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Research paper

A Case Study on Applying Equally and Mildly Balanced Neutrosophic Graphs to Optimize Urban Transportation Management

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Abstract

A flexible approach to interpreting balancedness in neutrosophic graphs is provided by the concept of a mild balanced single-valued neutrosophic (MB SVN) graph, which strives for an equitable representation while acknowledging the inherent inconsistencies in real-world data. Although reaching a condition of equal balance in Single Valued Neutrosophic (EB SVN) graphs would be ideal, in practice, the complexity and uncertainty of real-world data can pose difficulties for their application. In this research, we analyze subgraphs with varying densities, distinguishing between intense and feeble ones. Additionally, we discuss the characteristics of mild balanced SVN (MB SVN) graphs, wimpy balanced SVN (WB SVN) graphs, and equally balanced SVN (EB SVN) graphs. Analyzing the union and sum processes used to SVN-graphs is the main emphasis of our work. We have constructed an algorithm to find every balanced SVN-graph. Moreover, we have investigated how the traffic management system might benefit from MB SVN-subgraphs, WB SVN-subgraphs, and EB SVN-subgraphs. We have also thought about the possible application of mild balanced graphs in traffic control systems and route planning.

Keywords: *Density of SVN-graph; EB SVN-subgraphs; Feeble-subgraph; Intense-subgraph; MB SVN-subgraphs; WB SVN-subgraphs.*

1. Introduction

There is a graph $\dot{\mathcal{G}}$, and its density, denoted as $\dot{\mathfrak{D}}(\dot{\mathcal{G}})$It shows how connected things are in the whole network. This method uses fuzzy logic to deal with the unclear parts of graph problems that come up when network sizes grow quickly. Balanced graphs have $\dot{\mathfrak{D}}(\$) \leq \dot{\mathfrak{D}}(\dot{\mathcal{G}})$ for all subgraphs $\$$ of $\dot{\mathcal{G}}$. Inspired by density functions, the definition of balanced fuzzy started in the research of random graphs. Whereas a graph with null density has the lowest density, a full graph has the highest density. In graph theory, a balanced graph is a fundamental concept showing a network structure with equally distributed properties across its elements. Developing reliable and effective networks in many different applications depends on an understanding of and ability to evaluate balanced graphs. Many papers have been written on a balanced extension of a graph, and it finds great use in artificial intelligence, robotics, computer technology, signal processing, and decision-making. Modern data storage systems and communication technologies depend on error-correcting codes, created from balanced graphs. These codes depend on the regularity and connectedness properties of balanced graphs in order to find and correct errors brought in during transmission or storage. Balanced graphs are employed in coding theory to generate error-correcting codes, which are required for consistent data storage and transmission. Balanced graphs' symmetry and regularity help to create scripts that efficiently find and correct errors.

A balanced fuzzy graph is the concept combining fuzzy logic with graph theory. An extension of fuzzy graphs (FG), including the conceptual structure of intuitionistic fuzzy sets, is balanced intuitionistic fuzzy graphs (BIF-graphs). In the framework of intuitionistic fuzzy logic, a BIF-graph offers still another level of structure or limitations that maintains some kind of stability or equilibrium inside the graph. Actually, the Neutrosophic Set is another mathematical approach for addressing uncertainty, unpredictability, and erroneous data. Balanced neutrosophic graphs extend a feature of graph theory to neutrosophic logic, a variant of logic devised by Florentin Smarandache that extends fuzzy and intuitionistic fuzzy logic. In complex systems modeling, where component interactions can be confusing, conflicting, or changing, balanced neutrosophic graphs are quite helpful. In fields like social sciences, decision making, information science, and any other sector where traditional binary or fuzzy ways of graph representation may fall short of capturing the whole spectrum of contextual complexity, they are a useful tool for describing and researching networks.

(Amanathulla et al. 2021) has looked further into the required and sufficient conditions for balanced picture fuzzy graphs, a special type of image fuzzy graphs. (Nivethana et al. 2017) proposed feeble and intense subgraphs as well as equally and mildly balanced intuitionistic-fuzzy subgraphs, and the characteristics they possess. (Parvathi R et al. 2015) examined the complement of Intuitionistic-fuzzy graphs. Higher precision, system compatibility, and flexibility than classic and fuzzy models come from bipolar fuzzy models. (Akram et al. 2014) proposed the idea of balanced bipolar-FG. They also highlighted some characteristics connected with these graphs. (Karunambigai M G et al. 2014) Proposed Characteristics of balanced intuitionistic-FG. (Akram et al. 2014) have investigated new applications of intuitionistic fuzzy-digraphs in support systems and decision-making. Examining FG-operations, (Talal Al Hawary et al. 2011) developed balanced-FG. (M Akram et al. 2018) presented novel applications of bipolar fuzzy graphs for decision-making problems, together with a technique for computing the dominating number in our systems. (Sivasankar et al. 2022) Investigated some of their properties and presented the concept of balanced neutrosophic graphs (BNG) based on density functions. Balanced neutrophilic graphs show complex systems whereby the quantity of data and information varies with different degrees of precision. While neutrosophic graphs can allow the uncertainty of inconsistent and indeterminate information seen in any real-world event, fuzzy graphs might not generate enough viable responses. A new feature in graph theory, the single-valued neutrosophic graph (SVN-graph), is an extension of the FG and an intuitionistic-FG. SVN-graphs were first proposed and their component elements investigated by (Broumi et al. 2016). Inspired by the premise of a balanced graph and its modifications, we concentrated on developing balanced and strictly balanced in SVN-graphs. (Narmada Devi et al. 2018) have developed ideas of a balanced and exactly balanced neutrosophic complex graph, as well as a full neutrosophic complex graph. Balanced Fermatean neutrosophic graph and examined some of its properties in (Broumi et al. 2024).

The main goal of certain kinds of BNG is to make it easier to represent, analyze, and make decisions in cases where traditional binary or even fuzzy logic models aren't good enough because of rising levels of complexity, uncertainty, and indeterminacy. When analyzing and designing networks, like those in transportation, logistics, and telecommunications, MB-SVN graphs and EB-SVN graphs let you take into account unknown or unclear factors that affect connection, capacity, and trustworthiness. This might lead to strategies and plans that work better in risky situations. This paper is about MB-SVN subgraphs and EB-SVN subgraphs. In Section 1, an outline of the work and a study of the literature are given. Section 2 mostly addresses the fundamental definitions. Section 3 explores the ideas of MB-SVN subgraphs and EB-SVN subgraphs, feeble-intense subgraphs, and their characteristics. The work consists of investigating SVN-graph qualities under sum and union operations. Furthermore, it is shown that a MB- SVN graph cannot be obtained from an SVN graph with few strong edges unless it develops into a strong SVN graph. In Section 4, we investigate the utilization of the MB-SVN graph to optimize transportation management systems in metropolitan networks. This investigation examines the potential of MB-SVN graphs to improve the efficacy of transportation systems by assessing the accessibility of critical services in urban areas. In Section 5, the conclusion of the study on MB-SVN graphs and EB-SVN graphs is presented.

2. Preliminary

This section comprises several critical terms and concluding statements. First, we will examine the fundamentals before proceeding to the various types of balanced SVN graphs. The neutrosophic sets utilized to characterize the elements of SVN-graphs (Akram M et al. 2017, Ye S et al.2014) enable the simultaneous representation of truth-membership, indeterminacy-membership, and falsity-membership degrees.

Definition 2.1 (Sivasankar et al. 2022) A SVN-graph $\mathring{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ has a partial SVN-subgraph $\$ = (V', E')$ such that $V' \subseteq V$, where $T'_{\mathcal{Y}}(s) \leq T_{\mathcal{Y}}(s), I'_{\mathcal{Y}}(s) \leq I_{\mathcal{Y}}(s) F'_{\mathcal{Y}}(s) \leq F_{\mathcal{Y}}(s)$ for all $s \in V$ and $E' \subseteq E, \mathcal{T}'_{\mathcal{Z}}(s,r) \leq \mathcal{T}_{\mathcal{Z}}(s,r), \mathcal{I}'_{\mathcal{Z}}(s,r) \leq \mathcal{I}_{\mathcal{Z}}(s,r), \mathcal{F}'_{\mathcal{Z}}(s,r) \leq \mathcal{F}_{\mathcal{Z}}(s,r)$ for all $(s,r) \in E$

Definition 2.2 (Sivasankar et al. 2022) A SVN-graph $\mathring{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ of $\mathring{\mathcal{G}}^* = (\mathcal{V}, E)$ is referred strong SVN-graph if

$$\mathcal{T}_{\mathcal{Z}}(s,r) = \min\{\mathcal{T}_{\mathcal{Y}}(s), \mathcal{T}_{\mathcal{Y}}(r)\}$$
$$\mathcal{I}_{\mathcal{Z}}(s,r) = \min\{\mathcal{I}_{\mathcal{Y}}(s), \mathcal{I}_{\mathcal{Y}}(r)\}$$
$$\mathcal{F}_{\mathcal{Z}}(s,r) = \max\{\mathcal{F}_{\mathcal{Y}}(s), \mathcal{F}_{\mathcal{Y}}(r)\}, \forall s, r \in \mathcal{V}$$

Definition 2.3 (Sivasankar et al. 2022) The density value of an SVN-graph $\mathring{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ of $\mathcal{G}^* = (\mathcal{V}, E)$, is $\dot{\mathfrak{D}}(\dot{\mathcal{G}}) = \left(\dot{\mathfrak{D}}_T(\dot{\mathcal{G}}), \mathfrak{D}_I(\dot{\mathcal{G}}), \mathfrak{D}_F(\dot{\mathcal{G}})\right)$ where

$$\hat{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G}) = \frac{2\sum \mathcal{T}_{\mathcal{Z}}(s,r)}{\sum_{(s,r)\in\mathcal{V}} \mathcal{T}\mathcal{Y}(s) \wedge \mathcal{T}\mathcal{Y}(r)}, \text{for all s, r} \in \mathcal{V}$$
$$\hat{\mathfrak{D}}_{\mathcal{I}}(\hat{\mathcal{G}}) = \frac{2\sum \mathcal{I}_{\mathcal{Z}}(s,r)}{\sum_{(s,r)\in\mathcal{V}} \mathcal{I}_{\mathcal{Y}}(s) \vee \mathcal{I}_{\mathcal{Y}}(r)}, \text{for all s, r} \in \mathcal{V}$$
$$\hat{\mathfrak{D}}_{\mathcal{F}}(\hat{\mathcal{G}}) = \frac{2\sum \mathcal{F}_{\mathcal{Z}}(s,r)}{\sum_{(s,r)\in\mathcal{V}} \mathcal{F}_{\mathcal{Y}}(s) \vee \mathcal{F}_{\mathcal{Y}}(r)}, \text{for all s, r} \in \mathcal{V}$$

Definition 2.4 (Sivasankar et al. 2022) A SVN-graph $\hat{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ is referred to as balanced if $\mathfrak{D}(\$) \leq \mathfrak{D}(\hat{\mathcal{G}})$.
i.e. $\hat{\mathfrak{D}}_{\mathcal{T}}(\$) \leq \hat{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{I}}(\$) \leq \hat{\mathfrak{D}}_{\mathcal{I}}(\mathcal{G})$ and $\hat{\mathfrak{D}}_{\mathcal{F}}(\$) \leq \hat{\mathfrak{D}}_{\mathcal{F}}(\mathcal{G})$ for all subgraphs \$ of $\mathcal{G}$.

Definition 2.5 (Sivasankar et al. 2022) A SVN-graph $\dot{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ is referred to as strictly balanced if $\dot{\mathfrak{D}}(\$) = \dot{\mathfrak{D}}(\mathcal{G})$. i.e. $\dot{\mathfrak{D}}_{\mathcal{T}}(\$) = \dot{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G}), \dot{\mathfrak{D}}_{\mathcal{I}}(\$) = \dot{\mathfrak{D}}_{\mathcal{I}}(\mathcal{G})$ and $\dot{\mathfrak{D}}_{\mathcal{F}}(\$) = \dot{\mathfrak{D}}_{\mathcal{F}}(G)$ for all subgraphs \$ of $\dot{\mathcal{G}}$.

3. Mild and Equally Balanced Single Valued Neutrosophic Graphs

SVN-graphs can be thought of as strong, weak subgraphs. The structural features of a graph are indicated by its feeble and intense subgraphs, whereby the former signal low connectivity and the latter great connectivity. The degree of ambiguity and uncertainty that exists in complex networks that are explained by neutrosophic graph theory can be measured and understood with the help of. Of these concepts. Here, we introduce the concept of MB-SVN graphs, EBSVN graphs, and WB-SVN graphs. Specific attributes of the union and the sum of SVN-graphs are also shown.

Definition 3.1 A connected SVN-subgraph \$ of an SVN-graph $\mathcal{G} = (V, E)$ is referred Intense SVN-graph (ISVN-graph) if
(i). $V(\$) \subseteq V(\mathcal{G})$ and $E(\$) \subseteq E(\mathcal{G})$
(ii) $\hat{\mathfrak{D}}_{\mathcal{T}}(\$) \leq \hat{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{I}}(\$) \leq \hat{\mathfrak{D}}_{\mathcal{I}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{F}}(\$) \leq \hat{\mathfrak{D}}_{\mathcal{F}}(\mathcal{G})$

Definition 3.2 A connected SVN-subgraph \$ of an SVN-graph $\dot{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ is referred to as Feeble SVN-graph (FSVN-graph) if
(i). $\mathcal{Y}(\$) \subseteq \mathcal{Y}(\mathcal{G})$ and $\mathcal{Z}(\$) \subseteq \mathcal{Z}(\mathcal{G})$
(ii). $\hat{\mathfrak{D}}_{\mathcal{T}}(\$) > \hat{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{I}}(\$) > \hat{\mathfrak{D}}_{\mathcal{I}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{F}}(\$) > \hat{\mathfrak{D}}_{\mathcal{F}}(\mathcal{G})$

Example 3.1 Consider an SVN-graph $\dot{\mathrm{G}} = (\mathrm{Y}, \mathrm{Z})$ with vertices $\mathcal{V} = \{a, b, c, d, e\}$ and edges $E = \{ab, bc, cd, de, ea\}$.

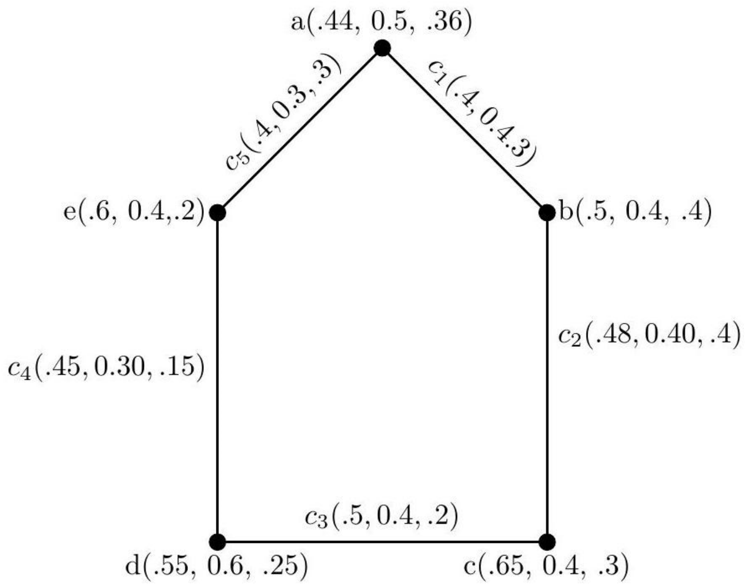

Fig. 1: SVN-graph

The density value of $\mathcal{T}, \mathcal{I}, \mathcal{F}$ - SVN-graph (figure 1) is as follows $D_T(\hat{\mathcal{G}}) = 1.80, D_I(\mathring{\mathcal{G}}) = 1.80, D_F(\mathring{\mathcal{G}}) = 1.580$. Table 1 reports all the available connected SVNsubgraphs found in the SVN-graphs $\mathcal{G}: (\mathcal{V}, E)$ in Figure 1; their $\mathcal{T}, \mathcal{I}, \mathcal{F}$-densities are calculated below: Table 1 shows that the ISVN-subgraphs are $\{\$_4, \$_8, \$_9, \$_{13}, \$_{14}, \$_{18}\}$, whereas the FSVN-subgraphs are $\{\$_2, \$_6, \$_7, \$_{11}, \$_{15}, \$_{20}\}$. Weak linkages in the general neutrosophic graph structure can match FSVN-subgraphs, suggesting reduced dependability or uncertainty in the underlying data. Within a neutrosophic graph, ISVN-subgraphs can be clusters, communities, or densely connected parts when the underlying information is quite trustworthy and the links are clearly defined.

Table 1: Density of SVN-subgraphs of $\mathring{\mathcal{G}}$ - Figure 1

Set of Vertices in a subgraph	$\mathrm{D}(\dot{\mathrm{G}}) = (\hat{\mathrm{D}}_{\mathrm{T}}(\mathrm{G}), \hat{\mathrm{D}}_{\mathrm{I}}(\mathrm{G}), \hat{\mathrm{D}}_{\mathrm{F}}(\mathrm{G}))$	**Set of vertices in a subgraph**	$\mathrm{D}(\dot{\mathrm{G}}) = (\hat{\mathrm{D}}_{\mathrm{T}}(\mathrm{G}), \hat{\mathrm{D}}_{\mathrm{I}}(\mathrm{G}), \hat{\mathrm{D}}_{\mathrm{F}}(\mathrm{G}))$
$\$_1 = \{a, b\}$	(1.82, 2, 1.5)	$\$_{11} = \{ab, bc, cd\}$	(1.85, 2, 1.64)
$\$_2 = \{b, c\}$	(1.92, 2, 2)	$\$_{12} = \{bc, cd, de\}$	(1.79, 1.83, 1.59)
$\$_3 = \{c, d\}$	(1.82, 2, 1.33)	$\$_{13} = \{cd, de, ea\}$	(1.75, 1.67, 1.43)
$\$_4 = \{e, d\}$	(1.64, 1.5, 1.2)	$\$_{14} = \{de, ea, ab\}$	(1.75, 1.67, 1.49)
$\$_5 = \{a, e\}$	(1.82, 1.5, 1.67)	$\$_{15} = \{ea, ab, bc\}$	(1.89, 1.83, 1.72)
$\$_6 = \{ab, bc\}$	(1.87, 2, 1.75)	$\$_{16} = \{ab, bc, cd, de\}$	(1.79, 1.89, 1.56)
$\$_7 = \{bc, cd\}$	(1.87, 2, 1.71)	$\$_{17} = \{bc, cd, de, ea\}$	(1.79, 1.75, 1.6)
$\$_8 = \{cd, de\}$	(1.73, 1.75, 1.27)	$\$_{18} = \{ab, cd, de, ea\}$	(1.77, 1.75, 1.45)
$\$_9 = \{de, ea\}$	(1.72, 1.5, 1.48)	$\$_{19} = \{ab, bc, de, ea\}$	(1.79, 1.75, 1.63)
$\$_{10} = \{ea, ab\}$	(1.82, 1.75, 1.58)	$\$_{20} = \{ab, bc, cd, ea\}$	(1.84, 2, 1.64)

Definition 3.3 A SVN-graph $\dot{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ It is called a Mild Balanced SVN-graph (MBSVN) if each of its connected subgraphs is an ISVN-subgraph.

Definition 3.4 A SVN-graph $\dot{\mathcal{G}} = (\mathcal{Y}, \mathcal{Z})$ is a Wimpy balanced SVN-graph (WB-SVN) if each of its connected subgraphs is a feeble SVN-subgraph.

Definition 3.5 A SVN-graph $\dot{\mathcal{G}} = \mathcal{Y}, \mathcal{Z})$ has two ISVN-connected subgraphs, $\$_1$ and $\$_2$. These are referred to as equally balanced SVN-subgraphs (EB-SVN) if (i). $\hat{\mathfrak{D}}_{\mathcal{T}}(\$_1) \leq \hat{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{T}}(\$_2) \leq \hat{\mathfrak{D}}_{\mathcal{T}}(\mathcal{G})$

$\mathfrak{D}_{\mathcal{I}}(\$_1) \leq \mathfrak{D}_{\mathcal{I}}(\mathcal{G}), \mathfrak{D}_{\mathcal{I}}(\$_2) \leq \mathfrak{D}_{\mathcal{I}}(\mathcal{G})$
$\hat{\mathfrak{D}}_{\mathcal{F}}(\$_1) \leq \hat{\mathfrak{D}}_{\mathcal{F}}(\mathcal{G}), \hat{\mathfrak{D}}_{\mathcal{F}}(\$_2) \leq \hat{\mathfrak{D}}_{\mathcal{F}}(\mathcal{G})$,
(ii). $\mathfrak{D}_{\mathcal{T}}(\$_1) = \mathfrak{D}_{\mathcal{T}}(\$_2), \mathfrak{D}_{\mathcal{I}}(\$_1) = \mathfrak{D}_{\mathcal{I}}(\$_2), \mathfrak{D}_{\mathcal{F}}(\$_1) = \mathfrak{D}_{\mathcal{F}}(\$_2)$

Definition 3.6 For every possible connected $\$_i$ of $\dot{\mathcal{G}}$, then $\hat{\mathcal{G}}^\circ: (\mathcal{Y}, \mathcal{Z})$ are called Strictly balanced SVN-subgraphs (SB-SVN), provided $\mathfrak{D}_T(\$_i) = \mathfrak{D}_T(\mathcal{G})$ and $\mathfrak{D}_I(\$_i) = \hat{\mathfrak{D}}_I(\mathcal{G}), \hat{\mathfrak{D}}_F(\$_i) = \hat{\mathfrak{D}}_F(\mathcal{G})$.

Proposition 3.1: If the graph $\dot{\mathcal{G}}$ is a strong SVN-graph, then $\dot{\mathfrak{D}}(\dot{\mathcal{G}})$ is equal to (2,2,2) and it contains SVN-subgraphs that are strictly balanced.
Proof Given that $\hat{\mathcal{G}}: (\mathcal{V}, E)$ Possesses strong edges for each side.
$\mathcal{T}_{\mathcal{Z}}(p_i, p_j) = \mathcal{T}_{\mathcal{Y}}(p_i) \wedge \mathcal{T}_{\mathcal{Y}}(p_j)$
$\mathcal{I}_{\mathcal{Z}}(p_i, p_j) = \mathcal{I}_{\mathcal{Y}}(p_i) \wedge \mathcal{I}_{\mathcal{Y}}(p_j)$
$\mathcal{F}_{\mathcal{Z}}(p_i, p_j) = \mathcal{F}_{\mathcal{Y}}(p_i) \vee \mathcal{F}_{\mathcal{Y}}(p_j)$, for all $p_i, p_j \in \mathcal{V}$
In accordance with the concept of SVN-graph density,

$$\hat{\mathfrak{D}}_T(\mathcal{G}) = \frac{2\sum T_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V} T_{\mathcal{Y}}(p_i)\wedge T_{\mathcal{Y}}(p_j)} = \frac{2T_{\mathcal{Y}}(p_i)\wedge T_{\mathcal{Y}}(p_j)}{\sum_{(p_i,p_j)\in V} T_{\mathcal{Y}}(p_i)\wedge T_{\mathcal{Y}}(p_j)} = 2$$

$$\hat{\mathfrak{D}}_I(\mathcal{G}) = \frac{2\sum I_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V} I_{\mathcal{Y}}(p_i)\wedge I_{\mathcal{Y}}(p_j)} = \frac{2I_{\mathcal{Y}}(p_i)\wedge I_{\mathcal{Y}}(p_j)}{\sum_{(p_i,p_j)\in V} I_{\mathcal{Y}}(p_i)\wedge I_{\mathcal{Y}}(p_j)} = 2$$

$$\hat{\mathfrak{D}}_F(\mathcal{G}) = \frac{2\sum F_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V} F_{\mathcal{Y}}(p_i)\vee F_{\mathcal{Y}}(p_j)} = \frac{2F_{\mathcal{Y}}(p_i)\vee F_{\mathcal{Y}}(p_j)}{\sum_{(p_i,p_j)\in V} F_{\mathcal{Y}}(p_i)\vee F_{\mathcal{Y}}(p_j)} = 2$$

Thus, $\hat{\mathfrak{D}}(\hat{\mathcal{G}}) = \left(\hat{\mathfrak{D}}_{\mathcal{T}}(\hat{\mathcal{G}}), \hat{\mathfrak{D}}_{\mathcal{I}}(\hat{\mathcal{G}}), \hat{\mathfrak{D}}_{\mathcal{F}}(\mathcal{G})\right) = (2,2,2)$. Additionally, for each of the SVN-subgraphs \$ of $\mathcal{G}, D(\$) = (2,2,2)$ since all of the linked SVN-subgraphs of $\mathcal{G} : (\mathcal{Y}, \mathcal{Z})$ Have strong edges. Consequently, SVN-graphs $\dot{\mathcal{G}}: (\mathcal{Y}, \mathcal{Z})$ is strictly balanced.□

Proposition 3.2 A SVN-graph with a few strong edges is never going to be a MB SVN-graph.
Proof: If an SVN-graph contains one or more strong edges, but not all of them, then the linked SVN-subgraph \$ That contains only strong edges has $D_{\mathcal{T}}(\$) = 2, D_{\mathcal{I}}(\$) = 2, D_{\mathcal{F}}(\$) = 2$. This leads to the conclusion that. $D(\$) = (2,2,2) > D(\mathcal{G})$. Because of this, it is not a mild balanced SVN-subgraph. □

Remark 3.1 It is important to note that SVN-subgraphs that have strong edges are usually feeble unless the SVN-graph is strong.

Theorem 3.3 When two equally balanced linked SVN-subgraphs share one or more vertices, their union is also equally balanced.
Proof Let $\hat{\mathcal{G}}: (\mathcal{Y}, \mathcal{Z})$ Be an SVN-graph with two EB SVN-connected subgraphs, $\$_1$ and $\$_2$, that share at least one vertex.
In accordance with the definition, $\$_1$ and $\$_2$ Are the EB SVN-connected subgraphs
$\therefore \dot{\mathfrak{D}}(\$_1) = \dot{\mathfrak{D}}(\$_2) \leq \dot{\mathfrak{D}}(\dot{\mathcal{G}})$

$$\dot{\mathfrak{D}}_{\mathcal{T}}(\$_1) = \frac{2\sum\mathcal{T}_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V(\$_1)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}\mathcal{Y}(p_j)} = \frac{2a}{b}$$

$$\hat{\mathfrak{D}}_{\mathcal{T}}(\$_2) = \frac{2\sum\mathcal{T}_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V(\$_2)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}\mathcal{Y}(p_j)} = \frac{2c}{d}$$

Since $\hat{\mathfrak{D}}_{\mathcal{T}}(\$_1) = \hat{\mathfrak{D}}_{\mathcal{T}}(\$_2) \Rightarrow \frac{2a}{b} = \frac{2c}{d} \Rightarrow \frac{a}{b} = \frac{c}{d} \Rightarrow \frac{c}{d} = \frac{ka}{kb}$

$$\mathfrak{D}_{\mathcal{T}}(\$_1) = D_{\mathcal{T}}(\$_2) = \frac{2a}{b}$$

$$\hat{\mathfrak{D}}_{\mathcal{T}}(\$_1 \cup \$_2) = \frac{2\left[\sum_{(p_i,p_j)\in E(\$_1)}\mathcal{T}_{\mathcal{Z}}(p_i,p_j) + \sum_{(p_i,p_j)\in E(\$_2)}\mathcal{T}_{\mathcal{Z}}(p_i,p_j)\right]}{\sum_{(p_i,p_j)\in V(\$_1)} T_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j) + \sum_{(p_i,p_j)\in V(\$_2)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j)}$$

$$= \frac{2(a+c)}{b+d} = \frac{2(a+ka)}{b+kb} = \frac{2a}{b}$$

$\Rightarrow \hat{\mathfrak{D}}_{\mathcal{T}}(\$_1 \cup \$_2) = \hat{\mathfrak{D}}_{\mathcal{T}}(\$_1) = \hat{\mathfrak{D}}_{\mathcal{T}}(\$_2)$,
Similarly $\hat{\mathfrak{D}}_{\mathcal{I}}(\$_1 \cup \$_2) = \hat{\mathfrak{D}}_{\mathcal{I}}(\$_1) = \hat{\mathfrak{D}}_{\mathcal{I}}(\$_2), \hat{\mathfrak{D}}_{\mathcal{F}}(\$_1 \cup \$_2) = \hat{\mathfrak{D}}_{\mathcal{F}}(\$_1) = \hat{\mathfrak{D}}_{\mathcal{F}}(\$_2)$.□

Theorem 3.4 Two connected SVN-graphs, $\mathring{\mathcal{G}}_1$ and $\mathring{\mathcal{G}}_2$ with at least one common vertex form an intense subgraph of the SVN-graph $\mathring{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2$.
Proof Let $\mathring{\mathcal{G}}_1: (\mathcal{Y}_1, \mathcal{Z}_1)$ and $\mathring{\mathcal{G}}_2: (\mathcal{Y}_2, \mathcal{Z}_2)$ be two connected SVN-graphs with at least one common vertex. Let $\dot{\mathfrak{D}}_{\mathcal{T}}(\dot{\mathcal{G}}_1) = \frac{2\sum\mathcal{T}_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V(\dot{\mathcal{G}}_1)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j)} = \frac{2a}{b}$ and

$$\dot{\mathfrak{D}}_{\mathcal{T}}(\dot{\mathcal{G}}_2) = \frac{2\sum\mathcal{T}_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V(\mathcal{G}_2)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j)} = \frac{2c}{d}$$

$$\frac{2\sum\mathcal{T}_{\mathcal{Z}}(p_i,p_j)}{\sum_{(p_i,p_j)\in V(\mathcal{G}_2)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j)} = \frac{2c}{d}$$

$$\hat{\mathfrak{D}}_{\mathcal{T}}(\dot{\mathcal{G}}_1 + \dot{\mathcal{G}}_2) = \frac{2\left[\sum_{(p_i,p_j)\in E(\$_1),E(\$_2)}\mathcal{T}_{\mathcal{Z}}(p_i,p_j) + \sum_{(p_i,p_j)\in E*}\mathcal{T}_{\mathcal{Z}}(p_i,p_j)\right]}{\sum_{(p_i,p_j)\in V(\$_1),V(\$_2)}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j) + \sum_{(p_i,p_j)\in V*}\mathcal{T}_{\mathcal{Y}}(p_i)\wedge\mathcal{T}_{\mathcal{Y}}(p_j)}$$

Here $\mathcal{V}^*$ and E^* are the vertices set and the strong edges set between every pair of non-common vertices of $\mathring{\mathcal{G}}_1$ and $\mathring{\mathcal{G}}_2$. Obviously $\mathcal{T}_Z(p_i p_j) = \mathcal{T}_y(p_i) \wedge \mathcal{T}_y(p_j)$ for all $p_i p_j \in E^*$, since we include a strong edge connecting each pair of $\mathring{\mathcal{G}}_1$ and $\mathring{\mathcal{G}}_2$ Noncommon vertices. That is, $\sum \mathcal{T}_Z(p_i p_j) = \sum \mathcal{T}_y(p_i) \wedge \mathcal{T}_y(p_j)$ for all $p_i p_j \in E^*$

$$\hat{\mathfrak{D}}_{\mathcal{T}}\left(\mathring{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2\right) = \frac{2(a+c+x)}{b+d+x} > \frac{2a}{b} > \frac{2c}{d}$$

$\therefore \dot{\mathfrak{D}}_{\mathcal{T}}\left(\dot{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2\right) > \mathfrak{D}_{\mathcal{T}}\left(\mathring{\mathcal{G}}_1\right)$ and $\hat{\mathfrak{D}}_{\mathcal{T}}\left(\mathring{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2\right) > \mathfrak{D}_{\mathcal{T}}\left(\mathring{\mathcal{G}}_2\right)$

Similarly, it can be shown that. $\mathfrak{D}_{\mathcal{I}}(\dot{\mathcal{G}}_1) < \mathfrak{D}_{\mathcal{I}}(\dot{\mathcal{G}}_1 + \dot{\mathcal{G}}_2)$ and $\dot{\mathfrak{D}}_{\mathcal{I}}(\mathcal{G}_2) < \dot{\mathfrak{D}}_{\mathcal{I}}(\dot{\mathcal{G}}_1 + \dot{\mathcal{G}}_2)$,

$\hat{\mathfrak{D}}_{\mathcal{F}}\left(\mathring{\mathcal{G}}_1\right) < \hat{\mathfrak{D}}_{\mathcal{F}}\left(\mathring{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2\right)$ and $\hat{\mathfrak{D}}_{\mathcal{F}}\left(\mathring{\mathcal{G}}_2\right) < \hat{\mathfrak{D}}_{\mathcal{F}}\left(\mathring{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2\right)$.

$\therefore \mathfrak{D}(\dot{\mathcal{G}}_1) < \mathfrak{D}(\dot{\mathcal{G}}_1 + \dot{\mathcal{G}}_2)$ and $\mathfrak{D}(\dot{\mathcal{G}}_2) < \mathfrak{D}(\dot{\mathcal{G}}_1 + \dot{\mathcal{G}}_2)$.

Thus, $\mathcal{G}_1$ and $\dot{\mathcal{G}}_2$ Are intense subgraphs of the sum of $\mathring{\mathcal{G}}_1$ and $\mathring{\mathcal{G}}_2$.

In particular, $\mathfrak{D}\left(\mathring{\mathcal{G}}_1\right) = \mathfrak{D}\left(\mathring{\mathcal{G}}_1 + \mathring{\mathcal{G}}_2\right) = \mathfrak{D}\left(\mathring{\mathcal{G}}_2\right)$ If all the graphs are strong SVN-graphs.□

Corollary 3.1 A SVN-graph is strictly balanced if all conceivable linked subgraphs are equally balanced.
Proof: One can show this by splitting the graph into two equally balanced linked subgraphs. The above-stated claim holds that the union of two equally balanced linked SVN-graph subgraphs is a strictly balanced SVN-graph.□

3.1 Algorithm for Identifying Balanced in SVN Graphs

In this subsection, we proposed an algorithm to test whether identifying balanced in SVN Graphs. Consider the SVN-graph $\mathring{\mathrm{G}}$: (Y, Z).

In this subsection, we proposed an algorithm to test whether identifying balanced in SVN Graphs. Consider the SVN-graph $\mathring{\mathcal{G}}:(\mathcal{Y}, \mathcal{Z})$

STEP 1: Compute the truth-density $(\hat{\mathfrak{D}}_T)$, indeterminacy-density $(\hat{\mathfrak{D}}_T)$ and falsity-density $(\dot{\mathfrak{D}}_T)$ of the SVN-graph $\dot{\mathcal{G}}$ as $\hat{\mathfrak{D}}(\dot{\mathcal{G}}) = (\dot{\mathfrak{D}}_T(\dot{\mathcal{G}}), \dot{\mathfrak{D}}_I(\dot{\mathcal{G}}), \dot{\mathfrak{D}}_F(\dot{\mathcal{G}}))$.

STEP 2: Generate all feasible connected subgraphs from the SVN-graph $\mathcal{G}$ as $\{\$_1, \$_2, \$_3 \ldots\}$.

STEP 3: Compute the density value $\hat{\mathfrak{D}}_T, \hat{\mathfrak{D}}_I$ and $\hat{\mathfrak{D}}_F$ for all the subgraphs as $\mathfrak{D}(\$_i) = (\mathfrak{D}_{\mathcal{T}}(\$_i), \mathfrak{D}_{\mathcal{I}}(\$_i), \mathfrak{D}_{\mathcal{F}}(\$_i))$, where $\mathrm{i} = 1,2,3 \ldots, \mathrm{n}$

STEP 4 :

(i). Test the condition if $\hat{\mathfrak{D}}_{\mathcal{T}}(\$_i) \leq \dot{\mathfrak{D}}(\dot{\mathcal{G}}), \hat{\mathfrak{D}}_{\mathcal{I}}(\$_i) \leq \dot{\mathfrak{D}}(\dot{\mathcal{G}})$ and $\dot{\mathfrak{D}}_{\mathcal{F}}(\$_i) \leq \dot{\mathfrak{D}}(\dot{\mathcal{G}})$ Then the graph is called an ISVN-subgraph.

(ii). Take any two intense SVN-subgraphs $\$_a$ and $\$_b$, if the (T, I, F)-density of $\$_a$ is equal to the ($\mathcal{T}, \mathcal{I}, \mathcal{F}$)-density of $\$_b$Then the two neutrosophic subgraphs represent EB SVN-subgraphs.

(iii). If $\hat{\mathfrak{D}}_{\mathcal{T}}(S_i) > \hat{\mathfrak{D}}(\hat{\mathcal{G}}), \hat{\mathfrak{D}}_{\mathcal{I}}(\$_i) > \hat{\mathfrak{D}}(\hat{\mathcal{G}})$ and $\hat{\mathfrak{D}}_{\mathcal{F}}(\$_i) > \hat{\mathfrak{D}}(\hat{\mathcal{G}})$Then the SVN-graph is called an FSVN-subgraph.

(iv). If $\hat{\mathfrak{D}}_{\mathcal{T}}(\$_i) = \dot{\mathfrak{D}}(\dot{\mathcal{G}}), \hat{\mathfrak{D}}_{\mathcal{I}}(\$_i) = \dot{\mathfrak{D}}(\dot{\mathcal{G}})$ and $\hat{\mathfrak{D}}_{\mathcal{F}}(\$_i) = \dot{\mathfrak{D}}(\dot{\mathcal{G}})$ Then the SVN-graph is called a STRICTLY balanced SVN-graph.

STEP 5: The collection of all intense SVN-subgraphs is called an MB SVN-graph.

STEP 6: The collection of all feeble SVN-subgraphs is called a WB SVN-graph.

The algorithm for identifying balanced SV-graphs provides a comprehensive and structured method for classifying subgraphs based on neutrosophic density parameters. It successfully captures truth, indeterminacy, and falsity characteristics, making it well-suited for complex systems such as social networks, semantic webs, and traffic networks. The theoretical time complexity of the algorithm is $\mathrm{O}(2^{\mathrm{n}} \cdot (\mathrm{n} + \mathrm{m}) + 4^{\mathrm{n}})$. The algorithm lays a strong theoretical foundation for further improvements and real-world adaptation. As the size of the traffic network grows, ensuring the algorithm's efficiency becomes increasingly important. Large urban networks are constantly changing in terms of traffic patterns. The system must be adaptable and capable of digesting these changes in real time, taking into account aspects such as traffic signal timing, congestion levels, and accidents. If the algorithm struggles to perform at greater scales, it may result in delayed route optimizations, reducing the system's effectiveness. What changes may be made to the algorithm for finding balanced SVN graphs so that it can efficiently scale to handle huge urban traffic networks while preserving real-time performance and accuracy. To enable the algorithm for finding balanced SVN graphs to efficiently scale for large urban traffic networks while preserving real-time performance and accuracy, we propose several modifications, which are demonstrated using the Tamluk network in the following application section.

Implementing Mild Balanced and Equally Balanced Single Valued Neutrosophic Graphs (MB-SVNGs and EB-SVNGs) in real-time transportation systems introduces a number of technical, computational, and data constraints. These are due to the inherent complexity of neutrosophic logic and the operational requirements of real-time decision-making in dynamic, uncertain contexts. Characteristics of Balanced SVNGs are investigated because they provide a systematic and flexible framework for managing the inherent uncertainty in transportation systems. Mild balanced SVNGs improve the intelligence, accuracy, and responsiveness of urban transportation systems by managing complexity using a mathematically sound, uncertainty-aware method. This study on Mild Balanced Neutrosophic Graphs establishes a basic framework for optimizing complicated transportation networks and paves the way for future studies that handle greater complexities. In particular, the concepts of mild balanced and equal balanced in SVNGs are well-suited to real-world traffic systems, where some degree of variation (mild imbalance) exists between connected segments, but overall stability (equal balance) is desired across the network. These properties enable a more flexible yet structured representation of traffic flow, congestion uncertainty, and dynamic routing behavior. The following section demonstrates how these graph structures can be implemented in an urban transportation context to improve decision-making, traffic prediction, and route optimization.

4. Implementation: Using Balanced Mild and Equally Balanced Neutrosophic Graphs to Enhance Urban Transportation Management Systems

This paper investigates the use of mild balanced neutrosophic graphs in the field of networking, more especially in the context of creating efficient transportation networks inside cities. Finding the presence of basic services such as shopping malls, universities, hospitals, railway stations, district courts, and schools is the main emphasis. By means of careful use of mild balanced neutrosophic graphs, the research intends to establish a harmonic integration of explicit and implicit knowledge, thereby guaranteeing a thorough and flexible framework for transportation management. The question about scaling the approach to larger or more complex SVN graphs, particularly in the context of real-world traffic management systems, relates to how effectively the algorithm for finding balanced SVN graphs can handle larger datasets, more complex graph structures, and real-time traffic scenarios. What benefits can be realized from incorporating these graph models in terms of traffic flow optimization and improved routing efficiency. These research questions focus on critical aspects like scalability, uncertainty handling, algorithmic efficiency, and real-time decision-making, which will guide further exploration and development of the MB SVN graph approach in traffic management systems. Urban transportation administration involves a multifaceted system that necessitates meticulous evaluation of a variety of factors, such as the accessibility of essential services. This research examines the utilization of mild balanced neutrosophic graphs as an instrument to improve the efficiency of transportation systems by assessing the accessibility of critical services within cities. The importance of a balanced approach to service availability is underscored by the study, which extends this concept to urban transportation management. To represent the explicit and implicit knowledge sources associated with the availability of services in cities, the research suggests the use of moderate balanced neutrosophic fuzzy graphs. The tiny Tamluk network depicted in Figure 2 has already been employed to determine the planarity score (Mahapatra et al. 2021). The Tamluk network refers to a transportation or road network model based on the town of Tamluk, which is a municipal area in West Bengal, India. In the context of research involving Mild Balanced Single Valued Neutrosophic (MB-SVN) graphs, the Tamluk network is often used as a case study to demonstrate how MB-SVN graphs can handle uncertainty in real-time transportation systems, such as route planning, traffic control, or congestion management. The investigation into the use of mild balanced single-valued neutrosophic graphs reveals that they provide a flexible and powerful framework for modeling systems where uncertainty and indeterminacy are inherent. Their application in urban traffic networks, route planning, and decision support demonstrates improved robustness and adaptability over classical graph models. For the current research on the mild and equally balanced SVN-graphs, we have consulted the same graph; vertices represent fundamental services and reflect [C - Tamluk college, ST- own School, H-Tamluk hospital, CO-Tamluk court, SH-Hamilton school, SO - Shopping Mall, SS- Santanamoye Girls school, D-D.M. office, R_1 - Matagini Rail station, R- Tamluk Railway station]. With truth, indeterminacy, and falsity membership-values show the proportion of sources, respectively, satisfied visitors of services. and edge membership-value of the truth, indeterminacy, and falsity are an average of the end vertices.

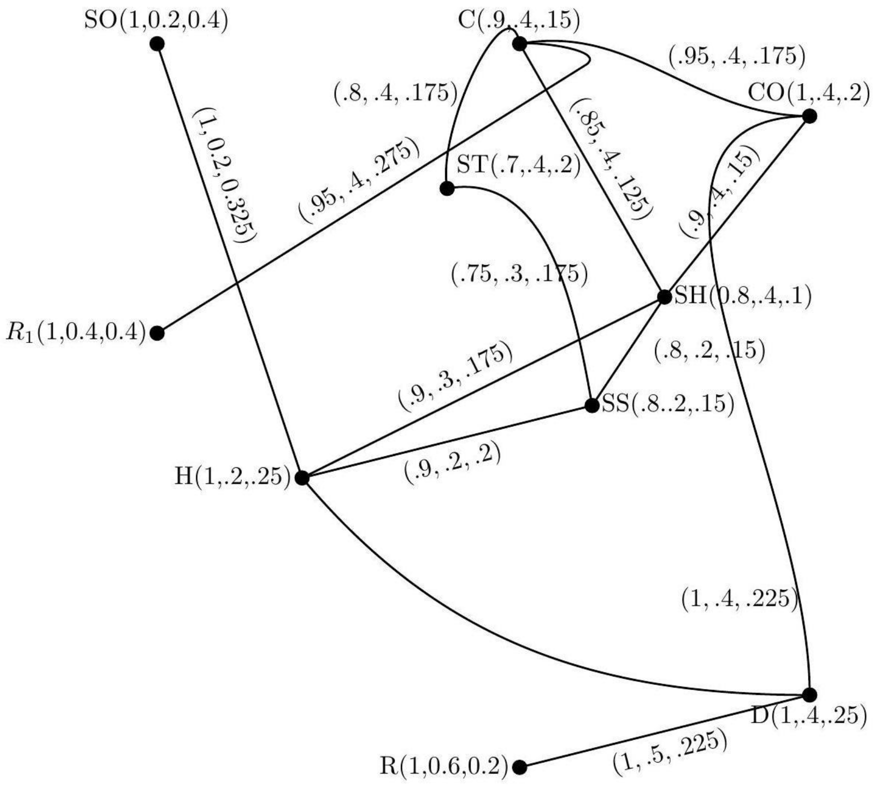

Fig. 2: SVN-graph representation of the Network at Tamluk

We found the density value of $\dot{\mathcal{G}}$ by means of the preceding graph's analysis; $\hat{\mathfrak{D}}(\hat{\mathcal{G}}) = (2.107,2.25,1.651)$ with $\mathfrak{D}(\$_{100}) = (2.07,2.220, 1.670)$, $\mathfrak{D}(\$_{102}) = (2.07,2.220,1.670)$, $\hat{\mathfrak{D}}(\$_{114}) = (2.102,2.250,1.64)$ and $\mathfrak{D}(\$_{115}) = (2.137,2.260,1.7)$.

Where $\$_{100} = \{SO, H, SH, C, CO, D, R\}$, $\$_{102} = \{SO, H, SS, SH, CO, D, R\}$, $\$_{114} = \{R_1, C, ST, SS, SH, CO, D, R\}$ and $\$_{115} = \{H, SS, ST, C, SH, CO, D, R\}$.

(1). Since $\hat{\mathfrak{D}}(\hat{\mathcal{G}}) > \hat{\mathfrak{D}}(\$_{100}), \hat{\mathfrak{D}}(\hat{\mathcal{G}}) > \hat{\mathfrak{D}}(\$_{102})$, and $\hat{\mathfrak{D}}(\hat{\mathcal{G}}) > \hat{\mathfrak{D}}(\$_{114})$, the intense subgraphs $\$_{100}, \$_{102}$, and $\$_{114}$ are referred to as "MB SVN-graphs". These networks (subgraphs) are extremely transported. The significant factor in transportation management is managed as follows: Organizing the logistical networks, examination of the movement of products throughout the supply chain, replenishment, route planning, cost analysis of tariffs and transportation, Bundling and consolidation, transport management optimization, and planning for the location.

(2). As $\mathfrak{D}(\dot{\mathcal{G}}) < \dot{\mathfrak{D}}(\$_{115}), \$_{115}$ is a subgraph that is feeble and is referred to as a "WB SVN-graph". This graph may be characterized by a low edge density or a limited number of connections between vertices.

so, since $\dot{\mathfrak{D}}(\dot{\mathcal{G}}) > \dot{\mathfrak{D}}(\$_{100}), \dot{\mathfrak{D}}(\dot{\mathcal{G}}) > \dot{\mathfrak{D}}(\$_{102})$, and $\dot{\mathfrak{D}}(\$_{100}) = \dot{\mathfrak{D}}(\$_{102})$.. Consequently, $\$_{100}$ and $\$_{102}$ are referred to as "EB SVN-graphs". To accomplish these goals, it is necessary to intercept all transportation routes at the same point with efficiency and maintain the route's effectiveness throughout. In certain optimization scenarios, they can ensure that traffic is allocated equitably among network nodes, as well as when uniform connections are preferable.

The MB SVN-subgraphs are particularly useful for modeling and solving traffic control problems because they provide a flexible representation that accounts for varying levels of uncertainty (e.g., fluctuating traffic volumes). For instance, if traffic data becomes less reliable at certain intersections, the MB SVN graphs can still produce reasonable approximations, helping the traffic management system make informed decisions even under uncertain conditions. WB SVN-subgraphs (wimpy balanced) and EB SVN-subgraphs (equally balanced) could be useful in different traffic scenarios. In a large urban network, these different types of graphs may help address different traffic patterns. For example, WB SVN graphs might be applied to less dense areas, where traffic flow is less variable, while MB SVN graphs might be more suited for high-density areas, where the data might be more inconsistent due to heavy traffic or accidents.

5. Conclusion

There are three types of SVN-graphs that we introduced in this research: mild, wimpy, and equally balanced. It is possible to apply the idea of weak and strong subgraphs to the SVN-graph. Additional research has focused on SVN-graphs that are aspectually balanced and formed by merging or summing two SVN-graphs that share vertices. An evaluation of a few real-world situations and the expectation of result-oriented research are made possible by the vast variety of applications of the mild balanced SVN-graph, which includes improving management strategies and industrial sector performance. Ultimately, these results bolster a structured approach to decision optimization, providing valuable insights for real-world applications and establishing the foundation for result-oriented research.
In conclusion, the MB SVN graph approach shows great potential for scaling up to large, complex urban traffic networks. The flexibility of MB SVN-subgraphs in modeling uncertain or fluctuating traffic data makes them particularly valuable for real-time traffic control systems. These graphs can be effectively used in high-density areas, where traffic data is more likely to be inconsistent or variable, while WB SVN graphs could be applied in less dense areas. In this study, we developed an algorithm for constructing balanced SVN graphs and demonstrated its application in traffic management through simulations using real-world traffic data from Tamluk city. The algorithm was able to account for inconsistencies in traffic data, yielding reliable results even in scenarios with missing or noisy data. However, a limitation of this approach is that it was tested only on simulated datasets, and its performance in highly dynamic, real-time conditions remains untested. Future research should focus on testing this model in large-scale urban environments, incorporating real-time data and addressing scalability concerns to improve its applicability in real-world traffic control systems.

Future Directions

Our research investigates mild balanced neutrosophic graphs, contributing to a better understanding of their features and applications. While existing understanding emphasizes these graphs' theoretical basis, there is a significant gap in their real-world validation and practical use. Future study could concentrate on using moderate balanced neutrosophic graphs for complex network analysis in unpredictable situations, including social networks, decision-making systems, and data mining. Furthermore, investigating algorithmic efficiency and integration with other neutrosophic structures could help both theoretical research and practical implementations. We plan to extend our research on soft neutrosophic balanced graphs and roughness in balanced neutrosophic graphs. Furthermore, future study will examine isomorphism, the direct product of two balanced neutrosophic graphs.

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