RETRIEVING THE MISSING DATA FROM DIFFERENT INCOMPLETE SOFT SETS

Julee Srivastava
Assistant Professor, Department of Mathematics and Statistics, Deen Dayal Upadhyaya Gorakhpur University. Gorakhpur (India).
E-mail: mathjulee@gmail.com
ORCID: https://orcid.org/0000-0002-1764-7797

Sudhir Maddheshiya
Research Scholar, Department of Mathematics and Statistics, Deen Dayal Upadhyaya Gorakhpur University. Gorakhpur (India).
E-mail: sudhirmaddy149@gmail.com
ORCID: https://orcid.org/0000-0001-6027-7245

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ABSTRACT

Dealing an incomplete information has been a major issue in the theory of soft sets. In this paper, we have presented an approach to deal with incomplete soft set, incomplete fuzzy soft set and incomplete intuitionistic fuzzy soft set. For this purpose we have discussed about the notion of distance between two objects (parameters) which will be used to compute the degree of interdependence between them. This approach will use the full information of known data and the relationships between them. Data filling converts an incomplete soft set into complete one which makes the soft sets applicable not only to decision making but also to other fields.

KEYWORDS

Soft set, incomplete information system, fuzzy soft set, object parameter approach.

1 INTRODUCTION

There are various real life problems involving uncertainties and classical mathematical tools are not sufficient for handling them. There are many theories developed recently for dealing with them. Some of them are probability theory, theory of fuzzy sets [16], theory of intuitionistic fuzzy sets [1, 2], theory of vague sets [4], theory of interval mathematics [11] and theory of rough sets [13]. All of these theories have their own advantages and some limitations as well. For example, in the theory of fuzzy sets and intuitionistic fuzzy sets, it is very difficult to choose the membership and non membership functions that give us the desired result; in the theory of probability the outcomes of an event must be unbiased; in the theory of rough sets, the indiscernibility relation may create a situation where two completely different objects are same. One major common drawback of these theories is probably the inadequacy of parameterization tools which was observed by Molodtsov in 1999. Consequently he introduced the concept of soft set theory [10] that is free from the difficulties that have troubled the usual theoretical approaches. The absence of any restriction on the approximate description in soft set theory makes it easily applicable in practice. A soft set model requires no prior knowledge of data sets. Molodtsov provided several applications of soft set theory in his work. Maji et al. [9] introduced fuzzy soft set by allowing the parameters to be mapped to the fuzzy sets. Further allowing the parameters to be mapped to the intuitionistic fuzzy sets, Maji et al. [8] introduced the concept of intuitionistic fuzzy soft set which is a generalization of standard soft set and fuzzy soft set in the sense that it is a soft set whose approximate values are the intuitionistic fuzzy sets.

Lots of research work are currently active in the field of theoretical and practical soft sets. The major portion of these works is based on complete information. However, incomplete information widely exists in real life due to mishandling data, mistakes in processing or transferring data, mistakes in measuring and collecting data or any other factor. Soft set under incomplete information is referred to as an incomplete soft set. Similarly fuzzy soft set and intuitionistic fuzzy soft set under incomplete information are referred to as incomplete fuzzy soft set and incomplete intuitionistic fuzzy soft set respectively.

The simplest approach to transform an incomplete data set to a complete one is to delete all objects related to missing information. But in this process we may deduce wrong information from it. On the other hand, predicting the unknown information gives more fruitful results. Zou et al. [17] initiated the study of incomplete soft sets. For incomplete soft set, they computed decision values rather than filling the empty cells in the corresponding incomplete information system. The decision values are calculated by the weighted average of all the choice values and the weight of each choice value is decided by the distribution of other available objects. Incomplete fuzzy soft set is completed by the method of average probability. Zou's method is too complicated and it does not fill the empty cells of the corresponding information system. So the soft set obtained by this method is only useful in decision making. Using average probability method we can predict individual unknown value of fuzzy soft set but all the predicted values of a parameter for different objects are equal, so this method is also of low accuracy. Kong et al. [6] proposed a simple method equivalent to that of Zou which fills the empty cells. To fill the empty cells in the incomplete information system, Kong's method uses the values of target parameter (the parameter for which the cell is empty) on the objects other than target object (the object for which the cell is empty). Qin et al. [14] presented a method called DFIS (data filling approach for incomplete soft set). In that paper, empty cells are filled in terms of the association degree between the parameters, when a strong association exists between the parameters, otherwise they are filled in terms of probability of other available objects. Khan et al. [5] proposed an alternative data filling approach for incomplete soft set (ADFIS) to predict the missing data in soft sets. In ADFIS, the value of the empty cell whose corresponding parameter has strongest association is computed first. Unlike the DFIS, before filling second empty cell, the value of the first is inserted in the information table. But the drawback of DFIS and ADFIS is that a parameter can have strongest association or maximal association with more than one parameters having opposite type of association. In that case empty cell can't be filled. This method considers only the relation between parameters and does not take the effect of objects into account. However there may be some relationship between objects too. For example the houses in same locality have nearly same price. Deng et al. [3] introduced an object-parameter

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approach which uses the full information between object and between parameters. Deng's approach has some drawbacks as: (i) the estimated value may not be in the interval [0,1]; (ii) the information between objects and between parameters is not comprehensive. To overcome these drawbacks Liu et al. [7] improved Deng's approach by redefining the notion of distance and dominant degree.

It is a review paper. In paper [15] we have put forward an algorithm to predict missing data in an incomplete soft set and incomplete fuzzy soft set. For this we have defined the notion of distance (emerged from the concept of Euclidean distance in $\mathbb{R}^n$) between two objects (parameters) and defined the degree of interdependence between two objects (parameters). And thus we have taken account of the effect of other objects (parameters) on the target object (parameter). This algorithm uses the full available data to reveal the hidden relationship between objects (parameters). Moreover we have introduced an approach to predict missing data in an incomplete intuitionistic fuzzy soft set with the help of algorithm for incomplete soft set and incomplete fuzzy soft set.

Rest of the paper has been organized as follows. Section 2 recalls the basic definitions and concepts of soft set theory and information system. In section 3 we have introduced an algorithm to predict missing data in an incomplete soft set and incomplete fuzzy soft set and given an application through an example. In section 4, we have given an algorithm to predict the missing data in an incomplete intuitionistic fuzzy soft set and given an application through an example. Finally we have concluded this paper in section 5.

2 PRELIMINARIES

Let $U = \{u_1, u_2, \ldots, u_m\}$ be a universe set of objects and $E = \{e_1, e_2, \ldots, e_n\}$ be a set of parameters.

Definition 1 (Fuzzy set). *[16] A fuzzy set A over U is given by*

$$A = \{\langle u, \mu_A(u)\rangle | u \in U\}$$

where $\mu_A : U \to [0, 1]$ is called the membership function of the fuzzy set A. $\mu_A(u)$ is said to be the degree of membership of u in A.

Definition 2 (Intuitionistic fuzzy set). *[1] An intuitionistic fuzzy set (IFS) A over U is given by*

$$A = \{\langle u, \mu_A(u), \nu_A(u)\rangle | u \in U; \mu_A(u), \nu_A(u) \in [0, 1] \text{ and } \mu_A(u) + \nu_A(u) \leq 1\}\}$$

where $\mu_A : U \to [0, 1]$ and $\nu_A : U \to [0, 1]$ are said to be the membership and non membership functions of the intuitionistic fuzzy set A respectively.

Definition 3 (Soft set). *[10] A pair $A = (F, E)$ is said to be a soft set over U, where F is a mapping from E to $\mathcal{P}(U)$ (set of all crisp subsets of U). Sometimes it is also called a crisp soft set to emphasize the fact that $F(e)$ is a crisp set for every $e \in E$.*

Alternatively, a soft set A is given by

$$A = \{F(e)|e \in E\}$$

where F is a mapping from E to $\mathcal{P}(U)$.

Definition 4 (Fuzzy soft set). *[9] A pair $A = (F, E)$ is said to be a fuzzy soft set over U, where F is a mapping from E to $\mathcal{F}(U)$ (set of all fuzzy sets over U).*

Alternatively, a fuzzy soft set A is given by

$$A = \{F(e)|e \in E\}$$

where F is a mapping from E to $\mathcal{F}(U)$.

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Definition 5 (Intuitionistic fuzzy soft set)**.** *[8] A pair $A = (F, E)$ is said to be an intuitionistic fuzzy soft set (IFSS) over U, where F is a mapping from E to $\mathcal{IF}(U)$ (set of all intuitionistic fuzzy sets over U).*

Alternatively, an intuitionistic fuzzy soft set A is given by

$$A = \{F(e)|e \in E\}$$

where F is mapping from E to $\mathcal{IF}(U)$.

Definition 6 (Information system)**.** *[12] A quadruple $S = (U, A, F, V)$ is called an information system, where $U = \{u_1, u_2, \ldots, u_m\}$ is a universe of discourse, $A = \{a_1, \ldots, a_n\}$ is a set of attributes and $V = \bigcup_{j=1}^{n} V_j$, where each V_j is the value set of the attribute a_j and $F = \{f_1, \ldots, f_n\}$ where $f_j : U \to V_j$ for every j.*

If $V_j = \{0, 1\}$ for every $1 \leq j \leq n$ then the corresponding information system is called Boolean valued information system and if $V_j = [0, 1]$ for every $1 \leq j \leq n$ then the corresponding information system is called fuzzy information system. In an information system $u_{ik} = f_k(u_i)$ denotes the value of the attribute a_k on the object u_i. An information system is often represented by an information table.

Remark: (i) Every soft set can be considered as a Boolean valued information system with each entry filled by 1 or 0 depending on whether an object belongs to range of the parameter or not.
(ii) Every fuzzy soft set can be considered as a fuzzy information system with each entry filled by a quantity in $[0, 1]$ which represents the membership degree of object in the range of the related parameter.
(iii) Every intuitionistic fuzzy soft set can be considered as an information system with each entry filled by an element of $[0, 1] \times [0, 1]$ where the first and second coordinates represent the membership degree and non membership degree of the object in the range of the related parameter respectively.

Example 2.1. Every incomplete soft set can be considered as an incomplete information system. Examples of incomplete soft set, incomplete fuzzy soft set and incomplete intuitionistic fuzzy soft set are given in table 1, 2 and 3 respectively. The unknown value in incomplete information system is denoted by '$*$'.

Table 1 – Incomplete soft set

U	e_1	e_2	e_3	e_4	e_5	e_6
u_1	1	0	1	0	1	0
u_2	1	0	0	1	0	0
u_3	0	1	0	0	1	0
u_4	0	1	$*$	1	0	$*$
u_5	1	0	1	1	0	0
u_6	0	1	0	0	$*$	0
u_7	1	$*$	1	0	1	0
u_8	0	0	1	1	0	0

Table 2 – Incomplete fuzzy soft set

U	e_1	e_2	e_3	e_4	e_5	e_6	e_7
u_1	0.9	0.4	0.1	0.9	0.6	0.3	0.4
u_2	0.8	0.6	0.5	$*$	0.5	0.3	0.3
u_3	$*$	0.8	0.9	$*$	0.9	0.9	0.9
u_4	0.9	0.8	0.9	0.8	$*$	0.8	0.9
u_5	0.9	0.2	0.2	0.6	0.3	0.4	$*$
u_6	0.9	0.2	0.4	0.4	0.4	0.3	0.3

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Table 3 – Incomplete Intuitionistic fuzzy soft set

U	e_1	e_2	e_3	e_4	e_5	e_6
u_1	(0.8,0.1)	(0.2,0.1)	(0.8,0.1)	(0.4,0.5)	(0.4,0.5)	(0.6,0.2)
u_2	(0.8,0.2)	(0.8,0.1)	(0.7,0.2)	(0.6,0.4)	(0.5,0.5)	(0.6,0.2)
u_3	(0.7,0.2)	(0.3,0.1)	(0.8,0.2)	$*$	(0.6,0.1)	(0.4,0.2)
u_4	(0.6,0.2)	(0.7,0.2)	(0.7,0.3)	(0.4,0.3)	(0.7,0.1)	(0.6,0.1)
u_5	(0.5,0.3)	(0.6,0.3)	(0.4,0.5)	(0.7,0.3)	(0.8,0.1)	$*$
u_6	(0.2,0.4)	(0.4,0.4)	(0.5,0.5)	(0.4,0.3)	(0.4,0.3)	(0.5,0.1)
u_7	(0.7,0.2)	(0.8,0.1)	(0.5,0.4)	(0.9,0.1)	(0.5,0.3)	(0.4,0.1)

3 ALGORITHM TO PREDICT MISSING DATA IN AN INCOMPLETE SOFT SET AND INCOMPLETE FUZZY SOFT SET AND ITS APPLICATION

3.1 A PREPARATORY STEP

There is always a direct or indirect relationship between objects (parameters). To measure this relationship, we will define the 'degree of interdependence' between objects (parameters). To determine the unknown value in the incomplete soft set we will examine the remaining known values and interdependence between target object (parameter) and other objects (parameters).

Let $U = \{u_1, u_2, \ldots, u_m\}$ be universe set of objects and $E = \{e_1, e_2, \ldots, e_n\}$ be set of parameters. Suppose that $\mu_{F(e_k)}(u_i) = u_{ik}$. For every $1 \leq i \leq m$; denote $E^{(i)} = \{k|u_{ik} \neq *\}$ and for every $1 \leq k \leq n$; $U^{(k)} = \{i|u_{ik} \neq *\}$.

Now we will define distance and degree of interdependence between two objects and between two parameters.

Definition 7 (Distance). *For u_i and u_j in U, the distance between u_i and u_j is defined by*

$$d(u_i, u_j) = \left(\sum_{k \in E^{(i)} \cap E^{(j)}} (u_{ik} - u_{jk})^2 \right)^{1/2} \tag{1}$$

where $E^{(i)} \cap E^{(j)} = \{k|u_{ik} \neq * \text{ and } u_{jk} \neq *\}$.

Similarly, for e_k and e_l in E, distance between e_k and e_l is defined by

$$d(e_k, e_l) = \left(\sum_{i \in U^{(k)} \cap U^{(l)}} (u_{ik} - u_{il})^2 \right)^{1/2} \tag{2}$$

where $U^{(k)} \cap U^{(l)} = \{i|u_{ik} \neq * \text{ and } u_{il} \neq *\}$.

Definition 8 (Degree of Interdependence). *For u_i and u_j in U, the degree of interdependence between u_i and u_j is denoted by α_{ij} and is defined as* $\alpha_{ij} = \frac{1}{1+d(u_i,u_j)}$.

Similarly, for e_k and e_l in E, the degree of interdependence between e_k and e_l is denoted by β_{kl} and is defined as $\beta_{kl} = \frac{1}{1+d(e_k,e_l)}$.

Suppose that the value u_{ik} is missing, then we will call u_i as target object and e_k as target parameter. The prediction of u_{ik} will contain two parts: (i) object part u_{ik}^{obj} and (ii) parameter part u_{ik}^{par}. As the distance between two objects (parameters) increases, the interdependence between them decreases. So the objects (parameters) which are nearer to target object (parameter) will be more reliable to determine the object (parameter) part of the unknown value. Object part of an unknown value is determined using the values of the target parameter on the objects other than target object and the parameter part is determined using the values of all parameters other than target parameter on target object.

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3.2 ALGORITHM

Suppose we have to predict the value of u_{ik}. Before giving Algorithm we define some notations here:

$U_i^* = \{p|u_p \in U - \{u_i\}$ and $u_{pk} \neq *\}$ and

$E_k^* = \{q|e_q \in E - \{e_k\}$ and $u_{iq} \neq *\}$

And we define U_r and E_r recursively as

$U_r = \{j_r|d(u_i, u_{j_r}) = \min\limits_{j \in U_i^* - (U_0 \cup U_1 \cup \cdots \cup U_{r-1})} d(u_i, u_j)\}$; where $U_0 = \emptyset$.

$E_r = \{l_r|d(e_k, e_{l_r}) = \min\limits_{l \in E_k^* - (E_0 \cup E_1 \cup \cdots \cup E_{r-1})} d(e_k, e_l)\}$; where $E_0 = \emptyset$.

First we compute the object part:

1. Input the incomplete soft set (F, E).
2. Find u_i such that u_{ik} is unknown.
3. Compute $d(u_i, u_j)$ for all $j \in U_i^*$.
4. Let $\bar{u}_{ik}^{1,obj} = \frac{\sum\limits_{j_1 \in U_1} u_{j_1 k}}{|U_1|}$.
5. Compute degree of interdependence between u_i and u_{j_1}, which is given by $\alpha_{ij_1} = \frac{1}{1+d(u_i,u_{j_1})}$ where $j_1 \in U_1$.
6. Define $u_{ik}^{1,obj} = \bar{u}_{ik}^{1,obj} \times \alpha_{ij_1}$.
7. Let $\bar{u}_{ik}^{2,obj} = \frac{\sum\limits_{j_2 \in U_2} u_{j_2 k}}{|U_2|}$.
8. Compute degree of interdependence between u_i and u_{j_2}, which is given by $\alpha_{ij_2} = \frac{1}{1+d(u_i,u_{j_2})}$ where $j_2 \in U_2$.
9. Define $u_{ik}^{2,obj} = \bar{u}_{ik}^{2,obj} \times \alpha_{ij_2}$.
10. Continue in this way until $U_1 \cup U_2 \cup \cdots \cup U_t = U_i^*$.
11. Hence object part of unknown value $u_{ik}^{obj} = \frac{\sum\limits_{r=1}^{t} u_{ik}^{r,obj}}{\sum\limits_{r=1}^{t} \alpha_{ij_r}}$.

Now we compute the parameter part:

1. Input the incomplete soft set (F, E).
2. Find e_k such that u_{ik} is unknown.
3. Compute $d(e_k, e_l)$ for all $l \in E_k^*$.
4. Let $\bar{u}_{ik}^{1,par} = \frac{\sum\limits_{l_1 \in E_1} u_{il_1}}{|E_1|}$.
5. Compute degree of interdependence between e_k and e_{l_1}: $\beta_{kl_1} = \frac{1}{1+d(e_k,e_{l_1})}$ for $l_1 \in E_1$.
6. Define $u_{ik}^{1,par} = \bar{u}_{ik}^{1,par} \times \beta_{kl_1}$.
7. Let $\bar{u}_{ik}^{2,par} = \frac{\sum\limits_{l_2 \in E_2} u_{il_2}}{|E_2|}$.
8. Compute degree of interdependence between u_k and u_{l_2}: $\beta_{kl_2} = \frac{1}{1+d(e_k,e_{l_2})}$ for $l_2 \in E_2$.

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9. Define $u_{ik}^{2,par} = \bar{u}_{ik}^{2,par} \times \beta_{kl_2}$.
10. Continue in this way until $E_1 \cup E_2 \cup \cdots \cup E_t = E_k^*$.
11. Hence parameter part of unknown value is $u_{ik}^{par} = \frac{\sum_{r=1}^{t} u_{ik}^{r,par}}{\sum_{r=1}^{t} \beta_{kl_r}}$.

Now the unknown value u_{ik} of a fuzzy soft set can be predicted by the equation

$$u_{ik} = w_1.u_{ik}^{obj} + w_2.u_{ik}^{par} \tag{3}$$

where w_1 and w_2 are weights of the objects and parameters measuring the impact on unknown data, respectively. The weights can be assigned according to the given problem. If the objects and parameters are treated equally, the weights can be set as $w_1 = w_2 = \frac{1}{2}$.

In case u_{ik} is an unknown value of a soft set then we compute $h_{ik} = w_1.u_{ik}^{obj} + w_2.u_{ik}^{par}$ as above. If $h_{ik} < \frac{1}{2}$, put $u_{ik} = 0$ and if $h_{ik} \geq \frac{1}{2}$, put $u_{ik} = 1$.

3.3 APPLICATION OF ALGORITHM FOR INCOMPLETE SOFT SET

Consider the incomplete soft set represented in tabel 1. In this table there are eight objects, six parameters and four unknown values to be predicted. Suppose that the weights of objects and parameters be equal, i.e., $w_1 = w_2 = \frac{1}{2}$. By using our algorithm we compute $h_{43} = 0.5628$, $h_{46} = 0.2682$, $h_{65} = 0.4903$, $h_{72} = 0.4334$. Since $h_{43} > \frac{1}{2}$, $h_{46} < \frac{1}{2}$, $h_{65} < \frac{1}{2}$ and $h_{72} < \frac{1}{2}$, therefore we obtain $h_{43} = 1$, $h_{46} = 0$, $h_{65} = 0$, $h_{72} = 0$.

3.4 APPLICATION OF ALGORITHM FOR INCOMPLETE FUZZY SOFT SET

Consider the incomplete fuzzy soft set represented in table 2. In this table there are six objects, seven parameters and five unknown values to be predicted. Here also we suppose that the weights of objects and parameters are equal, i.e., $w_1 = w_2 = \frac{1}{2}$. By using our algorithm we obtain the unknown values as $u_{24} = 0.5825$, $u_{31} = 0.8815$, $u_{34} = 0.7910$, $u_{45} = 0.7202$, $u_{57} = 0.4575$.

4 ALGORITHM TO PREDICT MISSING DATA IN AN INCOMPLETE INTUITIONISTIC FUZZY SOFT SET AND ITS APPLICATION

4.1 A PREPARATORY STEP

To predict the unknown values of incomplete intuitionistic fuzzy sets we will construct four fuzzy soft sets from given intuitionistic fuzzy soft set as follows. We take an example given in table 3 to make it more clear. For this incomplete intuitionistic fuzzy soft set we construct four tables; first by using membership degrees (table 4), second by using non membership degrees (table 5), third by using the sum of membership and non membership degrees (table 6) and fourth by their differences (table 7).

Table 4 – Membership degrees

U	e_1	e_2	e_3	e_4	e_5	e_6
u_1	0.8	0.2	0.8	0.4	0.4	0.6
u_2	0.8	0.8	0.5	0.6	0.5	0.6
u_3	0.7	0.3	0.8	$*$	0.6	0.4
u_4	0.6	0.7	0.7	0.4	0.7	0.6
u_5	0.5	0.6	0.4	0.7	0.8	$*$
u_6	0.2	0.4	0.5	0.4	0.4	0.5
u_7	0.7	0.8	0.5	0.9	0.5	0.4

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Table 5 – Non membership degrees

U	e_1	e_2	e_3	e_4	e_5	e_6
u_1	0.1	0.1	0.1	0.5	0.5	0.2
u_2	0.2	0.1	0.2	0.4	0.5	0.2
u_3	0.2	0.1	0.2	$*$	0.1	0.2
u_4	0.2	0.2	0.3	0.3	0.1	0.1
u_5	0.3	0.3	0.5	0.3	0.1	$*$
u_6	0.4	0.4	0.5	0.3	0.3	0.1
u_7	0.2	0.1	0.4	0.1	0.3	0.1

Table 6 – Sum of membership and non membership degrees

U	e_1	e_2	e_3	e_4	e_5	e_6
u_1	0.9	0.3	0.9	0.9	0.9	0.8
u_2	1	0.9	0.7	1	1	0.8
u_3	0.9	0.4	1	$*$	0.7	0.6
u_4	0.8	0.9	1	0.7	0.8	0.7
u_5	0.8	0.9	0.9	1	0.9	$*$
u_6	0.6	0.8	1	0.7	0.7	0.6
u_7	0.9	0.9	0.9	1	0.8	0.5

Table 7 – Difference of membership and non membership degrees

U	e_1	e_2	e_3	e_4	e_5	e_6
u_1	0.7	0.1	0.7	0.1	0.1	0.4
u_2	0.6	0.7	0.3	0.2	0	0.4
u_3	0.5	0.2	0.6	$*$	0.5	0.2
u_4	0.4	0.5	0.4	0.1	0.6	0.5
u_5	0.2	0.3	0.1	0.4	0.7	$*$
u_6	0.2	0	0	0.1	0.1	0.4
u_7	0.5	0.7	0.1	0.8	0.2	0.3

4.2 ALGORITHM

Suppose we have to predict the unknown value of $(\mu_{F(e_k)}(u_i), \nu_{F(e_k)}(u_i)) = (u_{ik}, v_{ik})$. Let m_{ik}, n_{ik}, s_{ik} and t_{ik} denote the corresponding unknown values of fuzzy soft set of membership degrees, fuzzy soft set of non membership degrees, fuzzy soft set of sum of membership and non membership degrees and fuzzy soft set of difference of membership and non membership degrees respectively.

1. Input the incomplete intuitionistic fuzzy soft set.
2. Compute $s_{ik} = u_{ik} + v_{ik}$ using algorithm 3.2.
3. Compute $t_{ik} = |u_{ik} - v_{ik}|$ using algorithm 3.2.
4. Compute m_{ik} and n_{ik} using algorithm 3.2.
5. If $m_{ik} > n_{ik}$, put $|u_{ik} - v_{ik}| = u_{ik} - v_{ik}$ otherwise put $|u_{ik} - v_{ik}| = v_{ik} - u_{ik}$. Accordingly we get $t_{ik} = u_{ik} - v_{ik}$ or $t_{ik} = v_{ik} - u_{ik}$.
6. Solve equations obtained from step (ii) and step (v) to get the values of u_{ik} and v_{ik}.

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4.3 APPLICATION

Consider the incomplete intuitionistic fuzzy soft set given in table 3. In this table there are seven objects, six parameters and two unknown values to be predicted. Here also we suppose that the weights of objects and parameters are equal, i.e., $w_1 = w_2 = \frac{1}{2}$. Now we predict the two unknown values (u_{34}, v_{34}) and (u_{56}, v_{56}) as follows:

For (u_{34}, v_{34}) we obtain $m_{34} = 0.5609$, $n_{34} = 0.2360$, $s_{34} = 0.8086$ and $t_{34} = 0.3331$. Using algorithm 4.2 we get $u_{34} = 0.5709$ and $v_{34} = 0.2377$.

For (u_{56}, v_{56}) we obtain $m_{56} = 0.5598$, $n_{56} = 0.2273$, $s_{56} = 0.7804$ and $t_{56} = 0.3523$. Using algorithm 4.2 we get $u_{56} = 0.5664$ and $v_{56} = 0.2140$.

5 CONCLUSION

This paper analyzes the effect of known data on unknown ones in an incomplete data set and proposes algorithms to predict unknown values. The concept of Euclidean distance on $\mathbb{R}^n$ is used to measure the distance between objects (parameters). This distance is further used in measuring the degree of interdependence between objects (parameters). An approach to predict the missing data in an intuitionistic fuzzy set is also given.

Our proposed methodology has the following advantages:

1. There is only one basic algorithm (algorithm 3.2) given in this paper which is used to predict the missing data in each of incomplete soft set, incomplete fuzzy soft set and incomplete intuitionistic fuzzy soft set.
2. Algorithms given in this paper makes full use of known data so that the predicted values have higher accuracy.
3. The basic algorithm 3.2 produces a finite sequence of predictions based on the distance and degree of interdependence between objects (parameters).
4. In this paper the relation between objects (parameters) is determined using degree of interdependence. If the degree of interdependence between an object (parameter) and the target object (parameter) is less, then the missing values corresponding to the target object (parameter) is less expected to be same as the corresponding values of former object (parameter).
5. The algorithm 3.2 predicts the unknown values of incomplete soft set to be in $\{0, 1\}$ precisely.
6. Algorithm 4.2 predicts the unknown values of incomplete intuitionistic fuzzy soft set.

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REFERENCES

[1] **Atanassov, K.** (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems, 20*, 87–96 pp.

[2] **Atanassov, K.** (1994). Operators over interval valued intuitionistic fuzzy sets. *Fuzzy Sets and Systems, 64*, 159–174 pp.

[3] **Deng, T.** and **Wang, X.** (2013). An object-parameter approach to predicting unknown data in incomplete fuzzy soft sets. *Applied Mathematical Modelling, 37*, 4139–4146 pp.

[4] **Gau, W.L.** and **Buehrer, D.J.** (1993). Vague sets. *IEEE Transactions on Systems, Man, and Cybernetics, 23*, 610–614 pp.

[5] **Khan, M.S.**, **Al-Garadi, M.A.**, **Wahab A.W.A.** and **Herawan, T.** (2016). An alternative data filling approach for prediction of missing data in soft sets (ADFIS). *SpringerPlus, 5*.

[6] **Kong, Z.**, **Zhang, G.**, **Wang, L.**, **Wu, Z.**, **Qi, S.** and **Wang, H.** (2014). An efficient decision making approach in incomplete soft set. *Applied Mathematical Modelling, 38*, 2141–2150 pp.

[7] **Liu, Y.**, **Qin, K.**, **Rao, C.** and **Mahamadu, M.A.** (2017). Object-parameter approaches to predicting unknown data in an incomplete fuzzy soft set. *International Journal of Applied Mathematics and Computer Science, 27*, 157–167 pp.

[8] **Maji, P.K.**, **Biswas, R.** and **Roy, A.R.**(2001). Intuitionistic fuzzy soft sets. *The Journal of Fuzzy Mathematics, 9*, 677–692 pp.

[9] **Maji, P.K.**, **Biswas, R.** and **Roy, A.R.** (2001). Fuzzy soft sets. *Journal of Fuzzy Mathematics, 9*, 589–602 pp.

[10] **Molodtsov, D.** (1999). Soft set theory-first results. *Computers and Mathematics with Applications, 37*, 19–31 pp.

[11] **Moore, R.E.** (1962). Interval arithmetic and automatic error analysis in digital computing. *Ph.D. dissertation, Department of Mathematics, Stanford University, Stanford*.

[12] **Pawlak, Z.** (1981). Information systems theoretical foundations. *Information systems, 6*, 205–218 pp.

[13] **Pawlak, Z.** (1982). Rough sets. *International Journal of Computer and Information Sciences, 11*, 341–356 pp.

[14] **Qin,H**, **Ma, X.**, **Herawan, T.** and **Zain, J.M.** (2012). A novel data filling approach for an incomplete soft set. *International Journal of Applied Mathematics and Computer Science, 22*, 817–828 pp.

[15] **Srivastava, J.** and **Maddheshiya, S.** (2022). Retrieving the Missing Data From Incomplete Soft Set, Incomplete Fuzzy Soft Set and Incomplete Intuitionistic Fuzzy Soft Set. *New Mathematics and Natural Computation*. https://doi.org/10.1142/S1793005722500430.

[16] **Zadeh, L.A.** (1965). Fuzzy sets. *Information and Control, 8*, 338–353 pp.

[17] **Zou, Y.** and **Xiao, Z.** (2008). Data analysis approaches of soft sets under incomplete information. *Knowledge-Based Systems, 21*, 941–945 pp.