# From Neutrosophic Soft Set to Effective Neutrosophic Soft Set Generalizations and Applications 

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#### Abstract

The Neutrosophic Soft Set (NSS) is an advanced and highly effective expansion of soft sets, specifically designed to handle parameterized values of alternatives. As an enhanced version of fuzzy soft sets, it provides a novel mathematical framework that offers significant advantages in dealing with uncertain information. This model is created by merging soft sets and neutrosophic sets, providing a robust approach to uncertainty management. Various algorithms have been proposed for making neutrosophic decisions using NSSs. However, these algorithms neglect external effective that influence the DecisionMaking (DM) process, focusing solely on parameters. To address this issue, the article introduces the concept of Effective Neutrosophic Soft Sets (ENSSs). Additionally, we extend and generalize the innovative concept of Effective Fuzzy Soft Sets (EFSSs) to accommodate three independent membership criteria, aiming to enhance effectiveness and realism. We also introduce operations on ENSSs, including subset, complement, union, intersection, AND, and OR, which are defined along with illustrative examples. Furthermore, we examine some of its properties. Moreover, we present applications of this concept in DM problems and Medical Diagnosis (MD).


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## 1. Introduction

Fuzzy set was introduced by Zadeh [31] as a new mathematical tool to deal with uncertain information. Soft Set was introduced by Molodtsov [20]. Practical problems in economics, engineering, medical science, et cetera were solved by soft set.
Maji et al. [17] defined some operations like AND, OR and operation of union and intersection. Several researchers, including Maji et al. [18], have utilized soft set theory to address Decision-Making (DM) problems. He presented an algorithm for selecting the optimal house using soft set theory.

Numerous researchers have explored the concept of soft set theory and its properties, investigating its applications in various domains. One notable application is found in the work of Roy and Maji [21]. The concept of soft multiset was introduced by Alkhazaleh et al. [10]. Majumdar and Samanta [19] introduced the generalized fuzzy soft set, as discussed in their research, which delves into different characteristics and applications related to DM and Medical Diagnosis (MD). A wider understanding of the fuzzy soft set concept entails the consideration of Possibility Fuzzy Soft Sets (PFSSs) [9].

They applied this in DM scenarios and introduced a measure of similarity between two PFSS, which they utilized in MD. Yan [30] introduced and explored
various fuzzy data classifications, such as fuzzy basic data types, fuzzy group data types, and fuzzy custom data types.

Smarandache [27] introduced neutrosophy, as outlined in as a novel approach for addressing issues characterized by imprecise, indeterminate, and inconsistent data.

The Neutrosophic Soft Set (NSS) is a hybrid of a soft set and a neutrosophic set, as specified by Maji [16].

In 2013, Broumi and Smarandach [13] introduced the concept of an intuitionistic NSS, detailing its operations and attributes. Neutrosophic sets have been employed to tackle practical DM dilemmas involving uncertain data [14]. Alkhazaleh and Salleh [8] proposed the idea of a soft expert set, which seeks to merge the perspectives of all experts into a cohesive model without requiring operations.

Soft expert set has different extensions and generalization such as; fuzzy soft expert sets [7], neutrosophic soft expert sets [23], generalized neutrosophic soft expert set [29] and Q-Neutrosophic Soft Expert Set (Q-NSES) [15].

The publications referenced in $[1,3,6,11,12]$ explore the advancements in Neutrosophic Soft Sets (NSSs), particularly focusing on their applications in DM processes and MD.

Smarandache [28] presented a new concept which is hypersoft set which deal with multi-attribute valued
function. The fundamentals of hypersoft set discussed by Saeed et al. [22] with related basic properties and operations such hypersoft subset, complement, union, intersection and aggregation operators with hypersoft set relation.

Neutrosophic Hyper-Soft Set (NHSS) was introduced by Saqlain et al. [24] to overcome the uncertainty problems. He introduces the concept of NHSS with operators, aimed at managing scenarios where attributes need to be subdivided into distinct attribute-valued sets within neutrosophic set contexts. NHSS was generalized into: Interval valued, m-Polar and m-Polar interval valued NHSSs and the operations are discussed with suitable examples by Saqlain and Xin [26]. Zulqarnain et al. [32] extended the aggregate operators of the NHSS. They applied these operators to address multi-criteria DM problems, incorporating distance-based similarity measures. Additionally, Saqlain et al. [25] introduced a single-valued NHSS, a multi-valued NHSS, and a tangent similarity measure for single-valued NHSSs, along with outlining their properties. He also introduced an algorithm in decision making applying single-valued NHSS dependent on the tangent similarity measure. Another development of NHSS appear in [2].

Alkhazaleh [4] introduced the novel idea of Effective Fuzzy Soft Set (EFSS), delineating its fundamental operations and properties. He elaborated on the impact of external effectiveness on soft sets. Moreover, he illustrated the practical application of this concept in solving problems related to DM with algorithm. Additionally, he provided an algorithm as an enhancement of the one proposed by Roy and Maji [21], and he conducted a comparison between the original and enhanced algorithms. Finally, he provide an application on MD.

Following this, a fresh idea emerged in this field under the title of the Effective Fuzzy Soft Expert Set (EFSES) [5], which combines the strengths of EFSSs and soft expert sets. By expanding upon the concept of EFSSs, we introduce the notion of Effective Neutrosophic Soft Sets (ENSSs) to leverage the advantages of both EFSSs and NSSs. This fusion enhances efficiency and practicality. The concept of EFSSs has been widened to encompass ENSSs, which consider the influence on three distinct membership functions. In this investigation, we introduce the concept of ENSSs. Moreover, we delve into the basic operations and characteristics of this concept using pertinent examples. Lastly, we illustrate an application in DM problems and MD.

## 2. Preliminary

In this section we recall some definitions required in this paper. Assume that $U$ be a universe, $P(U)$ be the power set of $U, E$ be parameters set and $A \subseteq E$.

## - Definition 1 [20]

A soft set over the set $U$ is denoted by a pair $(F, A)$ where $F$ represents a mapping from $A$ to the power set of $U$, i.e., $F: A \rightarrow P(U)$.

## - Definition 2 [21]

Consider an initial universal set $U$ and a set of parameters $E$. Let $I^{U}$ represent the power set of all fuzzy subsets of $U$. If $A$ is a subset of $E$, then $(F, E)$ is a fuzzy soft set over $U$ and $F$ is a mapping defined as $F: A \rightarrow I^{U}$.

## - Definition 3 [27]

A neutrosophic set $A$ over the universe of discourse $X$ is defined as $A=\left\{\left\langle x: T_{A}(x), I_{A}(x), F_{A}(x)\right\rangle ; x \in X\right\}$, where $T_{A}$; $I_{A} ; F_{A}: X \rightarrow[0,1]$ are functions with the constraint $0 \leq T_{A}(x)+I_{A}(x)+F_{A}(x) \leq 3$. Here, $T_{A}(x)$ represents the truthmembership function, $I_{A}(\mathrm{x})$ is the indeterminacymembership function, and $F_{A}(x)$ is the falsitymembership function.

## - Definition 4 [16]

Suppose $U$ is the initial universe set, and $E$ is a set of parameters with $A \subseteq E$. Let $P(U)$ represent the set of all neutrosophic sets of $U$. The pair $(F, A)$ is referred to as the soft neutrosophic set over $U$, where $F$ is a mapping defined as $F: A \rightarrow P(U)$.

## - Definition 5 [16]

Consider two NSSs $(F, A)$ and $(G, B)$ defined over the common universe $U$. The union of $(F, A)$ and $(G, B)$ is represented as $(F, A) \cup(G, B)$ and is defined as $(F$, $A) \cup(G, B)=(K, C)$, where $C=A \cup B$. The truthmembership, indeterminacy-membership, and falsitymembership of $(K, C)$ are determined as follows:

$$
\begin{aligned}
& T_{\mathcal{K}}(\varsigma)(m)= \begin{cases}T_{\mathcal{F}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{A}-\mathcal{B} \\
T_{\mathcal{G}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{B}-\mathcal{A} \\
\max \left(T_{\mathcal{F}}(\varsigma)(m), T_{\mathcal{G}}(e)(m)\right) ; & \text { if } \varsigma \in \mathcal{A} \cap \mathcal{B}\end{cases} \\
& I_{\mathcal{K}}(\varsigma)(m)= \begin{cases}I_{\mathcal{F}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{A}-\mathcal{B} \\
I_{G}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{B}-\mathcal{A} \\
\min \left(I_{\mathcal{F}}(\varsigma)(m), I_{\mathcal{G}}(\varsigma)(m)\right) ; & \text { if } \varsigma \in \mathcal{A} \cap \mathcal{B}\end{cases} \\
& F_{\mathcal{K}}(\varsigma)(m)= \begin{cases}F_{\mathcal{F}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{A}-\mathcal{B} \\
F_{\mathcal{G}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{B}-\mathcal{A} \\
\min \left(F_{\mathcal{F}}(\varsigma)(m), F_{\mathcal{G}}(\varsigma)(m)\right) ; & \text { if } \varsigma \in \mathcal{A} \cap \mathcal{B}\end{cases}
\end{aligned}
$$

## - Definition 6 [16]

Consider two NSSs $(F, A)$ and $(G, B)$ defined over the common universe $U$. The intersection of $(F, A)$ and ( $G$, $B$ ) is represented as $(F, A) \cap(G, B)$ and is defined as ( $F$, $A) \cap(G, B)=(H, C)$, where $C=A \cup B$. The truthmembership, indeterminacy-membership, and falsitymembership of $(K, C)$ are determined as follows:

$$
T_{\mathcal{H}}(\varsigma)(m)=\left\{\begin{array}{l}
T_{\mathcal{F}}(\varsigma)(m) \\
T_{\mathcal{G}}(\varsigma)(m) \\
\min \left(T_{\mathcal{F}}(\varsigma)(m), T_{\mathcal{G}}(e)(m)\right)
\end{array}\right.
$$

$$
\text { if } \varsigma \in \mathcal{A}-\mathcal{B}
$$

$$
\text { if } \varsigma \in \mathcal{B}-\mathcal{A}
$$

if $\varsigma \in \mathcal{A} \cap \mathcal{B}$

$$
\begin{aligned}
& I_{\mathcal{H}}(\varsigma)(m)= \begin{cases}I_{\mathcal{F}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{A}-\mathcal{B} \\
I_{G}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{B}-\mathcal{A} \\
\max \left(I_{\mathcal{F}}(\varsigma)(m), I_{\mathcal{G}}(\varsigma)(m)\right) ; & \text { if } \varsigma \in \mathcal{A} \cap \mathcal{B}\end{cases} \\
& F_{\mathcal{H}}(\varsigma)(m)= \begin{cases}F_{\mathcal{F}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{A}-\mathcal{B} \\
F_{\mathcal{G}}(\varsigma)(m) ; & \text { if } \varsigma \in \mathcal{B}-\mathcal{A} \\
\max \left(F_{\mathcal{F}}(\varsigma)(m), F_{G}(\varsigma)(m)\right) ; & \text { if } \varsigma \in \mathcal{A} \cap \mathcal{B}\end{cases}
\end{aligned}
$$

## - Definition 7 [4]

An effective set denoted as $\Lambda$ within a universe of discourse $A$, characterized by the function $\Lambda: A \longrightarrow[0,1]$. The set $A$ comprises effective parameters capable of modifying membership values, exerting a positive impact (or no impact) on these values upon application, and given by: $\Lambda=\left\{\left\langle a, \delta_{\Lambda}(a): a \in A\right\rangle\right\}$ where $\delta_{\Lambda}(a)$ is a membership degree.

## - Definition 8 [4]

Let $U$ be initial universal set, $E$ be a set of parameters, $A$ a set of effective parameters, and $\Lambda$ be an effective set over $A$. Assume that $I^{U}$ represent the collection of all fuzzy subsets of $U$. Then $(F, E)_{A}$ is an Effective Fuzzy Soft Set (EFSS) over $U$, and $F$ is a mapping defined as follows: $F: E \longrightarrow I^{U}$ This is outlined by:

$$
\begin{gathered}
F\left(e_{i}\right)_{\Lambda}=\left\{\frac{x_{j}}{\mu_{U}\left(x_{j}\right)_{\Lambda}}: x_{j} \in U, e_{i} \in E\right\}, \text { where } \forall a_{k} \in A, \\
\mu_{U}\left(x_{j}\right)_{\Lambda}=\left\{\begin{array}{l}
\mu_{U}\left(x_{j}\right)+\left[\frac{\left(1-\mu_{U}\left(x_{j}\right)\right) \sum_{k} \delta_{\Lambda_{x_{j}}}\left(a_{k}\right)}{|A|}\right], \text { if } \mu_{U}\left(x_{j}\right) \in(0,1) \\
\mu_{U}\left(x_{j}\right)
\end{array}\right.
\end{gathered}
$$

## - Definition 9 [4]

The complement of the effective set $\Lambda$ with respect to the set of effective parameters $A$ is represented as $\Lambda^{c}$, where the symbol $c$ indicates the fuzzy complement operation.

## - Definition 10 [4]

Consider $(F, E)_{A}$ EFSS. Then $\Lambda$ complement of $(F, E)_{A}$ is also EFSS denoted as $(F, E)_{\Lambda}{ }^{c}$, and $\Lambda^{c}$ is fuzzy complement of $\Lambda$. In this process, remain the fuzzy soft set $F$ unchange, and obtain the fuzzy complement $\Lambda^{c}$. Finally apply definition 8 to generate a new EFSS.

## - Definition 11 [4]

Consider $(F, E)_{\Lambda}$ EFSS. Then Soft $_{\text {complement }}$ of $(F, E)_{\Lambda}$ is also EFSS and denoted as $\left(F^{c}, E\right)_{\Lambda}$. Here, $F^{c}$ represents the fuzzy soft complement of $F$.

In this process, the effective set $\Lambda$ remains unchanged, and the complement of fuzzy soft set $F$ is obtained. Definition 8 is then applied to generate a new EFSS.

## - Definition 12 [4]

Assume that $\left(F, E_{1}\right)_{\Lambda_{1}}$ and $\left(G, E_{2}\right)_{\Lambda_{2}}$ be EFSSs over the universe $U$. Then union of these sets is also an EFSS $(\mathcal{H}, E)_{\Lambda_{s}}$ where $E=E_{I} \cup E_{2}$ and $\forall v \in E$, is given as follows:

$$
\mathcal{H}_{\Lambda_{s}}(v)= \begin{cases}\mathcal{F}_{\Lambda_{s}}(v) & \text { if } v \in E_{1}-E_{2} \\ \mathcal{G}_{\Lambda_{s}}(v) & \text { if } v \in E_{1}-E_{2} \\ (\mathcal{F} \cup \mathcal{G})_{\Lambda_{s}}(v) & \text { if } v \in E_{1} \cap E_{2}\end{cases}
$$

where $H$ represents the fuzzy soft union between $F$ and $G$ and $s$ denotes any $s$-norm.

## - Definition 13 [4]

Assume that $\left(\mathcal{F}, E_{1}\right)_{\Lambda_{1}}$ and $\left(\mathcal{G}, E_{2}\right)_{\Lambda_{2}}$ be EFSSs over the universe $U$. Then intersection of these sets is also a $\operatorname{EFSS}(\mathcal{K}, E)_{\Lambda_{s}}$ where $E=E_{1} \cup E_{2}$ and $\forall v \in E$, is given as follows:

$$
\mathcal{K}_{\Lambda_{t}}(v)= \begin{cases}\mathcal{F}_{\Lambda_{t}}(v) & \text { if } v \in E_{1}-E_{2} \\ \mathcal{G}_{\Lambda_{t}}(v) & \text { if } v \in E_{1}-E_{2} \\ (\mathcal{F} \cap \mathcal{G})_{\Lambda_{t}}(v) & \text { if } v \in E_{1} \cap E_{2}\end{cases}
$$

where $K$ represents the fuzzy soft union between $F$ and $G$ and $t$ denotes any $t$-norm.

## 3. Effective Neutrosophic Soft Set (ENSS)

In this section, we present the fundamental definition of Effective Neutrosophic Soft Set (ENSS), accompanied by examples and properties. Assume that $U$ be the initial universal set and $N(U)$ be the set of all neutrosophic subsets of $U$. Let $E$ be the set of parameters.

## - Definition 14

Define $A$ as effective parameters set, and $\Lambda$ as an effective set over $A$. Then $(\psi, E)_{\Lambda}$ is said to be ENSS over $U$, and $\psi$ is a mapping defined as $\psi: E \rightarrow N(U)$ and is given by:

$$
\psi(\mathrm{e})\left(x_{j}\right)_{\Lambda}=\left\{\frac{x_{j}}{\left\langle T_{U}\left(x_{j}\right)_{\Lambda^{\prime}} I_{U}\left(x_{j}\right)_{\Lambda^{\prime}} F_{U}\left(x_{j}\right)_{\Lambda}\right\rangle}: x_{j} \in U, \mathrm{e} \in E\right\}
$$

where,

$$
\begin{aligned}
T_{U}\left(x_{j}\right)_{\Lambda} & =\left\{\begin{array}{l}
T_{U}\left(x_{j}\right)+\left[\frac{\left[1-T_{U}\left(x_{j}\right)\right] \sum_{k} \delta_{\Delta x_{j}}\left(a_{k}\right)}{|A|}\right] \\
T_{U}\left(x_{j}\right)
\end{array} \text { if } T_{U}\left(x_{j}\right) \in[0,1] l_{U}\left(x_{j}\right)_{\Lambda}=I\left(x_{j}\right)\right. \\
F_{U}\left(x_{j}\right)_{\Lambda} & = \begin{cases}F_{U}\left(x_{j}\right)-\left[\frac{\left[F_{U}\left(x_{j}\right)\right] \sum_{k} \delta_{\Lambda x_{j}}\left(a_{k}\right)}{|A|}\right] & \text { if } F_{U}\left(x_{j}\right) \in[0,1] \\
F_{U}\left(x_{j}\right) & O . W\end{cases}
\end{aligned}
$$

## - Example 1

Consider the universe set $U=\left\{x_{1}, x_{2}, x_{3}\right\}$. Consider the parameters set $E=\left\{e_{1}, e_{2}, e_{3}, e_{4}, e_{5}, e_{6}\right\}$ and the effective parameters set $A=\left\{a_{1}, a_{2}, a_{3}, a_{4}\right\}$. Assume that the expert provides the effective set over A as follows:
$\Lambda\left(x_{1}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0}, \frac{a_{3}}{1}, \frac{a_{4}}{0.7}\right\}, \Lambda\left(x_{2}\right)=\left\{\frac{a_{1}}{0.4}, \frac{a_{2}}{0.5}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}$,
$\Lambda\left(x_{3}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.4}\right\}$
Consider the NSS $(\psi, E)$ given as follows:

$$
\begin{aligned}
(\psi, E)= & \left\{\left(e_{1}, \frac{x_{1}}{\langle 0.5,0.2,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.5\rangle}\right),\right. \\
& \left(e_{2}, \frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right),
\end{aligned}
$$

$$
\begin{aligned}
& \left(e_{3}, \frac{x_{1}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.7,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right), \\
& \left(e_{4}, \frac{x_{1}}{\langle 0.4,0.4,0.8\rangle}, \frac{x_{2}}{\langle 0.2,0.3,0.9\rangle}, \frac{x_{3}}{\langle 0.8,0.6,0.2\rangle}\right), \\
& \left(e_{5}, \frac{x_{1}}{\langle 0.3,0.6,0.5\rangle}, \frac{x_{2}}{\langle 0.5,0.3,0.2\rangle}, \frac{x_{3}}{\langle 0.8,0.5,0.4\rangle}\right), \\
& \left.\left(e_{6}, \frac{x_{1}}{\langle 0.7,0.6,0.5\rangle}, \frac{x_{2}}{\langle 0.6,0.5,0.7\rangle}, \frac{x_{3}}{\langle 0.2,0.1,0.3\rangle}\right)\right\}
\end{aligned}
$$

Now, we utilize definition 14 to determine

$$
\psi\left(e_{1}\right)\left(x_{j}\right)_{\Lambda}, \mathrm{j}=1,2,3
$$

$$
\begin{aligned}
& \psi\left(e_{1}\right)\left(x_{j}\right)_{\Lambda} \\
& =\left\{\begin{array}{l}
\frac{x_{1}}{\langle 0.5+[1-0.5(0.3+0+1+0.7) / 4], 0.2,0.4-[0.4(0.3+0+1+0.7) / 4]\rangle} \\
\left.\frac{x_{2}}{\langle 0.3+[1-0.3(0.4+0.5+1+1) / 4], 0.1,} 0.5-[0.5(0.4+0.5+1+1) / 4]\right\rangle
\end{array}\right. \\
& \frac{x_{3}}{\langle 0.3+[1-0.3(0.7+0+0.6+0.4) / 4], 0.3,0.5-[0.5(0.7+0+0.6+0.4) / 4]\rangle}, \\
& =\left\{\frac{x_{1}}{\langle 0.75,0.2,0.2\rangle}, \frac{x_{2}}{\langle 0.81,0.1,0.1\rangle}, \frac{x_{3}}{\langle 0.6,0.3,0.29\rangle}\right\}
\end{aligned}
$$

In a similar manner, the ensuing $\operatorname{ENSS}(\psi, E)_{\Lambda}$ is derived as follows:

$$
\begin{gathered}
(\psi, E)_{\Lambda}=\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.75,0.2,0.2\rangle}, \frac{x_{2}}{\langle 0.81,0.1,0.1\rangle}, \frac{x_{3}}{\langle 0.6,0.3,0.29\rangle}\right\rangle\right),\right. \\
\left(e_{2},\left\langle\frac{x_{1}}{\langle 0.6,0.4,0.35\rangle}, \frac{x_{2}}{\langle 0.81,0.6,0.22\rangle}, \frac{x_{3}}{\langle 0.48,0.4,0.35\rangle}\right\rangle\right), \\
\left(e_{4},\left\langle\frac{x_{1}}{\langle 0.7,0.4,0.4\rangle}, \frac{x_{2}}{\langle 0.78,0.3,0.25\rangle}, \frac{x_{3}}{\langle 0.89,0.6,0.12\rangle}\right\rangle\right), \\
\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.65,0.6,0.25\rangle}, \frac{x_{2}}{\langle 0.86,0.3,0.06\rangle}, \frac{x_{3}}{\langle 0.89,0.5,0.23\rangle}\right\rangle\right) \\
\left.\left(e_{6},\left\langle\frac{x_{1}}{\langle 0.85,0.6,0.25\rangle}, \frac{x_{2}}{\langle 0.89,0.5,0.2\rangle}, \frac{x_{3}}{\langle 0.54,0.1,0.17\rangle}\right\rangle\right)\right\}
\end{gathered}
$$

## - Definition 15

Assume that $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ and $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ are ENSSs over the universe $U$. Then $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ is termed an effective neutrosophic soft subset of $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ if the following holds:

1) $E_{l} \subset E_{2}$.
2) $\Lambda_{1}(x) \leq \Lambda_{2}(x)$.
3) $\begin{aligned} T_{\psi_{\Lambda_{1}}(e)}(x) \leq T_{\phi_{\Lambda_{2}}(e)}(x), I_{\psi_{\Lambda_{1}}(e)}(x) \leq I_{\phi_{\Lambda_{2}}(e)}(x), \\ F_{\psi_{\Lambda_{1}}(e)}(x) \geq F_{\phi_{\Lambda_{2}}(e)}(x) .\end{aligned}$
$\forall e \in E_{1}, x \in U$. We denote it by $\left(\forall e \in E_{1}, x \in U\right.$. We denote it by $\left(\psi, E_{1}\right)_{\Lambda_{1}} \subseteq\left(\phi, E_{2}\right)_{\Lambda_{2}}$.

## - Example 2

Let $E_{1}=\left\{e_{1}, e_{2}, e_{3}\right\} \quad \& E_{2}=\left\{e_{1}, e_{2}, e_{3}, e_{4}\right\}$, over the common universe $U=\left\{x_{1}, x_{2}, x_{3}, x_{4}\right\}$. Consider effective sets given as follows:
$\Lambda_{1}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0}, \frac{a_{3}}{0.1}, \frac{a_{4}}{0.2}\right\}, \Lambda_{1}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.5}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.2}\right\}$,
$\Lambda_{1}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0.1}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.1}\right\}, \Lambda_{1}\left(x_{4}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0.7}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.8}\right\}$
$\Lambda_{2}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.8}, \frac{a_{2}}{1}, \frac{a_{3}}{0.1}, \frac{a_{4}}{0.3}\right\}, \Lambda_{2}\left(x_{2}\right)=\left\{\frac{a_{1}}{1}, \frac{a_{2}}{1}, \frac{a_{3}}{0.7}, \frac{a_{4}}{0.6}\right\}$,
$\Lambda_{2}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.2}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.1}\right\}, \Lambda_{2}\left(x_{4}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.8}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.9}\right\}$
Consider NSSs given as follows:
$\left(\psi, E_{1}\right)=\left\{\left(e_{1}, \frac{x_{1}}{\langle 0.4,0.1,0.7\rangle}, \frac{x_{2}}{\langle 0.2,0.1,0.6\rangle}, \frac{x_{3}}{\langle 0.1,0.1,0.7\rangle}, \frac{x_{4}}{\langle 0.3,0.5,0.6\rangle}\right)\right\rangle$,

$$
\begin{aligned}
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.3,0.1,0.8\rangle}, \frac{x_{2}}{\langle 0.4,0.1,0.6\rangle}, \frac{x_{3}}{\langle 0.3,0.1,0.7\rangle}, \frac{x_{4}}{\langle 0.3,0.2,0.7\rangle}\right\rangle\right), \\
& \left.\left(e_{3},\left\langle\frac{x_{1}}{\langle 0.4,0.2,0.9\rangle}, \frac{x_{2}}{\langle 0.3,0.1,0.8\rangle}, \frac{x_{3}}{\langle 0.4,0.1,0.8\rangle}, \frac{x_{4}}{\langle 0.4,0.3,0.8\rangle}\right\rangle\right)\right\} \\
\left(\phi, E_{2}\right)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.5,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.3,0.4,0.5\rangle}, \frac{x_{3}}{\langle 0.2,0.1,0.5\rangle}, \frac{x_{4}}{\langle 0.4,0.6,0.2\rangle}\right\rangle\right),\right. \\
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.8,0.3,0.4\rangle}, \frac{x_{3}}{\langle 0.7,0.2,0.2\rangle}, \frac{x_{4}}{\langle 0.8,0.2,0.1\rangle}\right\rangle\right), \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.6,0.3,0.8\rangle}, \frac{x_{2}}{\langle 0.5,0.2,0.6\rangle}, \frac{x_{3}}{\langle 0.7,0.3,0.4\rangle}, \frac{x_{4}}{\langle 0.8,0.5,0.6\rangle}\right\rangle\right), \\
& \left.\left(e_{4},\left\langle\frac{x_{1}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.6,0.3,0.7\rangle}, \frac{x_{3}}{\langle 0.7,0.5,0.6\rangle}, \frac{x_{4}}{\langle 0.6,0.8,0.3\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

Then the ENSSs is given as follows:

$$
\begin{aligned}
& \left(\psi, E_{1}\right)_{\Lambda_{1}} \\
& =\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.46,0.1,0.63\rangle}, \frac{x_{2}}{\langle 0.5,0.1,0.38\rangle}, \frac{x_{3}}{\langle 0.30,0.1,0.54\rangle}, \frac{x_{4}}{\langle 0.63,0.5,0.32\rangle}\right\rangle\right)\right. \\
& \quad\left(e_{2},\left\langle\frac{x_{1}}{\langle 0.37,0.1,0.72\rangle}, \frac{x_{3}}{\langle 0.63,0.1,0.38\rangle}, \frac{x_{3}}{\langle 0.46,0.1,0.54\rangle}, \frac{x_{4}}{\langle 0.63,0.2,0.37\rangle}\right\rangle\right) \\
& \left.\left.\quad\left(e_{3}, \frac{x_{1}}{\langle 0.46,0.2,0.81\rangle}, \frac{x_{2}}{\langle 0.56,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.54,0.1,0.62\rangle}, \frac{x_{4}}{\langle 0.69,0.3,0.42\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

$\left(\phi, E_{2}\right)_{\Lambda_{2}}$
$=\left\{\left(e_{1}, \frac{x_{1}}{\langle 0.78,0.2,0.27\rangle}, \frac{x_{2}}{x_{1}}, \frac{x_{3}}{\langle 0.88,0.4,0.09\rangle}, \frac{x_{4}}{\langle 0.48,0.1,0.32\rangle}, \frac{x_{3}}{\langle 0.73,0.6,0.09\rangle}\right\rangle\right)$

$$
\begin{aligned}
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.87,0.2,0.27\rangle}, \frac{x_{2}}{\langle 0.97,0.3,0.07\rangle}, \frac{x_{3}}{\langle 0.81,0.2,0.13\rangle}, \frac{x_{4}}{\langle 0.91,0.2,0.05\rangle}\right\rangle\right) \text {, } \\
& \left.\left(e_{3}, \frac{x_{1}}{(0.82,0.3,0.36)}, \frac{x_{2}}{\langle 0.91,0.2,0.11\rangle}, \frac{x_{3}}{\langle 0.81,0.3,0.26\rangle}, \frac{x_{4}}{(0.91,0.5,0.27\rangle}\right)\right\rangle \text {, } \\
& \left.\left.\left(e_{4}, \frac{x_{1}}{\langle 0.87,0.2,0.27\rangle}, \frac{x_{2}}{\langle 0.93,0.3,0.12\rangle}, \frac{x_{3}}{\langle 0.81,0.5,0.39\rangle}, \frac{x_{4}}{\langle 0.82,0.8,0.14\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

It's clear $E_{1} \subset E_{2}, \Lambda_{1} \subset \Lambda_{2}$ and $T_{\psi_{\Lambda_{1}}(e)} \leq T_{\phi_{\Lambda_{2}}(e)}, I_{\psi_{\Lambda_{1}}(e)} \leq$ $I_{\phi_{\Lambda_{2}}(e)}, F_{\psi_{\Lambda_{1}}(e)} \geq F_{\phi_{\Lambda_{2}}(e)} \quad \forall e \in E_{1} . \quad$ Then $\left(\psi, E_{1}\right)_{\Lambda_{1}} \subset$ $\left(\phi, E_{2}\right)_{\Lambda_{2}}$.

## - Definition 16

Assume that $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ and $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ are ENSSs over $U$. Then $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ is equal to $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ and denoted by $\left(\psi, E_{1}\right)_{\Lambda_{1}}=\left(\phi, E_{2}\right)_{\Lambda_{2}}$ if $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ is an ENS subset of $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ and $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ is an ENS subset of $\left(\psi, E_{1}\right)_{\Lambda_{1}}$

## 4. Basic Operations

In this section, we introduce operations related to ENSS, specifically the subset, equal, complement, union, and intersection. We offer illustrative examples to elucidate these concepts and outline their fundamental properties.

## - Definition 17

Consider $(\psi, E)_{\Lambda}$ be ENSS. Then the Total complement of ( $\psi$, $E)_{\Lambda}$ is also ENSS and represented as $\left(\psi^{c}, E\right)_{\Lambda}{ }^{c}$. Here $\psi^{c}$ is neutrosophic complement of $\psi$ and $\Lambda^{c}$ stands for fuzzy complement of $\Lambda$.

In this process, both the fuzzy complement $\Lambda^{c}$ and the complement of NSS $\psi^{c}$ are obtained. Definition 14 is then applied to generate a new ENSS.

## - Definition 18

Consider $(\psi, E)_{\Lambda}$ be ENSS. Then the $\Lambda_{\text {complement }}$ of ( $\psi$, $E)_{\Lambda}$ is also ENSS represented as $(\psi, E)_{\Lambda}{ }^{c}$, here $\Lambda^{c}$ stands for any fuzzy complement of $\Lambda$. In this process, the NSS $\psi$ remains unchanged, and the fuzzy complement $\Lambda^{c}$ is
obtained. Definition 14 is then applied to generate a new ENSS.

## - Definition 19

Consider $(\psi, E)_{\Lambda}$ be ENSS. Then the Soft $t_{\text {complement }}$ of ( $\psi$, $E)_{\Lambda}$ is also ENSS and represented as $\left(\psi^{c}, E\right)_{\Lambda}$, here $\psi^{c}$ is neutrosophic soft complement of $\psi$. In this process, the effective set $\$ \backslash$ Lambda\$ remains unchanged, and the complement of NSS $\psi$ is obtained. Definition 14 is then applied to generate a new ENSS.

## - Example 3

Let $E=\left\{e_{1}, e_{2}, e_{3}\right\}$ over the common universe $U=\left\{x_{1}, x_{2}\right.$, $\left.x_{3}, x_{4}\right\}$. Consider effective sets given as follows:
$\Lambda\left(x_{1}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0}, \frac{a_{3}}{1}, \frac{a_{4}}{0.7}\right\}, \Lambda\left(x_{2}\right)=\left\{\frac{a_{1}}{0.4}, \frac{a_{2}}{0.5}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}$,
$\Lambda\left(x_{3}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.4}\right\}$
Consider the NSS $(\psi, E)$ given as follows:
$(\psi, E)=\left\{\left(e_{1}, \frac{x_{1}}{\langle 0.5,0.2,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.5\rangle}\right)\right.$,

$$
\begin{aligned}
& \left(e_{2}, \frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right) \\
& \left.\left(e_{3}, \frac{x_{1}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.7,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right)\right\}
\end{aligned}
$$

Now, we obtain the complement of effective set $\Lambda^{c}$ as follows:
$(\psi, E)^{c}=\left\{\left(e_{1}, \frac{x_{1}}{\langle 0.4,0.2,0.5\rangle}, \frac{x_{2}}{\langle 0.5,0.1,0.3\rangle}, \frac{x_{3}}{\langle 0.5,0.3,0.3\rangle}\right)\right.$,

$$
\begin{aligned}
& \left(e_{2}, \frac{x_{1}}{\langle 0.7,0.4,0.2\rangle}, \frac{x_{2}}{\langle 0.8,0.6,0.3\rangle}, \frac{x_{3}}{\langle 0.6,0.4,0.1\rangle}\right), \\
& \left.\left(e_{3}, \frac{x_{1}}{\langle 0.3,0.9,0.6\rangle}, \frac{x_{2}}{\langle 0.10 .7,0.4\rangle}, \frac{x_{3}}{\langle 0.2,0.1,0.8\rangle}\right)\right\}
\end{aligned}
$$

Now, we apply definitions $19,17,18$, and 14 to find Total $_{\text {complement }}, \Lambda_{\text {complement }}$ and Soft $_{\text {complement }}$ respectively.
To find Total complement $^{\text {, first we find }} \psi^{c}\left(e_{1}\right)\left(x_{j}\right)_{\Lambda^{c}, j}=$ 1,2,3 , as follows:
$\psi^{c}\left(e_{1}\right)\left(x_{j}\right)_{\Lambda^{c}}$


In a similar manner, we find Total $_{\text {complement }}=(\psi, E)^{c}{ }_{\Lambda^{c}}$ as shown below:
$(\psi, E)^{c}{ }_{\Lambda^{c}}=\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.7,0.2,0.25\rangle}, \frac{x_{2}}{\langle 0.64,0.1,0.22\rangle}, \frac{x_{3}}{x_{1}}\right\rangle\langle 0.79,0.3,0.13\rangle\right\rangle\right)$,

$$
\begin{aligned}
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.85,0.4,0.1\rangle}, \frac{x_{2}}{\langle 0.86,0.6,0.22\rangle}, \frac{x_{3}}{\langle 0.83,0.4,0.04\rangle}\right\rangle\right) \\
& \left.\left(e_{3},\left\langle\frac{x_{1}}{\langle 0.65,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.35,0.7,0.29\rangle}, \frac{x_{3}}{\langle 0.66,0.1,0.34\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

To find $\Lambda_{\text {complement }}$, first we find $\psi\left(e_{1}\right)\left(x_{j}\right)_{\Lambda^{c}}, j=1,2,3$ as follows:

$$
\begin{aligned}
& \psi\left(e_{1}\right)\left(x_{j}\right)_{\Lambda^{c}} \\
& =\left\{\begin{array}{c}
\frac{x_{1}}{\langle 0.5+[1-0.5(0.7+1+0+0.3) / 4], 0.2,0.4-[0.4(0.7+1+0+0.3) / 4]\rangle} \\
\frac{x_{2}}{\langle 0.3+[1-0.3(0.6+0.5+0+0) / 4], 0.1,0.5-[0.5(0.6+0.5+0+0) / 4]\rangle} \\
\left.\frac{x_{3}}{\langle 0.3+[1-0.3(0.3+1+0.4+0.6) / 4], 0.3,} 0.5-[0.5(0.3+1+0.4+0.6) / 4]\right\rangle
\end{array}\right.
\end{aligned}
$$

$=\left\{\frac{x_{1}}{\langle 0.75,0.2,0.2\rangle}, \frac{x_{2}}{\langle 0.49,0.1,0.36\rangle}, \frac{x_{3}}{\langle 0.70,0.3,0.21\rangle}\right\}$
In a similar manner, we find $\Lambda_{\text {complement }}=(\psi, E)_{\Lambda^{c}}$ as shown below:

$$
\begin{gathered}
(\psi, E)_{\Lambda^{c}}=\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.75,0.2,0.2\rangle}, \frac{x_{2}}{\langle 0.49,0.1,0.36\rangle}, \frac{x_{3}}{\langle 0.70,0.3,0.21\rangle}\right\rangle\right),\right. \\
\left(e_{2},\left\langle\frac{x_{1}}{\langle 0.6,0.4,0.35\rangle}, \frac{x_{2}}{\langle 0.49,0.6,0.58\rangle}, \frac{x_{3}}{\langle 0.62,0.4,0.26\rangle}\right\rangle\right), \\
\left.\left(e_{3},\left\langle\frac{x_{1}}{\langle 0.8,0.9,0.15\rangle}, \frac{x_{2}}{\langle 0.57,0.7,0.07\rangle}, \frac{x_{3}}{\langle 0.92,0.1,0.09\rangle}\right\rangle\right)\right\}
\end{gathered}
$$

To find Soft complement , first we find $\psi^{c}\left(e_{1}\right)\left(x_{j}\right)_{\Lambda}, j=$ 1,2,3 as follows:

$$
\begin{aligned}
& \psi^{c}\left(e_{1}\right)\left(x_{j}\right)_{\Lambda} \\
& =\left\{\begin{array}{l}
\left.\frac{x_{1}}{\left\langle 0.4+[1-0.4(0.3+0+1+0.7) / 4], x_{0}\right.} 0.2,0.5-[0.5(0.3+0+1+0.7) / 4]\right\rangle \\
\frac{x_{2}}{\langle 0.5+[1-0.5(0.4+0.5+1+1) / 4], 0.1,0.3-[0.3(0.4+0.5+1+1) / 4]\rangle}, \\
\frac{x_{3}}{\langle 0.5+[1-0.5(0.7+0+0.6+0.4) / 4], 0.3,0.3-[0.3(0.7+0+0.6+0.4) / 4]\rangle},
\end{array}\right. \\
& =\left\{\frac{x_{1}}{\langle 0.75,0.2,0.25\rangle}, \frac{x_{2}}{\langle 0.86,0.1,0.08\rangle}, \frac{x_{3}}{\langle 0.29,0.3,0.17\rangle}\right\}
\end{aligned}
$$

In a similar manner, we find the in a similar manner, we find the Soft complement $=(\psi, E)_{\Lambda}^{c}$ as shown below:

$$
\begin{aligned}
& (\psi, E)_{\Lambda}^{c} \\
& =\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.7,0.2,0.25\rangle}, \frac{x_{2}}{\langle 0.86,0.1,0.08\rangle}, \frac{x_{3}}{\langle 0.29,0.3,0.17\rangle}\right\rangle\right),\right. \\
& \quad\left(e_{2},\left\langle\frac{x_{1}}{\langle 0.85,0.4,0.1\rangle}, \frac{x_{2}}{\langle 0.95,0.6,0.08\rangle}, \frac{x_{3}}{\langle 0.77,0.4,0.06\rangle}\right\rangle\right), \\
& \left.\quad\left(e_{3},\left\langle\frac{x_{1}}{\langle 0.65,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.75,0.7,0.11\rangle}, \frac{x_{3}}{\langle 0.54,0.1,0.46\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

## - Proposition 1

Let $(\psi, E)_{\Lambda}$ be ENSS over the $U$. Then
a) Total $_{\text {complement }}\left(\right.$ Total $\left._{\text {complement }}(\psi, E)_{\Lambda}\right)=(\psi, E)_{\Lambda}$, $\left.\left((\psi, E)_{\Lambda^{c}}^{c}\right)^{c}=(\psi, E)_{\Lambda}\right)$.
b) $\Lambda_{\text {complement }}\left(\Lambda_{\text {complement }}(\psi, E)_{\Lambda}\right)=(\psi, E)_{\Lambda}$.
c) $\operatorname{Soft}_{\text {complement }}\left(\operatorname{Soft}_{\text {complement }}(\psi, E)_{\Lambda}\right)=(\psi, E)_{\Lambda}$.

## - Proof

We want to prove (a) as following:
Let $(\psi, E)_{\Lambda}$ be ENSS over the $U$ and $\forall x_{j} \in U, e \in E$

$$
\begin{gathered}
(\psi, E)_{\Lambda}=\left\{\left(e, \frac{x_{j}}{\left\langle T_{U}\left(x_{j}\right)_{\Lambda^{\prime}} I_{U}\left(x_{j}\right)_{\Lambda^{\prime}}, F_{U}\left(x_{j}\right)_{\Lambda}\right\rangle}\right)\right\} \\
(\psi, E)_{\Lambda^{c}}^{c}=\left\{\left(\mathrm{e}, \frac{x_{j}}{\left\langle F_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}} I_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}, T_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}\right\rangle}\right)\right\} \\
\left.\left((\psi, E)_{\Lambda^{c}}^{c}\right)^{c}=\left\{\left(\mathrm{e}, \frac{x_{j}}{\left\langle\left(T_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}\right)^{c},\left(I\left(x_{j}\right)_{\Lambda^{c}}\right)^{c},\left(F_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}\right)^{c}\right\rangle}\right\rangle\right)\right\}
\end{gathered}
$$

where,

$$
\begin{aligned}
& \left(T_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}\right)^{c}=T_{\left(U^{c} c\right.}\left(x_{j}\right)_{\left(\Lambda^{c}\right)^{c}} \\
& =\left\{\left\{\begin{array}{l}
\left\{\begin{array}{l}
T_{U^{c}}\left(x_{j}\right)+\left[\frac{\left[1-T_{U^{c}}\left(x_{j}\right)\right] \sum_{k} \delta_{\Lambda_{x_{j}}}\left(a_{k}\right)}{|A|}\right] \\
T_{U^{c}}\left(x_{j}\right)
\end{array} \text { if } T_{U}\left(x_{j}\right) \in[0,1]\right.
\end{array}\right\}^{c}\right. \\
& =\left\{\begin{array}{c}
T_{\left(U^{c}\right) c}\left(x_{j}\right)+\left[\frac{\left[1-T_{\left(U^{c}\right) c}\left(x_{j}\right)\right] \sum_{k} \delta_{\left.\left(\Lambda_{x_{j}}\right)^{c}\right)}{ }^{c}\left(a_{k}\right)}{|A|}\right] \\
T_{\left(U^{c}\right) c}\left(x_{j}\right)
\end{array} \text { if } T_{U}\left(x_{j}\right) \in[0,1]\right.
\end{aligned}
$$

$$
=\left\{\begin{array}{l}
T_{U}\left(x_{j}\right)+\left[\frac{\left[1-T_{U}\left(x_{j}\right)\right] \sum_{k} \delta_{\Lambda x_{j}}\left(a_{k}\right)}{|A|}\right] \\
T_{U}\left(x_{j}\right)
\end{array} \text { if } T_{U}\left(x_{j}\right) \in[0,1]=T_{U}\left(x_{j}\right)_{\Lambda}\right.
$$

So, $\left(T_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}\right)^{c}=T_{U}\left(x_{j}\right)_{\Lambda}$. Similarly, $\left(I\left(x_{j}\right)_{\Lambda^{c}}\right)^{c}=I_{U}\left(x_{j}\right)_{\Lambda}$ and $\left(F_{U^{c}}\left(x_{j}\right)_{\Lambda^{c}}\right)^{c}=F_{U}\left(x_{j}\right)_{\Lambda}$. Then $\left((\psi, E)_{\Lambda^{c}}^{c}\right)^{c}=(\psi, E)_{\Lambda}$.

The verification of (b) and (c) can be readily derived from their respective definitions.

## - Definition 20

Consider two ENSSs $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ and $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ over the common universe $U$. Then the union of these sets also is ENSS $(\Upsilon, E)_{\Lambda_{s}}$ where $E=E_{1} \cup E_{2}$ and $\forall \varsigma \in E$, is provided in the following manner:

$$
\Upsilon_{\Lambda_{s}}(v)=\left\{\begin{array}{c}
\psi_{\Lambda_{1}}(\varsigma) \\
\phi_{\Lambda_{2}}(\varsigma) \\
(\psi \cup \phi)_{\Lambda_{s}}(\varsigma)
\end{array}\right.
$$

$$
\begin{aligned}
& \text { if } \zeta \in E_{1}-E_{2} \\
& \text { if } \zeta \in E_{1}-E_{2} \\
& \text { if } \zeta \in E_{1} \cap E_{2}
\end{aligned}
$$

Here $\Upsilon$ represents the neutrosophic soft union between $\psi$ and $\phi, \Lambda_{s}=\max \left(\Lambda_{1}, \Lambda_{2}\right)$ and $s$ denotes any $s$-norm.

## - Example 4

Consider the effective set given as follows:
$\Lambda_{1}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0}, \frac{a_{3}}{1}, \frac{a_{4}}{0.7}\right\}, \Lambda_{1}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.4}, \frac{a_{2}}{0.5}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}$,
$\Lambda_{1}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.4}\right\}$
$\Lambda_{2}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.2}, \frac{a_{4}}{1}\right\}, \Lambda_{2}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.7}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.4}\right\}$,
$\Lambda_{2}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.9}\right\}$
Consider two NSSs given as follows:

$$
\begin{aligned}
\left(\psi, E_{1}\right)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.5,0.2,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.5\rangle}\right\rangle\right),\right. \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.7,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right\rangle\right), \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.4,0.4,0.8\rangle}, \frac{x_{2}}{\langle 0.2,0.3,0.9\rangle}, \frac{x_{3}}{\langle 0.8,0.6,0.2\rangle}\right\rangle\right) \\
\left(\phi, E_{2}\right)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{2}}{\langle 0.1,0,0.4\rangle}, \frac{x_{3}}{\langle 0.4,0.2,0.9\rangle}\right\rangle\right),\right. \\
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right\rangle\right), \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.5,0.3,0.9\rangle}, \frac{x_{2}}{\langle 0.4,0.2,0.7\rangle}, \frac{x_{3}}{\langle 0.9,0.3,0.4\rangle}\right\rangle\right), \\
& \left.\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.3,0.6,0.5\rangle}, \frac{x_{2}}{\langle 0.5,0.3,0.2\rangle}, \frac{x_{3}}{\langle 0.8,0.5,0.4\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

Now, we employ the basic fuzzy union operation to find $\Lambda_{s}$ from $\Lambda_{1}$ and $\Lambda_{2}$ in the following manner:
$\Lambda_{s}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0.5}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}, \Lambda_{s}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.4}, \frac{a_{2}}{0.7}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}$
$\Lambda_{s}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.9}\right\}$
Then, the NSS union $(\Upsilon, E)$ givn as follows:

$$
\begin{aligned}
(\Upsilon, E)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.5,0.1,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0,0.4\rangle}, \frac{x_{3}}{\langle 0.4,0.2,0.5\rangle}\right\rangle\right),\right. \\
& \left.\left(e_{2}, \frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right\rangle\right), \\
& \left.\left(e_{3}, \frac{x_{1}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.7,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right\rangle\right), \\
& \left.\left(e_{4}, \frac{x_{1}}{\langle 0.5,0.3,0.8\rangle}, \frac{x_{2}}{\langle 0.4,0.2,0.7\rangle}, \frac{x_{3}}{\langle 0.9,0.3,0.2\rangle}\right\rangle\right),
\end{aligned}
$$

$$
\left.\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.3,0.6,0.5\rangle}, \frac{x_{2}}{\langle 0.5,0.3,0.2\rangle}, \frac{x_{3}}{\langle 0.8,0.5,0.4\rangle}\right\rangle\right)\right\}
$$

Then by using definitions 20 and 14 we get the following ENSS

$$
\begin{aligned}
(\Upsilon, E)_{\Lambda_{s}}= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.9,0.1,0.08\rangle}, \frac{x_{2}}{\langle 0.84,0,0.09\rangle}, \frac{x_{3}}{\langle 0.81,0.2,0.16\rangle}\right\rangle\right),\right. \\
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.84,0.4,0.14\rangle}, \frac{x_{2}}{\langle 0.84,0.6,0.18\rangle}, \frac{x_{3}}{\langle 0.71,0.4,0.2\rangle}\right\rangle\right), \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.92,0.9,0.06\rangle}, \frac{x_{2}}{\langle 0.87,0.7,0.02\rangle}, \frac{x_{3}}{\langle 0.94,0.1,0.07\rangle}\right\rangle\right), \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.9,0.3,0.16\rangle}, \frac{x_{2}}{\langle 0.87,0.2,0.16\rangle}, \frac{x_{3}}{\langle 0.97,0.3,0.07\rangle}\right\rangle\right), \\
& \left.\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.86,0.6,0.1\rangle}, \frac{x_{2}}{\langle 0.89,0.3,0.05\rangle}, \frac{x_{3}}{\langle 0.94,0.5,0.13\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

## - Definition 21

Consider two ENSSs $\left(\psi, E_{1}\right)_{\Lambda_{1}}$ and $\left(\phi, E_{2}\right)_{\Lambda_{2}}$ over the common universe $U$. Then the intersection of these sets also is ENSS $(\Omega, E)_{\Lambda_{t}}$ where $E=E_{1} \cup E_{2}$ and $\forall \varsigma \in E$, is provided in the following manner:

$$
\Omega_{\Lambda_{t}}(v)=\left\{\begin{array}{lr}
\psi_{\Lambda_{1}}(\varsigma) & \text { if } \varsigma \in E_{1}-E_{2} \\
\phi_{\Lambda_{2}}(\varsigma) & \text { if } \varsigma \in E_{1}-E_{2} \\
(\psi \cap \phi)_{\Lambda_{s}}(\varsigma) & \text { if } \varsigma \in E_{1} \cap E_{2}
\end{array}\right.
$$

Here $\Omega$ represents the neutrosophic soft union between $\psi$ and $\phi, \Lambda_{t}=\min \left(\Lambda_{1}, \Lambda_{2}\right)$ and $t$ denotes any $t$-norm.

## - Example 5

Consider example 4, then we employ the basic fuzzy intersection operation to find $\Lambda_{t}$ from $\Lambda_{1}$ and $\Lambda_{2}$ in the following manner:
$\Lambda_{t}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0}, \frac{a_{3}}{0.2}, \frac{a_{4}}{0.7}\right\}, \Lambda_{t}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.4}\right\}$,
$\Lambda_{t}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.4}\right\}$
Then, the NSS intersection $(\Omega, E)$ given as follows:

$$
\begin{aligned}
(\Omega, E)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.3,0.2,0.5\rangle}, \frac{x_{2}}{\langle 0.1,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.9\rangle}\right\rangle\right),\right. \\
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right\rangle\right), \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.7,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right\rangle\right), \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.4,0.4,0.9\rangle}, \frac{x_{2}}{\langle 0.2,0.3,0.9\rangle}, \frac{x_{3}}{\langle 0.8,0.6,0.4\rangle}\right\rangle\right), \\
& \left.\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.3,0.6,0.5\rangle}, \frac{x_{2}}{\langle 0.5,0.3,0.2\rangle}, \frac{x_{3}}{\langle 0.8,0.5,0.4\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

Now, by using definitions 21 and 14 , we get ENSS $(\Omega, E)_{\Lambda_{t}}$ as follows:
$(\Omega, E)_{\Lambda_{t}}=\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.51,0.2,0.35\rangle}, \frac{x_{2}}{\langle 0.55,0.1,0.25\rangle}, \frac{x_{3}}{\langle 0.46,0.3,0.4\rangle}\right\rangle\right)\right.$,

$$
\begin{aligned}
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.44,0.4,0.49\rangle}, \frac{x_{2}}{\langle 0.65,0.6,0.4\rangle}, \frac{x_{3}}{\langle 0.30,0.4,0.47\rangle}\right\rangle\right), \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.72,0.9,0.21\rangle}, \frac{x_{2}}{\langle 0.7,0.7,0.05\rangle}, \frac{x_{3}}{\langle 0.85,0.1,0.16\rangle}\right\rangle\right) \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.58,0.4,0.63\rangle}, \frac{x_{2}}{\langle 0.6,0.3,0.45\rangle}, \frac{x_{3}}{\langle 0.85,0.6,0.31\rangle}\right\rangle\right), \\
& \left.\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.51,0.6,0.35\rangle}, \frac{x_{2}}{\langle 0.75,0.3,0.1\rangle}, \frac{x_{3}}{\langle 0.85,0.5,0.31\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

## - Proposition 2

Let $\left(\psi, E_{1}\right)_{\Lambda_{1}},\left(\phi, E_{2}\right)_{\Lambda_{2}}$ and $\left(\sigma, E_{3}\right)_{\Lambda_{3}}$ be three ENSSs over the common universe $U$. Then,

1) $\left(\psi, E_{1}\right)_{\Lambda_{1}} \cup\left(\phi, E_{2}\right)_{\Lambda_{2}}=\left(\phi, E_{2}\right)_{\Lambda_{2}} \cup\left(\psi, E_{1}\right)_{\Lambda_{1}}$
2) $\left(\psi, E_{1}\right)_{\Lambda_{1}} \cap\left(\phi, E_{2}\right)_{\Lambda_{2}}=\left(\phi, E_{2}\right)_{\Lambda_{2}} \cap\left(\psi, E_{1}\right)_{\Lambda_{1}}$

- Proof

1) Let $\forall v \in E$. In the subsequent proof, the first two cases are straightforward; therefore, we focus solely on the third case.

$$
\begin{aligned}
& \left(\psi, E_{1}\right)_{\Lambda_{1}} \cup\left(\phi, E_{2}\right)_{\Lambda_{2}}= \\
& \left\{e,\left\langle v /\left(\max \left(T_{\psi_{\Lambda_{1}}}(v), T_{\phi_{\Lambda_{2}}}(v)\right)\right),\left(\min \left(I_{\psi_{\Lambda_{1}}}(v), I_{\phi_{\Lambda_{2}}}(v)\right)\right),\right.\right. \\
& \left.\left.\left(\min \left(F_{\psi_{\Lambda_{1}}}(v), F_{\phi_{\Lambda_{2}}}(v)\right)\right)\right\rangle, \Lambda_{s}(v)=\max \left(\Lambda_{1}(v), \Lambda_{2}(v)\right)\right\} \\
& =\left\{e,\left\langle v /\left(\max \left(T_{\phi_{\Lambda_{2}}}(v), T_{\psi_{\Lambda_{1}}}(v)\right)\right),\left(\min \left(I_{\phi_{\Lambda_{2}}}(v), I_{\psi_{\Lambda_{1}}}(v)\right)\right),\right.\right. \\
& \left.\quad\left(\min \left(F_{\phi_{\Lambda_{2}}}(v), F_{\psi_{\Lambda_{1}}}(v)\right)\right)\right\rangle, \Lambda_{s}(v) \\
& \left.=\max \left(\Lambda_{2}(v), \Lambda_{1}(v)\right)\right\} \\
& =\left(\phi, E_{2}\right)_{\Lambda_{2}} \cup\left(\psi, E_{1}\right)_{\Lambda_{1}}
\end{aligned}
$$

2) The proof is straightforward.

## 5. AND and OR Operations

Within this section, we define the AND and OR operations and scrutinize their individual properties.

## - Definition 22

Consider two ENSSs $\left(\psi, \mathrm{E}_{1}\right)_{\Lambda_{1}}$ and $\left(\phi, \mathrm{E}_{2}\right)_{\Lambda_{2}}$ over the universe $U$. AND operation between these sets, written as $\left(\psi, \mathrm{E}_{1}\right)_{\Lambda_{1}} \wedge\left(\phi, \mathrm{E}_{2}\right)_{\Lambda_{2}}$, is defined as

$$
\left(\psi, \mathrm{E}_{1}\right)_{\Lambda_{1}} \wedge\left(\phi, \mathrm{E}_{2}\right)_{\Lambda_{2}}=\left(\Theta, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)_{\Lambda_{t}}
$$

where $\Theta_{\Lambda_{t}}(a, b)=(\psi(a) \cap \phi(b))_{\Lambda_{t}}: \forall(a, b) \in \mathrm{E}_{1} \times \mathrm{E}_{2} \cap$ is effective neutrosophic soft intersection and $t$ represents any $t$-norm.

## - Example 6

Consider the effective sets given as follows:
$\Lambda_{1}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0}, \frac{a_{3}}{1}, \frac{a_{4}}{0.7}\right\}, \Lambda_{1}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.4}, \frac{a_{2}}{0.5}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}$
$\Lambda_{1}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.4}\right\}$
$\Lambda_{2}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.2}, \frac{a_{4}}{1}\right\}, \Lambda_{2}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.7}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.4}\right\}$
$\Lambda_{2}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.9}\right\}$
Consider two NSSs given as follows:

$$
\begin{aligned}
\left(\psi, E_{1}\right)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.5,0.2,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.5\rangle}\right\rangle\right),\right. \\
& \left.\left(e_{3},\left\langle\frac{x_{1}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.7,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right\rangle\right)\right\} \\
\left(\phi, E_{2}\right)= & \left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{2}}{\langle 0.1,0,0.4\rangle}, \frac{x_{3}}{\langle 0.4,0.2,0.9\rangle}\right\rangle\right),\right. \\
& \left.\left(e_{2},\left\langle\frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

We employ the basic fuzzy intersection operation to find $\Lambda_{t}$ from $\Lambda_{1}$ and $\Lambda_{2}$ in the following manner:
$\Lambda_{t}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0}, \frac{a_{3}}{0.2}, \frac{a_{4}}{0.7}\right\}, \Lambda_{t}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.4}\right\}$,
$\Lambda_{t}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.4}\right\}$

Through the utilization of the neutrosophic soft intersection, we obtain $\left(\psi, E_{1}\right) \wedge\left(\phi, E_{2}\right)=\left(\Theta, E_{1} \times E_{2}\right)$ as follows:

$$
\begin{aligned}
\left(\Theta, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)=\{ & \left(\left(e_{1}, e_{1}\right), \frac{x_{1}}{\langle 0.3,0.2,0.5\rangle}, \frac{x_{2}}{\langle 0.1,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.9\rangle}\right), \\
& \left(\left(e_{1}, e_{2}\right), \frac{x_{1}}{\langle 0.2,0.4,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right), \\
& \left.\left(\left(e_{3}, e_{1}\right), \frac{x_{1}}{\langle 0.3,0.9,0.5\rangle}, \frac{x_{2}}{\langle 0.1,0.7,0.4\rangle}, \frac{x_{3}}{\langle 0.4,0.2,0.9\rangle}\right)\right) \\
& \left.\left(\left(e_{3}, e_{2}\right), \frac{x_{1}}{\langle 0.2,0.9,0.7\rangle}, \frac{x_{2}}{\langle 0.3,0.7,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.4,0.6\rangle}\right)\right\}
\end{aligned}
$$

Then, by using definitions 22 and 14 we get the ENSES $\left(\Theta, E_{1} \times E_{2}\right)_{\Lambda_{t}}$ as follows:

$$
\begin{aligned}
& \left(\Theta, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)_{\Lambda_{t}} \\
= & \left\{\left(\left(e_{1}, e_{1}\right), \frac{x_{1}}{\langle 0.51,0.2,0.35\rangle}, \frac{x_{2}}{\langle 0.55,0.1,0.25\rangle}, \frac{x_{3}}{\langle 0.46,0.3,0.69\rangle}\right)\right. \\
& \left(\left(e_{1}, e_{2}\right), \frac{x_{1}}{\langle 0.32,0.4,0.59\rangle}, \frac{x_{2}}{\langle 0.65,0.6,0.4\rangle}, \frac{x_{3}}{\langle 0.30,0.4,0.47\rangle}\right) \\
& \left(\left(e_{3}, e_{1}\right), \frac{x_{1}}{\langle 0.51,0.9,0.35\rangle}, \frac{x_{2}}{\langle 0.55,0.7,0.2\rangle}, \frac{x_{3}}{\langle 0.53,0.2,0.69\rangle}\right) \\
& \left.\left(\left(e_{3}, e_{2}\right), \frac{x_{1}}{\langle 0.44,0.9,0.49\rangle}, \frac{x_{2}}{\langle 0.65,0.7,0.4\rangle}, \frac{x_{3}}{\langle 0.3,0.4,0.47\rangle}\right)\right\}
\end{aligned}
$$

## - Definition 23

Consider two ENSSs $\left(\psi, \mathrm{E}_{1}\right)_{\Lambda_{1}}$ and $\left(\phi, \mathrm{E}_{2}\right)_{\Lambda_{2}}$ over the universe $U$. OR operation between these sets, written as $\left(\psi, \mathrm{E}_{1}\right)_{\Lambda_{1}} \vee\left(\phi, \mathrm{E}_{2}\right)_{\Lambda_{2}}$, is defined as

$$
\left(\psi, \mathrm{E}_{1}\right)_{\Lambda_{1}} \vee\left(\phi, \mathrm{E}_{2}\right)_{\Lambda_{2}}=\left(\Sigma, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)_{\Lambda_{s}}
$$

where $\Sigma_{\Lambda_{s}}(a, b)=(\psi(a) \cup \phi(b))_{\Lambda_{s}}: \forall(a, b) \in E_{1} \times E_{2}$, $U$ is effective neutrosophic soft union and $s$ represents any $s$-norm.

## - Example 7

Consider example 6, we employ the basic fuzzy union operation to obtain $\Lambda s$ from $\Lambda_{1}$ and $\Lambda_{2}$ in the following manner:
$\Lambda_{s}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0.5}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}, \Lambda_{s}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.4}, \frac{a_{2}}{0.7}, \frac{a_{3}}{1}, \frac{a_{4}}{1}\right\}$,
$\Lambda_{s}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.7}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.6}, \frac{a_{4}}{0.9}\right\}$
Through the utilization of the neutrosophic soft intersection, we obtain $\left(\psi, \mathrm{E}_{1}\right) \vee\left(\phi, \mathrm{E}_{2}\right)=\left(\Sigma, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)$ as follows:

$$
\begin{aligned}
\left(\Sigma, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)= & \left\{\left(e_{1}, e_{1}\right), \frac{x_{1}}{\langle 0.5,0.1,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0,0.4\rangle}, \frac{x_{3}}{\langle 0.4,0.2,0.5\rangle}\right), \\
& \left(\left(e_{1}, e_{2}\right),\left\{\frac{x_{1}}{\langle 0.5,0.2,0.4\rangle}, \frac{x_{2}}{\langle 0.3,0.1,0.5\rangle}, \frac{x_{3}}{\langle 0.3,0.3,0.5\rangle}\right\}\right), \\
& \left(\left(e_{3}, e_{1}\right), \frac{x_{1}}{\langle 0.6,0.1,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right), \\
& \left.\left(\left(e_{3}, e_{2}\right), \frac{x_{1}}{\langle 0.6,0.4,0.3\rangle}, \frac{x_{2}}{\langle 0.4,0.6,0.1\rangle}, \frac{x_{3}}{\langle 0.8,0.1,0.2\rangle}\right)\right\}
\end{aligned}
$$

Now, by using definitions 23 and 14 we get the ENSS $\left(\Sigma, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)_{\Lambda_{s}}$ as follows:

$$
\begin{aligned}
\left(\Sigma, \mathrm{E}_{1} \times \mathrm{E}_{2}\right)_{\Lambda_{s}}= & \left\{\left(\left(e_{1}, e_{1}\right), \frac{x_{1}}{\langle 0.9,0.1,0.08\rangle}, \frac{x_{2}}{\langle 0.83,0,0.1\rangle}, \frac{x_{3}}{\langle 0.81,0.2,0.16\rangle}\right),\right. \\
& \left(\left(e_{1}, e_{2}\right), \frac{x_{1}}{\langle 0.9,0.2,0.08\rangle}, \frac{x_{2}}{\langle 0.84,0.1,0.11\rangle}, \frac{x_{3}}{\langle 0.77,0.3,0.16\rangle}\right)
\end{aligned}
$$

$$
\begin{aligned}
& \left(\left(e_{3}, e_{1}\right), \frac{x_{1}}{\langle 0.92,0.1,0.06\rangle}, \frac{x_{2}}{\langle 0.87,0,0.02\rangle}, \frac{x_{3}}{\langle 0.67,0.1,0.07\rangle}\right), \\
& \left.\left(\left(e_{3}, e_{2}\right), \frac{x_{1}}{\langle 0.92,0.4,0.06\rangle}, \frac{x_{2}}{\langle 0.87,0.6,0.02\rangle}, \frac{x_{3}}{\langle 0.94,0.1,0.07\rangle}\right)\right\}
\end{aligned}
$$

## 6. An Application of ENSS in Decision Making Problem

In this section, we illustrate how ENSSs can be applied to handle decision-making challenges. To commence, we revisit some fundamental definitions.

## - Definition 24 [16]

A comparison matrix is a matrix with rows labeled by object names $h_{1}, h_{2}, \ldots, h_{n}$ and columns labeled by parameters $e_{1}, e_{2}, \ldots, e_{m}$. The entries $c_{i j}$ are computed using the formula $c_{i j}=a+b-c$, where ' $a$ ' is the integer calculated as the count of how many times $T_{h_{i}}\left(e_{j}\right)$ exceeds or equal to $T_{h_{k}}\left(e_{j}\right)$ ', for $h_{i} \neq h_{k}, \forall h_{k} \in \mathrm{U}, ~ ' b$ ' is the integer calculated as the count of how many times $I_{h_{i}}\left(e_{j}\right)$ exceeds or equals to $I_{h_{k}}\left(e_{j}\right)^{\prime}$, is for $h_{i} \neq h_{k}, \forall h_{k}$ $\in U$, and ' $c$ ' the integer calculated as the count of how many times $F_{h_{i}}\left(e_{j}\right)$ exceeds or equals $F_{h_{k}}\left(e_{j}\right)^{\prime}$ for $h_{i} \neq h_{k}, \forall h_{k} \in U$.

## - Definition 25[16]

The score assigned to an object $h_{i}$, for all $i$ is denoted as $s_{i}$ and is computed as $s_{i}=\sum_{j} c_{i j}$. Subsequently, we introduce an algorithm designed for the optimal choice of an item.

### 6.1. Algorithm

As a combination of Alkhazaleh [4] algorithm for EFSS and Maji [16] algorithm for NSS, we get the following Algorithm (1) for ENSS:

## Algorthim 1: ENSS

1. Provide the effective sets of parameters $\Lambda_{1}$ and $\Lambda_{2}$ as input.
2. Input the $\operatorname{NSS}(H, A)$
3. Provide the NSSs $\left(\psi, E_{1}\right)$ and $\left(\phi, E_{2}\right)$ as input.
4. Obtain an effective set $\Lambda_{s}$ from $\Lambda_{1}$ and $\Lambda_{2}$.
5. Obtain the NSS $(\sigma, E)$ as required.
6. Calculate the resulting $\operatorname{ENSS}(\sigma, E)_{\Lambda_{s}}$ accordingly.
7. Construct comparison table of ENSS.
8. Calculate the score $s_{i}$ of $h_{i}$, for all $i$.
9. The optimal choice is $s_{k}=\max _{i} s_{i}$

### 6.2. Application in a Decision-Making Problem

## - Example 8

Consider the set of mobile phones $U=\left\{x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6}\right\}$ and the set of parameters $E=\left\{e_{1}, e_{2}, e_{3}, e_{4}, e_{5}, e_{6}\right\}$ where $E_{l}=\left\{e_{1}, e_{3}, e_{4}, e_{6}\right\}$ and $E_{2}=\left\{e_{1}, e_{2}, e_{3}, e_{4}, e_{5}\right\}$ and $e_{1}=\operatorname{Ram}$, $e_{2}=$ Memory, $\quad e_{3}=$ Battery Power, $e_{4}=$ Camera, $e_{5}=$ Resolution and $e_{6}=$ Water Proof. Consider the set of effective parameters $A=\left\{a_{1}, a_{2}, a_{3}, a_{4}\right\}$ such that $a_{1}$ : Every component is produced in the primary factory $a_{2}$ : It underwent reassembly at the primary factory, $a_{3}$ : It was in the possession of a single owner, not shared by multiple individuals, and $a_{4}$ : The software is operating in its most recent version. Consider the effective set over $A$ for every $x_{i}$ in $U$, as provided in the following manner:
$\Lambda_{1}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.8}, \frac{a_{2}}{0.2}, \frac{a_{3}}{0.1}, \frac{a_{4}}{0.2}\right\}, \Lambda_{1}\left(x_{2}\right)=\left\{\frac{a_{1}}{1}, \frac{a_{2}}{0.2}, \frac{a_{3}}{0.7}, \frac{a_{4}}{0.2}\right\}$,
$\Lambda_{1}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0.2}, \frac{a_{3}}{0.5}, \frac{a_{4}}{0.1}\right\}, \Lambda_{1}\left(x_{4}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.4}\right\}$,
$\Lambda_{1}\left(x_{5}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.4}, \frac{a_{3}}{0.4}, \frac{a_{4}}{0.2}\right\}, \Lambda_{1}\left(x_{6}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0.1}, \frac{a_{3}}{0.2}, \frac{a_{4}}{0.5}\right\}$,
$\Lambda_{2}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.6}, \frac{a_{2}}{1}, \frac{a_{3}}{0.1}, \frac{a_{4}}{0.3}\right\}, \Lambda_{2}\left(x_{2}\right)=\left\{\frac{a_{1}}{0.5}, \frac{a_{2}}{1}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.6}\right\}$,
$\Lambda_{2}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.1}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.1}\right\}, \Lambda_{2}\left(x_{4}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0.8}, \frac{a_{3}}{0.2}, \frac{a_{4}}{0.9}\right\}$,
$\Lambda_{2}\left(x_{5}\right)=\left\{\frac{a_{1}}{0.1}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.3}\right\}, \Lambda_{2}\left(x_{6}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.1}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.4}\right\}$
Consider the NSSs given as follows:

$$
\begin{aligned}
& \begin{array}{l}
\left(\psi, E_{1}\right)=x_{1} \\
\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.5,0.3,0.8\rangle}, \frac{x_{2}}{\langle 0.2,0.6,0.8\rangle}, \frac{x_{3}}{\langle 0.1,0.1,0.5\rangle}, \frac{x_{4}}{\langle 0.3,0.8,0.2\rangle}, \frac{x_{5}}{\langle 0.6,0.5,0.3\rangle}, \frac{x_{6}}{\langle 0.3,0.1,0.5\rangle}\right\rangle\right),\right.
\end{array} \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.6,0.4,0.8\rangle}, \frac{x_{2}}{\langle 0.4,0.3,0.6\rangle}, \frac{x_{3}}{\langle 0.7,0.5,0.4\rangle}, \frac{x_{4}}{x_{2}}\langle 0.8,0.6,0.7\rangle, \frac{x_{5}}{\langle 0.4,0.7,0.9\rangle}, \frac{x_{6}}{\langle 0.1,0.1,0.9\rangle}\right\rangle\right) \text {, } \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.7,0.4,0.6\rangle}, \frac{x_{2}}{\langle 0.4,0.3,0.8\rangle}, \frac{x_{3}}{x_{1}} \frac{x_{2}}{\langle 0.7,0.5,0.6\rangle}, \frac{x_{4}}{x_{3}}\langle 0.4,0.8,0.6\rangle, \frac{x_{5}}{x_{4}} \begin{array}{c}
\langle 0.8,0.3,0.4\rangle \\
x_{5}
\end{array}, \frac{x_{6}}{\langle 0.4,0.2,0.7\rangle}\right\rangle\right) \text {, } \\
& \left.\left(e_{6},\left\langle\frac{x_{1}}{\langle 0.5,0.6,0.8\rangle}, \frac{x_{2}}{\langle 0.6,0.8,0.1\rangle}, \frac{x_{3}}{\langle 0.5,0.2,0.6\rangle}, \frac{x_{4}}{\langle 0.8,0.6,0.7\rangle}, \frac{x_{5}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{6}}{\langle 0.8,0.3,0.4\rangle}\right\rangle\right)\right\} \\
& \begin{array}{l}
\left(\phi, E_{2}\right)= \\
\left\{\left(e_{1},\left\langle\frac{x_{1}}{\langle 0.3,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.3,0.4,0.5\rangle}, \frac{x_{3}}{\langle 0.2,0.3,0.7\rangle}, \frac{x_{4}}{\langle 0.4,0.6,0.7\rangle}, \frac{x_{5}}{\langle 0.8,0.4,0.5\rangle}, \frac{x_{6}}{\langle 0.5,0.2,0.3\rangle}\right\rangle\right)\right.
\end{array} \\
& \left(e_{2},\left\langle\frac{x_{1}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.8,0.3,0.4\rangle}, \frac{x_{3}}{\langle 0.7,0.2,0.2\rangle}, \frac{x_{4}}{\langle 0.8,0.2,0.1\rangle}, \frac{x_{5}}{\langle 0.7,0.8,0.3\rangle}, \frac{x_{6}}{\langle 0.8,0.5,0.6\rangle}\right\rangle\right) \text {, } \\
& \left(e_{3},\left\langle\frac{x_{1}}{\langle 0.4,0.3,0.9\rangle}, \frac{x_{2}}{\langle 0.5,0.2,0.8\rangle}, \frac{x_{3}}{\langle 0.6,0.3,0.5\rangle}, \frac{x_{4}}{\langle 0.5,0.5,0.6\rangle}, \frac{x_{5}}{\langle 0.6,0.8,0.2\rangle}, \frac{x_{6}}{\langle 0.2,0.1,0.8\rangle}\right\rangle\right) \text {, } \\
& \left(e_{4},\left\langle\frac{x_{1}}{\langle 0.5,0.2,0.8\rangle}, \frac{x_{2}}{\langle 0.6,0.4,0.7\rangle}, \frac{x_{3}}{\langle 0.4,0.5,0.7\rangle}, \frac{x_{4}}{\langle 0.6,0.9,0.3\rangle}, \frac{x_{5}}{\langle 0.6,0.1,0.5\rangle}, \frac{x_{6}}{\langle 0.7,0.4,0.6\rangle}\right\rangle\right) \text {, } \\
& \left.\left(e_{5},\left\langle\frac{x_{1}}{\langle 0.6,0.1,0.8\rangle}, \frac{x_{2}}{\langle 0.8,0.5,0.2\rangle}, \frac{x_{3}}{\langle 0.8,0.3,0.6\rangle}, \frac{x_{4}}{\langle 0.7,0.3,0.4\rangle}, \frac{x_{5}}{\langle 0.7,0.5,0.6\rangle}, \frac{x_{6}}{\langle 0.7,0.6,0.8\rangle}\right\rangle\right)\right\}
\end{aligned}
$$

We employ the basic fuzzy union operation to derive $\Lambda_{s}$ from $\Lambda_{1}$ and $\Lambda_{2}$ in the following manner:
$\Lambda_{s}\left(x_{1}\right)=\left\{\frac{a_{1}}{0.8}, \frac{a_{2}}{1}, \frac{a_{3}}{0.1}, \frac{a_{4}}{0.3}\right\}, \Lambda_{s}\left(x_{2}\right)=\left\{\frac{a_{1}}{1}, \frac{a_{2}}{1}, \frac{a_{3}}{0.7}, \frac{a_{4}}{0.6}\right\}$,
$\Lambda_{s}\left(x_{3}\right)=\left\{\frac{a_{1}}{0.3}, \frac{a_{2}}{0.2}, \frac{a_{3}}{0.8}, \frac{a_{4}}{0.1}\right\}, \Lambda_{s}\left(x_{4}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.8}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.9}\right\}$,
$\Lambda_{s}\left(x_{5}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.5}, \frac{a_{3}}{0.4}, \frac{a_{4}}{0.3}\right\}, \Lambda_{s}\left(x_{6}\right)=\left\{\frac{a_{1}}{0.2}, \frac{a_{2}}{0.1}, \frac{a_{3}}{0.3}, \frac{a_{4}}{0.5}\right\}$
Then, we determine $(\sigma, E)=\left(\psi, E_{1}\right) \cup\left(\phi, E_{2}\right)$ in the following manner:

$$
\begin{aligned}
(\sigma, E) & =\left\{\left(e_{1}, \frac{x_{1}}{\langle 0.5,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.3,0.4,0.5\rangle}, \frac{x_{3}}{\langle 0.2,0.1,0.5\rangle}, \frac{x_{4}}{\langle 0.4,0.6,0.2\rangle}, \frac{x_{5}}{\langle 0.8,0.4,0.3\rangle}, \frac{x_{6}}{\langle 0.5,0.1,0.3\rangle}\right)\right. \\
& \left(e_{2}, \frac{x_{1}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.8,0.3,0.4\rangle}, \frac{x_{3}}{\langle 0.7,0.2,0.2\rangle}, \frac{x_{4}}{\langle 0.8,0.2,0.1\rangle}, \frac{x_{5}}{\langle 0.7,0.8,0.3\rangle}, \frac{x_{6}}{\langle 0.8,0.5,0.6\rangle}\right), \\
& \left(e_{3}, \frac{x_{1}}{\langle 0.6,0.3,0.8\rangle}, \frac{x_{2}}{\langle 0.5,0.2,0.6\rangle}, \frac{x_{3}}{\langle 0.7,0.3,0.4\rangle}, \frac{x_{4}}{\langle 0.8,0.5,0.6\rangle}, \frac{x_{5}}{\langle 0.6,0.7,0.2\rangle}, \frac{x_{6}}{\langle 0.2,0.1,0.8\rangle}\right), \\
& \left(e_{4}, \frac{x_{1}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{2}}{\langle 0.6,0.3,0.7\rangle}, \frac{x_{3}}{\langle 0.7,0.5,0.6\rangle}, \frac{x_{4}}{\langle 0.6,0.8,0.3\rangle}, \frac{x_{5}}{\langle 0.8,0.1,0.4\rangle}, \frac{x_{6}}{\langle 0.7,0.2,0.6\rangle}\right), \\
& \left(e_{5}, \frac{x_{1}}{\langle 0.6,0.1,0.8\rangle}, \frac{x_{2}}{\langle 0.8,0.5,0.2\rangle}, \frac{x_{3}}{\langle 0.8,0.3,0.6\rangle}, \frac{x_{4}}{\langle 0.7,0.3,0.4\rangle}, \frac{x_{5}}{\langle 0.7,0.5,0.6\rangle}, \frac{x_{6}}{\langle 0.7,0.6,0.8\rangle}\right) \\
& \left.\left(e_{6}, \frac{x_{1}}{\langle 0.5,0.6,0.8\rangle}, \frac{x_{2}}{\langle 0.6,0.8,0.1\rangle}, \frac{x_{3}}{\langle 0.5,0.2,0.6\rangle}, \frac{x_{4}}{\langle 0.8,0.6,0.7\rangle}, \frac{x_{5}}{\langle 0.7,0.2,0.6\rangle}, \frac{x_{6}}{\langle 0.8,0.3,0.4\rangle}\right)\right\}
\end{aligned}
$$

Then the ENSS is given as follows:

$$
\begin{aligned}
& (\sigma, \mathrm{E})_{\Lambda_{s}}=\left\{\left(e_{1}, \frac{x_{1}}{\langle 0.78,0.2,0.27\rangle}, \frac{x_{2}}{\langle 0.88,0.4,0.09\rangle}, \frac{x_{3}}{\langle 0.48,0.1,0.32\rangle}, \frac{x_{4}}{\langle 0.73,0.6,0.09\rangle}, \frac{x_{5}}{\langle 0.87,0.4,0.2\rangle}, \frac{x_{6}}{\langle 0.64,0.1,0.22\rangle}\right),\right. \\
& \quad\left(e_{2}, \frac{x_{1}}{\langle 0.87,0.2,0.27\rangle}, \frac{x_{2}}{\langle 0.97,0.3,0.07\rangle}, \frac{x_{3}}{\langle 0.81,0.2,0.13\rangle}, \frac{x_{5}}{\langle 0.91,0.2,0.05\rangle}, \frac{x_{5}}{\langle 0.81,0.8,0.2\rangle}, \frac{x_{6}}{\langle 0.86,0.5,0.44\rangle}\right), \\
& \quad\left(e_{3}, \frac{x_{1}}{\langle 0.82,0.3,0.36\rangle}, \frac{x_{2}}{\langle 0.91,0.2,0.11\rangle}, \frac{x_{3}}{\langle 0.81,0.3,0.26\rangle}, \frac{x_{4}}{\langle 0.91,0.5,0.27\rangle}, \frac{x_{5}}{\langle 0.74,0.7,0.13\rangle}, \frac{x_{6}}{\langle 0.42,0.1,0.58\rangle}\right), \\
& \left(e_{4}, \frac{x_{1}}{\langle 0.87,0.2,0.27\rangle}, \frac{x_{2}}{\langle 0.93,0.3,0.12\rangle}, \frac{x_{3}}{\langle 0.81,0.5,0.39\rangle}, \frac{x_{4}}{\langle 0.82,0.8,0.14\rangle}, \frac{x_{5}}{\langle 0.87,0.1,0.26\rangle}, \frac{x_{6}}{\langle 0.78,0.2,0.44\rangle}\right), \\
& \left(e_{5}, \frac{x_{1}}{\langle 0.82,0.1,0.36\rangle}, \frac{x_{2}}{\langle 0.97,0.5,0.04\rangle}, \frac{x_{3}}{\langle 0.87,0.3,0.39\rangle}, \frac{x_{4}}{\langle 0.87,0.3,0.18\rangle}, \frac{x_{5}}{\langle 0.81,0.5,0.39\rangle}, \frac{x_{6}}{\langle 0.78,0.6,0.58\rangle}\right), \\
& \left.\left(e_{6}, \frac{x_{1}}{\langle 0.78,0.6,0.36\rangle}, \frac{x_{2}}{\langle 0.93,0.8,0.02\rangle}, \frac{x_{3}}{\langle 0.68,0.2,0.39\rangle}, \frac{x_{4}}{\langle 0.91,0.6,0.32\rangle}, \frac{x_{5}}{\langle 0.81,0.2,0.39\rangle}, \frac{x_{6}}{\langle 0.86,0.3,0.29\rangle}\right)\right\}
\end{aligned}
$$

The ENSS $(\sigma, E)$. is presented in Table 1.
Table 1. Shows the tabular representation of ( $\sigma, E$ ).

| $\boldsymbol{E}$ | $\boldsymbol{e}_{\mathbf{1}}$ | $\boldsymbol{e}_{\mathbf{2}}$ | $\boldsymbol{e}_{\mathbf{3}}$ | $\boldsymbol{e}_{\mathbf{4}}$ | $\boldsymbol{e}_{\mathbf{5}}$ | $\boldsymbol{e}_{\mathbf{6}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{U} \boldsymbol{x}_{\mathbf{1}}$ | $\langle 0.5,0.2,0.6\rangle$ | $\langle 0.7,0.2,0.6\rangle$ | $\langle 0.6,0.3,0.8\rangle$ | $\langle 0.7,0.2,0.6\rangle$ | $\langle 0.6,0.1,0.8\rangle$ | $\langle 0.5,0.6,0.8\rangle$ |
| $\boldsymbol{x}_{\mathbf{2}}$ | $\langle 0.3,0.4,0.5\rangle$ | $\langle 0.8,0.3,0.4\rangle$ | $\langle 0.5,0.2,0.6\rangle$ | $\langle 0.6,0.3,0.7\rangle$ | $\langle 0.8,0.5,0.2\rangle$ | $\langle 0.6,0.8,0.1\rangle$ |
| $\boldsymbol{x}_{3}$ | $\langle 0.2,0.1,0.5\rangle$ | $\langle 0.7,0.2,0.2\rangle$ | $\langle 0.7,0.3,0.4\rangle$ | $\langle 0.7,0.5,0.6\rangle$ | $\langle 0.8,0.3,0.6\rangle$ | $\langle 0.5,0.2,0.6\rangle$ |
| $\boldsymbol{x}_{4}$ | $\langle 0.4,0.6,0.2\rangle$ | $\langle 0.8,0.2,0.1\rangle$ | $\langle 0.8,0.5,0.6\rangle$ | $\langle 0.6,0.8,0.3\rangle$ | $\langle 0.7,0.3,0.4\rangle$ | $\langle 0.8,0.6,0.7\rangle$ |
| $\boldsymbol{x}_{5}$ | $\langle 0.8,0.4,0.3\rangle$ | $\langle 0.7,0.8,0.3\rangle$ | $\langle 0.6,0.7,0.2\rangle$ | $\langle 0.8,0.1,0.4\rangle$ | $\langle 0.7,0.5,0.6\rangle$ | $\langle 0.7,0.2,0.6\rangle$ |
| $\boldsymbol{x}_{6}$ | $\langle 0.5,0.1,0.3\rangle$ | $\langle 0.8,0.5,0.6\rangle$ | $\langle 0.2,0.1,0.8\rangle$ | $\langle 0.7,0.2,0.6\rangle$ | $\langle 0.7,0.6,0.8\rangle$ | $\langle 0.8,0.3,0.4\rangle$ |

Through the utilization of Maji algorithm [16], we determine the comparison table and score table for ( $\sigma$, $E)$ as presented in Tables 2 and 3 respectively002E

Table 2. Comparison table of $(\sigma, E)$.

| $\boldsymbol{E}$ | $\boldsymbol{e}_{\mathbf{1}}$ | $\boldsymbol{e}_{\mathbf{2}}$ | $\boldsymbol{e}_{\mathbf{3}}$ | $\boldsymbol{e}_{\mathbf{4}}$ | $\boldsymbol{e}_{\mathbf{5}}$ | $\boldsymbol{e}_{\mathbf{6}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{x}_{\mathbf{1}}$ | 1 | -1 | 1 | 2 | -5 | 0 |
| $\boldsymbol{x}_{\mathbf{2}}$ | 1 | 5 | -1 | -1 | 9 | 7 |
| $\boldsymbol{x}_{\mathbf{3}}$ | -3 | 4 | 6 | 4 | 4 | -1 |
| $\boldsymbol{x}_{\mathbf{4}}$ | 7 | 7 | 6 | 6 | 4 | 4 |
| $\boldsymbol{x}_{\mathbf{5}}$ | 7 | 5 | 8 | 4 | 4 | 1 |
| $\boldsymbol{x}_{\mathbf{6}}$ | 3 | 4 | -5 | 3 | 3 | 6 |

Table 3. Score table $s_{i}$ of $(\sigma, E)$.

| $\boldsymbol{U}$ | $\boldsymbol{S}_{\boldsymbol{i}}$ |
| :---: | :---: |
| $x_{1}$ | -2 |
| $x_{2}$ | 20 |
| $x_{3}$ | 14 |
| $x_{4}$ | 34 |
| $x_{5}$ | 29 |
| $x_{6}$ | 14 |

The optimal selection is $x_{4}$.Thus, based on the Maji algorithm [16], we determine that phone 4 is the optimal choice for NSS.

The ENSS $(\sigma, E)_{\Lambda_{s}}$. is presented in Tables 4.

Table 4. Tabular representation of $(\sigma, E)_{\Lambda_{s}}$.

| $\boldsymbol{E}$ | $\boldsymbol{e}_{\mathbf{1}}$ | $\boldsymbol{e}_{\mathbf{2}}$ | $\boldsymbol{e}_{\mathbf{3}}$ | $\boldsymbol{e}_{\mathbf{4}}$ | $\boldsymbol{e}_{\mathbf{5}}$ | $\boldsymbol{e}_{\mathbf{6}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{U} \boldsymbol{x}$ |  |  |  |  |  |  |
| $\boldsymbol{x}_{\mathbf{1}}$ | $\langle 0.78,0.2,0.27\rangle$ | $\langle 0.87,0.2,0.27\rangle$ | $\langle 0.82,0.3,0.36\rangle$ | $\langle 0.87,0.2,0.27\rangle$ | $\langle 0.82,0.1,0.36\rangle$ | $\langle 0.78,0.6,0.36\rangle$ |
| $\boldsymbol{x}_{\mathbf{2}}$ | $\langle 0.88,0.4,0.09\rangle$ | $\langle 0.97,0.3,0.07\rangle$ | $\langle 0.91,0.2,0.11\rangle$ | $\langle 0.93,0.3,0.12\rangle$ | $\langle 0.97,0.5,0.04\rangle$ | $\langle 0.93,0.8,0.02\rangle$ |
| $\boldsymbol{x}_{\mathbf{3}}$ | $\langle 0.48,0.1,0.32\rangle$ | $\langle 0.81,0.2,0.13\rangle$ | $\langle 0.81,0.3,0.26\rangle$ | $\langle 0.81,0.5,0.39\rangle$ | $\langle 0.87,0.3,0.39\rangle$ | $\langle 0.68,0.2,0.39\rangle$ |
| $\boldsymbol{x}_{\mathbf{4}}$ | $\langle 0.73,0.6,0.09\rangle$ | $\langle 0.91,0.2,0.05\rangle$ | $\langle 0.91,0.5,0.27\rangle$ | $\langle 0.82,0.8,0.14\rangle$ | $\langle 0.87,0.3,0.18\rangle$ | $\langle 0.91,0.6,0.32\rangle$ |
| $\boldsymbol{x}_{\mathbf{5}}$ | $\langle 0.87,0.4,0.2\rangle$ | $\langle 0.81,0.8,0.2\rangle$ | $\langle 0.74,0.7,0.13\rangle$ | $\langle 0.87,0.1,0.26\rangle$ | $\langle 0.81,0.5,0.39\rangle$ | $\langle 0.81,0.2,0.39\rangle$ |
| $\boldsymbol{x}_{\mathbf{6}}$ | $\langle 0.64,0.1,0.22\rangle$ | $\langle 0.86,0.5,0.44\rangle$ | $\langle 0.42,0.1,0.58\rangle$ | $\langle 0.78,0.2,0.44\rangle$ | $\langle 0.78,0.6,0.58\rangle$ | $\langle 0.86,0.3,0.29\rangle$ |

By using Algorithm (1), we find the comparison table and score table of $(\sigma, E)_{\Lambda_{s}}$ as in Tables 5 and 6 respectively.

Table 5. Comparison table of $(\sigma, E)_{\Lambda_{s}}$.

| $\mathbf{U}$ | $\boldsymbol{e}_{\mathbf{1}}$ | $\boldsymbol{e}_{\mathbf{2}}$ | $\boldsymbol{e}_{\mathbf{3}}$ | $\boldsymbol{e}_{\mathbf{4}}$ | $\boldsymbol{e}_{\mathbf{5}}$ | $\boldsymbol{e}_{\mathbf{6}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{x}_{\mathbf{1}}$ | 1 | 1 | 2 | 3 | 0 | 2 |
| $\boldsymbol{x}_{\mathbf{2}}$ | 8 | 7 | 6 | 8 | 9 | 10 |
| $\boldsymbol{x}_{\mathbf{3}}$ | -4 | 1 | 3 | 1 | 2 | -4 |
| $\boldsymbol{x}_{\mathbf{4}}$ | 6 | 6 | 6 | 6 | 5 | 6 |
| $\boldsymbol{x}_{\mathbf{5}}$ | 6 | 3 | 5 | 2 | 1 | -2 |
| $\boldsymbol{x}_{\mathbf{6}}$ | -1 | 2 | -5 | -3 | 0 | 4 |

Table 6. Score table $S_{i}$ of $(\sigma, E)_{\Lambda_{s}}$

| $\boldsymbol{U}$ | $\boldsymbol{S}_{\boldsymbol{i}}$ |
| :---: | :---: |
| $x_{1}$ | 9 |
| $x_{2}$ | 48 |
| $x_{3}$ | -1 |
| $x_{4}$ | 35 |
| $x_{5}$ | 18 |
| $x_{6}$ | -3 |

Our decision to choose mobile phone 2 is evident, given that it achieves the highest score of 48, attributed to $x_{2}$. However, upon comparison with the Maji algorithm [16] employed for NSS without effective parameters, we deduce that the ENSS has altered the decision from phone 4 to phone 2.

## 7. An Application of ENSS in Medical Diagnosis

## - Example 9

Suppose that a group of four patients, denoted as $P=\left\{p_{1}\right.$, $\left.p_{2}, p_{3}, p_{4}\right\}$, who are currently hospitalized due to illness. The hospital's diagnostic specialist has listed specific symptoms to diagnose the patients' conditions. $S=\left\{s_{1}\right.$, $s_{2}, s_{3}, s_{4}, s_{5}, s_{6}, s_{7}, s_{8}, s_{9}, s_{10}, s_{11}, s_{12}, s_{13}, s_{14}, s_{15}, s_{16}, s_{17}$, $\left.s_{18}, s_{19}, s_{20}\right\}$. Here, $s_{1}=$ Fever, $s_{2}=$ dry cough, $s_{3}=$ loose motion, $s_{4}=$ breathing difficulty or experiencing shortness of breath, $s_{5}=$ headache, $s_{6}=$ tiredness,
$s_{7}=$ aches, $s_{8}=$ runny nose, $s_{9}=$ sore throat, $\mathrm{s}_{10}=$ acute pneumonia, $s_{11}=$ rash, $s_{12}=$ diarrhoea, $s_{13}=$ pain in the bones and joints, $s_{14}=$ nausea, $s_{15}=$ vomiting, $s_{16}=$ pain behind the eyes, $s_{17}=$ chills, $\mathrm{s}_{18}=$ sweating, $s_{19}=$ abdominal pain and $s_{20}=$ swollen glands.

Furthermore, let $D=\left\{d_{1}, d_{2}, d_{3}, d_{4}\right\}$ represent a group of illnesses, where COVID-19, $d_{2}=$ dengue fever, $d_{3}=$ malaria, $d_{4}=$ typhoid. Consider $A=\left\{a_{1}, a_{2}, a_{3}, a_{4}, a_{5}\right.$, $\left.a_{6}, a_{7}, a_{8}, a_{9}\right\}$ where $a_{1}=$ During the two weeks prior, he journeyed to a nation in Europe, America, Africa, or East Asia, $a_{2}=\mathrm{He}$ came into close proximity (within 6 feet) with an individual who has COVID-19, $a_{3}=\mathrm{He}$ works at medical institutions, $a_{4}=\mathrm{He}$ regularly utilizes public transportation as part of his job routine, $a_{5}=\mathrm{He}$ eats out at restaurants or indulges in fast food, $a_{6}=\mathrm{He}$ was situated in an area with calm water, especially during the early morning and evening hours, $a_{7}=\mathrm{He}$ used to sleep without any covering or protection from mosquitoes, $a_{8}=$ Eating food that is raw or inadequately cooked, and $a_{9}=$ Eating foods and beverages purchased from roadside vendors.

We identify the everyday activities and lifestyles of the sick individuals as delineated in Table 7.

Table 7. The everyday activities and lifestyles of the sick individuals.


The association between the mentioned parameters and the specified disease is depicted in Table 8 in the following manner:

Table 8. The relationship between parameters and diseases.

| $\boldsymbol{A}$ | $\boldsymbol{a}_{\mathbf{1}}$ | $\boldsymbol{a}_{\mathbf{2}}$ | $\boldsymbol{a}_{\mathbf{3}}$ | $\boldsymbol{a}_{\mathbf{4}}$ | $\boldsymbol{a}_{\mathbf{5}}$ | $\boldsymbol{a}_{\mathbf{6}}$ | $\boldsymbol{a}_{\mathbf{7}}$ | $\boldsymbol{a}_{\mathbf{8}}$ | $\boldsymbol{a}_{\boldsymbol{9}}$ | $\left\|\boldsymbol{a}_{\boldsymbol{j}}\right\|$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{D}$ |  |  |  |  |  |  |  |  |  |  |
| $\boldsymbol{d}_{\mathbf{1}}$ | Yes | Yes | Yes | Yes | No | No | No | No | No | 4 |
| $\boldsymbol{d}_{\mathbf{2}}$ | Yes | No | No | No | No | Yes | Yes | No | No | 3 |
| $\boldsymbol{d}_{\mathbf{3}}$ | Yes | No | No | No | No | Yes | Yes | No | No | 3 |
| $\boldsymbol{d}_{\mathbf{4}}$ | Yes | No | No | No | Yes | No | No | Yes | Yes | 4 |

Tables ranging from 9 to 12 depict $\Lambda_{d_{j}}\left(p_{i}\right)$ for each patient concerning the designated diseases, as described below:

Table 9. Table presentation of $\Lambda_{d_{1}}\left(p_{i}\right)$.

| $\boldsymbol{p}_{\boldsymbol{i}}$ | $\boldsymbol{a}_{\mathbf{1}}$ | $\boldsymbol{a}_{\mathbf{2}}$ | $\boldsymbol{a}_{\mathbf{3}}$ | $\boldsymbol{a}_{\mathbf{4}}$ | $\boldsymbol{a}_{\mathbf{5}}$ | $\boldsymbol{a}_{\mathbf{6}}$ | $\boldsymbol{a}_{\mathbf{7}}$ | $\boldsymbol{a}_{\mathbf{8}}$ | $\boldsymbol{a}_{\mathbf{9}}$ | Sum |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\boldsymbol{p}_{\mathbf{1}} \boldsymbol{d}_{\mathbf{1}}$ | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 3 |
| $\boldsymbol{p}_{\mathbf{2}} \boldsymbol{d}_{\mathbf{1}}$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $\boldsymbol{p}_{\mathbf{3}} \boldsymbol{d}_{\mathbf{1}}$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $\boldsymbol{p}_{4} \boldsymbol{d}_{\mathbf{1}}$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |

Table 10. Table presentation of $\Lambda_{d_{2}}\left(p_{i}\right)$.

| $\boldsymbol{A}$ | $\boldsymbol{a}_{\mathbf{1}}$ | $\boldsymbol{a}_{\mathbf{2}}$ | $\boldsymbol{a}_{\mathbf{3}}$ | $\boldsymbol{a}_{\mathbf{4}}$ | $\boldsymbol{a}_{\mathbf{5}}$ | $\boldsymbol{a}_{\mathbf{6}}$ | $\boldsymbol{a}_{\mathbf{7}}$ | $\boldsymbol{a}_{\mathbf{8}}$ | $\boldsymbol{a}_{\mathbf{9}}$ | Sum |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\boldsymbol{p}_{\mathbf{1}} \boldsymbol{d}_{\mathbf{2}}$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $\boldsymbol{p}_{\mathbf{2}} \boldsymbol{d}_{\mathbf{2}}$ | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| $\boldsymbol{p}_{\mathbf{3}} \boldsymbol{d}_{\mathbf{2}}$ | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 3 |
| $\boldsymbol{p}_{\mathbf{4}} \boldsymbol{d}_{\mathbf{2}}$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 11. Table presentation of $\Lambda_{d_{3}}\left(p_{i}\right)$.

| $\boldsymbol{A}$ | $\boldsymbol{a}_{\mathbf{1}}$ | $\boldsymbol{a}_{\mathbf{2}}$ | $\boldsymbol{a}_{\mathbf{3}}$ | $\boldsymbol{a}_{\mathbf{4}}$ | $\boldsymbol{a}_{\mathbf{5}}$ | $\boldsymbol{a}_{\mathbf{6}}$ | $\boldsymbol{a}_{\mathbf{7}}$ | $\boldsymbol{a}_{\mathbf{8}}$ | $\boldsymbol{a}_{\mathbf{9}}$ | Sum |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\boldsymbol{p}_{\boldsymbol{i}} \boldsymbol{d}_{\mathbf{3}}$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $\boldsymbol{p}_{\mathbf{2}} \boldsymbol{d}_{\mathbf{3}}$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| $\boldsymbol{p}_{\mathbf{3}} \boldsymbol{d}_{\mathbf{3}}$ | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 3 |
| $\boldsymbol{p}_{\mathbf{4}} \boldsymbol{d}_{\mathbf{3}}$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 12. Table presentation of $\Lambda_{d_{4}}\left(p_{i}\right)$.

| $\boldsymbol{A}$ | $\boldsymbol{a}_{\mathbf{1}}$ | $\boldsymbol{a}_{\mathbf{2}}$ | $\boldsymbol{a}_{\mathbf{3}}$ | $\boldsymbol{a}_{\mathbf{4}}$ | $\boldsymbol{a}_{\mathbf{5}}$ | $\boldsymbol{a}_{\mathbf{6}}$ | $\boldsymbol{a}_{\mathbf{7}}$ | $\boldsymbol{a}_{\mathbf{8}}$ | $\boldsymbol{a}_{\boldsymbol{9}}$ | Sum |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\boldsymbol{p}_{\boldsymbol{i}}$ |  |  |  |  |  |  |  |  |  |  |
| $\boldsymbol{p}_{\mathbf{1}} \boldsymbol{d}_{\mathbf{4}}$ | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 3 |
| $\boldsymbol{p}_{\mathbf{2}} \boldsymbol{d}_{\mathbf{4}}$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 2 |
| $\boldsymbol{p}_{\mathbf{3}} \boldsymbol{d}_{\mathbf{4}}$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 |
| $\boldsymbol{p}_{\mathbf{4}} \boldsymbol{d}_{\mathbf{4}}$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 3 |

Suppose the tabular representation of $(\psi, S)$ patient symptom given in Tables 13 to 16 .

Table 13. Table presentation of $(\psi, S) 1^{\text {st }}$ part.

| $S$ | ${ }^{1} 1$ | $s_{2}$ | $S_{3}$ | $s 4$ | ${ }_{5}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.7,0.2,0.5> | <0.3,0.1,0.2> | <0.3,0.1,0.5> | <0.2,0.3,0.5> | <0.8,0.3,0.6> |
| $p_{2}$ | <0.4,0.1,0.2> | <0.6,0,0.3> | <0.7,0.2,0.5> | <0.5,0.1,0.2> | <0.3,0,0.2> |
| $p_{3}$ | <0.9,0.1,0.4> | <0.5,0.1,0.3> | <0.5,0.2,0.7> | <0.3,0.4,0.5> | <0.8,0.2,0.6> |
| $p_{4}$ | <0.6,0.1,0.3> | $<0.8,0.1,0.2\rangle$ | <0.8,0.4,0.7> | <0.7,0.2,0.3> | <0.5,0.3,0.4> |

Table 14. Table presentation of $(\psi, S) 2^{\text {nd }}$ part.

| ${ }_{p}$ | $s_{6}$ | $s_{7}$ | S8 | S9 | $s_{10}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $P_{1}$ | <0.9,0.1,0.5> | <0.3,0,0.8> | <0.8,0.2,0.6> | <0.7,0.1,0.5> | <0.5,0.1,0.8> |
| $\mathrm{P}_{2}$ | <0.8,0.4,0.2> | <0.3,0.1,0.7> | <0.6,0.4,0.8> | <0.3,0.5,0.1> | <0.2,0.3,0.7> |
| $P_{3}$ | <0.9,0.2,0.5> | <0.4,0.1,0.8> | <0.5,0.4,0.6> | <0.5,0.2,0.7> | <0.4,0.3,0.6> |
| $P_{4}$ | <0.6,0.4,0.7> | <0.3,0.4,0.7> | <0.6,0.5,0.4> | <0.5,0.4,0.8> | <0.8,0.4,0.5> |

Table 15. Table presentation of $(\psi, S) 3^{\text {rd }}$ part.

|  | s11 | $s_{12}$ | $s_{13}$ | $s_{14}$ | $s_{15}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $P_{1}$ | <0.6,0.2,0.3> | <0.8,0.3,0.4> | <0.7,0.1,0.4> | <0.3,0.2,0.9> | <0.1,0.3,0.5> |
| $\mathrm{P}_{2}$ | <0.9,0.2,0.6> | <0.4,0.2,0.5> | <0.3,0.1,0.7> | <0.2,0,0.3> | <0.7,0.2,0.4> |
| $P_{3}$ | <0.8,0.1,0.5> | <0.7,0.2,0.4,> | <0.9,0.2,0.1> | <0.6,0.1,0.4> | <0.1,0.2,0.7> |
| $P_{4}$ | <0.9,0.3,0.2> | <0.5,0.3,0.6> | <0.5,0.1,0.4> | <0.7,0.3,0.5> | <0.7,0.3,0. |

Table 16. Table presentation of $(\psi, S) 4^{\text {th }}$ part.

| $\boldsymbol{S}$ | $s_{16}$ | $s_{17}$ | $s_{18}$ | $s_{19}$ | $s_{20}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $P_{1}$ | <0.2,0.1,0.4> | <0.8,0.4,0.6> | <0.5,0.3,0.7> | <0.4,0,0.2> | <0.1,0.6,0.3> |
| $\mathrm{P}_{2}$ | <0.2,0.3,0.9> | <0.1,0.5,0.3> | <0.2,0.2,0.9> | <0.4,0.2,0.7> | <0.8,0.4,0.5> |
| $P_{3}$ | $<0.3,0.2,0.5>$ | <0.5,0.3,0.7,> | \ll0.4,0.2,0.8> | <0.7,0.5,0.6> | <0.3,0.5,0.4> |
| $P_{4}$ | <0.7,0.3,0.9> | <0.2,0.5,0.3> | $\langle 0.1,0.1,0.7\rangle$ | <0.5,0.2,0.4> | <0.8,0.4,0.6> |

The table presentation of $(\phi, S)$ representing the model symptoms, is provided in the tables from Tables 17 to 20.

Table 17. Table presentation of $(\phi, S) 1^{\text {st }}$ part.

| $\underset{D}{S}$ | $s_{1}$ | $s_{2}$ | $s_{3}$ | $s_{4}$ | $s_{5}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $d_{1}$ | <1,1,0> | <1,1,0> | <1,1,0> | <1,1,0> | <0.5,0.5,0.5> |
| $d_{2}$ | <0,0,1> | <0,0,1> | $\langle 0,0,1\rangle$ | <0.5,0.5,0.5> | <1,1,0> |
| $d_{3}$ | <1,1,0> | <0.5,0.5,0.5,> | <0,0,1> | <0,0,1> | <1,1,0> |
| $d_{4}$ | <1,1,0> | <0.5,0.5,0.5> | $\langle 0,0,1\rangle$ | <0,0,1> | <,1,1,0> |

Table 18. Table presentation of $(\phi, S) 2^{\text {nd }}$ part.

| $D$ | $s 6$ | S7 | S8 | S9 | $s_{10}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $d_{1}$ | <0,0,1> | <0.5,0.5,0.5> | <0.5,0.5,0.5> | <0.5,0.5,0.5> | <1,1,0> |
| $d_{2}$ | <0.5,0.5,0.5> | <0,0,1> | <0,0,1> | <0,0,1> | <0,0,1> |
| $d_{3}$ | <0,0,1> | <1,1,0> | <0,0,1> | <0,0,1> | $\langle 0,0,1\rangle$ |
| $d_{4}$ | <1,1,0> | <1,1,0> | <0,0,1> | <0,0,1> | <0,0,1> |

Table 19. Table presentation of $(\phi, S) 3^{\text {rd }}$ part.

| $\boldsymbol{S}$ | $\boldsymbol{s}_{\mathbf{1 1}}$ | $\boldsymbol{s}_{\mathbf{1 2}}$ | $\boldsymbol{s}_{\mathbf{1 3}}$ | $\boldsymbol{s}_{\mathbf{1 4}}$ | $\boldsymbol{s}_{\mathbf{1 5}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{D} \boldsymbol{~}$ |  |  |  |  |  |
| $\boldsymbol{d}_{\boldsymbol{I}}$ | $\langle 0,0,1\rangle$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 0,0,1\rangle$ | $\langle 0,0,1\rangle$ | $\langle 0,0,1\rangle$ |
| $\boldsymbol{d}_{\boldsymbol{2}}$ | $\langle 1,1,0\rangle$ | $\langle 0,0,1\rangle$ | $\langle 1,1,0\rangle$ | $\langle 1,1,0\rangle$ | $\langle 1,1,0\rangle$ |
| $\boldsymbol{d}_{\mathbf{3}}$ | $\langle 0,0,1\rangle$ | $\langle 0,0,1\rangle$ | $\langle 1,1,0\rangle$ | $\langle 1,1,0\rangle$ | $\langle 1,1,0\rangle$ |
| $\boldsymbol{d}_{\mathbf{4}}$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 1,1,0\rangle$ | $\langle 1,1,0\rangle$ | $\langle 1,1,0\rangle$ | $\langle 0,0,1\rangle$ |

Table 20. Table presentation of $(\phi, S) 4^{\text {th }}$ part.

| $\boldsymbol{S}$ | $\boldsymbol{s}_{\mathbf{1 6}}$ | $\boldsymbol{s}_{\mathbf{1 7}}$ | $\boldsymbol{s}_{\mathbf{1 8}}$ | $\boldsymbol{s}_{\mathbf{1 9}}$ | $\boldsymbol{s}_{\mathbf{2 0}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{D} \boldsymbol{d}$ |  |  |  |  |  |
| $\boldsymbol{d}_{\boldsymbol{1}}$ | $\langle 0,0,1\rangle$ | $\langle 0,0,1\rangle$ | $\langle 0,0,1\rangle$ | $<0,0,1\rangle$ | $\langle 0,0,1\rangle$ |
| $\boldsymbol{d}_{\mathbf{2}}$ | $\langle 1,1,0\rangle$ | $\langle 0,0,1\rangle$ | $\langle 0,0,1\rangle$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 1,1,0\rangle$ |
| $\boldsymbol{d}_{\mathbf{3}}$ | $\langle 0,0,1\rangle$ | $\langle 1,1,0\rangle$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 0,0,1\rangle$ |
| $\boldsymbol{d}_{\mathbf{4}}$ | $\langle 0,0,1\rangle$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 0.5,0.5,0.5\rangle$ | $\langle 1,1,0\rangle$ | $\langle 0,0,1\rangle$ |

We form the ENSS utilizing definition 14 and the information from Tables 13 to 16, presented in Tables 21 to 40 .

Table 21. Table presentation of $(\psi, S)_{\Lambda_{d_{1}}} 1^{\text {st }}$ part.

| $\begin{gathered} S \\ P \end{gathered}$ | $s_{1}$ | $s_{2}$ | $s_{3}$ | $s_{4}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.93,0.2,0.13> | <0.83,0.1,0.05> | <0.83,0.1,0.13> | <0.83,0.1,0.13> |
| $\boldsymbol{p}_{2}$ | <0.55,0.1,0.15> | <0.7,0,0.23> | <0.78,0.2,0.38> | <0.63,0.1,0.15> |
| $p_{3}$ | <0.93,0.1,0.3> | <0.63,0.1,0.23> | <0.63,0.2,0.53> | <0.48,0.4,0.38> |
| $p_{4}$ | <0.7,0.1,0.23> | <0.85,0.1,0.15> | <0.85, $0.4,0.45>$ | <0.78,0.2,0.23> |

Table 22. Table presentation of $(\psi, S)_{\Lambda_{d_{1}}} 2^{\text {nd }}$ part.

| $P$ | $s_{5}$ | $s_{6}$ | $s_{7}$ | $s_{8}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.95,0.3,0.15> | <0.98,0.1,0.13> | <0.83,0,0.2> | <0.95,0.2,0.15> |
| $\boldsymbol{p}_{2}$ | <0.48,0,0.15> | <0.85,0.4,0.15> | $<0.48,0.1,0.53>$ | <0.7,0.4, 0.6 > |
| $p_{3}$ | <0.85,0.2,0.45> | <0.93,0.2,0.38> | <0.55,0.1,0.6> | <0.63,0.4,0.45> |
| $p_{4}$ | <0.63,0.3, 0.3 > | <0.7,0.4,0.53> | <0.48,0.4,0.53> | <0.7,0.5,0.3> |

Table 23. Table presentation of $(\psi, S)_{\Lambda_{d_{1}}} 3^{\text {rd }}$ part.

| $\begin{gathered} \boldsymbol{S} \\ \boldsymbol{P} \end{gathered}$ | $s_{9}$ | $s_{10}$ | $s_{11}$ | $s_{12}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.93,0.1,0.13> | <0.88,0.1,0.2> | <0.9,0.2,0.08> | <0.95,0.3,0.1> |
| $\boldsymbol{p}_{2}$ | <0.48,0.5,0.08> | <0.4,0.3,0.53> | <0.93,0.2.0.45> | <0.55,0.2,0.38> |
| $p_{3}$ | <0.63,0.2,0.53> | <0.55,0.3,0.45> | <0.85,0.1,0.38> | <0.78,0.2,0.3> |
| $p_{4}$ | <0.53,0.4,0.6> | <0.85, $0.4,0.38$ > | <0.93,0.3,0.15> | <0.63,0.3,0.45> |

Table 24. Table presentation of $(\psi, S)_{\Lambda_{d_{1}}} 4^{\text {th }}$ part.

| $\begin{gathered} \boldsymbol{S} \\ \hline \end{gathered}$ | $s_{13}$ | $s_{14}$ | $s_{15}$ | $s_{16}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.93,0.1,0.1> | <0.83,0.2,0.23> | <0.78,0.3,0.13> | <0.8,0.1,0.1> |
| $\boldsymbol{p}_{2}$ | <0.48,0.1,0.53> | <0.4,0,0.23> | <0.78,0.2.0.3> | <0.4,0.3, 0.68 > |
| $p_{3}$ | <0.93,0.2,0.08> | <0.7,0.1,0.3> | <0.33,0.2,0.53> | <0.48,0.2,0.38> |
| $p_{4}$ | <0.63,0.1,0.3> | <0.78,0.3,0.38> | <0.78,0.3,0.3> | <0.78,0.3,0.68> |

Table 25 . Table presentation of $(\psi, S)_{\Lambda_{d_{1}}} 5^{\text {th }}$ part.

| $P$ | $s_{17}$ | $s_{18}$ | $s_{19}$ | $s_{20}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.95,0.4,0.15> | <0.88,0.3,0.18> | <0.85,0,0.05> | <0.78,0.6,0.08> |
| $\boldsymbol{p}_{2}$ | <0.33,0.5,0.23> | <0.4,0.2,0.68> | <0.55,0.2.0.53> | <0.85,0.4,0.38> |
| $p_{3}$ | <0.63,0.3,0.53> | <0.55,0.2,0.6> | <0.78,0.5,0.45> | <0.48,0.5,0.3> |
| $p_{4}$ | <0.4,0.5,0.23> | <0.33,0.1,0.53> | <0.63,0.2,0.3> | <0.85,0.4, $0.45>$ |

Table 26. Table presentation of $(\psi, S)_{\Lambda_{d_{2}}} 1^{\text {st }}$ part.

| $\stackrel{S}{P}$ | $s_{1}$ | $s_{2}$ | $s_{3}$ | $s_{4}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.8,0.2,0.33> | <0.53,0.1,0.13> | <0.53,0.1,0.33> | <0.47,0.3,0.33> |
| $\boldsymbol{p}_{2}$ | <0.6,0.1,0.13> | <0.73,0,0.2> | <0.8,0.2,0.33> | <0.67,0.1,0.13> |
| $p_{3}$ | <1,0.1,0> | <1,0.1,0> | <1,0.2,0> | <1,0.4,0> |
| $p_{4}$ | <0.6,0.1,0.3> | <0.8,0.1,0.2> | <0.8,0.4,0.6> | <0.7,0.2,0.3> |

Table 27. Table presentation of $(\psi, S)_{\Lambda_{d_{2}}} 2^{\text {nd }}$ part.

| $P$ | $s_{5}$ | $s_{6}$ | $s_{7}$ | $s_{8}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.87,0.3,0.4> | <0.93,0.1,0.33> | <0.53,0,0.53> | <0.87,0.2,0.4> |
| $p_{2}$ | <0.53,0,0.13> | <0.87,0.4,0.13> | <0.53,0.1,0.47> | <0.73,0.4,0.53> |
| $p_{3}$ | <1,0.2,0> | <1,0.2,0> | <1,0.1,0> | <1,0.4,0> |
| $p_{4}$ | <0.5,0.3,0.4> | <0.6,0.4,0.7> | <0.3,0.4,0.7> | <0.6,0.5, 0.4$\rangle$ |

Table 28. Table presentation of $(\psi, S)_{\Lambda_{d_{2}}} 3^{\text {rd }}$ part.

| $\boldsymbol{S}$ | $\boldsymbol{s}_{\mathbf{9}}$ | $\boldsymbol{s}_{\mathbf{1 0}}$ | $\boldsymbol{s}_{\mathbf{1 1}}$ | $\boldsymbol{s}_{\mathbf{1 2}}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{P}\rangle$ |  |  |  |  |
| $\boldsymbol{p}_{\mathbf{1}}$ | $\langle 0.8,0.1,0.33\rangle$ | $\langle 0.67,0.1,0.53\rangle$ | $\langle 0.73,0.2,0.2\rangle$ | $\langle 0.87,0.3,0.27\rangle$ |
| $\boldsymbol{p}_{\mathbf{2}}$ | $\langle 0.53,0.5,0.07\rangle$ | $\langle 0.47,0.3,0.47\rangle$ | $\langle 0.93,0.2,0.4\rangle$ | $\langle 0.6,0.2,0.33\rangle$ |
| $\boldsymbol{p}_{\mathbf{3}}$ | $\langle 1,0.2,0\rangle$ | $\langle 1,0.3,0\rangle$ | $\langle 1,0.1,0\rangle$ | $\langle 1,0.2,0\rangle$ |
| $\boldsymbol{p}_{4}$ | $\langle 0.5,0.4,0.8\rangle$ | $\langle 0.8,0.4,0.5\rangle$ | $\langle 0.9,0.3,0.2\rangle$ | $\langle 0.5,0.3,0.6\rangle$ |

Table 29. Table presentation of $(\psi, S)_{\Lambda_{d_{2}}} 4^{\text {th }}$ part.

| $P$ | $s_{13}$ | $s_{14}$ | $s_{15}$ | $s_{16}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.8,0.1,0.27> | <0.53,0.2,0.6> | <0.4,0.3,0.33> | <0.47,0.1,0.27> |
| $\boldsymbol{p}_{2}$ | <0.53,0.1,0.47> | <0.47,0,0.2> | <0.8,0.2,0.27> | <0.47,0.3,0.6> |
| $p_{3}$ | <1,0.2,0> | <1,0.1,0> | <1,0.2,0> | <1,0.2,0> |
| $p_{4}$ | <0.5,0.1,0.4> | <0.7,0.3,0.5> | <0.7,0.3,0.4> | <0.7,0.3,0.9> |

Table 30. Table presentation of $(\psi, S)_{\Lambda_{d_{2}}} 5^{\text {th }}$ part.

| $\stackrel{S}{P}$ | $s_{17}$ | $s_{18}$ | $s_{19}$ | $s_{20}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{p}_{1}$ | <0.87,0.4,0.4> | <0.67,0.3,0.47> | <0.6,0,0.13> | <0.4,0.6,0.2> |
| $\boldsymbol{p}_{2}$ | <0.4,0.5,0.2> | <0.47,0.2,0.6> | <0.6,0.2,0.47> | <0.87,0.4,0.33> |
| $p_{3}$ | <1,0.3,0> | <1,0.2,0> | <1,0.5, 0 > | <1,0.5,0> |
| $p_{4}$ | <0.2,0.5,0.3> | <0.1,0.1,0.7> | <0.5,0.2,0.4> | <0.8,0.4,0.6> |

Table 31. Table presentation of $(\psi, S)_{\Lambda_{d_{3}}} 1^{\text {st }}$ part.

| $\stackrel{S}{P}$ | $s_{1}$ | $s_{2}$ | $s_{3}$ | $s_{4}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.8,0.2,0.33> | <0.53,0.1,0.13> | <0.53,0.1,0.33> | <0.47,0.3,0.33> |
| $\boldsymbol{p}_{2}$ | <0.6,0.1,0.13> | $<0.73,0,0.2\rangle$ | <0.8,0.2,0.33> | <0.67,0.1,0.13> |
| $p_{3}$ | <1,0.1,0> | <1,0.1,0> | <1,0.2,0> | <1,0.4, 0 > |
| $p_{4}$ | <0.6,0.1,0.3> | $<0.8,0.1,0.2>$ | <0.8,0.4,0.6> | <0.7,0.2,0.3> |

Table 32. Table presentation of $(\psi, S)_{\Lambda_{d_{3}}} 2^{\text {nd }}$ part.

| $\stackrel{S}{P}$ | $s_{5}$ | $s_{6}$ | $s_{7}$ | $s_{8}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{p}_{1}$ | <0.87,0.3,0.4> | <0.93,0.1,0.33> | <0.53,0,0.53> | <0.87,0.2,0.4> |
| $\boldsymbol{p}_{2}$ | <0.53,0,0.13> | $<0.87,0.4,0.13\rangle$ | <0.53,0.1, 0.47> | <0.73,0.4,0.53> |
| $p_{3}$ | <1,0.2,0> | <1,0.2,0> | <1,0.1,0> | <1,0.4, 0 > |
| $p_{4}$ | <0.5,0.3,0.4> | <0.6,0.4,0.7> | <0.3,0.4,0.7> | <0.6,0.5,0.4> |

Table 33. Table presentation of $(\psi, S)_{\Lambda_{d_{3}}} 3^{\text {rd }}$ part.

| $\boldsymbol{P}$ | $s_{9}$ | $\boldsymbol{s}_{10}$ | $s_{11}$ | $s_{12}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{p}_{1}$ | <0.8,0.1,0.33> | <0.67,0.1,0.53> | <0.73,0.2,0.2> | <0.87,0.3,0.27> |
| $\boldsymbol{p}_{2}$ | <0.53,0.5,0.07> | <0.47,0.3,0.47> | <0.93,0.2,0.4> | <0.6,0.2,0.33> |
| $p_{3}$ | <1,0.2,0> | <1,0.3,0> | <1,0.1,0> | <1,0.2,0> |
| $p_{4}$ | <0.5,0.4,0.8> | <0.8,0.4,0.5> | <0.9,0.3,0.2> | <0.5,0.3,0.6> |

Table 34. Table presentation of $(\psi, S)_{\Lambda_{d_{3}}} 4^{\text {th }}$ part.

| $\boldsymbol{S}$ | $\boldsymbol{s}_{13}$ | $\boldsymbol{s}_{14}$ | $\boldsymbol{s}_{15}$ | $\boldsymbol{s}_{16}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{P} \boldsymbol{n}$ |  |  |  |  |
| $\boldsymbol{p}_{\boldsymbol{1}}$ | $\langle 0.8,0.1,0.27\rangle$ | $\langle 0.53,0.2,0.6\rangle$ | $\langle 0.4,0.3,0.33\rangle$ | $\langle 0.47,0.1,0.27\rangle$ |
| $\boldsymbol{p}_{2}$ | $\langle 0.53,0.1,0.47\rangle$ | $\langle 0.47,0,0.2\rangle$ | $\langle 0.8,0.2,0.27\rangle$ | $\langle 0.47,0.3,0.6\rangle$ |
| $\boldsymbol{p}_{3}$ | $\langle 1,0.2,0\rangle$ | $\langle 1,0.1,0\rangle$ | $\langle 1,0.2,0\rangle$ | $\langle 1,0.2,0\rangle$ |
| $\boldsymbol{p}_{4}$ | $\langle 0.5,0.1,0.4\rangle$ | $\langle 0.7,0.3,0.5\rangle$ | $\langle 0.7,0.3,0.4\rangle$ | $\langle 0.7,0.3,0.9\rangle$ |

Table 35. Table presentation of $(\psi, S)_{\Lambda_{d_{3}}} 5^{\text {th }}$ part.

| $P$ | $s_{17}$ | $s_{18}$ | $s_{19}$ | $s_{20}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.87,0.4,0.4> | <0.67,0.3, 0.47 > | <0.6,0,0.13> | <0.4,0.6,0.2> |
| $p_{2}$ | $\langle 0.4,0.5,0.2\rangle$ | <0.47,0.2,0.6> | <0.6,0.2,0.47> | <0.87,0.4,0.33> |
| $p_{3}$ | <1,0.3,0> | <1,0.2,0> | <1,0.5,0> | <1,0.5,0> |
| $p_{4}$ | <0.2,0.5,0.3> | <0.1,0.1,0.7> | <0.5,0.2,0.4> | <0.8,0.4,0.6> |

Table 36. Table presentation of $(\psi, S)_{\Lambda_{d_{4}}} 1^{\text {st }}$ part.

| $P$ | $s_{1}$ | $s_{2}$ | $s_{3}$ | $s_{4}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.93,0.2,0.13> | <0.83,0.1,0.05> | <0.83,0.1,0.13> | <0.8,0.3,0.13> |
| $\boldsymbol{p}_{2}$ | <0.85,0.1,0.05> | <0.9,0,0.08> | <0.93,0.2,0.13> | <0.88,0.1,0.05> |
| $p_{3}$ | <0.93,0.1,0.3> | <0.63,0.1,0.23> | <0.63,0.2,0.53> | <0.48,0.4,0.38> |
| $p_{4}$ | <0.8,0.1,0.15> | <0.9,0.1,0.1> | <0.9,0.4,0.3> | <0.85,0.2,0.15> |

Table 37. Table presentation of $(\psi, S)_{\Lambda_{d_{4}}} 2^{\text {nd }}$ part.

| $\boldsymbol{S}$ | $\boldsymbol{s}_{\mathbf{5}}$ | $\boldsymbol{s}_{\mathbf{6}}$ | $\boldsymbol{s}_{\mathbf{7}}$ | $\boldsymbol{s}_{\mathbf{8}}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\boldsymbol{P}\rangle$ |  |  |  |  |
| $\boldsymbol{p}_{\mathbf{1}}$ | $<0.95,0.3,0.15>$ | $<0.98,0.1,0.13>$ | $<0.83,0,0.2>$ | $<0.95,0.2,0.15>$ |
| $\boldsymbol{p}_{\mathbf{2}}$ | $<0.83,0,0.05>$ | $<0.95,0.4,0.05>$ | $<0.83,0.1,0.18>$ | $<0.9,0.4,0.2\rangle$ |
| $\boldsymbol{p}_{\mathbf{3}}$ | $<0.85,0.2,0.45>$ | $<0.93,0.2,0.38>$ | $<0.55,0.1,0.6>$ | $<0.63,0.4,0.45>$ |
| $\boldsymbol{p}_{4}$ | $<0.75,0.3,0.22>$ | $<0.8,0.4,0.35>$ | $<0.65,0.4,0.35>$ | $<0.8,0.5,0.2>$ |

Table 38. Table presentation of $(\psi, S)_{\Lambda_{d_{4}}} 3^{\text {rd }}$ part.

| $P$ | S9 | $s_{10}$ | $s_{11}$ | $s_{12}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.93,0.1,0.13> | <0.88,0.1,0.2> | <0.9,0.2,0.08> | <0.95,0.3, $0.1>$ |
| $p_{2}$ | <0.83,0.5,0.03> | <0.8,0.3,0.18> | <0.98,0.2,0.15> | <0.85,0.2,0.13> |
| $p_{3}$ | <0.63,0.2,0.53> | <0.55,0.3,0.45> | <0.85, $0.1,0.38$ > | <0.78,0.2,0.3> |
| $p_{4}$ | <0.75,0.4,0.4> | <0.9,0.4,0.25> | <0.95,0.3,0.1> | <0.75,0.3, $0.3>$ |

Table 39. Table presentation of $(\psi, S)_{\Lambda_{d_{4}}} 4^{\text {th }}$ part.

| $P$ | $s_{13}$ | $s_{14}$ | $s_{15}$ | $s_{16}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.93,0.1,0.1> | <0.83,0.2,0.23> | <0.78,0.3,0.13> | <0.8,0.1,0.1> |
| $\boldsymbol{p}_{2}$ | <0.83,0.1,0.18> | <0.8,0,0.08> | <0.93,0.2,0.1> | <0.8,0.3, 0.23 > |
| $p_{3}$ | <0.93,0.2,0.08> | <0.7,0.1,0.3> | <0.33,0.2,0.53> | <0.48,0.2,0.38> |
| $p_{4}$ | <0.75,0.1,0.2> | <0.85, $0.3,0.25>$ | <0.85, $0.3,0.2>$ | <0.85,0.3,0.45> |

Table 40. Table presentation of $(\psi, S)_{\Lambda_{d_{4}}} 5^{\text {th }}$ part.

| $P$ | $S_{17}$ | $s_{18}$ | $S_{19}$ | $S_{20}$ |
| :---: | :---: | :---: | :---: | :---: |
| $p_{1}$ | <0.95,0.4,0.15> | <0.88,0.3,0.18> | <0.85,0,0.05> | <0.78,0.6,0.08> |
| $p_{2}$ | <0.78,0.5,0.08> | <0.8,0.2,0.23> | <0.85,0.2,0.18> | $<0.95,0.4,0.13>$ |
| $p_{3}$ | <0.63,0.3,0.53> | <0.55,0.2,0.6> | <0.88,0.5,0.45> | $<0.48,0.5,0.3>$ |
| $p_{4}$ | <0.6,0.5, 0.15 > | <0.55,0.1,0.35> | <0.75,0.2,0.1> | $<0.9,0.4,0.3>$ |

Ultimately, the score table is generated by evaluating the similarity of each row in the Tables 21 to 36 and every row in Tables 17 to 20. This includes finding the highest value for each patient and the diseases associated with these values. The following formula is then used to calculate the similarity:

$F_{S}=\frac{\sum_{l}^{20}\left|F_{\psi_{\Lambda_{d_{\mathrm{i}}}}\left(p_{i}\right)\left(s_{l}\right)}-F_{\phi\left(p_{i}\right)\left(s_{l}\right)}\right|}{\sum_{l}^{20}\left|F_{\psi_{\Lambda_{d_{\mathrm{i}}}}\left(p_{i}\right)\left(s_{l}\right)}+F_{\phi\left(p_{i}\right)\left(s_{l}\right)}\right|}$
Then, $S\left(p_{i}, d_{j}\right)=\frac{1-T_{S}+1-I_{S}+1-F_{S}}{3}$
The result can be obtained as follows:

$$
\begin{aligned}
& 1-T_{S}=1-\frac{|0.93-1|+|0.83-1|+|0.83-1|+|0.8-1|}{|0.93+1|+|0.83+1|+|0.83+1|+|0.8+1|} \\
& \frac{+|0.95-0.5|+|0.98-0|+|0.83-0.5|+|0.95-0.5|}{+|0.95+0.5|+|0.98+0|+|0.83+0.5|+|0.95+0.5|} \\
& \frac{+|0.93-0.5|+|0.88-1|+|0.9-0|+|0.95-0.5|}{+|0.93+0.5|+|0.88+1|+|0.9+0|+|0.95+0.5|} \\
& \frac{+|0.93-0|+|0.83-0|+|0.78-0|+|0.8-0|}{+|0.93+0|+|0.83+0|+|0.78+0|+|0.8+0|} \\
& \frac{+|0.95-0|+|0.88-0|+|0.85-0|+|0.78-0|}{+|0.95+0|+|0.88+0|+|0.85+0|+|0.78+0|}=1-\frac{11.52}{25.06}=0.54
\end{aligned}
$$

$$
\begin{aligned}
1-I_{S} & =1-\frac{|0.2-1|+|0.1-1|+|0.1-1|+|0.3-1|}{|0.2+1|+|0.1+1|+|0.1+1|+|0.3+1|} \\
& \frac{+|0.3-0.5|+|0.1-0|+|0-0.5|+|0.2-0.5|}{+|0.3+0.5|+|0.1+0|+|0+0.5|+|0.2+0.5|} \\
& \frac{+|0.1-0.5|+|0.1-1|+|0.2-0|+|0.3-0.5|}{+|0.1+0.5|+|0.1+1|+|0.2+0|+|0.3+0.5|} \\
& \frac{+|0.1-0|+|0.2-0|+|0.3-0|+|0.1-0|}{+|0.1+0|+|0.2+0|+|0.3+0|+|0.1+0|} \\
& +|0.4-0|+|0.3-0|+|0-0|+|0.6-0| \\
& +|0.4+0|+|0.3+0|+|0+0|+|0.6+0| \\
= & 1-\frac{8.1}{11.5}=0.29 \\
1-F_{S}= & 1-\frac{|0.13-0|+|0.05-0|+|0.13-0|+|0.13-0|}{|0.13+0|+|0.05+0|+|0.13+0|+|0.13+0|} \\
& \frac{+|0.15-0.5|+|0.13-1|+|0.2-0.5|+|0.15-0.5|}{+|0.15+0.5|+|0.13+1|+|0.2+0.5|+|0.15+0.5|} \\
& \frac{+|0.13-0.5|+|0.2-0|+|0.08-1|+|0.1-0.5|}{+|0.13+0.5|+|0.2+0|+|0.08+1|+|0.1+0.5|} \\
& \frac{+|0.1-1|+|0.23-1|+|0.13-1|+|0.1-1|}{+|0.1+1|+|0.23+1|+|0.13+1|+|0.1+1|} \\
& \frac{+|0.15-1|+|0.18-1|+|0.05-1|+|0.08-1|}{+|0.15+1|+|0.18+1|+|0.05+1|+|0.08+1|} \\
= & 1-\frac{11.18}{15.72}=0.29 \\
& \left(p_{1}, d_{1}\right)=\frac{0.54+0.29+0.29}{3}=0.37
\end{aligned}
$$

Table 41. $S\left(p_{i}, d_{j}\right)$.

| $\boldsymbol{p}$ | $\boldsymbol{d}_{\mathbf{1}}$ | $\boldsymbol{d}_{\mathbf{2}}$ | $\boldsymbol{d}_{\mathbf{3}}$ | $\boldsymbol{d}_{\mathbf{4}}$ |
| :--- | :--- | :--- | :--- | :--- |
| $\boldsymbol{p}^{\boldsymbol{p}}$ |  |  |  |  |
| $\boldsymbol{p}_{\boldsymbol{1}}$ | 0.37 | $\mathbf{0 . 4 5}$ | 0.43 | 0.40 |
| $\boldsymbol{p}_{\mathbf{2}}$ | $\mathbf{0 . 4 7}$ | 0.44 | 0.42 | 0.43 |
| $\boldsymbol{p}_{\mathbf{3}}$ | 0.47 | 0.33 | 0.29 | $\mathbf{0 . 5 3}$ |
| $\boldsymbol{p}_{\mathbf{4}}$ | 0.53 | $\mathbf{0 . 5 4}$ | 0.47 | 0.46 |

By employing similar calculations, we derive the score table, as shown in Table 41. Analysis of Table 41 reveals that the first sick individual is diagnosed with dengue fever, the second sick individual is suffering from COVID-19, the third sick individual is affected by typhoid, and the fourth sick individual is diagnosed with dengue fever.

## 8. Conclusions

In this paper, we have introduced the concept of ENSS which is more effective and useful with some of its properties. Also, the basic operations on ENSS namely complement, union and intersection have been defined. Finally, we have presented an application of ENSS in a DM problem and in MD.

This article makes a significant contribution by introducing new inquiries that can inspire further research efforts. As research progresses and reveals additional questions, the content presented in this article establishes a foundation for more thorough investigation into ENSS. Key areas for future research encompass advanced concepts like Q-Effective Neutrosophic Soft Sets (Q-ENSSs) and their applications, effective neutrosophic hypersoft sets with applications, and their generalizations. Additionally, there is a need to examine algebraic structures linked to

ENSS, including groups, rings, fields, or vector spaces, alongside exploring applications in real-world domains. Funding

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## Conflicts of Interest

"The authors declare no conflict of interest."

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