# A New Approach to Neutrosophic Soft Sets and their Application in Decision Making

**R.K. Mohanty [1,2], B.K. Tripathy [1,3,*]**

[1] VIT, Vellore, Tamil Nadu – 632014, India;
[2] rknmohanty@gmail.com
[3] tripathybk@vit.ac.in

* Correspondence: tripathybk@vit.ac.in

**Abstract:** In literature, several models which can handle uncertainty in datasets have been introduced. Fuzzy set introduced by Zadeh in 1965, is one of the earliest such models and Atanassov generalised it by introducing the notion of Intuitionistic fuzzy sets(IFS) in 1986. However, these models are handicaped due to their inadequacy as parameterization tools. The notion of Soft sets (SS) was introduced by Molodtsov in 1999 to solve this problem. Almost at the same time, Neutrosophic set (NS) model was introduced by Smarandache, which is a huge generalisation of IFS. As has been the practice, the hybrid model of SS and NS was proposed to frame the notion of Neutrosophic Soft Set (NSS) by Ali and Smaranche in 2015 and studied their properties. Since its inception, one of the major areas of application of Soft Sets has been that of Multi-criterian Decision Making (MCDM). Many problems in MCDM were solved by using hybrid models of SS. Following this trend, in this paper, we develop an algorithm basing upon NSS to handle the problem of MCDM in the selection of faculty through an interview prcess. For this, we had to introduce an improved score function which is used to rank the candidates basing upon several of their characteristics including interview perfromances. This application is better handled by the NSS model as is evident from the results. We illustrated the superiority of our proposed algorithm by providing a comparative analysis with many exieting algorithms in the literature.

**Keywords:** Fuzzy Set; Intuitionistic fuzzy set; Soft Set; Neutrosophic Set; Neutrosophic soft set; Multicriteria Decision Making.

## 1. Introduction

The notion of FSs [1] is one of the most popular mathematical model to handle uncertainty and vagueness. In contrast to classical notion of sets where the elements of the set are characterised by either "does not belongs" or "belongs" to a set; notion of FSs provides a grade of membership to each element through a membership function. Sometimes, in real-life situations, it is not easy to define membership functions. So, to capture more uncertainty, Zadeh proposed the notion of interval valued fuzzy sets [2]. However, there are situations exist, where grade of membership is not complement to non-membership values. Both the notions of fuzzy set and the notions of interval valued fuzzy sets can not capture such kind of uncertainty. To handle such kind of scenarios, Atanassov [3, 4] introduced the notions of IFS where hesitation function comes into picture, if the membership and non-mebership are not complement of eachother. An IFS becomes a fuzzy set when the hesitation becomes zero. Similarly a fuzzy set becomes a classical set, if the membership value is restricted to either one or zero. Atanassov [5] further generalised the concept of IFS and introduced interval valued IFS.

In all the uncertainty based models discussed above, we need to define a membership function. However, by using a single mebership function is not enough to handle all kind of uncertainties involve in some situations. It will create sutuations like adding weight parameter to a length parameter. It happens due to lack of parameterization tools in the previous models. To handle such issues, Moldtsov [6] introduced the notion of soft set in 1999. It adds topological features to the notions of set theory. In soft sets, each one of the parmeters from a parameter set are associated with a subset of the universe of discourse. Recently, soft sets and its hybrid models are gaining popularity for their ability to handle uncertainty in multicriteria decision making. Due to its topological nature and availability of parameterization tool, its easier and convinient to capture uncertainty in decision making problems using soft sets or any of its hybrid models.

Tripathy et al [7] redefined the notions soft set using characteristic functions approach which seems to be more convenient and easy to understand incomparison to its previous models. Later, there are many more hybrids models were proposed using the same concept [8-17]. There are several papers published on hybrid models of soft set and their application in MCDM.

One more contemporaries of the notions of soft set is the concept NSs [18] proposed by smarandache. It is a generalization of IFSs. In contrast to other generalisations or hybrid models of IFSs; in NSs, the membership, non-mebership and hesitation functions are independent of each other. So, the sum of the grades of Truthness, Falsity and Indeterminacy can vary in the interval $[0^-, 3^+]$. There are several articles on NSs and its hybrid models in literature to solve multicriteria decision-making problem [19-30].

Maji [31] introduced the concept of NSSs.

This paper provides a new approach to redefine the notions of NSS. It redefines some operations of NSS using characterastic function approach [7, 8]. An application in decision making using NSS is also discussed in this article.

## 2. Definitions and Notions

To understand the proposed model, we need to understand some prerequisite models which are discussed in this section.

Let $U$ be a universal set and $E$ be a set of parameters.

### *2.1. Soft Set*

A soft set is a collection of parameterized family of subsets. A soft set over $U$ is denoted by $(F, E)$ and is defined as

$$F : E \to P(U)$$

where $P(U)$ is the power set of $U$ .

### *2.2 Fuzzy Set*

A fuzzy set $A$ drawn from $U$ is given by its membership function $\mu_A$ where $\mu_A : U \to [0,1]$ such that $\forall x \in U$ , $\mu_A(x)$ is the grade of membership of $x$ in $A$ . A fuzzy set reduces to a crisp set when $\mu_A : U \to \{0,1\}$ .

### *2.3 Fuzzy Soft Set*

A fuzzy soft set over $U$ is denoted by $(F_m, E)$ and is defined as

$$F_m : E \to FP(U)$$

where $FP(U)$ is the set of all fuzzy subsets of $U$ .

*2.4 Intuitionistic fuzzy set*

An IFS A over a universe of discourse $U$ is a pair $(m_A, n_A)$ , where $m_A : U \to [0,1]$ and $n_A : U \to [0,1]$, called the membership and non-membership functions of A respectively are such that for any $x \in U$ , $0 \le m_A(x) + n_A(x) \le 1$.

The function given by $\pi_A(x) = 1 - m_A(x) - n_A(x)$ is called the hesitation function associated with A.

*2.5 Intuitionistic fuzzy soft set*

An IFSS (F, E) over a universal discourse $U$ is defined as

$$F : E \to IFP(U)$$

Where, $IFP(U)$ is the powerset of all IFSs in $U$ .

**3. Neutrosophic Sets**

A neutrosophic set $B$ over a universe of discourse $U$ is defined as $B = \{\langle x, T_B(x), I_B(x), F_B(x)\rangle, \forall x \in U\}$, where $(T_B, I_B, F_B) : U \to ]0^-, 1^+[$ . $T_B, I_B, F_B$ are called as the Truthness, Indeterminacy and Falsity membership functions of $B$ respectively.

In real life engineering applications, it is difficult to use non-standard real values. Hence in this article, the value range for the NSs are restricted to the subsets of $[0,1]$ .

*3.1 Neutrosophic subset*

A neutrosophic set $B$ is said to be a neutrosophic subset of $A$ denoted by $B \subseteq A$ iff $\forall x \in U$ , $T_B(x) \le T_A(x), I_B(x) \ge I_A(x), F_B(x) \ge F_A(x)$.

*3.2 Union of two NS*

Union of two NSs $A$ and $B$ denoted by $A \bigcup B$ is defined as

$$A \bigcup B = \{\max(T_A, T_B), \min(I_A, I_B), \min(F_A, F_B)\}$$

*3.3 Intersection of two NS*

Intersection of two NSs $A$ and $B$ denoted by $A \bigcup B$ is defined as

$$A \bigcap B = \{\min(T_A, T_B), \max(I_A, I_B), \max(F_A, F_B)\}$$

**4. Neutrosophic Soft Set**

A neutrosophic set $(F_B, E)$ over a universe of discourse $U$ is defined as

$$F : E \to NPow(U)$$

Where, $NPow(U)$ is the neutrosophic powerset of $U$.

A NSS $(F_B, E)$ can also be defined using membership function approach (Tripathy et. al, 2016) as follows.

The set of parametric membership functions of NSS $(F_B, E)$ defined over $(U, E)$ as shown below.

$(F_B, E) = \{(F_B, E)(e) : e \in E\}$ such that $\forall e \in E$, $\left\{T_{(F_B,E)(e)}, I_{(F_B,E)(e)}, F_{(F_B,E)(e)}\right\} : U \to ]0^-, 1^+[$

and $\forall x \in U$, the membership function is defined as

$$T_{(F_B,E)(e)}(x) = \alpha,\ \alpha \in ]0^-, 1^+[\ ;$$

$$I_{(F_B,E)(e)}(x) = \beta,\ \beta \in ]0^-, 1^+[\ ;\ \text{and}$$

$$F_{(F_B,E)(e)}(x) = \lambda,\ \lambda \in ]0^-, 1^+[\ .$$

*4.1 Neutrosophic soft subset*

A NSS $(F_B, E)$ is said to be a neutrosophic soft subset of $(F_A, E)$ denoted by $(F_B, E) \subseteq (F_A, E)$ if $\forall x \in U$, $T_{(F_B,E)(e)}(x) \le T_{(F_A,E)(e)}(x)$, $I_{(F_B,E)(e)}(x) \ge I_{(F_A,E)(e)}(x)$, $F_{(F_B,E)(e)}(x) \ge F_{(F_A,E)(e)}(x)$.

*4.2 Union of two Neutrosophic soft Sets*

Union of two NSSs $(F_A, E)$ and $(F_B, E)$ denoted by $(F_{A\cup B}, E)$ is defined as

$$(F_{A\cup B}, E) = \left\{\begin{matrix} \max\left(T_{(F_A,E)(e)}(x), T_{(F_B,E)(e)}(x)\right), \min\left(I_{(F_A,E)(e)}(x), I_{(F_B,E)(e)}(x)\right), \\ \min\left(F_{(F_A,E)(e)}(x), F_{(F_B,E)(e)}(x)\right) \end{matrix}\right\}$$

*4.3 Intersection of two Neutrosophic soft Sets*

Intersection of two NSSs $A$ and $B$ denoted by $A \bigcup B$ is defined as

$$(F_{A\cap B}, E) = \left\{\begin{matrix} \min\left(T_{(F_A,E)(e)}(x), T_{(F_B,E)(e)}(x)\right), \max\left(I_{(F_A,E)(e)}(x), I_{(F_B,E)(e)}(x)\right), \\ \max\left(F_{(F_A,E)(e)}(x), F_{(F_B,E)(e)}(x)\right) \end{matrix}\right\}$$

## 4. Application of Neutrosophic Soft Sets in Decision Making

An application of NSSs in multicriteria decision making is provided in this section. As a generalised model of IFS [3], NS [18] inherently a good mathematical model to handle uncertainty. Molodtsov [6] has given many applications of soft sets in the introductory article. Recently, hybrid models of soft sets are among the popular models to handle multicriteria decision making problems. There are everal articles in literature using NSS model to handle multicriteria decision making problems. This article provides a new approach for decision making using notions of NSS.

There are two types of parameters (Tripathy et al. 2016),
i) Positive Parameters and
ii) Negative Parameters.
A parameter which is having positive impact on decision making is called as positive parameter and if the parameter is having negative impact on decision-making, then that is called as negative parameter.

A priority value is expressed through a real number lies in [-1, 1] and is attached to each parameter as per the degree of impact of the parameter on the user's decision-making. For positive parameters the priority value lies in [0,1] and for the negative parameter the priority value lies in [-1,0].

Sometimes we may have a parameter which is given zero priority by the user irrespective of the type of the category of the parameter that can be either positive or negative. Though these parameters would not affect user's decision-making usually, but the effect comes into picture during close comparisons. For example, one can say, if everything is good, price does not matter. But, if two same things are available with different prices, everyone will choose the thing with lower price. These kinds of situations are ignored in the existing approaches. In this paper, these kinds of situations managed by giving a very low priority value which won't affect the decision choices until there is a close comparison.

A small user defined value $d$ is used in the application, which helps to maintain better precision in results. In this application, value of $d$ is taken as 0.001. To manage parameters with zero priority, a small priority value is attached to the parameter instead of zero. The formula to compute the priority value to be attached with a parameter having zero priority is given below.

$$p_0 = \frac{sign(\text{User's Priority}(P_n)) \times d}{\sum_{1}^{n} Abs(\text{User's Priority}(P_n))} \tag{4.1}$$

Where, Abs $\rightarrow$ Absolute value
Sign $\rightarrow$ Signum Function

To make comparisons among different sets values, the values need to be normalized. In this paper, the formula used for normalizing values is given below.

$$\text{Normalized priority} = \frac{P_n}{\sum_{1}^{n} \text{Priority}(P_n)} \tag{4.2}$$

To compare a series of values $V_i, i = 1, 2, ..., n$ and get a comparison value; the following formula can be used.

$$Comparison\ Score(V_i) = nV_i - \sum_{j=1}^{n} V_j \qquad (4.3)$$

for $i, j = 1, 2, ..., n$.

To use NSs in decision making, a score function is needed to compute the score and order the neutrosophic values. The formula given in Equation (4.4) is used to compute the score from a neutrosophic value.

$$NS\_Score(T, I, F) = ((T*(1+2d)) - F + dI\left[1+\min\{1, T+(I/2)\} - \min\{1, F+(I/2)\}\right]$$

$$Score = \begin{cases} \dfrac{NS\_Score(T,I,F)}{1+\frac{7}{2}d}, & if\ NS\_Score(T,I,F) > 0; \\ NS\_Score(T,I,F), & Otherwiese. \end{cases} \qquad (4.4)$$

where, $d$ $\rightarrow$very small positive real number. (In this paper $d$ =0.01)
$T, I, F$ $\rightarrow$Represents Truthness, Indeterminacy and Falsity values, respectively.
$Score(T, F, I)$ $\rightarrow$Score function for the Neutrosophic value $(T, F, I)$.

The formula in (4.4) provides a real number from a particular neutrosophic value. This formula will be extremely helpful to resolve neutrosophic decision making problems. The formula will reduce a neutrosophic set problem to a bipolar fuzzy set problem. The basic structure of the formula is $T - F + I*(\min(1, T+\frac{I}{2}) - \min(1, F+\frac{I}{2}))$. The formula is based on optimistic approach. So, the truth value is boosted by a small margin to tackle the problem when $T = F$. To reduce the effect of $I*(\min(1, T+\frac{I}{2}) - \min(1, F+\frac{I}{2}))$ value, so that , it would not overshadow the T value which may lead to wrong decision making, it is multiplied by a small positive real number $d$. Value of $d$ is taken as 0.01 in this article.

| T | I | F | Score |
|---|---|---|---|
| 1 | 1 | 0 | 1 |
| 1 | 0.8 | 0 | 0.99787 |
| 1 | 0.6 | 0 | 0.99536 |
| 1 | 0.4 | 0 | 0.99246 |
| 1 | 0.2 | 0 | 0.98918 |
| 1 | 0 | 0 | 0.98551 |
| 1 | 0.2 | 0.2 | 0.8234 |
| 1 | 0.4 | 0.4 | 0.6256 |
| 1 | 0.6 | 0.6 | 0.4266 |
| 1 | 0.8 | 0.8 | 0.228 |
| 1 | 1 | 1 | 0.03 |
| 1 | 0.8 | 1 | 0.028 |
| 1 | 0.6 | 1 | 0.026 |
| 1 | 0.4 | 1 | 0.024 |
| 1 | 0.2 | 1 | 0.022 |
| 1 | 0 | 1 | 0.02 |
| 0.8 | 0.2 | 0.8 | 0.018 |
| 0.6 | 0.4 | 0.6 | 0.016 |
| 0.4 | 0.6 | 0.4 | 0.014 |
| 0.2 | 0.8 | 0.2 | 0.012 |
| 0 | 1 | 0 | 0.01 |
| 0 | 0.8 | 0 | 0.008 |
| 0 | 0.6 | 0 | 0.006 |
| 0 | 0.4 | 0 | 0.004 |
| 0 | 0.2 | 0 | 0.002 |
| 0 | 0 | 0 | 0 |
| 0 | 0.2 | 0.2 | -0.1984 |
| 0 | 0.4 | 0.4 | -0.3976 |
| 0 | 0.6 | 0.6 | -0.5976 |
| 0 | 0.8 | 0.8 | -0.7968 |
| 0 | 1 | 1 | -0.995 |
| 0 | 0.8 | 1 | -0.9968 |
| 0 | 0.6 | 1 | -0.9982 |
| 0 | 0.4 | 1 | -0.9992 |
| 0 | 0.2 | 1 | -0.9998 |
| 0 | 0 | 1 | -1 |


Figure 1. Score from a neutrosophic value

In Figure 1, we can see that the score function is working fine and giving an intuitive score for each of the value. The graph in Figure 1 seems inverted "Z" shape due to the limited number of data points in that region. If we provide a greater number of data points in the graph, it gives a smoother line.

Graphs in Figure 2 provide a perspective in the change of score value with a constant value of either T or F.

| T | I | F | NS Score (T Constant) |
|---|---|---|---|
| 0.6 | 0 | 0 | 0.6 |
| 0.6 | 0.2 | 0 | 0.6 |
| 0.6 | 0.4 | 0 | 0.6 |
| 0.6 | 0.6 | 0 | 0.6 |
| 0.6 | 0.8 | 0 | 0.6 |
| 0.6 | 1 | 0 | 0.6 |
| 0.6 | 0 | 0.2 | 0.4 |
| 0.6 | 0.2 | 0.2 | 0.4 |
| 0.6 | 0.4 | 0.2 | 0.4 |
| 0.6 | 0.6 | 0.2 | 0.4 |
| 0.6 | 0.8 | 0.2 | 0.4 |
| 0.6 | 1 | 0.2 | 0.4 |
| 0.6 | 0 | 0.4 | 0.2 |
| 0.6 | 0.2 | 0.4 | 0.2 |
| 0.6 | 0.4 | 0.4 | 0.2 |
| 0.6 | 0.6 | 0.4 | 0.2 |
| 0.6 | 0.8 | 0.4 | 0.2 |
| 0.6 | 1 | 0.4 | 0.2 |
| 0.6 | 0 | 0.6 | 0 |
| 0.6 | 0.2 | 0.6 | 0 |
| 0.6 | 0.4 | 0.6 | 0 |
| 0.6 | 0.6 | 0.6 | 0 |
| 0.6 | 0.8 | 0.6 | 0 |
| 0.6 | 1 | 0.6 | 0 |
| 0.6 | 0 | 0.8 | -0.2 |
| 0.6 | 0.2 | 0.8 | -0.2 |
| 0.6 | 0.4 | 0.8 | -0.2 |
| 0.6 | 0.6 | 0.8 | -0.2 |
| 0.6 | 0.8 | 0.8 | -0.2 |
| 0.6 | 1 | 0.8 | -0.2 |
| 0.6 | 0 | 1 | -0.4 |
| 0.6 | 0.2 | 1 | -0.4 |
| 0.6 | 0.4 | 1 | -0.4 |
| 0.6 | 0.6 | 1 | -0.4 |
| 0.6 | 0.8 | 1 | -0.4 |
| 0.6 | 1 | 1 | -0.4 |

| T | I | F | NS Score (F Constant) |
|---|---|---|---|
| 0 | 0 | 0.6 | -0.6 |
| 0.2 | 0 | 0.6 | -0.6 |
| 0.4 | 0 | 0.6 | -0.6 |
| 0.6 | 0 | 0.6 | -0.6 |
| 0.8 | 0 | 0.6 | -0.6 |
| 1 | 0 | 0.6 | -0.6 |
| 0 | 0.2 | 0.6 | -0.4 |
| 0.2 | 0.2 | 0.6 | -0.4 |
| 0.4 | 0.2 | 0.6 | -0.4 |
| 0.6 | 0.2 | 0.6 | -0.4 |
| 0.8 | 0.2 | 0.6 | -0.4 |
| 1 | 0.2 | 0.6 | -0.4 |
| 0 | 0.4 | 0.6 | -0.2 |
| 0.2 | 0.4 | 0.6 | -0.2 |
| 0.4 | 0.4 | 0.6 | -0.2 |
| 0.6 | 0.4 | 0.6 | -0.2 |
| 0.8 | 0.4 | 0.6 | -0.2 |
| 1 | 0.4 | 0.6 | -0.2 |
| 0 | 0.6 | 0.6 | 0 |
| 0.2 | 0.6 | 0.6 | 0 |
| 0.4 | 0.6 | 0.6 | 0 |
| 0.6 | 0.6 | 0.6 | 0 |
| 0.8 | 0.6 | 0.6 | 0 |
| 1 | 0.6 | 0.6 | 0 |
| 0 | 0.8 | 0.6 | 0.2 |
| 0.2 | 0.8 | 0.6 | 0.2 |
| 0.4 | 0.8 | 0.6 | 0.2 |
| 0.6 | 0.8 | 0.6 | 0.2 |
| 0.8 | 0.8 | 0.6 | 0.2 |
| 1 | 0.8 | 0.6 | 0.2 |
| 0 | 1 | 0.6 | 0.4 |
| 0.2 | 1 | 0.6 | 0.4 |
| 0.4 | 1 | 0.6 | 0.4 |
| 0.6 | 1 | 0.6 | 0.4 |
| 0.8 | 1 | 0.6 | 0.4 |
| 1 | 1 | 0.6 | 0.4 |

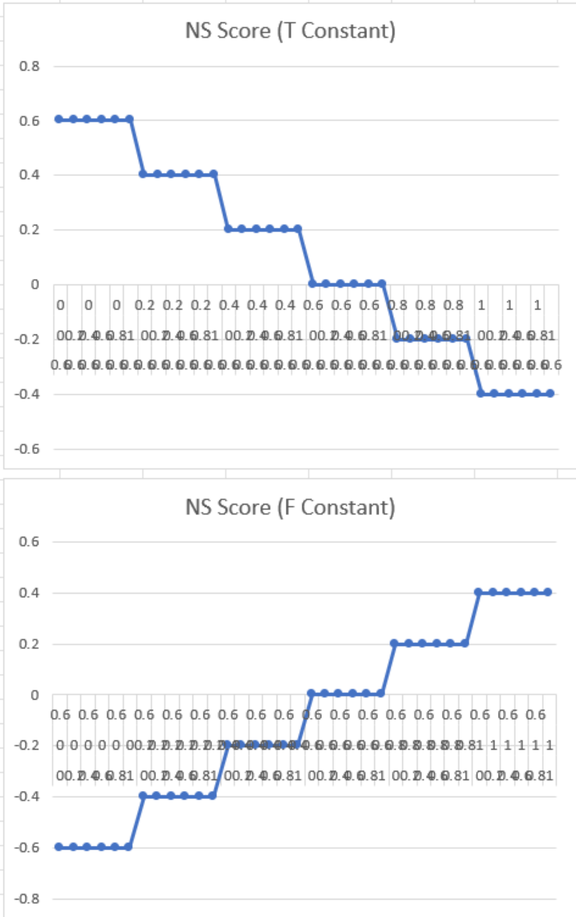


Figure 2. Score comparison when either T or F value is constant.

*4.1 Algorithm*

Step 1: Get the priority values of parameters from the user.

Step 1.1: Compute the priority for the parameters having zero priority using the formula in Equation (4.1).

Step 1.2: Compute the normalized priority using the formula in Equation (4.2).

Step 1.3: Rank the parameters as per their absolute priority values.

Step 2: Get the data in neutrosophic format.

Step 2.1: Construct the Truthness Table, Indeterminacy Table and Falsity Table by Segregating the columns of Truthness, Indeterminacy and Falsity values for each parameter.

Step3: Construct the Truthness Priority Table, Indeterminacy Priority Table and Falsity Priority Table by multiplying the priority values to their corresponding Truthness, Indeterminacy and Falsity values.

Step 4: Construct the Comparison Tables for Truthness, Indeterminacy and Falsity values by using the formula given in Equation (4.3) for each column.

Step 4.1: Get the comparison score, by computing the sum of the comparison scores for each competitor.

Step 4.2: Normalize comparison scores of all comparison tables using the formula in Equation (4.2).

Step 5: Construct the decision table by taking the normalized scores from comparison tables for Truthness, Indeterminacy and Falsity values.

Step 5.1: Compute the neutrosophic score by using the formula in the Equation (4.4)

Step 5.2: Rank the competitors according to their final score (neutrosophic score).

Step 5.3: If multiple participants are getting same score, for those participants with same score, repeat all the previous steps ignoring the parameter having lowest rank. Continue the process until all participants getting a distinct rank or reaching the comparison with only the values for the highest ranked parameter.

*4.2 Application*

The application provided here is selection of faculties in an interview process.

The parameters considered for the selection are Teaching, Research, Academic, Presentation, Subject Knowledge, Communication Skill, Gaps, Body Language, Nativity. The parameters are represented respectively as a set of parameters $\rho = \{\rho_1, \rho_2, \rho_3, \rho_4, \rho_5, \rho_6, \rho_7, \rho_9\}$.

Let us assume that there are 10 participants given by $U = \{\square_1, \square_2, \square_3, \square_4, \square_5, \square_6, \square_7, \square_9, \square_{10}\}$ shortlisted after the interview. The authorities assign the priority for each parameter as per their requirements. If there are any parameters having zero priority, a small priority needs to be assigned that can be computed using formula in Equation (4.1). Normalize the priority values using formula in Equation (4.2). Rank the parameters by their absolute priority values. Because, the priority becomes negative due to the negative parameter, but the effect of the priority value remains same irrespective of the type of the parameter. Table 1 shows all the data about the parameters and the priorities assigned to those parameters.

Parameter Rank: Parameters are ranked as per their absolute priority value. In Table 1, it can be noticed that the User's priority for the parameter Gaps ( $\rho_7$ ) is a negative number, because the parameter Gaps is a negative parameter. But the significance of a parameter in decision making is depends on its absolute priority value. So, the parameters $\rho_6, \rho_7, \rho_8$ are having same parameter rank. Parameter ranks plays a vital role to resolve the problem when two participants are having same final score. In that case, we can ignore one or more less significant parameters.

**Table 1.** Parameter Table

| **Parameters** | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| User's Priority | .20 | .40 | .30 | .20 | .30 | .10 | -0.10 | .10 | 0 |
| Handling Zero Priority | .20 | .40 | .30 | .20 | .30 | .10 | -0.10 | .10 | .01 |
| Normalized Priority | .117 | .234 | .176 | .117 | .176 | .059 | -0.059 | .059 | .003 |
| Parameter Rank | 4 | 1 | 2 | 4 | 2 | 6 | 6 | 6 | 9 |

The quality of all the participants evaluated and can be represented in a NSS as shown in Table 2. Construct the Truthness Table, Indeterminacy Table and Falsity Table (Tables 3, 4, 5) by segregating the columns of Truthness, Indeterminacy and Falsity values for every parameter.

Construct the Truthness Priority Table, Indeterminacy Priority Table and Falsity Priority Table (Tables 6, 7, 8) by multiplying the priority values to their corresponding Truthness, Indeterminacy and Falsity values. Priority Tables are having both -ve and +ve real numbers. Because, after multiplying with priority values, the data are not necessarily positive. It can be any real number.

Construct the Comparison Tables for Truthness, Indeterminacy and Falsity values by using the formula given in Equation (4.3) for each column (Tables 9,10,11). Get the comparison score, by computing the sum of the comparison scores for each competitor. Normalize comparison scores of all comparison tables using the formula in Equation (4.2).

**Table 2.** Data in Neutrosophic soft set model

| $\rho$ | $\rho_1$ | | | $\rho_2$ | | | $\rho_3$ | | | $\rho_4$ | | | $\rho_5$ | | | $\rho_6$ | | | $\rho_7$ | | | $\rho_8$ | | | $\rho_9$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $U$ | T | I | F | T | I | F | T | I | F | T | I | F | T | I | F | T | I | F | T | I | F | T | I | F | T | I | F |
| □ 1 | .09 | .7 | .28 | .25 | .25 | .07 | .48 | .19 | .75 | .62 | .64 | .07 | .18 | .97 | .25 | .86 | .28 | .51 | .85 | .16 | .9 | .12 | .79 | .71 | .56 | .71 | .97 |
| □ 2 | .68 | .33 | .13 | .94 | .98 | .93 | .41 | .79 | .88 | .69 | .69 | .95 | .48 | .87 | .81 | .25 | .75 | .43 | .19 | .7 | .74 | .83 | .23 | .22 | .81 | .06 | .08 |
| □ 3 | .79 | .57 | .25 | .84 | .45 | .96 | .06 | .4 | .41 | .5 | .47 | .56 | .18 | .82 | .23 | .62 | .28 | .9 | .09 | .24 | .63 | .02 | .33 | .22 | .38 | .84 | .02 |
| □ 4 | .01 | .57 | .27 | .44 | .3 | .66 | .85 | .59 | .32 | .99 | .98 | .88 | .55 | .11 | .85 | .68 | .88 | .95 | .49 | .38 | .24 | .67 | .83 | .85 | .17 | .36 | .89 |
| □ 5 | .87 | .02 | .91 | .66 | .97 | .86 | .62 | .68 | .24 | .71 | .45 | .35 | .97 | .14 | .96 | .39 | .76 | .74 | .76 | .22 | .53 | .69 | .29 | .7 | .26 | .13 | .9 |
| □ 6 | .61 | .27 | .31 | .55 | .6 | .3 | .95 | .17 | .5 | .36 | .37 | .51 | .14 | .7 | .19 | .38 | .73 | .04 | .57 | .69 | .53 | .22 | .77 | .47 | .37 | .88 | .24 |
| □ 7 | .96 | .82 | .33 | .49 | .49 | .34 | .65 | .02 | .71 | .61 | .07 | .66 | .71 | .68 | .17 | .46 | .84 | .12 | .83 | .14 | .73 | .16 | .24 | .29 | .83 | .86 | .83 |
| □ 8 | .04 | .34 | .02 | .39 | .56 | .76 | .07 | .12 | .48 | .85 | .73 | .28 | .53 | .38 | .32 | .23 | .98 | .32 | .78 | .11 | .2 | .49 | .23 | .55 | .09 | .35 | .29 |
| □ 9 | .19 | .55 | .1 | .97 | .67 | .88 | .37 | .81 | .37 | .53 | .24 | .84 | .84 | .19 | .99 | .5 | .4 | .45 | .6 | .05 | .95 | .9 | .72 | .74 | .01 | .52 | .59 |
| □ 10 | .05 | .79 | .01 | .82 | .05 | .8 | .48 | .56 | .38 | .13 | .11 | .71 | .96 | .7 | .26 | .81 | .5 | .72 | .2 | .56 | .47 | .18 | .85 | .55 | .53 | .24 | .18 |

**Table 3.** Truthness Table

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| □ 1 | .09 | .25 | .48 | .62 | .18 | .86 | .85 | .12 | .56 |
| □ 2 | .68 | .94 | .41 | .69 | .48 | .25 | .19 | .83 | .81 |
| □ 3 | .79 | .84 | .06 | .5 | .18 | .62 | .09 | .02 | .38 |
| □ 4 | .01 | .44 | .85 | .99 | .55 | .68 | .49 | .67 | .17 |
| □ 5 | .87 | .66 | .62 | .71 | .97 | .39 | .76 | .69 | .26 |
| □ 6 | .61 | .55 | .95 | .36 | .14 | .38 | .57 | .22 | .37 |
| □ 7 | .96 | .49 | .65 | .61 | .71 | .46 | .83 | .16 | .83 |
| □ 8 | .04 | .39 | .07 | .85 | .53 | .23 | .78 | .49 | .09 |
| □ 9 | .19 | .97 | .37 | .53 | .84 | .5 | .6 | .9 | .01 |
| □ 10 | .05 | .82 | .48 | .13 | .96 | .81 | .2 | .18 | .53 |

**Table 4.** Indeterminacy Table

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| □ 1 | .7 | .25 | .19 | .64 | .97 | .28 | .16 | .79 | .71 |
| □ 2 | .33 | .98 | .79 | .69 | .87 | .75 | .7 | .23 | .06 |
| □ 3 | .57 | .45 | .4 | .47 | .82 | .28 | .24 | .33 | .84 |
| □ 4 | .57 | .3 | .59 | .98 | .11 | .88 | .38 | .83 | .36 |
| □ 5 | .02 | .97 | .68 | .45 | .14 | .76 | .22 | .29 | .13 |
| □ 6 | .27 | .6 | .17 | .37 | .7 | .73 | .69 | .77 | .88 |
| □ 7 | .82 | .49 | .02 | .07 | .68 | .84 | .14 | .24 | .86 |
| □ 8 | .34 | .56 | .12 | .73 | .38 | .98 | .11 | .23 | .35 |
| □ 9 | .55 | .67 | .81 | .24 | .19 | .4 | .05 | .72 | .52 |
| □ 10 | .79 | .05 | .56 | .11 | .7 | .5 | .56 | .85 | .24 |

**Table 5.** Falsity Table

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| □ 1 | .28 | .07 | .75 | .07 | .25 | .51 | .9 | .71 | .97 |
| □ 2 | .13 | .93 | .88 | .95 | .81 | .43 | .74 | .22 | .08 |
| □ 3 | .25 | .96 | .41 | .56 | .23 | .9 | .63 | .22 | .02 |
| □ 4 | .27 | .66 | .32 | .88 | .85 | .95 | .24 | .85 | .89 |
| □ 5 | .91 | .86 | .24 | .35 | .96 | .74 | .53 | .7 | .9 |
| □ 6 | .31 | .03 | .5 | .51 | .19 | .04 | .53 | .47 | .24 |
| □ 7 | .33 | .34 | .71 | .66 | .17 | .12 | .73 | .29 | .83 |
| □ 8 | .02 | .76 | .48 | .28 | .32 | .32 | .2 | .55 | .29 |
| □ 9 | .1 | .88 | .37 | .84 | .99 | .45 | .95 | .74 | .59 |
| □ 10 | .01 | .8 | .38 | .71 | .26 | .72 | .47 | .55 | .18 |

**Table 6.** Priority Table for Truthness

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| □ 1 | .011 | .059 | .084 | .073 | .032 | .050 | -0.050 | .007 | .002 |
| □ 2 | .080 | .220 | .072 | .081 | .084 | .015 | -0.011 | .049 | .003 |
| □ 3 | .093 | .197 | .011 | .059 | .032 | .036 | -0.005 | .001 | .001 |
| □ 4 | .001 | .103 | .149 | .116 | .097 | .040 | -0.029 | .039 | .001 |
| □ 5 | .102 | .155 | .109 | .083 | .171 | .023 | -0.045 | .040 | .001 |
| □ 6 | .072 | .129 | .167 | .042 | .025 | .022 | -0.033 | .013 | .001 |
| □ 7 | .113 | .115 | .114 | .072 | .125 | .027 | -0.049 | .009 | .003 |
| □ 8 | .005 | .091 | .012 | .100 | .093 | .013 | -0.046 | .029 | .000 |
| □ 9 | .022 | .227 | .065 | .062 | .148 | .029 | -0.035 | .053 | .000 |
| □ 10 | .006 | .192 | .084 | .015 | .169 | .047 | -0.012 | .011 | .002 |

**Table 7.** Priority Table for Indeterminacy

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| □ 1 | .082 | .059 | .033 | .075 | .171 | .016 | -0.009 | .046 | .002 |
| □ 2 | .039 | .230 | .139 | .081 | .153 | .044 | -0.041 | .013 | .000 |
| □ 3 | .067 | .106 | .070 | .055 | .144 | .016 | -0.014 | .019 | .003 |
| □ 4 | .067 | .070 | .104 | .115 | .019 | .052 | -0.022 | .049 | .001 |
| □ 5 | .002 | .227 | .120 | .053 | .025 | .045 | -0.013 | .017 | .000 |
| □ 6 | .032 | .141 | .030 | .043 | .123 | .043 | -0.040 | .045 | .003 |
| □ 7 | .096 | .115 | .004 | .008 | .120 | .049 | -0.008 | .014 | .003 |
| □ 8 | .040 | .131 | .021 | .086 | .067 | .057 | -0.006 | .013 | .001 |
| □ 9 | .064 | .157 | .142 | .028 | .033 | .023 | -0.003 | .042 | .002 |
| □ 10 | .093 | .012 | .098 | .013 | .123 | .029 | -0.033 | .050 | .001 |

**Table 8.** Priority Table for Falsity

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ |
|---|---|---|---|---|---|---|---|---|---|
| □ 1 | .033 | .016 | .132 | .008 | .044 | .030 | -0.053 | .042 | .003 |
| □ 2 | .015 | .218 | .155 | .111 | .142 | .025 | -0.043 | .013 | .000 |
| □ 3 | .029 | .225 | .072 | .066 | .040 | .053 | -0.037 | .013 | .000 |
| □ 4 | .032 | .155 | .056 | .103 | .149 | .056 | -0.014 | .050 | .003 |
| □ 5 | .107 | .202 | .042 | .041 | .169 | .043 | -0.031 | .041 | .003 |
| □ 6 | .036 | .007 | .088 | .060 | .033 | .002 | -0.031 | .028 | .001 |
| □ 7 | .039 | .080 | .125 | .077 | .030 | .007 | -0.043 | .017 | .003 |
| □ 8 | .002 | .178 | .084 | .033 | .056 | .019 | -0.012 | .032 | .001 |
| □ 9 | .012 | .206 | .065 | .098 | .174 | .026 | -0.056 | .043 | .002 |
| □ 10 | .001 | .188 | .067 | .083 | .046 | .042 | -0.028 | .032 | .001 |

**Table 9. Comparison** Table for Truthness

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ | **Score** | **Normalized Score** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| □ 1 | -0.397 | -0.903 | -0.025 | 0.025 | -0.658 | 0.200 | -0.184 | -0.181 | 0.005 | -2.117 | 0.038 |
| □ 2 | 0.294 | 0.715 | -0.148 | 0.107 | -0.130 | -0.157 | 0.203 | 0.236 | 0.014 | 1.134 | 0.808 |
| □ 3 | 0.423 | 0.481 | -0.763 | -0.116 | -0.658 | 0.060 | 0.261 | -0.239 | -0.001 | -0.552 | 0.409 |
| □ 4 | -0.491 | -0.457 | 0.626 | 0.458 | -0.007 | 0.095 | 0.027 | 0.142 | -0.008 | 0.385 | 0.631 |
| □ 5 | 0.517 | 0.059 | 0.222 | 0.130 | 0.732 | -0.075 | -0.131 | 0.154 | -0.005 | 1.601 | 0.919 |
| □ 6 | 0.212 | -0.199 | 0.802 | -0.280 | -0.728 | -0.081 | -0.020 | -0.122 | -0.001 | -0.417 | 0.441 |
| □ 7 | 0.623 | -0.340 | 0.274 | 0.013 | 0.274 | -0.034 | -0.172 | -0.157 | 0.015 | 0.495 | 0.657 |
| □ 8 | -0.456 | -0.574 | -0.746 | 0.294 | -0.042 | -0.169 | -0.143 | 0.036 | -0.011 | -1.810 | 0.110 |
| □ 9 | -0.280 | 0.786 | -0.218 | -0.081 | 0.503 | -0.011 | -0.038 | 0.277 | -0.013 | 0.924 | 0.759 |
| □ 10 | -0.444 | 0.434 | -0.025 | -0.550 | 0.714 | 0.171 | 0.197 | -0.145 | 0.004 | 0.356 | 0.624 |

**Table 10. Comparison** Table for Indeterminacy

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ | **Score** | **Normalized Score** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| □ 1 | 0.239 | -0.661 | -0.427 | 0.193 | 0.728 | -0.211 | 0.097 | 0.154 | 0.007 | 0.119 | 0.568 |
| □ 2 | -0.195 | 1.050 | 0.628 | 0.252 | 0.552 | 0.064 | -0.220 | -0.175 | -0.015 | 1.943 | 1.000 |
| □ 3 | 0.087 | -0.192 | -0.058 | -0.006 | 0.464 | -0.211 | 0.050 | -0.116 | 0.012 | 0.029 | 0.546 |
| □ 4 | 0.087 | -0.544 | 0.276 | 0.592 | -0.784 | 0.141 | -0.032 | 0.177 | -0.005 | -0.093 | 0.518 |
| □ 5 | -0.558 | 1.027 | 0.434 | -0.029 | -0.732 | 0.070 | 0.062 | -0.140 | -0.013 | 0.122 | 0.568 |
| □ 6 | -0.265 | 0.159 | -0.463 | -0.123 | 0.253 | 0.053 | -0.214 | 0.142 | 0.013 | -0.444 | 0.434 |
| □ 7 | 0.380 | -0.098 | -0.726 | -0.475 | 0.218 | 0.117 | 0.108 | -0.169 | 0.013 | -0.632 | 0.390 |
| □ 8 | -0.183 | 0.066 | -0.550 | 0.299 | -0.310 | 0.199 | 0.126 | -0.175 | -0.005 | -0.533 | 0.413 |
| □ 9 | 0.063 | 0.324 | 0.663 | -0.276 | -0.644 | -0.141 | 0.161 | 0.113 | 0.001 | 0.265 | 0.602 |
| □ 10 | 0.345 | -1.130 | 0.223 | -0.428 | 0.253 | -0.082 | -0.138 | 0.189 | -0.009 | -0.777 | 0.355 |

**Table 11.** Comparison Table for Falsity

| $(U,\rho)$ | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_7$ | $\rho_8$ | $\rho_9$ | **Score** | **Normalized Score** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| □ 1 | 0.022 | -1.311 | 0.433 | -0.599 | -0.445 | -0.005 | -0.181 | 0.106 | 0.016 | -1.963 | 0.074 |
| □ 2 | -0.154 | 0.706 | 0.661 | 0.433 | 0.540 | -0.052 | -0.087 | -0.182 | -0.014 | 1.851 | 0.978 |
| □ 3 | -0.013 | 0.776 | -0.165 | -0.025 | -0.480 | 0.224 | -0.022 | -0.182 | -0.017 | 0.097 | 0.562 |
| □ 4 | 0.011 | 0.073 | -0.324 | 0.351 | 0.610 | 0.253 | 0.206 | 0.188 | 0.013 | 1.381 | 0.867 |
| □ 5 | 0.761 | 0.542 | -0.464 | -0.271 | 0.804 | 0.130 | 0.036 | 0.100 | 0.014 | 1.651 | 0.931 |
| □ 6 | 0.057 | -1.405 | -0.007 | -0.083 | -0.550 | -0.280 | 0.036 | -0.035 | -0.009 | -2.276 | 0.000 |
| □ 7 | 0.081 | -0.678 | 0.362 | 0.093 | -0.586 | -0.233 | -0.081 | -0.141 | 0.011 | -1.171 | 0.262 |
| □ 8 | -0.283 | 0.307 | -0.042 | -0.353 | -0.322 | -0.116 | 0.230 | 0.012 | -0.007 | -0.574 | 0.403 |
| □ 9 | -0.189 | 0.589 | -0.236 | 0.304 | 0.856 | -0.040 | -0.210 | 0.123 | 0.003 | 1.201 | 0.824 |
| □ 10 | -0.294 | 0.401 | -0.218 | 0.151 | -0.427 | 0.118 | 0.072 | 0.012 | -0.011 | -0.197 | 0.493 |

Construct the decision table by taking the normalized scores from comparison tables for Truthness, Indeterminacy and Falsity values (Table 12). Compute the neutrosophic score by using the formula in the Equation (4.4). Rank the competitors according to their final score (neutrosophic score). If multiple participants are getting same score, for those participants with same score, repeat all the previous steps ignoring the parameter having lowest rank. Continue the process until all participants getting a distinct rank or reaching the comparison with only the values for the highest ranked parameter.

**Table 12.** Decision Table

| Candidates | Truthness Score | Indeterminacy Score | Falsity Score | Neutrosophic Score | Rank |
|---|---|---|---|---|---|
| □ 1 | 0.0377 | 0.5676 | 0.0741 | -0.0301 | 5 |
| □ 2 | 0.8082 | 1.0000 | 0.9783 | -0.1440 | 8 |
| □ 3 | 0.4087 | 0.5464 | 0.5624 | -0.1409 | 7 |
| □ 4 | 0.6307 | 0.5175 | 0.8668 | -0.2189 | 9 |
| □ 5 | 0.9190 | 0.5684 | 0.9308 | 0.0123 | 4 |
| □ 6 | 0.4405 | 0.4342 | 0.0000 | 0.4556 | 1 |
| □ 7 | 0.6569 | 0.3896 | 0.2619 | 0.4136 | 2 |
| □ 8 | 0.1103 | 0.4132 | 0.4034 | -0.2879 | 10 |
| □ 9 | 0.7586 | 0.6022 | 0.8241 | -0.0443 | 6 |
| □ 10 | 0.6239 | 0.3553 | 0.4928 | 0.1476 | 3 |

In this application, participant C6 is the best fit candidate as per requirements. If multiple candidates need to be selected, it can be selected as per their rankings.

*4.3 Comparative Analysis*

This section provides a comparison analysis with other existing decision-making approaches by using the common neutrosophic data as given in Table 13. Table 14 provides the result of the comparative analysis that establishes the correctness of the approach used in this article.

**Table 13.** Neutrosophic data for comparison

| | $e_1$ | $e_2$ | $e_3$ |
|---|---|---|---|
| $x_1$ | (0.5, 0.4, 0.7) | (0.7, 0.5, 0.1) | (0.6, 0.6, 0.3) |
| $x_2$ | (0.6, 0.5, 0.6) | (0.6, 0.2, 0.2) | (0.5, 0.4, 0.4) |
| $x_3$ | (0.7, 0.3, 0.5) | (0.7, 0.2, 0.1) | (0.7, 0.5, 0.4) |
| $x_4$ | (0.6, 0.4, 0.5) | (0.7, 0.4, 0.2) | (0.5, 0.6, 0.4) |

**Table 14.** Comparison study with some existing methods

| Method | The final ranking | The optimal alternative |
|---|---|---|
| Peng and Liu [32] Algorithm 1 | $x_3 \succ x_2 \succ x_4 \succ x_1$ | $x_3$ |
| Peng and Liu [32] Algorithm 2 | $x_3 \succ x_4 \succ x_1 \succ x_2$ | $x_3$ |
| Peng and Liu [32] Algorithm 3 | $x_3 \succ x_4 \succ x_2 \succ x_1$ | $x_3$ |
| Deli and Broumi [33] | $x_3 \succ x_4 \succ x_1 \succ x_2$ | $x_3$ |
| Maji [34] | $x_3 \succ x_4 \succ x_1 \succ x_2$ | $x_3$ |
| Karaaslan [35] | $x_3 \succ x_4 \succ x_1 \succ x_2$ | $x_3$ |
| Deli and Broumi [36] | $x_3 \succ x_4 \succ x_1 \succ x_2$ | $x_3$ |
| **Proposed Algorithm** | $x_3 \succ x_1 \succ x_4 \succ x_2$ | $x_3$ |

**Reason behind the obtained result**: $x_3$ is best of all in both $T$ (higher) and $F$ (Lower) aspects. Similarly, $x_2$ is worst of all in both $T$ (higher) and $F$ (Lower) values. $x_1 \succ x_4$ because $x_1$ in 2nd and 3rd parameter is having lower $F$ value. Other values are just cancelling out each other as $F$ and $T$ both are increasing or decreasing. It seems, the ordering is logical, which matches with the outcome of our algorithm.

## 5. Conclusions

In this article an MCDM algorithm based on NSS is introduced to model an interview process and rank the candidates. A general score function is introduced, in the algorithm by taking into account the three parameters of a NS (namely Truth, falsity and Indeterminancy). It is capable of ordering the neutrosophic values efficiently. To show the adequateness of the approach and establish its superiority, the results are compared with those of many of the existing algorithms in this direction It is to note that the outcome of the algorithm is natural and matches with the anticipations. Further extensions of our algorithm can be carried out by considering the generalisations of the soft set model in thr fom of Hypersoftset, IndermSoftset, IndetermHyperSoftset, Tree Softset and PlithogenicHyperSoftset models.

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