Algorithms for Covid-19 Outbreak using Soft Set Theory: Estimation and Application

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Algorithms for Covid-19 outbreak using soft set theory: estimation and application

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Abstract

Coronavirus disease (COVID-19) is a novel pandemic disease. COVID-19 originates from SARS-COV2 and represents the cause of a potentially fatal disease as a global public health problem. However, we have to renew our knowledge about the symptoms of this disease day by day. If we look generally; although the main symptoms seen in this epidemic are fever, cough and shortness of breath, cases without symptoms are also reported. Moreover, in severe cases, pneumonia, severe respiratory failure, kidney failure and death may develop. In this paper, it is suggested that all the different symptoms that may occur in various regions of the world should be taken into consideration and each region should be evaluated within itself. Moreover, in order to have an idea of the general situation, it was taken into account in the average case. For this, two algorithms were built by using soft set theory. The first of the algorithms focuses on the analysis of the relationships between the symptoms and aims to measure a possible effect of the symptoms on each other. The second one aims to identify the most dominant symptom. The results obtained by utilizing both algorithms argue that it is more useful to examine different regions in order to better manage the epidemic. Moreover, some consistent results have been obtained as to which parameters a person should show first in order to Covid test.

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1. Introduction

One of the most important properties to be addressed in order to increase the robustness of the results obtained in data analysis is the elimination of uncertainty. However, it is often not an easy task to decompose the existing uncertainty to eliminate the uncertainty. For this reason, many mathematical approaches developed for data analysis have been insufficient to achieve these goals. Fuzzy sets [4], rough sets [3] and intuitionistic fuzzy sets [1] are some of the main mathematical approaches that aim to eliminate the uncertainty in data analysis. Obtaining more successful results with these set types has led to divergences from classical mathematics aimed at eliminating uncertainty. However, the fact that they are not practical in expressing the uncertainty has brought some difficulties in the functioning of the decision-making processes. Molodtsov [2] suggested soft sets, considering that the main reason for these difficulties is the lack of a parameterization tool. Since objects providing parameters can be expressed in a soft set, it is a very successful mathematical model for processing decision-making processes that focus on the selection of the best option. These sets are still used in many studies aiming to eliminate

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the uncertainty [5–11].

One of the biggest uncertainty problems faced today is how we should act to defeat the Covid-19 epidemic. With the emergence of the Covid-19 epidemic disease, no definitive treatment has yet been found for this disease. However, some interesting differences have been identified in how this epidemic behaves in many countries. For example; in Italy, the death rate due to this epidemic is quite high, despite strong restrictions on social interactions. In contrast, despite the fact that some social isolations are not implemented in Japan [12], the death rate due to Covid-19 is at a very low level. The reason for these different observations is thought to be based on differences in medical care standards as well as differences in cultural norms. Besides these, differences in Covid-19 mortality morbidity between countries or regions can be partially explained by policies on Bacillus Calmette-Guérin (BCG) vaccination [13]. The reasons for these differences can be increased. This paper has been analyzed how a decision-making process should be managed for the following uncertainty problems encountered in this epidemic that has taken the world under its influence.

- What symptoms should a person be expected to show in order to have a Covid test? This is a very important problem in terms of workload and cost.
- Can measurement of this difference be made as a result of the possible difference in the symptoms observed in different regions? That is, can the symptoms be analyzed by making a comparison between regions? In this way, the variability of the measures to be taken can be mentioned.
- How can interactions between symptoms be measured? Thus, by determining the dominance of a symptom among other symptoms, the effect of symptoms on the disease can be observed more easily.
- For these uncertainty problems, the concepts of interaction function and parametric effect function were introduced and two algorithms based on them were proposed.

The paper is structured as follows: in section 2, we recall some basic notions in a soft set. Next, section 3 is about structuring some technical formulations for decision-making algorithms built in the later section of the paper. In addition, the concepts given in this section are examined in detail. Section 4 is the part where the main results of the paper are given. In this section, two algorithms for the Covid-19 pandemic are proposed. Moreover, these algorithms can manage decision-making processes in many uncertain environments. Algorithms were analyzed in detail and the results obtained were examined. Finally, we conclude the paper in section 5.

2. Preliminaries

In this section, some basic concepts for soft set theory, which this paper focuses on, are reminded.

Throughout this paper, let U be an initial universe and S^X denotes the power set of $X \subseteq U$. Also, E be a set of parameters and A, B, C be non-empty subsets of E.

Definition 2.1. [2] A soft set F_A over $X \subseteq U$, denoted by F_A^X, is a set defined by $f_A^X : E \to S^X$ such that $f_A^X(e) = \emptyset$ if $e \notin A$. Here, f_A^X is called approximate function of F_A^X, and the value $f_A^X(e)$ is a set called e-element of F_A^X for all $e \in E$. Thus a soft set over X can be represented by

$$F_A^X = \{(e, f_A^X(e)) : e \in E, f_A^X(e) \in S^X\} \tag{2.1}$$

Note that the set of all soft sets over $X \subseteq U$ will be denoted by $S(X)$.

Example 2.2. Assume that $X = \{u_1, u_2, u_3, u_4, u_5, u_6\} \subseteq U$ is the set of some vehicles in a gallery and $A = \{e_1, e_2, e_3, e_4\} \subseteq E$ is the set of some key parameters that stand out from the vehicles in this gallery, where e_i $(i = 1, 2, 3, 4)$ stand for "technological", "fast", "cheap" and "safety",respectively. Anyone who comes to the gallery can construct a soft set F_A^X to express the properties of the vehicles that express the parameters they want. If a person's choices are $f_A^X(e_1) = \{u_2, u_4, u_5, u_6\}$, $f_A^X(e_2) = \{u_1, u_2, u_3, u_4, u_5\}$, $f_A^X(e_3) = \{u_1, u_3, u_4, u_6\}$ and $f_A^X(e_4) = \{u_1, u_2, u_4, u_5, u_6\}$; the soft set F_A^X is expressed as

$$F_A^X = \left\{ \begin{array}{c} (e_1, \{u_2, u_4, u_5, u_6\}), (e_2, \{u_1, u_2, u_3, u_4, u_5\}), \\ (e_3, \{u_1, u_3, u_4, u_6\}), (e_4, \{u_1, u_2, u_4, u_5, u_6\}) \end{array} \right\}.$$

Definition 2.3. [14] Let $F_A^X \in S(X)$. Then,
(i) if $f_A^X(e) = \emptyset$ for all $e \in E$, then F_A^X is called an empty soft set and denoted by $\widetilde{\Phi_A}$.
(ii) if $f_A^X(e) = X$ for all $e \in A \subseteq E$, then F_A^X is called an A-universal soft set and denoted by $\widetilde{X_A}$.
(iii) if $f_A^X(e) = X$ and $A = E$ for all $e \in E$, then F_A^X is called an universal soft set and denoted by $\widetilde{X_E}$.

Definition 2.4. [14] Let $F_A^X, F_B^X \in S(X)$. Then,
(i) $F_A^X \subseteq F_B^X$ if $f_A^X(e) \subseteq f_B^X(e)$ for all $e \in E$.
(ii) $F_A^X = F_B^X$ if $F_A^X \subseteq F_B^X$ and $F_B^X \subseteq F_A^X$.
(iii) Complement: $\left[F_A^X\right]^c$, where $\left[f_A^X\right]^c : E \to S^X$, such that $\left[f_A^X\right]^c(e) = \emptyset$ if $e \notin A$, defined as $\left[f_A^X\right]^c(e) = X - f_A^X(e)$ for all $e \in A$. It is easy to see that $\left[\left[F_A^X\right]^c\right]^c = F_A^X$, $\left[\widetilde{\Phi_A}\right]^c = \widetilde{X_E}$.

Definition 2.5. [14] Let $F_A^X, F_B^X \in S(X)$. Then,
(i) union F_A^X and F_B^X, denoted by $F_A^X \tilde{\cup} F_B^X$, is a soft set defined by $f_{A\tilde{\cup}B}^X(e) = f_A^X(e) \cup f_B^X(e)$ for all $e \in E$.
(ii) intersection F_A^X and F_B^X, denoted by $F_A^X \tilde{\cap} F_B^X$, is a soft set defined by $f_{A\tilde{\cap}B}^X(e) = f_A^X(e) \cap f_B^X(e)$ for all $e \in E$.

Proposition 2.6. *[14] Let $F_A^X \in S(X)$. Then,*
(i) $F_A^X \tilde{\cup} F_A^X = F_A^X$, $F_A^X \tilde{\cap} F_A^X = F_A^X$
(ii) $F_A^X \tilde{\cup} \widetilde{\Phi_A} = F_A^X$, $F_A^X \tilde{\cap} \widetilde{\Phi_A} = \widetilde{\Phi_A}$
(iii) $F_A^X \tilde{\cup} \widetilde{X_E} = \widetilde{X_E}$, $F_A^X \tilde{\cap} \widetilde{X_E} = F_A^X$
(iv) $F_A^X \tilde{\cup} \left[F_A^X\right]^c = \widetilde{X_E}$, $F_A^X \tilde{\cap} \left[F_A^X\right]^c = \widetilde{\Phi_A}$

3. Technical Formulations

This section provides some technical formulations necessary for the algorithms built in the next section. In addition, some technical analyzes are detailed.

Definition 3.1. Let $F_A^X \in S(X)$. The following mapping is used to get information about what parameters each object in F_A^X provides or does not:

$$\gamma_{F_A}^X(e_i)(u_j) = \left\{ \begin{array}{ll} 1, & u \in f_A^X(e_i) \\ 0, & u \notin f_A^X(e_i) \end{array} \right. \tag{3.1}$$

The mapping given here is in the form of $\gamma_{F_A}^X : E \times U \to \{0, 1\}$.

Definition 3.2. Let $F_A^X \in S(X)$. The relationship between the parameters provided by the objects belonging to F_A^X expressed by using the following mapping:

$$\Upsilon_{F_A}^X(e_i,e_j) = 1 - \left[\frac{1}{|X|}\sum_{k=1}^{|X|}\left|\gamma_{F_A}^X(e_i)(u_k) - \gamma_{F_A}^X(e_j)(u_k)\right|\right] \tag{3.2}$$

This mapping is called the "Interaction Function" and is in the form of $\Upsilon_{F_A}^X : A \times A \rightarrow [0,1]$ for $e_i \neq e_j$. Also $|X|$ is the cardinality of X.

Let $X_1, X_2, ..., X_m \subseteq U$ be discrete universe sets (i.e. $\cap_{l=1}^m X_l = \emptyset$) for $m \in \mathbb{Z}^+$. In this case, the interactions between parameters for the soft set $F_A^{X_N}$ expressed for $\cup_{l=1}^m X_l = X_N$, which occurs by the union of more than one discrete universe set, are calculated as follows:

$$\Upsilon_{F_A}^{X_N}(e_i,e_j) = 1 - \left[\frac{1}{|X_N|}\sum_{l=1}^{m}\sum_{k=1}^{|X_l|}\left|\gamma_{F_A}^{X_l}(e_i)(u_k) - \gamma_{F_A}^{X_l}(e_j)(u_k)\right|\right] \tag{3.3}$$

where $|X_N| = \sum_{l=1}^m |X_l|$ and $e_i \neq e_j$. Here, $|X_l|$ and $|X_N|$ are the cardinality of X_l and X_N, respectively.

Remark 3.3. The interaction function aims to assist us in determining what kind of interaction between parameters in a soft set. In this way, we can easily understand whether a parameter has an effect on other parameters. In addition, determining the interaction value caused by this effect helps us to interpret the effect of parameters on objects.

Remark 3.4. The closer the value $\Upsilon_{F_A}^X(e_i,e_j)$ is to 1, the stronger the relationship exists between the parameters $e_i - e_j$. Otherwise, the closer to zero this value is taken, the weaker the relationship exists between the parameters $e_i - e_j$.

Proposition 3.5. *Let $X_1, X_2, ..., X_m \subseteq U$, $\cup_{l=1}^m X_l = X_N \subseteq U$ for $\cap_{l=1}^m X_l = \emptyset$ and $m \in \mathbb{Z}^+$. Also, $F_A^{X_N} \in S(X)$. Then, $\Upsilon_{F_A}^{X_N}(e_i,e_j) = \Upsilon_{F_A}^{X_N}(e_j,e_i)$ for all $e_i, e_j \in A$ and $e_i \neq e_j$.*

Proof. It is clear from Definition 3.2. □

Proposition 3.6. *Let $|A| = p$. In this case, the total different interaction number of all parameters in A is $\frac{p(p-1)}{2}$.*

Proof. Since the interaction of a parameter with itself is not accepted, the total interaction with each parameter other than itself is $[p-1]$ for A. When we consider this situation for each parameter in A, the total number of interactions is $[p(p-1)]$. However, since $\Upsilon_{F_A}^X(e_i,e_j) = \Upsilon_{F_A}^X(e_j,e_i)$ for all $e_i, e_j \in A$ and $e_i \neq e_j$, the total different interaction number is halved. The proof is complete. □

Definition 3.7. Let $F_A^X \in S(X)$. As a result of interactions between all parameters in F_A^X, the sum of the interactions of one parameter with all other parameters indicates the total effect of that parameter on all objects belonging to X for F_A^X. This total effect expressed by using the following mapping:

$$\Gamma_{F_A}^X(e_i) = \sum_{j=1}^{s(A)} \Upsilon_{F_A}^X(e_i,e_j) \tag{3.4}$$

This mapping is called the "Parametric Effect Function" and is in the form of $\Gamma_{F_A}^X : E \rightarrow [0, |A|-1]$ for $e_i \neq e_j$. Here, $|A|$ is the cardinality of A.

Remark 3.8. Using the "Parametric Effect Function", a comparison is made about the dominance of the parameters provided by the objects in the universe for a soft set. In other words, in order to make an estimation of the belonging of an object to the soft set, it must be able to provide the dominant parameters in this soft set.

4. Decision-making methods based on soft sets

In this section, two algorithms based on soft sets are proposed. One of these aims to determine what kind of relationship exists between the parameters of objects belonging to the universe set for a soft set. The other is to determine which parameters are more dominant on the objects for a soft set. In this way, it is aimed to detect objects with more dominant parameters.

The first proposed algorithm is aimed to detect the interactions between parameters for a soft set and it is constructed as follows:

Algorithm 1 Determine the strongest relationship between parameters for a soft set.

Require: $X_1, X_2, ..., X_m \subseteq U$, $A \subseteq E$, for $\cap_{l=1}^{m} X_l = \emptyset$, $\bigcup_{l=1}^{m} X_l = X_N$ and $1 \leq l \leq m$.

Step 1: Input the soft sets $F_A^{X_l}$ as follows:

$$F_A^{X_l} = \left\{ \left(e, f_A^{X_l}(e)\right) : e \in E, f_A^{X_l}(e) \in S^{X_l} \right\}$$

Step 2: With the help of soft sets $F_A^{X_l}$, construct the soft set $F_A^{X_N}$ as follows:

$$F_A^{X_N} = \left\{ \left(e, f_A^{X_N}(e)\right) : e \in E, \bigcup_{l=1}^{m} f_A^{X_l}(e) = f_A^{X_N}(e) \in S^{X_N} \right\}$$

Step 3: Calculate all interactions between parameters in soft sets $F_A^{X_l}$ and $F_A^{X_N}$ using the "Interaction Function".

Step 4: Find $max_{1\leq i,j\leq |A|} \Upsilon_{F_A}^{X_l}(e_i, e_j)$ and $max_{1\leq i,j\leq |A|} \Upsilon_{F_A}^{X_N}(e_i, e_j)$ for $e_i \neq e_j$.

The second proposed algorithm is aimed to determine which parameters can more dominantly represent the objects in the universe set for a soft set and it is constructed as follows:

Algorithm 2 Determine the strongest parameter on which objects are affected for a soft set.

Require: $X_1, X_2, ..., X_m \subseteq U$, $A \subseteq E$, for $\cap_{l=1}^{m} X_l = \emptyset$, $\bigcup_{l=1}^{m} X_l = X_N$ and $1 \leq l \leq m$.

Step 1: Input the soft sets $F_A^{X_l}$ as follows:

$$F_A^{X_l} = \left\{ \left(e, f_A^{X_l}(e)\right) : e \in E, f_A^{X_l}(e) \in S^{X_l} \right\}$$

Step 2: With the help of soft sets $F_A^{X_l}$, construct the soft set $F_A^{X_N}$ as follows:

$$F_A^{X_N} = \left\{ \left(e, f_A^{X_N}(e)\right) : e \in E, \bigcup_{l=1}^{m} f_A^{X_l}(e) = f_A^{X_N}(e) \in S^{X_N} \right\}$$

Step 3: Calculate the total effect of all parameters in soft sets $F_A^{X_l}$ and $F_A^{X_N}$ on objects belonging to X_l and X_N by using "Parametric Effect Function", respectively.

Step 4: Find $max_{1\leq i\leq |A|} \Gamma_{F_A}^{X_l}(e_i)$ and $max_{1\leq i\leq |A|} \Gamma_{F_A}^{X_N}(e_i)$ for $e_i \neq e_j$.

Now, the algorithms given are associated with Covid-19 disease, an epidemic that occurs almost throughout our world. Thus, two issues were highlighted:

- Interactions between different symptoms in each area of the disease

- Dominance among different symptoms in each area of disease

Example 4.1. Let's take 15 patients with Covid-19 disease from three different regions. Let's find out which symptoms the patients from these regions show the most, and these symptoms are breath, severe cough, fatigue, sore throat and high fever.

Our problem has two stages:

(i) The first step is to determine whether there is an interaction between the symptoms for each region and to observe the effects of the symptoms on each other. In this way, it is determined which symptoms are observed in people with the disease first. It is also determined how effective a symptom is in the emergence of other symptoms.

(ii) The second step is to observe the possible existence of a difference in the dominance of symptoms for each region. If this difference occurs, it is concluded that patients in different regions may experience the disease in a different way. In this way, the measures to be taken for different regions can be differentiated and contribute to taking the most correct measures.

Now, let's solve the two-stage problem by making use of the given algorithms.

Let U be the general universe set and $A = \{e_1, e_2, e_3, e_4, e_5\} \subseteq E$ be the parameter set for $i = 1, 2, ..., 5$, the parameters e_i stand for "shortness of breath", "severe cough", "fatigue", "sore throat" and "high fever", respectively. For $X_1 = \{u_1, u_2, u_3, ..., u_{15}\}$, $X_2 = \{u_{16}, u_{17}, u_{18}, ..., u_{30}\}$, $X_3 = \{u_{31}, u_{32}, u_{33}, ..., u_{45}\}$ and $X_1, X_2, X_3 \subseteq U$, then the soft sets $F_A^{X_1}$, $F_A^{X_2}$ and $F_A^{X_3}$ are given by

$$F_A^{X_1} = \Big\{(e_1, f_A^{X_1}(e_1)), (e_2, f_A^{X_1}(e_2)), (e_3, f_A^{X_1}(e_3)), (e_4, f_A^{X_1}(e_4)), (e_5, f_A^{X_1}(e_5))\Big\},$$

$$F_A^{X_2} = \Big\{(e_1, f_A^{X_2}(e_1)), (e_2, f_A^{X_2}(e_2)), (e_3, f_A^{X_2}(e_3)), (e_4, f_A^{X_2}(e_4)), (e_5, f_A^{X_2}(e_5))\Big\}$$

and

$$F_A^{X_3} = \Big\{(e_1, f_A^{X_3}(e_1)), (e_2, f_A^{X_3}(e_2)), (e_3, f_A^{X_3}(e_3)), (e_4, f_A^{X_3}(e_4)), (e_5, f_A^{X_3}(e_5))\Big\}$$

where

$$\begin{aligned}
f_A^{X_1}(e_1) &= \{u_6, u_7, u_{10}, u_{12}, u_{13}, u_{15}\},\\
f_A^{X_1}(e_2) &= \{u_4, u_5, u_7, u_8, u_{10}, u_{11}, u_{13}, u_{15}\},\\
f_A^{X_1}(e_3) &= \{u_1, u_3, u_4, u_6, u_8, u_9, u_{12}, u_{14}\},\\
f_A^{X_1}(e_4) &= \{u_1, u_2, u_3, u_5, u_7, u_9, u_{10}, u_{11}, u_{12}, u_{15}\},\\
f_A^{X_1}(e_5) &= \{u_4, u_6, u_{11}, u_{13}, u_{14}\},
\end{aligned}$$

$$\begin{aligned}
f_A^{X_2}(e_1) &= \{u_{16}, u_{18}, u_{20}, u_{22}, u_{23}, u_{24}, u_{25}, u_{26}, u_{28}, u_{29}\},\\
f_A^{X_2}(e_2) &= \{u_{16}, u_{18}, u_{21}, u_{22}, u_{24}, u_{25}, u_{30}\},\\
f_A^{X_2}(e_3) &= \{u_{17}, u_{18}, u_{21}, u_{24}, u_{27}, u_{30}\},\\
f_A^{X_2}(e_4) &= \{u_{17}, u_{19}, u_{20}, u_{22}, u_{24}, u_{27}, u_{28}\},\\
f_A^{X_2}(e_5) &= \{u_{16}, u_{18}, u_{19}, u_{21}, u_{22}, u_{25}, u_{28}, u_{30}\},
\end{aligned}$$

and

$$\begin{aligned}
f_A^{X_3}(e_1) &= \{u_{31}, u_{32}, u_{33}, u_{34}, u_{36}, u_{37}, u_{38}, u_{41}, u_{42}, u_{43}, u_{44}, u_{45}\},\\
f_A^{X_3}(e_2) &= \{u_{32}, u_{34}, u_{37}, u_{38}, u_{40}, u_{42}, u_{43}, u_{45}\},\\
f_A^{X_3}(e_3) &= \{u_{31}, u_{35}, u_{37}, u_{41}, u_{44}, u_{45}\},\\
f_A^{X_3}(e_4) &= \{u_{38}, u_{39}, u_{40}, u_{43}, u_{44}\},\\
f_A^{X_3}(e_5) &= \{u_{32}, u_{34}, u_{35}, u_{38}, u_{43}, u_{45}\}.
\end{aligned}$$

Using the soft sets $F_A^{X_1}$, $F_A^{X_2}$ and $F_A^{X_3}$, the soft set $F_A^{X_N}$ for $\bigcup_{l=1}^{3} X_l = X_N$ is expressed as follows:

$$F_A^{X_N} = \Big\{(e_1, f_A^{X_N}(e_1)), (e_2, f_A^{X_N}(e_2)), (e_3, f_A^{X_N}(e_3)), (e_4, f_A^{X_N}(e_4)), (e_5, f_A^{X_N}(e_5))\Big\}$$

where

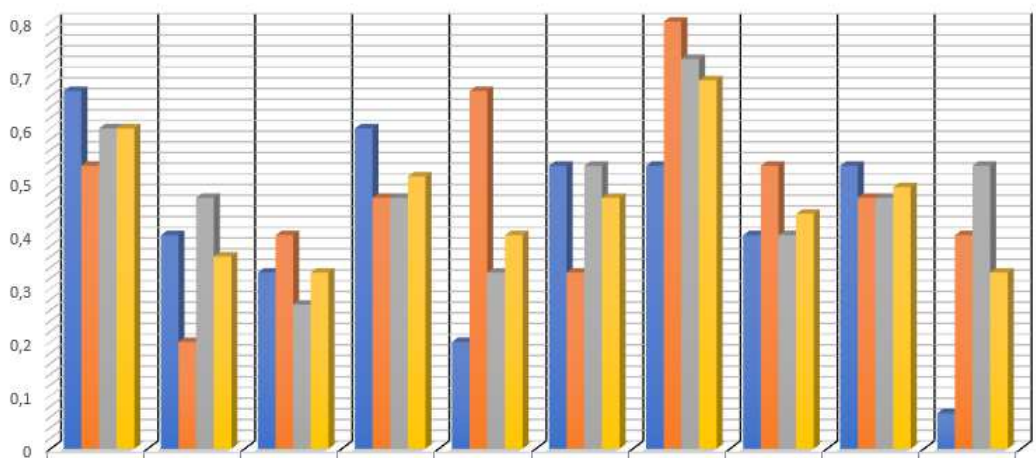
$$\begin{aligned}
f_A^{X_N}(e_1) &= \left\{\begin{array}{c} u_6, u_7, u_{10}, u_{12}, u_{13}, u_{15}, u_{16}, u_{18}, u_{20}, u_{22}, u_{23}, u_{24}, u_{25}, u_{26}, \\ u_{28}, u_{29}, u_{31}, u_{32}, u_{33}, u_{34}, u_{36}, u_{37}, u_{38}, u_{41}, u_{42}, u_{43}, u_{44}, u_{45} \end{array}\right\},\\
f_A^{X_1}(e_2) &= \left\{\begin{array}{c} u_4, u_5, u_7, u_8, u_{10}, u_{11}, u_{13}, u_{15}, u_{16}, u_{18}, u_{21}, u_{22}, u_{24}, \\ u_{25}, u_{30}, u_{32}, u_{34}, u_{37}, u_{38}, u_{40}, u_{42}, u_{43}, u_{45} \end{array}\right\},\\
f_A^{X_1}(e_3) &= \left\{\begin{array}{c} u_1, u_3, u_4, u_6, u_8, u_9, u_{12}, u_{14}, u_{17}, u_{18}, u_{21}, u_{24}, \\ u_{27}, u_{30}, u_{31}, u_{35}, u_{37}, u_{41}, u_{44}, u_{45} \end{array}\right\},\\
f_A^{X_1}(e_4) &= \left\{\begin{array}{c} u_1, u_2, u_3, u_5, u_7, u_9, u_{10}, u_{11}, u_{12}, u_{15}, u_{17}, u_{19}, u_{20}, \\ u_{22}, u_{24}, u_{27}, u_{28}, u_{38}, u_{39}, u_{40}, u_{43}, u_{44} \end{array}\right\},\\
f_A^{X_1}(e_5) &= \left\{\begin{array}{c} u_4, u_6, u_{11}, u_{13}, u_{14}, u_{16}, u_{18}, u_{19}, u_{21}, u_{22}, \\ u_{25}, u_{28}, u_{30}, u_{32}, u_{34}, u_{35}, u_{38}, u_{43}, u_{45} \end{array}\right\}.
\end{aligned}$$

For step (i)**:** Let's use the interaction function to comment on the interactions of parameters in the soft sets $F_A^{X_1}$, $F_A^{X_2}$, $F_A^{X_3}$ and $F_A^{X_N}$. For example, the values $\Upsilon_{F_A}^{X_2}(e_2, e_5)$ and $\Upsilon_{F_A}^{X_N}(e_2, e_5)$ for $F_A^{X_2}$ and $F_A^{X_N}$ are calculated as follows:

$$\Upsilon_{F_A}^{X_2}(e_2, e_5) = 1 - \left[\frac{1}{15}\sum_{k=1}^{15}\left|\gamma_{F_A}^{X_2}(e_2)(u_k) - \gamma_{F_A}^{X_2}(e_5)(u_k)\right|\right] = 1 - \frac{3}{15} = 0,8$$

$$\Upsilon_{F_A}^{X_N}(e_2, e_5) = 1 - \left[\frac{1}{45}\sum_{l=1}^{3}\sum_{k=1}^{|X_l|}\left|\gamma_{F_A}^{X_l}(e_2)(u_k) - \gamma_{F_A}^{X_l}(e_5)(u_k)\right|\right] = 1 - \frac{7+3+4}{45} = 0,69$$

The calculated results for each universe sets of all parameter interactions are given in Figure 1. (The line $i - j$ in Figure 1 represents the interaction between the parameters $e_i - e_j$ for $1 \leq i, j \leq 5$ and $i \neq j$.)



	1-2	1-3	1-4	1-5	2-3	2-4	2-5	3-4	3-5	4-5
X_1	0,67	0,4	0,33	0,6	0,2	0,53	0,53	0,4	0,53	0,067
X_2	0,53	0,2	0,4	0,47	0,67	0,33	0,8	0,53	0,47	0,4
X_3	0,6	0,47	0,27	0,47	0,33	0,53	0,73	0,4	0,47	0,53
X_N	0,6	0,36	0,33	0,51	0,4	0,47	0,69	0,44	0,49	0,33

X_1 X_2 X_3 X_N

Figure 1. All interactions between parameters in the parameter set for all universes

As can be seen from the results in Figure 1, all parameter interactions in the soft set $F_A^{X_N}$ are the average of the results obtained for the soft sets $F_A^{X_1}$, $F_A^{X_2}$ and $F_A^{X_3}$. This is actually a direct result of Definition 3.2.

When we look at the relationships between the parameters in X_1 for $F_A^{X_1}$, we understand that the relationship between the parameters $e_1 - e_2$ for $max_{1\leq i,j\leq 5}\Upsilon_{F_A}^{X_1}(e_i, e_j) = 0,67$ is the strongest. We can also examine the relationships of each parameter among other parameters. For example, all interactions of parameter e_4 among other parameters are as follows,

$$\Upsilon_{F_A}^{X_1}(e_4, e_1) = 0,33$$
$$\Upsilon_{F_A}^{X_1}(e_4, e_2) = 0,53$$
$$\Upsilon_{F_A}^{X_1}(e_4, e_3) = 0,4$$
$$\Upsilon_{F_A}^{X_1}(e_4, e_5) = 0,067$$
$$max_{1\leq j\leq 5}\Upsilon_{F_A}^{X_1}(e_4, e_j) = max_{1\leq i\leq 5}\Upsilon_{F_A}^{X_1}(e_i, e_4) = 0,53$$

In other words, we can say that the strongest of all interactions between e_4 and the other symptoms is the interaction with e_2. Moreover, $max_{1\leq i,j\leq 5}\Upsilon_{F_A}^{X_1}(e_i, e_j) = 0,8$ for X_2 is indicates that the interaction between the parameters $e_2 - e_5$ is the strongest of all other interactions.

In the X_N, which is a combination of these three discrete universes, $max_{1\leq i,j\leq 5}\Upsilon_{F_A}^{X_N}(e_i, e_j) = 0,69$ shows us that the interaction between the parameters $e_2 - e_5$ is the strongest in the general case. That is, a person who we do not know is belonging to the X_N universe is expected to show the symptoms e_2 and e_5 first in order to have the Covid-19 test.

The reason why we examine the general universe set separately here is that we want to measure changes in specific parts of the interaction between parameters in the general universe set. In this way, different measures can be taken to prevent the spread of the epidemic by observing possible different changes in different regions. In addition, by observing the change of interactions, the parameters that can cause this change in an abnormal situation can be analyzed. Moreover, the disease may mutate, or some unknown causes may differentiate the interaction between the symptoms of the disease. Briefly, measuring any change that may occur in different parts of the world can help us to control the course of the disease.

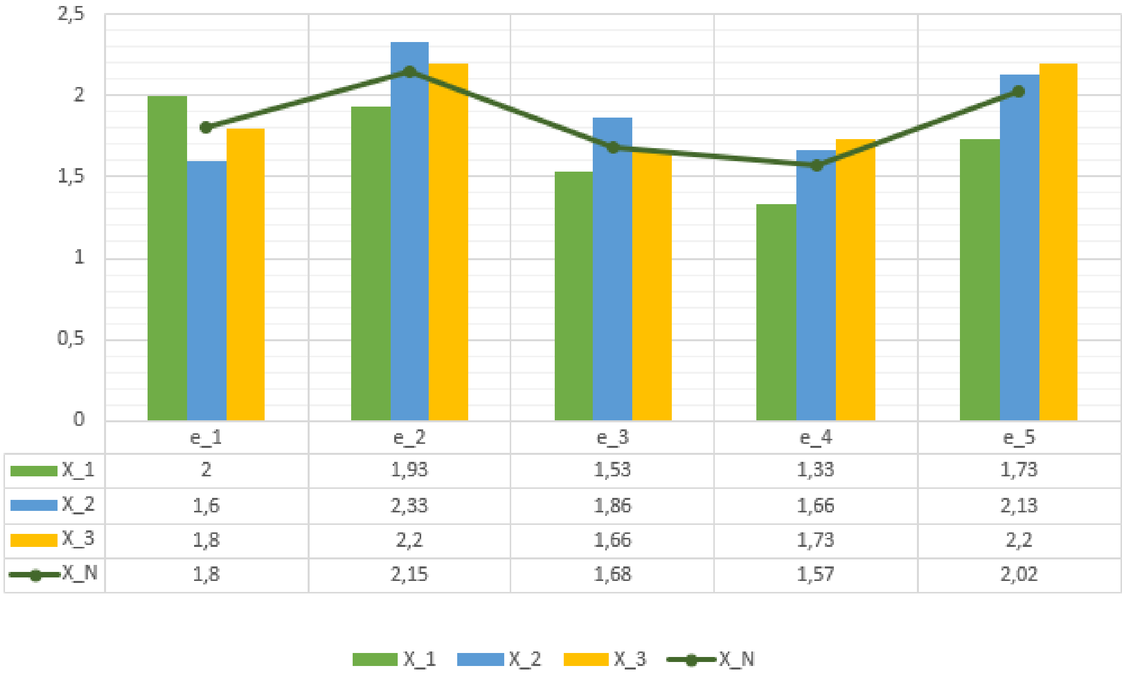
For step (ii)**:** Detection of interactions between parameters introduces uncertainty about which parameter is most dominant. For example, after detecting that the interaction between symptoms e_2 and e_5 is stronger than other interactions, there may be situations where we need to understand which of these two symptoms is one step ahead of the other. In this case, the "Parametric Effect Function" should be used by making use of Algorithm 2 to determine the most dominant parameter. Now, two sample calculations for the universe X_N are given as follows.

$$\Gamma_{F_A}^{X_N}(e_2) = \sum_{j=1}^{5} \Upsilon_{F_A}^{X_N}(e_2, e_j) = \begin{bmatrix} \Upsilon_{F_A}^{X_N}(e_2, e_1) + \Upsilon_{F_A}^{X_N}(e_2, e_3) \\ +\Upsilon_{F_A}^{X_N}(e_2, e_4) + \Upsilon_{F_A}^{X_N}(e_2, e_5) \end{bmatrix} = \begin{bmatrix} 0,6 + 0,4 \\ +0,47 + 0,69 \end{bmatrix} = 2,15$$

and

$$\Gamma_{F_A}^{X_N}(e_5) = \sum_{j=1}^{5} \Upsilon_{F_A}^{X_N}(e_5, e_j) = \begin{bmatrix} \Upsilon_{F_A}^{X_N}(e_5, e_1) + \Upsilon_{F_A}^{X_N}(e_5, e_2) \\ +\Upsilon_{F_A}^{X_N}(e_5, e_3) + \Upsilon_{F_A}^{X_N}(e_5, e_4) \end{bmatrix} = \begin{bmatrix} 0,51 + 0,69 \\ +0,49 + 0,33 \end{bmatrix} = 2,02.$$

Therefore, for X_N, e_2 should be higher precedence than the symptom e_5 in the criteria that should be searched for testing. Calculations for all universes are given in Figure 2.



	e_1	e_2	e_3	e_4	e_5
X_1	2	1,93	1,53	1,33	1,73
X_2	1,6	2,33	1,86	1,66	2,13
X_3	1,8	2,2	1,66	1,73	2,2
X_N	1,8	2,15	1,68	1,57	2,02

Figure 2. Total effects of parameters to all universes

As can be seen, the results in universe X_N are the average of the results in other universes. This is a clear result of Definition 3.7.

According to the universes X_1, X_2, X_3 and X_N, the most dominant parameters are e_1, e_2, $e_2 - e_5$ and e_2, respectively. Similarly, the universes in which parameters e_1, e_2, e_3, e_4

and e_5 are the most dominant are X_1, X_2, X_2, X_3 and X_2, respectively. Based on these comments, an example can be given as follows: For a person from the universe X_2 to have a Covid test, the most important symptom must be e_2. Similarly, this symptom should be e_1 in the universe X_1. It is clear that detecting these differences is very important in the fight against the epidemic. Therefore, it is predicted that utilizing the proposed algorithms in the fight against the epidemic can have a significant positive contribution.

The algorithms proposed in this paper are not only for the Covid-19 pandemic. However, the solution to this pandemic, which is considered to be one of the most important uncertainty problems today, is discussed to strengthen the motivation of this paper. The contributions of the proposed algorithms to the decision-making process can be expressed as follows:

• Both proposed algorithms deal with the uncertain environments encountered in a problem by separating them into different universe sets. This takes into account the possible difference of relations between the parameters providing the objects. This situation is also compared with the general universe set, allowing for a better analysis of uncertainty environments.

• In Algorithm 1, the interactions between the parameters for a soft set are calculated and thus, the relationships between the parameters are analyzed. Thus, we can determine which parameter dominates over which parameters. This allows us to analyze the information on which parameters the uncertainty problem poses a problem.

• Algorithm 2 determines which parameters are most dominant for a soft set and informs us which parameters the objects provide more. Thus, in order for an object to be the most ideal object in the uncertainty problem, it is interpreted that it must implement the most dominant parameter.

• It has been exemplified above how these algorithms, which are built-in terms of analyzing the relationships between parameters in an uncertainty problem and determining the most dominant parameter, play an active role in the selection of the ideal object. In addition, since the steps of both algorithms are related to each other, considering them together in an environment of uncertainty contributes to more accurate management of the decision-making process.

5. Conclusion

Since Covid-19 is a pandemic disease, it must be controlled before it spreads further in a region. In addition, the symptoms of this pandemic are too many to be underestimated. For this reason, the main symptoms detected in a region should be taken into account. Especially in terms of workload and cost, it is a very important issue that the Covid test should be performed in case of which symptoms are observed. In this paper, which focuses on such issues, two algorithms are proposed considering soft set theory, which is a very successful mathematical model in uncertainty environments. By considering both algorithms together, it is aimed to prevent the uncertainty situations stated as follows:

• Which people should be tested for Covid first?
• How important is it to consider the possible different symptoms of Covid patients encountered in different regions in order to manage the epidemic?
• Can different measures be taken against the pandemic, thanks to the detection of the relationships between the symptoms seen in Covid patients?
• Is it possible to observe possible differences between the dominant symptoms seen in

patients encountered in different regions?

It is thought that the algorithms built for these uncertainty problems can be a good source of motivation for the studies on the pandemic. The possibilities of the world are limited in order to prevent this epidemic. Therefore, in order to overcome the epidemic, we must have priority goals to detect the symptoms of the disease correctly, to test the right people and to apply an early treatment process as much as possible. Since a decision-making process based on soft set theory is built in this paper, some hybrid mathematical models such as fuzzy parameterized fuzzy soft sets [16], virtual fuzzy parameterized soft sets [17], intuitionistic fuzzy parameterized soft sets [20], interval-valued intuitionistic fuzzy parameterized soft sets [21], fuzzy soft sets [19], bipolar fuzzy parameterized soft sets[18], bipolar fuzzy soft sets [22] and bipolar neutrosophic soft sets [15], in which soft sets are also used, can be used in future studies on the pandemic.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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