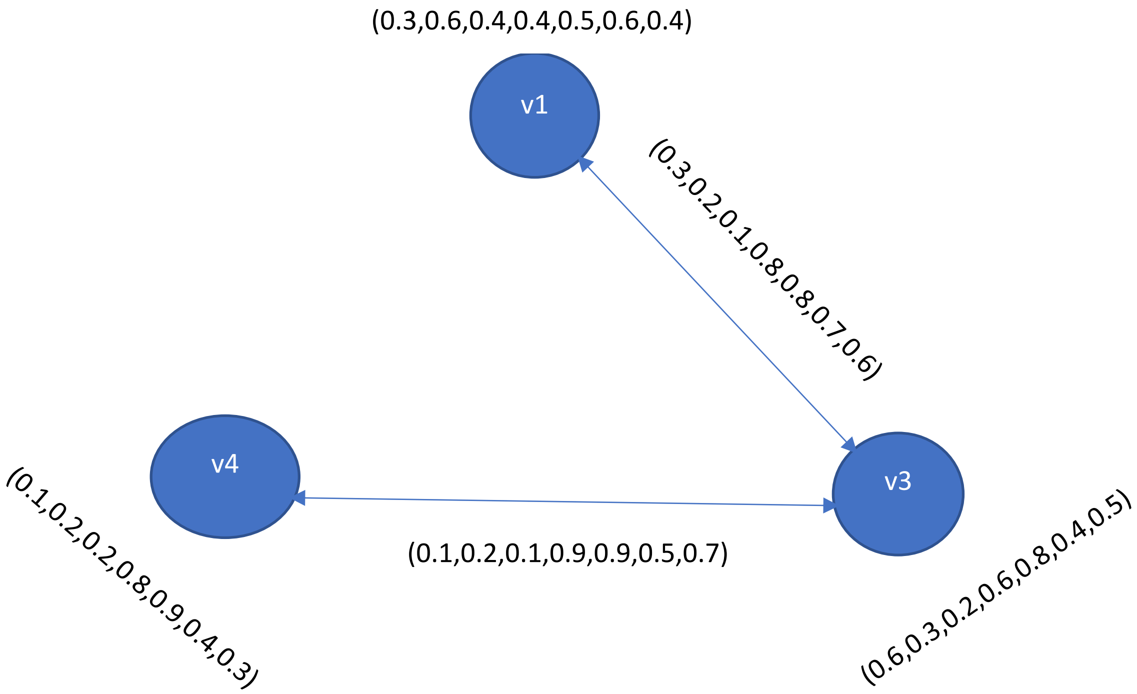
Table 3

	$\mathcal{v}_1$	$\mathcal{v}_3$	$\mathcal{v}_4$
T'_{H_1}	0.3	0.6	0.1
M'_{H_1}	0.6	0.3	0.2
C'_{H_1}	0.4	0.2	0.2
I'_{H_1}	0.4	0.6	0.8
U'_{H_1}	0.5	0.8	0.9
F'_{H_1}	0.6	0.4	0.4
K'_{H_1}	0.4	0.5	0.3

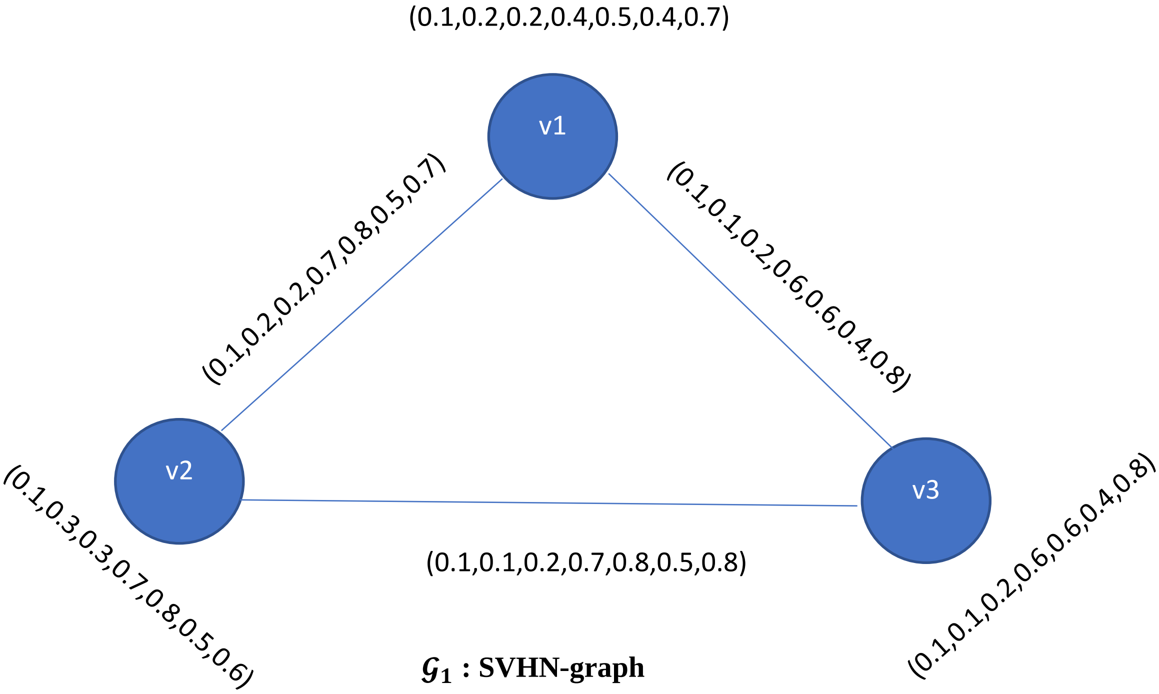
Table 4

	$(\mathcal{v}_{1,}\mathcal{v}_3)$	$(\mathcal{v}_3, \mathcal{v}_4)$
T'_{H_2}	0.3	0.1
M'_{H_2}	0.2	0.2
C'_{H_2}	0.1	0.1
I'_{H_2}	0.8	0.9
U'_{H_2}	0.8	0.9
F'_{H_2}	0.7	0.5
K'_{H_2}	0.6	0.7

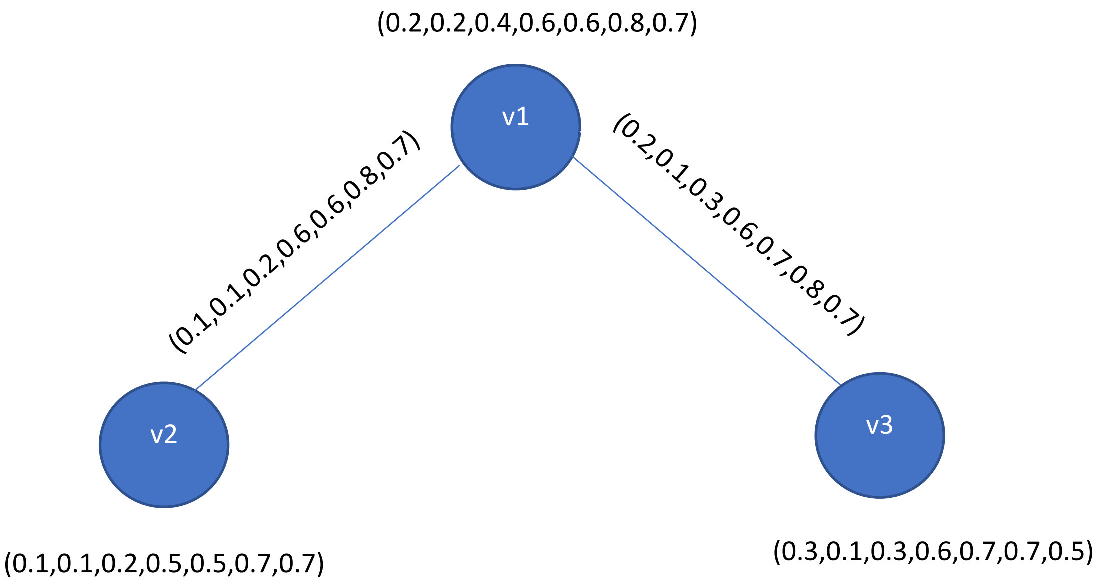
The above table is shown in the following diagram.



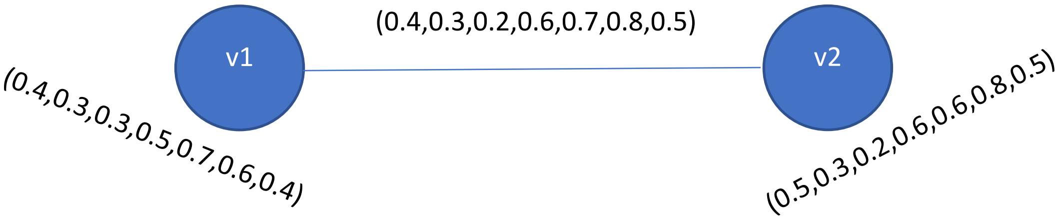
Example 3.3. $\mathcal{G}_1$ is a SVHN-graph. $H_1{}^*$ is a partial SVHN-subgraph and $H_2{}^*$ is a SVHN-subgraph of $\mathcal{G}_1$.



$\mathcal{G}_1$ **: SVHN-graph**



$H_1{}^*$ **: partial SVHN-subgraph**



$H_2{}^*$: SVHN-subgraph of $\mathcal{G}_1$

Definition 3.4. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$. Afterward, the complement of $\mathcal{G} = (H_1, H_2)$ is an SVHN-graph $\bar{\mathcal{G}}$ of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ where

(i) $\bar{T}_{H_1}(v_i) = T_{H_1}(v_i), \bar{M}_{H_1}(v_i) = M_{H_1}(v_i), \bar{C}_{H_1}(v_i) = C_{H_1}(v_i), \bar{I}_{H_1}(v_i) = I_{H_1}(v_i), \bar{U}_{H_1}(v_i) = U_{H_1}(v_i), \bar{F}_{H_1}(v_i) = F_{H_1}(v_i), \bar{K}_{H_1}(v_i) = K_{H_1}(v_i)$;

(ii) $\bar{T}_{H_2}(v_i, v_j) = \min\{T_{H_1}(v_i), T_{H_1}(v_j)\} - T_{H_2}(v_i, v_j), \bar{M}_{H_2}(v_i, v_j) = \min\{M_{H_1}(v_i), M_{H_1}(v_j)\} - M_{H_2}(v_i, v_j), \bar{C}_{H_2}(v_i, v_j) = \min\{C_{H_1}(v_i), C_{H_1}(v_j)\} - C_{H_2}(v_i, v_j), \bar{I}_{H_2}(v_i, v_j) = \max\{I_{H_1}(v_i), I_{H_1}(v_j)\} - I_{H_2}(v_i, v_j), \bar{U}_{H_2}(v_i, v_j) = \max\{U_{H_1}(v_i), U_{H_1}(v_j)\} - U_{H_2}(v_i, v_j),$

$\bar{F}_{H_2}(v_i, v_j) = \max\{F_{H_1}(v_i), F_{H_1}(v_j)\} - F_{H_2}(v_i, v_j),$

$\bar{K}_{H_2}(v_i, v_j) = \max\{K_{H_1}(v_i), K_{H_1}(v_j)\} - K_{H_2}(v_i, v_j)$, for every $(v_i, v_j) \in \mathcal{E}$.

Definition 3.5. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph. Afterwards, the vertices v_i and v_j are called adjacent in $\mathcal{G} = (H_1, H_2)$ if and only if $T_{H_2}(v_i, v_j) = \min\{T_{H_1}(v_i), T_{H_1}(v_j)\}, M_{H_2}(v_i, v_j) = \min\{M_{H_1}(v_i), M_{H_1}(v_j)\}, C_{H_2}(v_i, v_j) = \min\{C_{H_1}(v_i), C_{H_1}(v_j)\}, I_{H_2}(v_i, v_j) = \max\{I_{H_1}(v_i), I_{H_1}(v_j)\}, U_{H_2}(v_i, v_j) = \max\{U_{H_1}(v_i), U_{H_1}(v_j)\}, F_{H_2}(v_i, v_j) = \max\{F_{H_1}(v_i), F_{H_1}(v_j)\}, K_{H_2}(v_i, v_j) = \max\{K_{H_1}(v_i), K_{H_1}(v_j)\}$.

Example 3.4. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN graph, which is specified in the following table values.

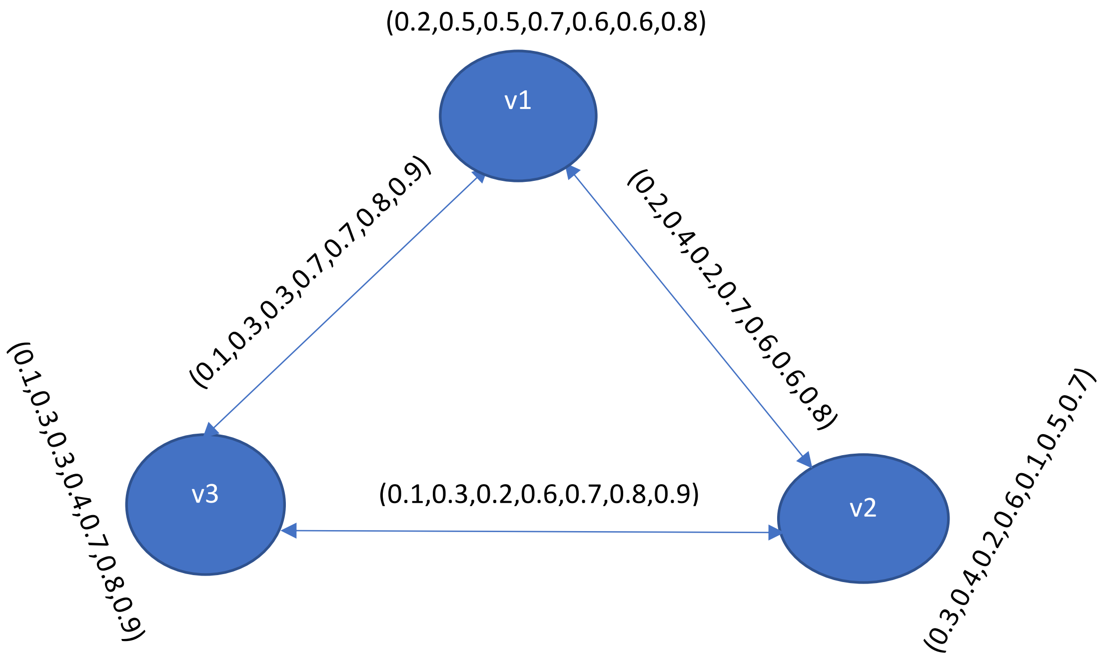
Table 5

	v_1	v_2	v_3
T_{H_1}	0.2	0.3	0.1
M_{H_1}	0.5	0.4	0.3
C_{H_1}	0.5	0.2	0.3
I_{H_1}	0.7	0.6	0.4
U_{H_1}	0.6	0.1	0.7
F_{H_1}	0.6	0.5	0.8
K_{H_1}	0.8	0.7	0.9

Table 6

	(v_1, v_2)	(v_2, v_3)	(v_3, v_1)
T_{H_2}	0.2	0.1	0.1
M_{H_2}	0.4	0.3	0.3
C_{H_2}	0.2	0.2	0.3
I_{H_2}	0.7	0.6	0.7
U_{H_2}	0.6	0.7	0.7
F_{H_2}	0.6	0.8	0.8
K_{H_2}	0.8	0.9	0.9

The above table is shown in the following diagram.



Definition 3.6. In an SVHN-graph, $\mathcal{G} = (H_1, H_2)$, a vertex $v_j \in \mathfrak{V}$ is called an isolated vertex if there exists no edge incident at v_j.

Example 3.5. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN graph, which is specified by the following table values.

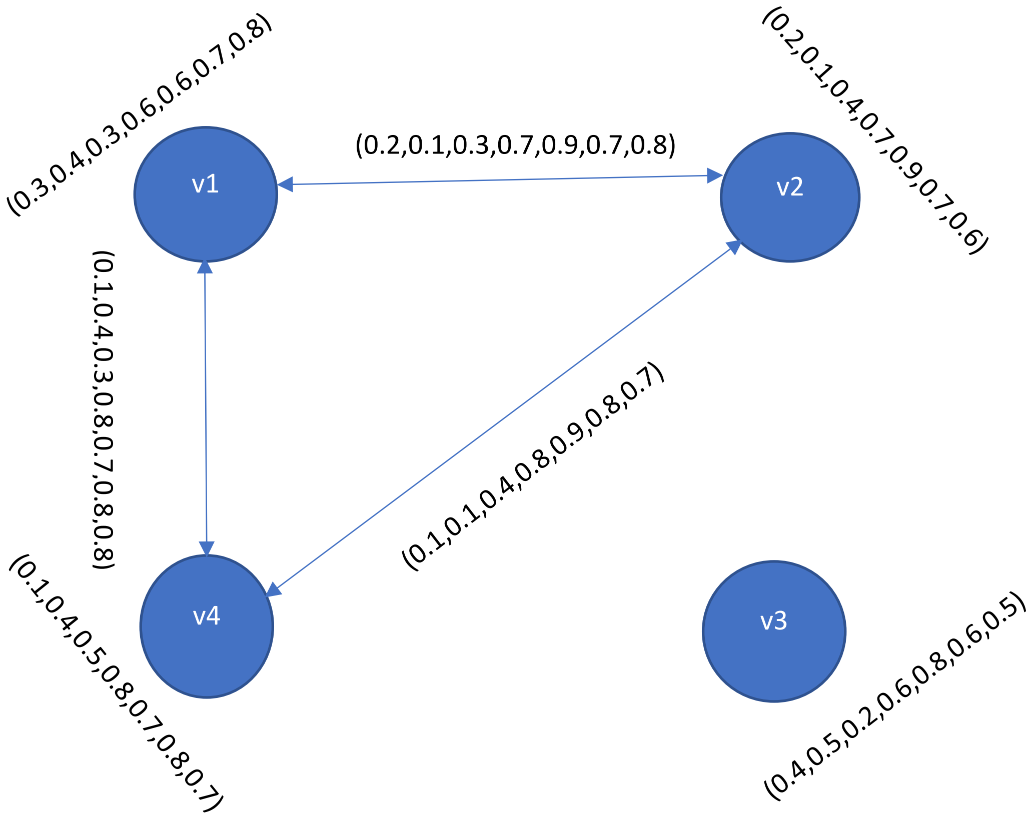
Table 7

	v_1	v_2	v_3	v_4
T_{H_1}	0.3	0.2	0.4	0.1
M_{H_1}	0.4	0.1	0.5	0.4
C_{H_1}	0.3	0.4	0.2	0.5
I_{H_1}	0.6	0.7	0.6	0.8
U_{H_1}	0.6	0.9	0.8	0.7
F_{H_1}	0.7	0.7	0.6	0.8
K_{H_1}	0.8	0.6	0.5	0.7

Table 8

	(v_1,v_2)	(v_2,v_4)	(v_4,v_1)
T_{H_2}	0.2	0.1	0.1
M_{H_2}	0.1	0.1	0.4
C_{H_2}	0.3	0.4	0.3
I_{H_2}	0.7	0.8	0.8
U_{H_2}	0.9	0.9	0.7
F_{H_2}	0.7	0.8	0.8
K_{H_2}	0.8	0.7	0.8

The above table is shown in the following diagram.



Definition 3.7. Let $\mathcal{G} = (H_1, H_2)$ is an SVHN graph. Here v_0 and v_n be two vertices in $\mathcal{G} = (H_1, H_2)$. Then an SVHN path $H_1(v_0, v_n)$ in an SVHN-graph $\mathcal{G} = (H_1, H_2)$ is a sequence of different vertices $k_0, k_1 \dots \dots k_n$ such that $T_{H_2}(v_{i-1}, v_i) > 0, M_{H_2}(v_{i-1}, v_i) > 0, C_{H_2}(v_{i-1}, v_i) > 0, I_{H_2}(v_{i-1}, v_i) > 0, U_{H_2}(v_{i-1}, v_i) > 0, F_{H_2}(v_{i-1}, v_i) > 0, K_{H_2}(v_{i-1}, v_i) > 0$, where $0 \le i \le n$. Here $n(\ge 1)$ is called the length of the path $H_1(v_0, v_n)$. The consecutive pairs (v_{i-1}, v_i) $(0 \le i \le n)$ are called the edges of the path $H_1(v_0, v_n)$. The path $H_1(v_0, v_n)$ is called a cycle if $v_0 = v_n$, where $n \ge 3$.

Definition 3.8. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph. Afterwards, $\mathcal{G} = (H_1, H_2)$ is said to be an SVHN-connected graph if there exists at least one SVHN path between two vertices.

Remark 3.2. If an SVHN-graph $\mathcal{G} = (H_1, H_2)$ is not an SVHN-C-graph, then it is called an SVHN Dis-connected graph.

Definition 3.9. A pendant vertex is a vertex with exactly one edge incident on it in a single-valued neutrosophic graph $\mathcal{G} = (H_1, H_2)$. It is referred to as a non-pendent vertex otherwise.

A pendant edge is an edge with a pendent vertex in a single-valued neutrosophic graph. $\mathcal{G} = (H_1, H_2)$ incident. It is referred to as a non-pendent edge otherwise.

A support of the pendent edge is a vertex that is next to the pendent vertex in a single-valued neutrosophic graph.

Example 3.6. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph, which is specified by the following table values.

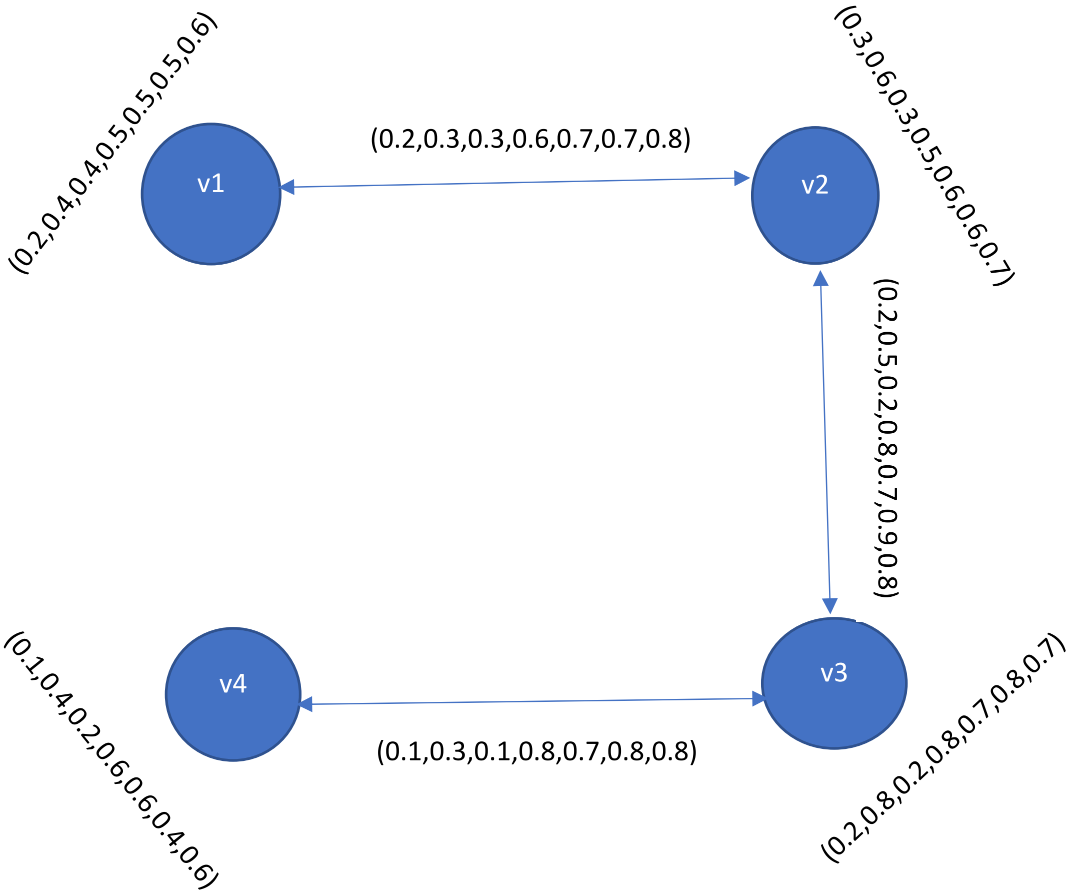
Table 9

	v_1	v_2	v_3	v_4
T_{H_1}	0.2	0.3	0.2	0.1
M_{H_1}	0.4	0.6	0.8	0.4
C_{H_1}	0.4	0.3	0.2	0.2
I_{H_1}	0.5	0.5	0.8	0.6
U_{H_1}	0.5	0.6	0.7	0.6
F_{H_1}	0.5	0.6	0.8	0.4
K_{H_1}	0.6	0.7	0.7	0.6

Table 10

	(v_1,v_2)	(v_2,v_3)	(v_3,v_4)
T_{H_2}	0.2	0.2	0.1
M_{H_2}	0.3	0.5	0.3
C_{H_2}	0.3	0.2	0.1
I_{H_2}	0.6	0.8	0.8
U_{H_2}	0.7	0.7	0.7
F_{H_2}	0.7	0.9	0.8
K_{H_2}	0.8	0.8	0.8

The above table is shown in the following diagram.



Definition 3.10. A SVHN-graph $\mathcal{G} = (H_1, H_2)$ of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is said to be a complete SVHN graph if $T_{H_2}(v_i, v_j) = \min\{T_{H_1}(v_i), T_{H_1}(v_j)\}$, $M_{H_2}(v_i, v_j) = \min\{M_{H_1}(v_i), M_{H_1}(v_j)\}$, $C_{H_2}(v_i, v_j) = \min\{C_{H_1}(v_i), C_{H_1}(v_j)\}$, $I_{H_2}(v_i, v_j) = \max\{I_{H_1}(v_i), I_{H_1}(v_j)\}$, $U_{H_2}(v_i, v_j) = \max\{U_{H_1}(v_i), U_{H_1}(v_j)\}$, $F_{H_2}(v_i, v_j) = \max\{F_{H_1}(v_i), F_{H_1}(v_j)\}$, $K_{H_2}(v_i, v_j) = \max\{K_{H_1}(v_i), K_{H_1}(v_j)\}$ for every $v_i, v_j \in \mathfrak{V}$.

Example 3.7. Let $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is a graph, where $\mathfrak{V} = \{v_1, v_2, v_3\}$ and $\mathcal{E} = \{(v_1, v_2), (v_2, v_3), (v_3, v_1)\}$ be specified by the following table values.

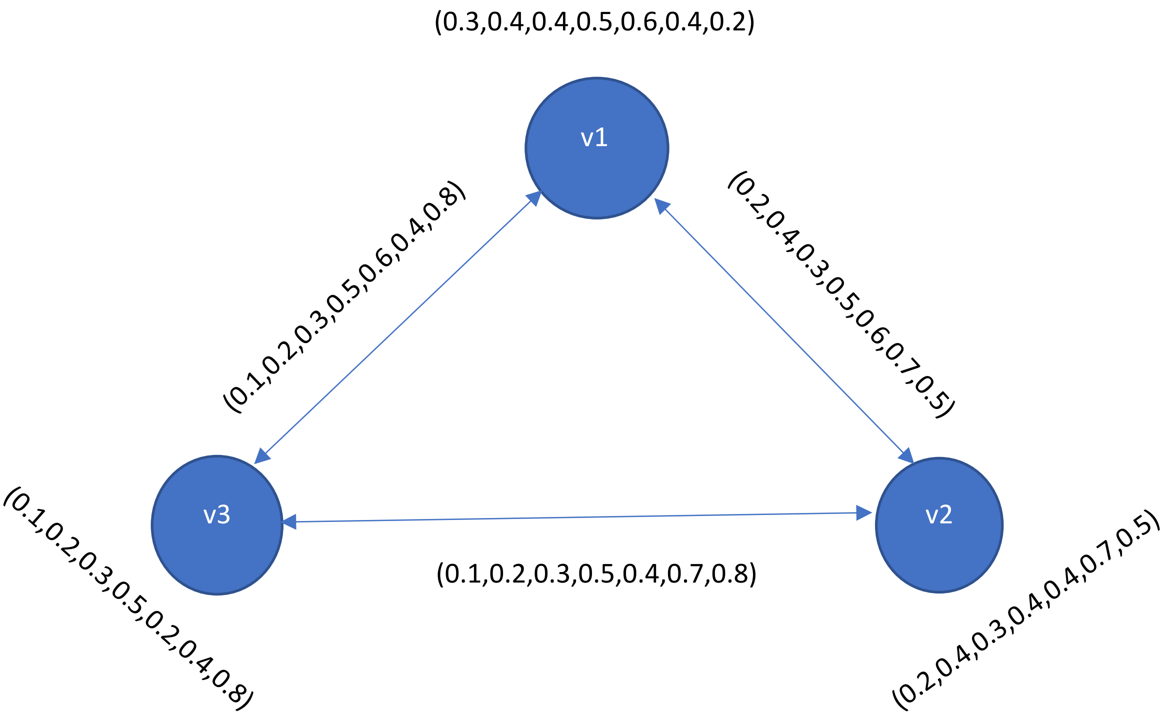
Table 11

	v_1	v_2	v_3
T_{H_1}	0.3	0.2	0.1
M_{H_1}	0.4	0.4	0.2
C_{H_1}	0.4	0.3	0.3
I_{H_1}	0.5	0.4	0.5
U_{H_1}	0.6	0.4	0.2
F_{H_1}	0.4	0.7	0.4
K_{H_1}	0.2	0.5	0.8

Table 12

	(v_1,v_2)	(v_2,v_3)	(v_3,v_1)
T_{H_2}	0.2	0.1	0.1
M_{H_2}	0.4	0.2	0.2
C_{H_2}	0.3	0.3	0.3
I_{H_2}	0.5	0.5	0.5
U_{H_2}	0.6	0.4	0.6
F_{H_2}	0.7	0.7	0.4
K_{H_2}	0.5	0.8	0.8

The above table is shown in the following diagram.



Definition 3.11. An SVHN-graph $\mathcal{G} = (H_1, H_2)$ of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is called bipartite SVHN-graph if the graph $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is a bipartite graph.

Example 3.8. Let $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ be a graph, where $\mathfrak{V} = \{v_1, v_2, v_3, v_4, v_5\}$ and $\mathcal{E} = \{(v_1,v_2),(v_1,v_3),(v_1,v_4),(v_1,v_5),(v_2,v_3),(v_2,v_4),(v_2,v_5),(v_3,v_5)\}$ and $\mathcal{G} = (H_1, H_2)$ be an SVHN graph specified by the following table values.

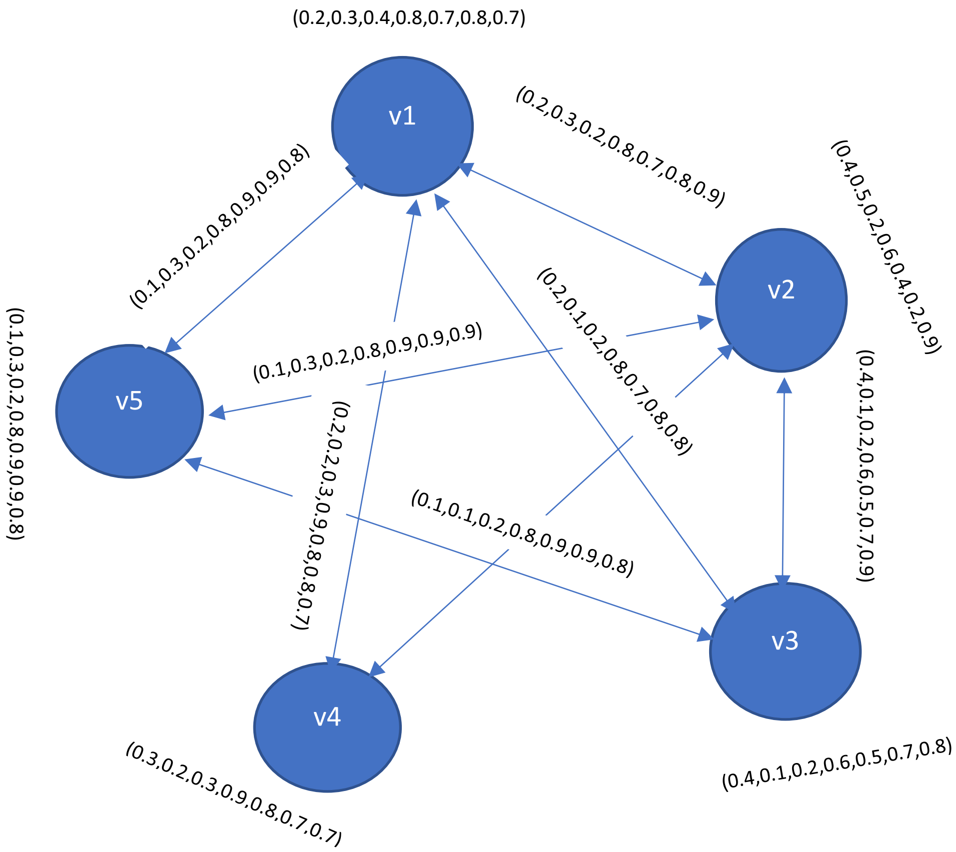
Table 13

	v_1	v_2	v_3	v_4	v_5
T_{H_1}	0.2	0.4	0.4	0.3	0.1
M_{H_1}	0.3	0.5	0.1	0.2	0.3
C_{H_1}	0.4	0.2	0.2	0.3	0.2
I_{H_1}	0.8	0.6	0.6	0.9	0.8
U_{H_1}	0.7	0.4	0.5	0.8	0.9
F_{H_1}	0.8	0.2	0.7	0.7	0.9
K_{H_1}	0.7	0.9	0.8	0.7	0.8

Table 14

	(v_1,v_2)	(v_1,v_3)	(v_1,v_4)	(v_1,v_5)	(v_2,v_3)	(v_2,v_4)	(v_2,v_5)	(v_3,v_5)
T_{H_2}	0.2	0.2	0.2	0.1	0.4	0.3	0.1	0.1
M_{H_2}	0.3	0.1	0.2	0.3	0.1	0.2	0.3	0.1
C_{H_2}	0.2	0.2	0.3	0.2	0.2	0.2	0.2	0.2
I_{H_2}	0.8	0.8	0.9	0.8	0.6	0.9	0.8	0.8
U_{H_2}	0.7	0.7	0.8	0.9	0.5	0.8	0.9	0.9
F_{H_2}	0.8	0.8	0.8	0.9	0.7	0.7	0.9	0.9
K_{H_2}	0.9	0.8	0.7	0.8	0.9	0.9	0.9	0.8

The above table is shown in the following diagram.



Definition 3.12. Let $\mathcal{G} = (H_1, H_2)$ be an SVHN-graph. Afterwards, the degree of the vertex $\mathcal{v}$ is specified by.

$$d(\mathcal{v}) = \left(d_T(\mathcal{v}), d_M(\mathcal{v}), d_C(\mathcal{v}), d_I(\mathcal{v}), d_U(\mathcal{v}), d_F(\mathcal{v}), d_K(\mathcal{v})\right)$$

where $d_T(\mathcal{v})$ = degree of membership in the absolute truth membership vertex $\mathcal{v}$

= total of all edges' absolute truth memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} T_{H_2}(u, \mathcal{v})$

$d_M(\mathcal{v})$ = degree of membership in the relative truth vertex $\mathcal{v}$

= total of all edges' relative truth memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} M_{H_2}(u, \mathcal{v})$

$d_C(\mathcal{v})$ = degree of membership in the contradiction vertex $\mathcal{v}$

= total of all edges' contradiction memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} C_{H_2}(u, \mathcal{v})$

$d_I(\mathcal{v})$ = degree of membership in the ignorance vertex $\mathcal{v}$

= total of all edges' ignorance memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} I_{H_2}(u, \mathcal{v})$

$d_U(\mathcal{v})$ = degree of membership in the unknown vertex $\mathcal{v}$

= total of all edges' unknown memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} U_{H_2}(u, \mathcal{v})$

$d_F(\mathcal{v})$ = degree of membership in the absolute falsity vertex $\mathcal{v}$

= total of all edges' absolute falsity memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} F_{H_2}(u, \mathcal{v})$

$d_K(\mathcal{v})$ = degree of membership in the relative falsity vertex $\mathcal{v}$

= total of all edges' relative falsity memberships that are incident on it

= $\sum_{u \neq \mathcal{v}} K_{H_2}(u, \mathcal{v})$

Example 3.9. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ Be specified by the following table values.

Table 15

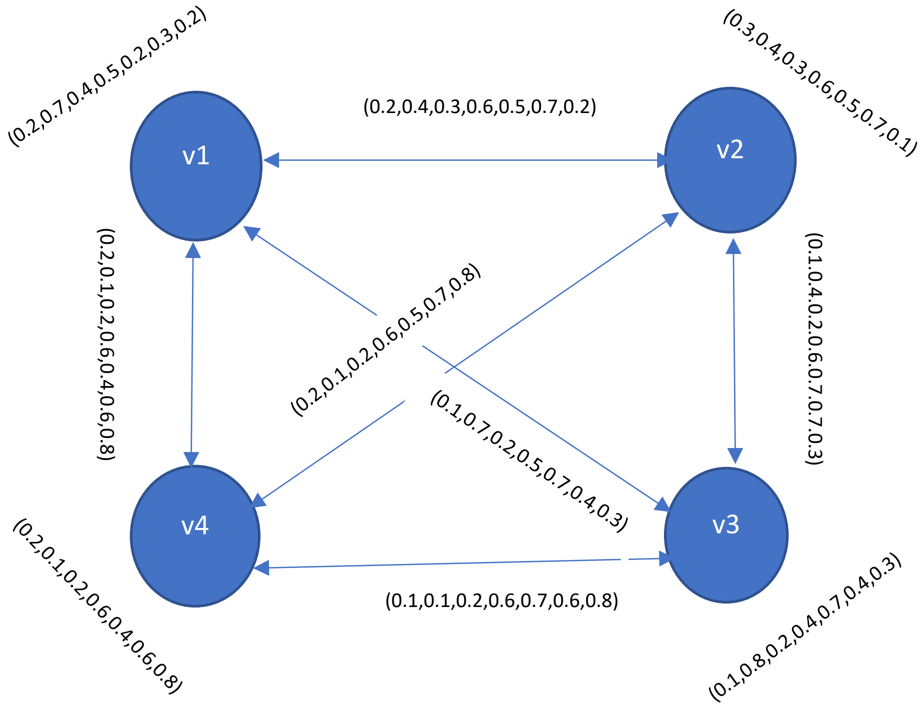
	$\mathcal{v}_1$	$\mathcal{v}_2$	$\mathcal{v}_3$	$\mathcal{v}_4$
T_{H_1}	0.2	0.3	0.1	0.2
M_{H_1}	0.7	0.4	0.8	0.1

C_{H_1}	0.4	0.3	0.2	0.2
I_{H_1}	0.5	0.6	0.4	0.6
U_{H_1}	0.2	0.5	0.7	0.4
F_{H_1}	0.3	0.7	0.4	0.6
K_{H_1}	0.2	0.1	0.3	0.8

Table 16

	$(\mathcal{v}_1,\mathcal{v}_2)$	$(\mathcal{v}_1,\mathcal{v}_3)$	$(\mathcal{v}_1,\mathcal{v}_4)$	$(\mathcal{v}_2,\mathcal{v}_3)$	$(\mathcal{v}_2,\mathcal{v}_4)$	$(\mathcal{v}_3,\mathcal{v}_4)$
T_{H_2}	0.2	0.1	0.2	0.1	0.2	0.1
M_{H_2}	0.4	0.7	0.1	0.4	0.1	0.1
C_{H_2}	0.3	0.2	0.2	0.2	0.2	0.2
I_{H_2}	0.6	0.5	0.6	0.6	0.6	0.6
U_{H_2}	0.5	0.7	0.4	0.7	0.5	0.7
F_{H_2}	0.7	0.4	0.6	0.7	0.7	0.6
K_{H_2}	0.2	0.3	0.8	0.3	0.8	0.8

The above table is shown in the following diagram.



Definition 3.13. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$. Afterwards, $\mathcal{G} = (H_1, H_2)$ Is called a constant SVHN graph if the degree of each vertex is the same. i.e.,$d(\mathcal{v}) = (p_1, p_2, p_3, p_4, p_5, p_6, p_7)$, for every $\mathcal{v} \in \mathfrak{V}$.

Example 3.10. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ Be specified by the following table values.

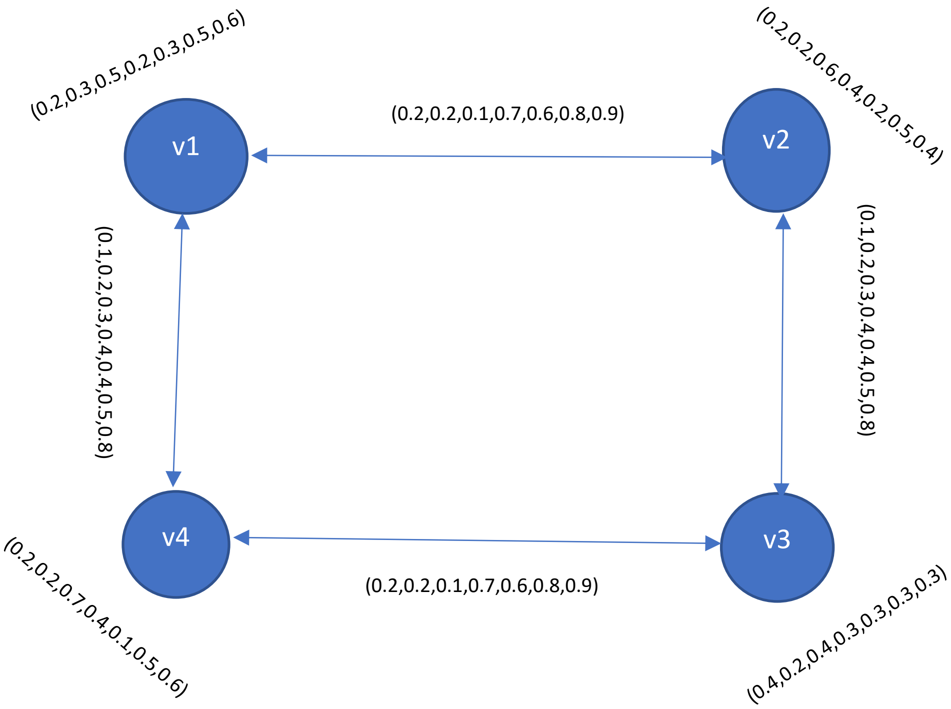
Table 17

	$\mathcal{v}_1$	$\mathcal{v}_2$	$\mathcal{v}_3$	$\mathcal{v}_4$
T_{H_1}	0.2	0.2	0.4	0.2
M_{H_1}	0.3	0.2	0.2	0.2
C_{H_1}	0.5	0.6	0.4	0.7
I_{H_1}	0.2	0.4	0.3	0.4
U_{H_1}	0.3	0.2	0.3	0.1
F_{H_1}	0.5	0.5	0.3	0.5
K_{H_1}	0.6	0.4	0.3	0.6

Table 18

	$(\mathcal{v}_1,\mathcal{v}_2)$	$(\mathcal{v}_2,\mathcal{v}_3)$	$(\mathcal{v}_3,\mathcal{v}_4)$	$(\mathcal{v}_4,\mathcal{v}_1)$
T_{H_2}	0.2	0.1	0.2	0.1
M_{H_2}	0.2	0.2	0.2	0.2
C_{H_2}	0.1	0.3	0.1	0.3
I_{H_2}	0.7	0.4	0.7	0.4
U_{H_2}	0.6	0.4	0.6	0.4
F_{H_2}	0.8	0.5	0.8	0.5
K_{H_2}	0.9	0.8	0.9	0.8

The above table is shown in the following diagram.



Definition 3.14. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph. Afterward, the order of $\mathcal{G} = (H_1, H_2)$, described by $O(\mathcal{G})$ is specified by $O(\mathcal{G}) = \big(O_T(\mathcal{G}), O_M(\mathcal{G}), O_C(\mathcal{G}), O_I(\mathcal{G}), O_U(\mathcal{G}), O_F(\mathcal{G}), O_K(\mathcal{G})\big)$,where

$O_T(\mathcal{G}) = \sum_{\mathcal{v}\in\mathfrak{V}} T_{H_1}$ represents the T-order of $\mathcal{G} = (H_1, H_2)$

$O_M(\mathcal{G}) = \sum_{v \in \mathfrak{V}} M_{H_1}$ represents the M-order of $\mathcal{G} = (H_1, H_2)$

$O_C(\mathcal{G}) = \sum_{v \in \mathfrak{V}} C_{H_1}$ represents the C-order of $\mathcal{G} = (H_1, H_2)$

$O_I(\mathcal{G}) = \sum_{v \in \mathfrak{V}} I_{H_1}$ represents the I-order of $\mathcal{G} = (H_1, H_2)$

$O_U(\mathcal{G}) = \sum_{v \in \mathfrak{V}} U_{H_1}$ represents the U-order of $\mathcal{G} = (H_1, H_2)$

$O_F(\mathcal{G}) = \sum_{v \in \mathfrak{V}} F_{H_1}$ represents the F-order of $\mathcal{G} = (H_1, H_2)$

$O_K(\mathcal{G}) = \sum_{v \in \mathfrak{V}} K_{H_1}$ represents the K-order of $\mathcal{G} = (H_1, H_2)$

Example 3.11. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ As shown in Example 3.7. Here, the order of SVHN-graph $\mathcal{G} = (H_1, H_2)$ is $O(\mathcal{G}) = (0.6, 1.0, 1.0, 1.4, 1.2, 1.5, 1.5)$.

Definition 3.15. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph. Here, the size of $\mathcal{G} = (H_1, H_2)$,

described by $S(\mathcal{G})$ is specified by $S(\mathcal{G}) = \left(S_T(\mathcal{G}), S_M(\mathcal{G}), S_C(\mathcal{G}), S_I(\mathcal{G}), S_U(\mathcal{G}), S_F(\mathcal{G}), S_K(\mathcal{G})\right)$, where

$S_T(\mathcal{G}) = \sum_{u \neq v} T_{H_2}(u, v)$ represents the T-size of $\mathcal{G} = (H_1, H_2)$

$S_M(\mathcal{G}) = \sum_{u \neq v} M_{H_2}(u, v)$ represents the M-order of $\mathcal{G} = (H_1, H_2)$

$S_C(\mathcal{G}) = \sum_{u \neq v} C_{H_2}(u, v)$ represents the C-order of $\mathcal{G} = (H_1, H_2)$

$S_I(\mathcal{G}) = \sum_{u \neq v} I_{H_2}(u, v)$ represents the I-order of $\mathcal{G} = (H_1, H_2)$

$S_U(\mathcal{G}) = \sum_{u \neq v} U_{H_2}(u, v)$ represents the U-order of $\mathcal{G} = (H_1, H_2)$

$S_F(\mathcal{G}) = \sum_{u \neq v} F_{H_2}(u, v)$ represents the F-order of $\mathcal{G} = (H_1, H_2)$

$S_K(\mathcal{G}) = \sum_{u \neq v} K_{H_2}(u, v)$ represents the K-order of $\mathcal{G} = (H_1, H_2)$

Example 3.12. Let $\mathcal{G} = (H_1, H_2)$ Be an SVHN-graph of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ As shown in Example 3.7. Then, the order of the SVHN-graph $\mathcal{G} = (H_1, H_2)$ is $S(\mathcal{G}) = (0.4, 0.8, 0.9, 1.5, 1.6, 1.8, 2.1)$.

Definition 3.16. A single valued heptapartitioned neutrosophic graph $\mathcal{G} = (H_1, H_2)$ of $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ is called strong single valued heptapartitioned neutrosophic graph if

$T_{H_2}(v_i, v_j) = \min\{T_{H_1}(v_i), T_{H_1}(v_j)\}$, $M_{H_2}(v_i, v_j) = \min\{M_{H_1}(v_i), M_{H_1}(v_j)\}$, $C_{H_2}(v_i, v_j) = \min\{C_{H_1}(v_i), C_{H_1}(v_j)\}$, $I_{H_2}(v_i, v_j) = \max\{I_{H_1}(v_i), I_{H_1}(v_j)\}$, $U_{H_2}(v_i, v_j) = \max\{U_{H_1}(v_i), U_{H_1}(v_j)\}$, $F_{H_2}(v_i, v_j) = \max\{F_{H_1}(v_i), F_{H_1}(v_j)\}$, $K_{H_2}(v_i, v_j) = \max\{K_{H_1}(v_i), K_{H_1}(v_j)\}$ for every $v_i, v_j \in \mathfrak{V}$.

Example 3.13. Let $\tilde{\mathcal{G}} = (\mathfrak{V}, \mathcal{E})$ Be a graph, where $\mathfrak{V} = \{v_1, v_2, v_3, v_4\}$ and $\mathcal{E} = \{(v_1, v_2), (v_2, v_3), (v_3, v_4), (v_4, v_1)\}$. Let H_1 be a SVHN subset of $\mathfrak{V}$ and let H_2 be a single valued neutrosophic subset of $\mathcal{E}$ denoted by the following table.

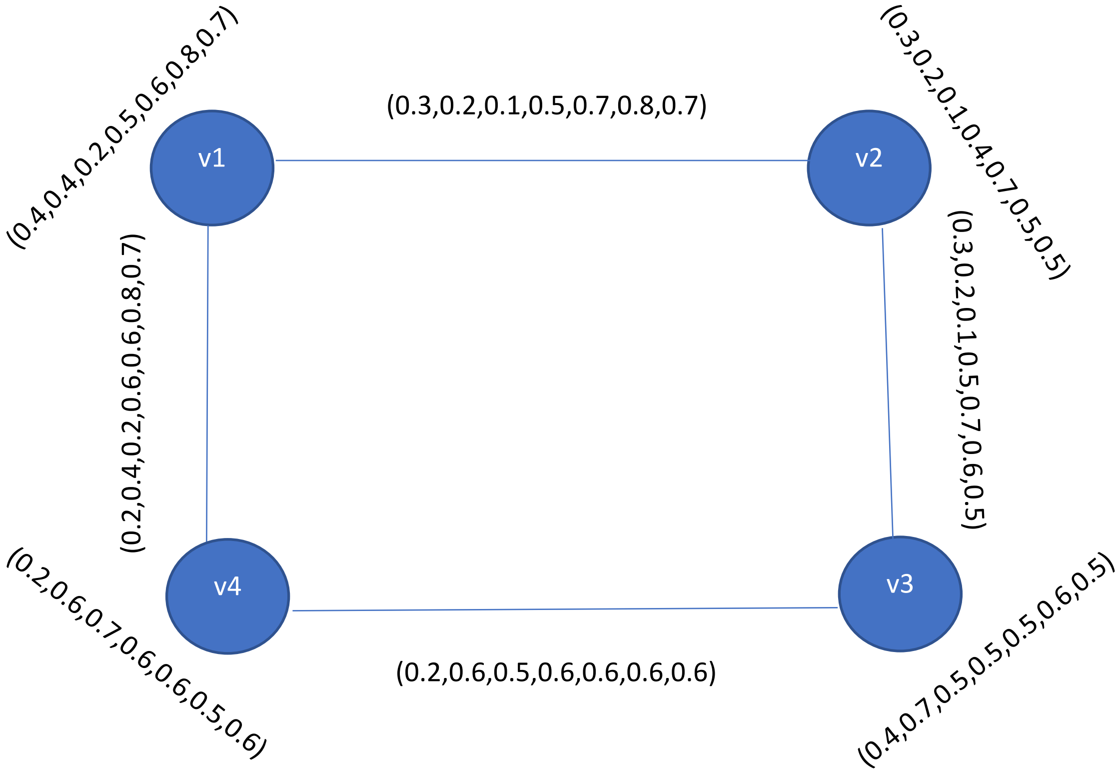
Table 19

	v_1	v_2	v_3	v_4
T_{H_1}	0.4	0.3	0.4	0.2
M_{H_1}	0.4	0.2	0.7	0.6
C_{H_1}	0.2	0.1	0.5	0.7
I_{H_1}	0.5	0.4	0.5	0.6

U_{H_1}	0.6	0.7	0.5	0.6
F_{H_1}	0.8	0.5	0.6	0.5
K_{H_1}	0.7	0.5	0.5	0.6

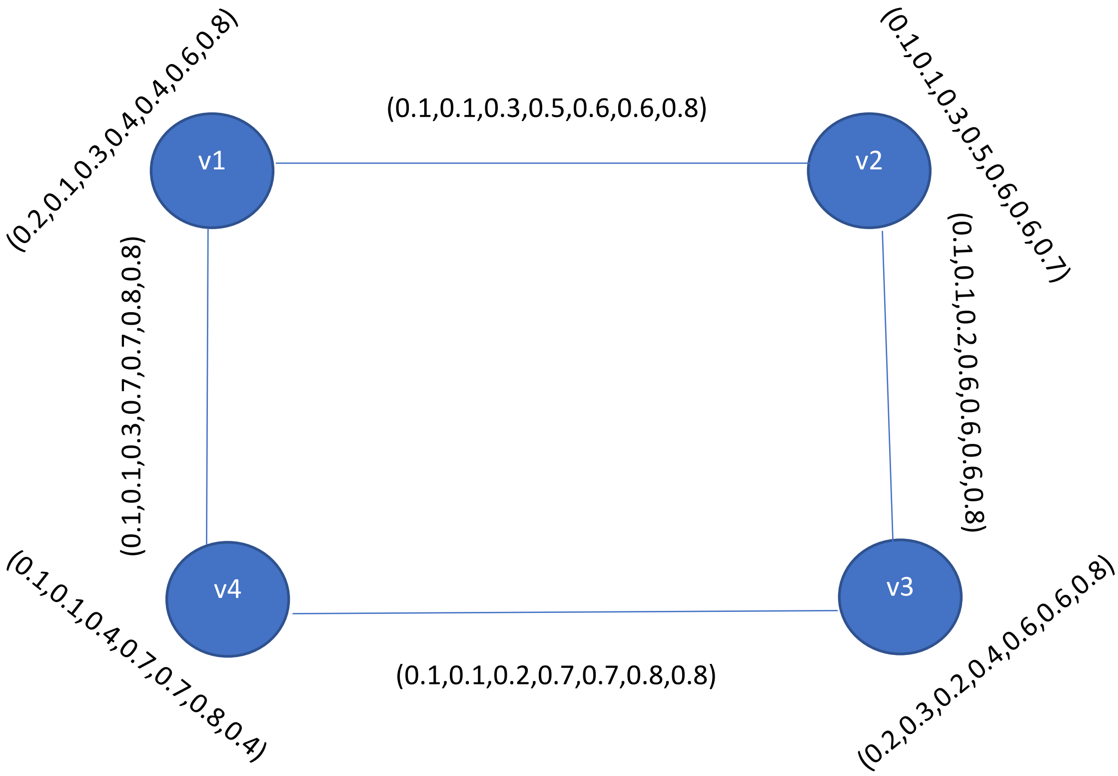
Table 20

	(v_1,v_2)	(v_2,v_3)	(v_3,v_4)	(v_4,v_1)
T_{H_2}	0.3	0.3	0.2	0.2
M_{H_2}	0.2	0.2	0.6	0.4
C_{H_2}	0.1	0.1	0.5	0.2
I_{H_2}	0.5	0.5	0.6	0.6
U_{H_2}	0.7	0.7	0.6	0.6
F_{H_2}	0.8	0.6	0.6	0.8
K_{H_2}	0.7	0.5	0.6	0.7

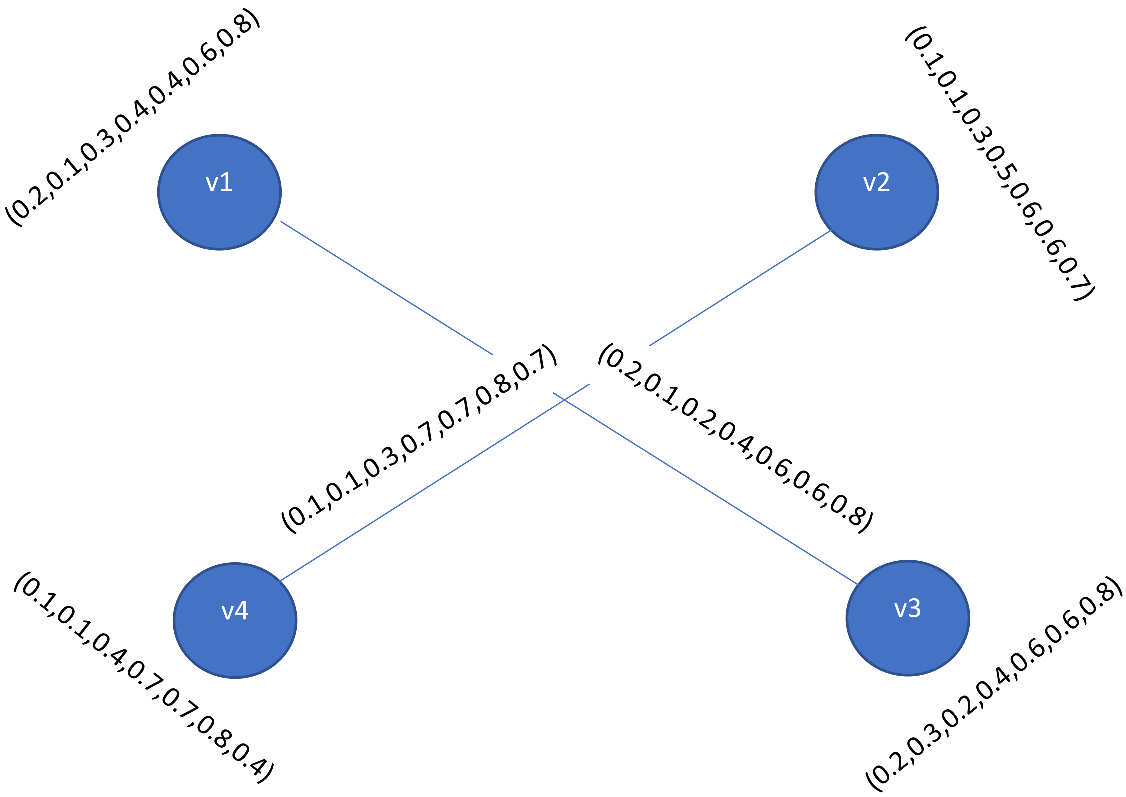


It is easy to see that $\mathcal{G}$ is a strong single valued heptapartitioned neutrosophic graph of $\tilde{\mathcal{G}}$.

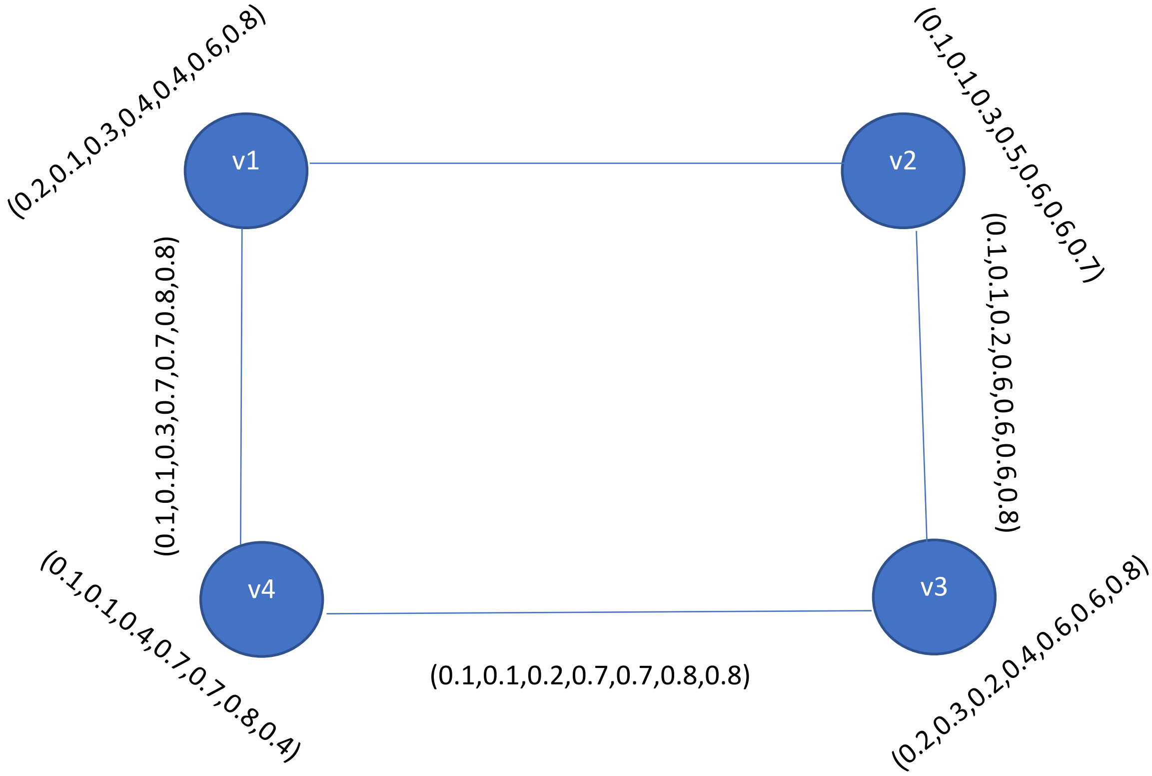
Example 3.14. When $\mathcal{G} = \bar{\bar{\tilde{\mathcal{G}}}}$ if and only if $\mathcal{G}$ is a strong single valued heptapartitioned neutrosophic graph.



$\mathcal{G}$: strong single valued heptapartitioned neutrosophic graph



$\overline{\mathcal{G}}$ **: strong single valued heptapartitioned neutrosophic graph**



$\mathcal{G} = \overline{\overline{\mathcal{G}}}$ **: strong single valued heptapartitioned neutrosophic graph**

Conclusion: The Single-Valued Heptapartitioned Neutrosophic (SVHN) graph is introduced in this study, along with definitions for its degree, order, and size, and an examination of its characteristics. These definitions serve as the foundation for several conclusions that are backed up by instances that confirm the ideas and conclusions put forth. Within the neutrosophic framework, we hope that the method outlined here will stimulate more investigation into SVHN graphs and their applications to practical issues.

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