

# A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19)

Kannan Govindan<sup>a,b,\*</sup>, Hassan Mina<sup>c</sup>, Behrouz Alavi<sup>d</sup>

<sup>a</sup> China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai 201306, China

<sup>b</sup> Centre for Sustainable Supply Chain Engineering, Department of Technology and Innovation, Danish Institute for Advanced Study, University of Southern Denmark, Odense M 5230, Denmark

<sup>c</sup> School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

<sup>d</sup> Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran



## ARTICLE INFO

### Keywords:

Disaster management  
Epidemic outbreaks  
Healthcare supply chain disruption mitigation  
Fuzzy inference system  
COVID-19

## ABSTRACT

The disasters caused by epidemic outbreaks is different from other disasters due to two specific features: their long-term disruption and their increasing propagation. Not controlling such disasters brings about severe disruptions in the supply chains and communities and, thereby, irreparable losses will come into play. Coronavirus disease 2019 (COVID-19) is one of these disasters that has caused severe disruptions across the world and in many supply chains, particularly in the healthcare supply chain. Therefore, this paper, for the first time, develops a practical decision support system based on physicians' knowledge and fuzzy inference system (FIS) in order to help with the demand management in the healthcare supply chain, to reduce stress in the community, to break down the COVID-19 propagation chain, and, generally, to mitigate the epidemic outbreaks for healthcare supply chain disruptions. This approach first divides community residents into four groups based on the risk level of their immune system (namely, very sensitive, sensitive, slightly sensitive, and normal) and by two indicators of age and pre-existing diseases (such as diabetes, heart problems, or high blood pressure). Then, these individuals are classified and are required to observe the regulations of their class. Finally, the efficiency of the proposed approach was measured in the real world using the information from four users and the results showed the effectiveness and accuracy of the proposed approach.

## 1. Introduction

A disaster is any event that occurs suddenly and whose impact may increase in intensity; it stops society from its normal functioning and causes losses to life, economies, and the environment (Kilci et al., 2015; Kaur and Singh, 2019). Disaster management involves the fulfillment of some operations before and after the occurrence of a disaster in order to reduce its detrimental effects (Galindo and Batta, 2013; Oruc and Kara, 2018; Sarma et al., 2019). COVID-19 is a disaster that hit the globe in late 2019 and has involved about 203 countries, affected more than 754,000 people, and taken the life of about 36,500 individuals up to the end of March 2020. It should be mentioned that these statistics pertain to the end of March 2020; significantly, the numbers of infected people and mortality rates change every day (WHO, 2020).

\* Corresponding author at: China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai 201306, China.

E-mail address: [kgov@iti.sdu.dk](mailto:kgov@iti.sdu.dk) (K. Govindan).

In fact, COVID-19 is an infectious disease resulting from a previous variant of the coronavirus (Ting et al., 2020). Before its outbreak in Wuhan, China, in December 2019, this was an unknown viral disease. Fever, tiredness, and dry cough are among the most common symptoms of this virus (Huang et al., 2020; Rothan and Byrareddy, 2020; Wang et al., 2020). Patients may also exhibit nasal congestion or a runny nose, aches and pains, sore throat, or diarrhea. These symptoms generally do not begin with severity; they may develop little by little. In fact, some infected individuals may not even feel unwell and, hence, remain unaware that they are contagious. Most affected people recover from the disease without any specific treatment and hospitalization. About 17% of COVID-19 sufferers experience severe illness and breathe with difficulty. People of higher age and those with underlying medical conditions, including diabetes, heart problems, or high blood pressure, are at greater risk of suffering more seriously from its negative effects (United Nations, 2020).

One of the problems now confronting societies is the lack of equipment to successfully encounter this virus. This virus propagates rapidly, so any failure in dealing with its prevalence dramatically increases the number of infected people. If communities are faced with a shortage of medical/healthcare equipment, an increase in the number of infected people can initiate an irreparable and incredible catastrophe. The provision of some strategies and solutions to reduce the outbreak rate of this disease, and the coordinated management of infected people, can lead to the breakdown or deceleration of the virus chain since no definitive cure has been identified for the disease at this point. Healthcare equipment and services, such as coronavirus testing kits, masks, gloves, etc. are not available to all the people in the society. Therefore, an effective way to make optimal use of the available healthcare equipment and to manage the demands in the healthcare supply chain is to identify and classify the individuals with and without COVID-19 and, accordingly, to propose instructions/regulations for each class. Generally, the main purpose of this study is to respond to the following research questions: How is it possible to develop a decision support system in order to classify community members for the management of demand in the healthcare supply chain? How to disrupt the virus chain itself? How to control the outbreak of an epidemic to mitigate its impact on the healthcare supply chain?

### 1.1. Contribution statement

This paper proposes a decision support system based on physicians' knowledge and fuzzy inference system (FIS) in order to classify community members with the objective of managing demand in a healthcare supply chain and breaking down or decelerating the virus chain. As a highly practical tool, FIS has been proposed on the basis of expert knowledge in the realm of fuzzy set theory in order to deal with the nonlinear mapping of input to output variables. Since COVID-19 is a new disease and reliable datasets pertaining to this disease are not available, it is desired to use the FIS approach, which is based on expert knowledge. In addition, the input and output variables in this approach do not follow a linear function; therefore, FIS makes it possible to define the proper functions (rules) for different conditions. This is another rationale for the employment of FIS in this paper. The healthcare chain proposed in this paper is a two-echelon chain, including community members (service recipients) and the healthcare system (service providers). In this supply chain, healthcare equipment and services provided by the healthcare system are considered as the product. The structure under study of the healthcare supply chain is shown in Fig. 1. In the proposed approach, any sudden increase of demands in the healthcare supply chain is first prevented based on regulations notified to each class. Secondly, disruptions must be mitigated in this chain. In addition, community members' stress is reduced when the reach of the COVID-19 virus decreases. To increase the accuracy of the proposed decision support system, criteria including age and pre-existing diseases (such as diabetes, heart problems, or high blood pressure) have been considered in addition to the three main criteria of fever, tiredness, and dry cough. Generally, the contributions of this study can be summarized as follows:

- Developing a decision support system based on FIS to manage demand in a healthcare supply chain, to break down or decelerate

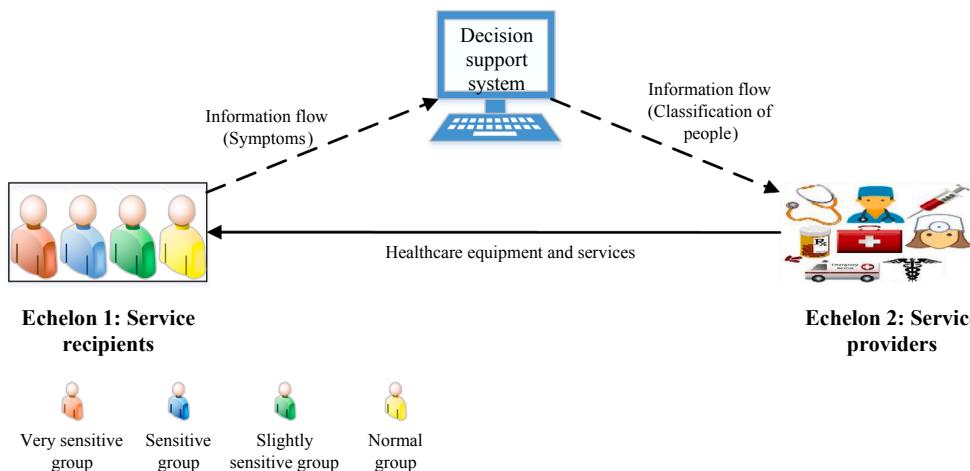


Fig. 1. The structure of the healthcare supply chain under study.

- the virus chain, and to control the outbreak of an epidemic to mitigate its impact on the healthcare supply chain
- Grouping people (service recipients) based on two criteria, including age and pre-existing diseases (such as diabetes, heart problems, or high blood pressure) and providing an independent classification method for each group
- Evaluating the efficiency of the proposed approach using real world data and its validity by a sensitivity analysis procedure.

The rest of this paper is structured as follows. In [Section 2](#), we review the literature on disaster management, epidemic outbreaks, and FIS. The problem statement and proposed approach are presented in [Section 3](#). We apply a case study for evaluating the efficiency of our proposed approach in [Section 4](#). Finally, a sensitivity analysis and conclusion are explained in [Section 5](#) and [6](#), respectively.

## 2. Literature review

To date, a large number of studies have been done on supply chain network design under disruptions in a variety of domains, such as supplier selection and order allocation ([Prasanna Venkatesan and Goh, 2016](#)), biofuel supply chain ([Fattah and Govindan, 2018](#)), reverse supply chain ([Hosseini-Motlagh et al., 2019](#)), blood supply chain ([Hamdan and Diabat, 2020](#)), fashion supply chain ([Zhao et al., 2020](#)), etc. by means of mathematical programming tools. In this regard, some studies have even touched upon the impacts of epidemic outbreaks on supply chains ([Ivanov, 2020](#); [Choi, 2020](#)). In the following, [Section 2.1](#) examines the concept of disaster management. [Section 2.2](#) discusses the studies undertaken in operations management related to diseases or epidemic outbreaks. At the end, [Section 2.3](#) is dedicated to the introduction of FIS.

### 2.1. Disaster management

As suggested by [Carter \(1992\)](#), a disaster management cycle is an attempt to plan the strategies and measures that are at play from the beginning to the end of a disaster's lifespan. This framework has been repeatedly modified ([Tomasini and Wassenhove, 2009](#)) in such a way that it currently entails two phases (relief and development) and four activities (preparedness, rehabilitation, response, and mitigation) ([Ahmadi et al., 2015](#)). In addition, both of the mentioned phases have some activities as subcategories. For example, response and rehabilitation are two activities included in the relief phase, and the two other activities, preparedness and mitigation, are placed in the development phase ([Goldschmidt and Kumar, 2016](#); [Loree and Aros-Vera, 2018](#)).

Activities and measures preplanned to guarantee the effectiveness of responses to the impact of risks and threats, such as pertinent hazards warnings or the temporary evacuation of occupants from homes and workplaces exposed to disasters, fall within the category of **preparedness** ([Shahparvari et al., 2016](#)). Indeed, these activities seek to minimize the negative effects of such disasters and to devise relevant strategies within the realm of socio-economic, physical, and environmental domains ([Wang and Wang, 2019](#)). In this regard, efforts to provide effective **responses** should encompass various factors, such as resources, urgent measures for life saving, environmental conservation, and the socio-economic and political status of the affected society ([Altay and Green, 2006](#)).

In the same way, activities grouped within the **rehabilitation** domain seek not only to rebuild damaged areas and properties but also to establish a new situation significantly better than the previous one. Rehabilitation actions are designed to avoid similar detrimental effects of future disasters by exercising resilience ([Goldschmidt and Kumar, 2016](#)).

**Mitigation** efforts seek to either prevent the initiation of a disaster or to decrease the damages that may come into play ([Sheu, 2016](#); [Hossain and Paul, 2018](#)).

### 2.2. Epidemic outbreaks of disease

Epidemic outbreaks are specifically considered among supply chain disruptions. Further, they denote a particular variety of threat in the supply chain, which is recognized by the three following components: (1) the presence of long-term and unexpected scaling disruption, (2) disruption propagation in the supply chain and epidemic outbreak propagation in the population, and (3) disruptions in the infrastructure of logistics, demand, and supply. In contrast to most disruption threats and risks, epidemic outbreaks are minor at the outset, but they develop and spread over various geographic areas very quickly ([He and Liu, 2015](#)). The latest pertinent examples include MERS, SARS, Swine flu, Ebola, and the newest one, coronavirus. The COVID-19 outbreak started in Wuhan, China and quickly affected the Chinese economy; as a result, supplies in worldwide supply chains were considerably diminished. Accordingly, [Araz et al. \(2020\)](#) has asserted that the outbreak of this viral disease is one of the most critical disruptions to occur in recent decades and, thereby, it is ravaging a large portion of supply chains across the world.

To investigate epidemic outbreaks that struck before that of COVID-19, one will find limited information in connection with supply chain measures. For example, [Johanis \(2007\)](#) analyzed a pandemic response plan that was designed at Toronto's Pearson International Airport after undergoing the harmful effects of SARS epidemic outbreak in 2002–2003. This virus terribly influenced the global airline industry; in fact, airlines in Taiwan suspended about 30% of international flights ([Chou et al., 2004](#)). However, the spread rate of the SARS virus and China's role in the critical situation of SARS totally differed from that of the current COVID-19 virus; accordingly, SARS had lower adverse effects on the SCs. Similarly, the spread of the Ebola virus badly affected worldwide logistics ([BSI, 2014](#)). In this regard, [Büyüktahkin et al. \(2018\)](#) and [Calnan et al. \(2018\)](#) shed some light on the valuable experiences obtained while Ebola virus was dominant. They called for the development of a decision-support framework through which epidemic outbreaks might be predicted and their effects on the supply chains could be facilitated. With such a framework, required measures and logistic policies could be adopted during and following the disaster. [Ivanov \(2020\)](#) studied the impact of epidemic outbreaks on

supply chain networks. He specifically considered the propagation of the COVID-19 virus on global networks using characteristics of the uncertainty type. As for the methodology, Anylogic software was used to predict and simulate both short- and long-term impacts. Experiments show that closing and opening dates of facilities are the most impactful factors in the propagation. The results could help decision makers to mitigate the uncertainties and to curb or decelerate propagation.

### 2.3. Fuzzy inference system

As a nonlinear system, FIS is obtained from the integration of expert system technology and fuzzy logic (Lin et al., 2012). This system includes a set of fuzzy IF-THEN rules that are arranged based on experts' or decision-makers' knowledge. Such rules are used in this system for simulating the process of human reasoning. FIS has some advantages, such as the benefiting from human knowledge and changeable rules to indicate experts' judgment (Asklany et al., 2011; Tavana et al., 2019). In this vein, fuzzy logic modeling techniques fall within two groups, either the Mamdani (Mamdani and Assilian, 1993) or the Takagi-Sugeno-Kang (Sugeno, 1985). The fuzzy sets of antecedents and their consequences are the constituents of Mamdani models, but only the antecedents are placed in the Takagi-Sugeno-Kang model where the consequence here entails linear equations. The main purpose of fuzzy relational equation models is to create such fuzzy relation matrices based on data of the input-output process (Khajeh and Modarress, 2010). In this manner, Takagi-Sugeno-Kang FIS undergoes some problems, especially regarding the accomplishment of the multi-parameter synthetic evaluation and the weight assessment of inputs and fuzzy rules. The positive features of the Mamdani model – particularly, its legibility and understandability – are evident to laypersons. The Mamdani FIS is advantageous over other models in terms of output expression (Chai et al., 2009).

FIS is an applied tool in various areas, such as risk management (Ilbahar et al., 2018; Chung et al., 2019), supplier selection (Amindoust et al., 2012; Jain and Singh, 2020; Jain et al., 2020), manufacturing systems evaluation (Pourjavad and Mayorga, 2019), healthcare supply chain (Nazari et al., 2018), and so forth.

In this paper, a Mamdani FIS is used to classify the community residents so demand can be managed in a healthcare supply chain under the disaster arising from COVID-19. Further, the model strives to control epidemic outbreaks of this disease and to mitigate supply chains disruptions that pertain to healthcare supply chains.

However, the use of expert-based and management tools to control epidemic outbreaks and to mitigate supply chain disruptions has not received much attention. Accordingly, a decision support system based on FIS and physicians' knowledge is developed for this purpose in this study.

## 3. Problem statement and proposed approach

Many societies have proposed solutions to address disasters and have taken measures tailored to their preparedness, response, rehabilitation, and mitigation activities regarding disaster control. For example, many countries minimize human, economic, and environmental losses in the face of disasters such as floods, earthquakes, storms, etc. by means of proper disaster management (Rezaei-Malek et al., 2016; Acar and Kaya, 2019). Effective management of these kinds of disasters benefits from past similar experiences and historical data (Yan et al., 2017). Such disasters are not of epidemic scale and they affect only parts of a country; further, they last for a short duration. The localized nature of such disasters presents the possibility that non-affected countries can help the disaster-stricken society. However, the ability to assist takes a different shape when a novel, long-running, and rapidly growing disaster such as COVID-19 emerges. Such a disastrous situation confuses decision-makers and governments and disrupts almost all community activities and supply chains. Since COVID-19 is a new and unknown virus, it has many unknown aspects and, thereby, the identification of and access to some of these aspects is time-consuming and costly; more importantly, it endangers the lives of many humans. Many communities face a shortage of medical and human resources (treatment staff) under such conditions due to the high rate of disease outbreaks. This heightened demand for services leads to disruptions among many supply chains, but especially with the healthcare supply chain. Therefore, the prioritization of community members for the provision of better services and solutions to manage the demand in the healthcare supply chain can improve government performance and reduce disruptions in this chain. In this paper, a decision support system based on the FIS and physicians' knowledge is developed to classify and prioritize community members in terms of the severity of physical condition. The proposed decision support system aims at using mitigation activities to reduce the effects of COVID-19, reduce disruptions in the healthcare supply chains to provide better service to disadvantaged communities, and, ultimately, to manage the increased demand in the healthcare supply chain. However, it should be noted that it is not possible to give all people in one community the same prescription. In other words, each group of the society has specific characteristics that differentiate their needs from those of another group. Thus, older residents and those with pre-existing diseases (such as diabetes, heart problems, or high blood pressure) are more vulnerable according to World Health Organization (WHO) reports. Accordingly, the community members are subdivided into four groups based on their level of vulnerability to COVID-19:

- Very sensitive group: People over 60 years of age who suffers at least one of the diseases of diabetes, heart problems, or high blood pressure.
- Sensitive group: People below 60 years of age with at least one of the diseases of diabetes, heart problems, or high blood pressure.
- Slightly sensitive group: People over 60 years of age with no diseases.
- Normal group: People below 60 years of age with no diseases.

When it comes to the classification of the members of the aforementioned groups, various approaches based on FIS accomplish that. In other words, the FIS is used to classify individuals of the society, but the fuzzy inference rules will be different for each group

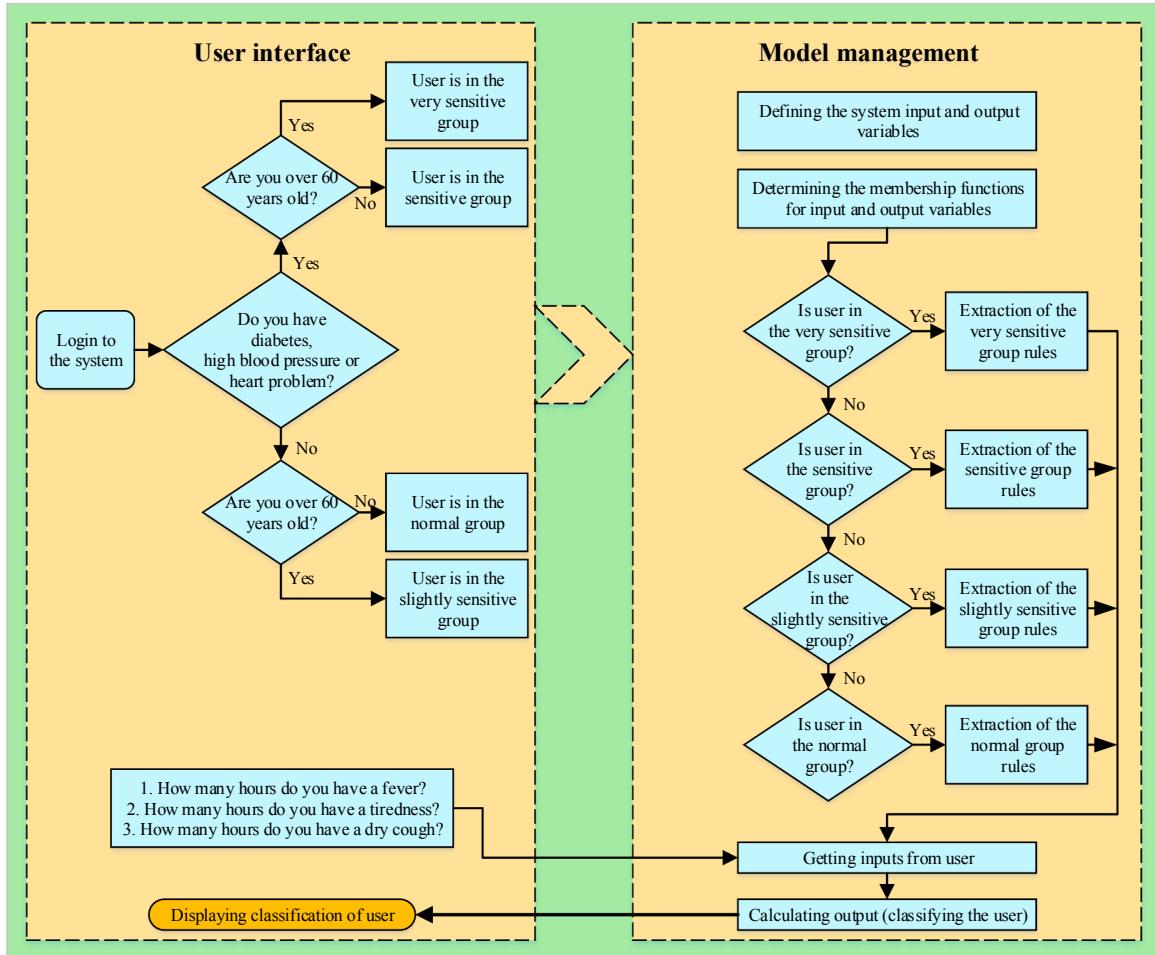


Fig. 2. The structure of proposed decision support system.

of people in the society. In Fig. 2, the structure of the decision support system for demand management in the healthcare supply chain has been depicted. This proposed decision support system, indeed, acts as a connecting bridge between service recipients and service providers in the healthcare supply chain. The service recipients are classified by inserting their information and responding to the questions presented by the system; then, they are informed about the type of services that they should receive from service providers. In this way, this decision support system provides the grounds for demand management in the healthcare supply chain by classifying the service recipients. The proposed approach is also described in the following steps:

**Step 1:** In this step, the assessment criteria of individuals' physical condition in the community is determined. According to the WHO reports, three criteria, namely fever, tiredness, and dry cough are the early symptoms of COVID-19. They are considered as the input variables of the FIS. In addition, the classification of the community members acts as the output variable of this system. Then, the membership functions of the input and output variables should be defined. The input variables consist of three membership functions, (low, mid, and high). The output variable is composed of five membership functions as follows:

- Class 1: Here, individuals who do not exhibit disease symptoms and have normal conditions are placed. These individuals are required to observe the healthcare tips and do their daily activities in accordance with the restrictions and guidelines set by their statesmen.
- Class 2: In this group, the individuals are placed who are suspicious of the disease and, thereby, should be quarantined and restricted in their relationship with others until their condition is identified although they may have a normal condition.
- Class 3: This group includes individuals who are suspected of having the mild disease and, in case they are proven to be infected, they do not need to be hospitalized and should be quarantined at home.
- Class 4: This group consists of members who are suspected of having a severe illness and need to be hospitalized if their disease is confirmed; however, they do not require intensive care.
- Class 5: This group contains those individuals who are suspected of suffering from serious illness and should be kept under intensive care in a hospital if their disease is proven.

Based on the proposed membership functions, the assessed individuals fall into one of these five classes.

**Step 2:** In this step, the fuzzy inference rules are determined by related experts and physicians for making a link between the input and output variables. It is noteworthy that a different set of fuzzy inference rules will be defined for each group of people in the society.

**Step 3:** In this step, the community members are assessed. For this purpose, the user enters the system; then, the proposed FIS is activated for the groups after it is determined to which group the user belongs. Finally, the user is evaluated and classified by responding to three questions about fever, tiredness, and dry cough.

#### 4. Case study

In this section, the performance of the proposed decision support system is evaluated using the latest WHO information on COVID-19 and physicians' knowledge in this domain. It should be noted that the evaluated criteria of the community members have been selected based on reports issued by the WHO; furthermore, physicians' knowledge has contributed to extract fuzzy inference rules and determine membership functions. The following presents a step-by-step implementation of the proposed approach:

**Step 1:** In this step, the input and output variables of the system are first determined. Fever, tiredness, and dry cough are defined as the input variables and the classification of community members is defined as the output variable of this system. Input variables entail the three membership functions of low, mid, and high; output variables include five membership functions (classes). It is also noteworthy that the membership functions of the input variables vary for different groups. In Fig. 3, the membership functions of the input variables have been presented for each group. The membership functions of the output variable are illustrated in Fig. 4.

**Step 2:** In this step, the fuzzy inference rules are determined by the physicians' knowledge for the four defined groups. The proposed FIS contains three input variables and three membership functions that have been defined for each input variable; therefore, there will be  $3^3 = 27$  fuzzy inference rules for each group of individuals. After the extraction of the fuzzy inference rules and their implementation in MATLAB R2016b software using FIS Editor GUI toolbox, one can observe the relationship between the input and output variables in the three-dimensional space. In Figs. 5–8, the fuzzy inference rules have been shown in three-dimensional space for normal, slightly sensitive, sensitive, and very sensitive groups, respectively.

**Step 3:** In this step, the individuals in the society are classified. For this purpose, the following three questions are asked from the users:

- How many hours do you have a fever?
- How many hours do you have a tiredness?
- How many hours do you have a dry cough?

The responses obtained from these questions are considered as inputs in the rule viewer box of the FIS and, finally, the output is computed. The system output is always a value within the range of zero to one. If the value obtained as the output lies exactly in one membership function (class), the user will belong to that class. However, if the resulting number falls between two membership functions, then the membership degree is considered as the selection index. To this end, the membership degree of the output variable is calculated for both classes. If the membership degree is the same for both classes, it does not matter in which class it will be placed. But, if the membership degree for class A is greater than that for class B, it should be placed in class A. The following is an example illustrating the efficiency of the proposed approach.

Assume that there are four users as follows:

- User 1: This user belongs to the very sensitive group.
- User 2: This user belongs to the sensitive group.
- User 3: This user belongs to the slightly sensitive group.
- User 4: This user belongs to the normal group.

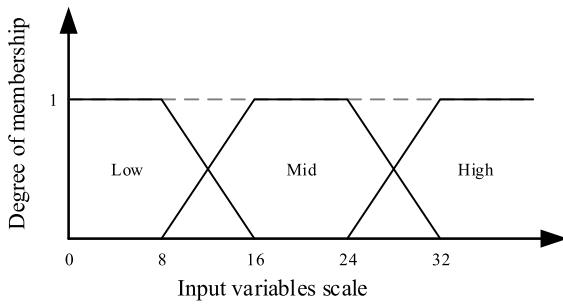
The answers given to the questions by each of these users are presented in Table 1.

The values presented in Table 1 are considered as the inputs into the proposed FIS. The output variable value calculated for each user is reported in Table 2.

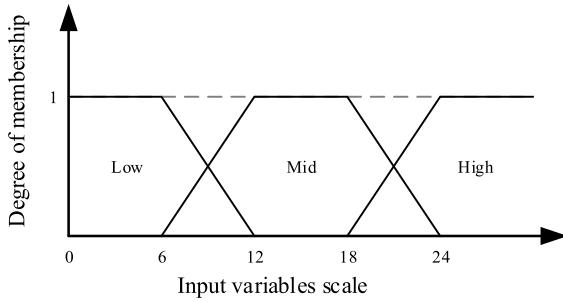
For the classification of users, it is benefited from the results of Table 2 and the membership functions (classes) presented in Fig. 4. As it can be observed, the output value for user 1 is equal to 0.662. Although this value lies between classes 3 and 4 in Fig. 4, it has been placed on the right side of the intersection of the two classes; in other words, it has a tendency to class 4. Thus, user 1 will be placed in class 4. The output values for users 1, 2, and 3 are equal to 0.51, 0.509, and 0.502, respectively. According to Fig. 4, these values are only in class 3; hence, these three users belong to class 3.

#### 5. Sensitivity analysis and discussion

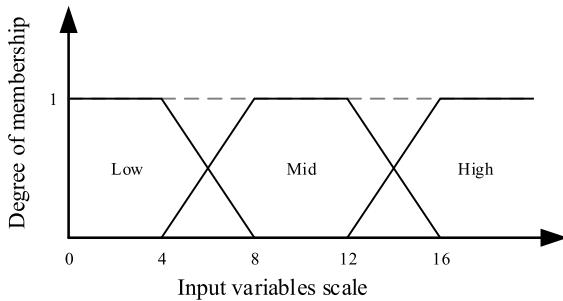
In this section, four scenarios, based on changing the user groups, are used to assess the performance of the proposed approach. In the case study section, it was assumed that there were four users, each of whom belonged to one of the four defined groups. In the current section, to do the sensitivity analysis of the proposed approach, it is assumed that the desired user belongs to any of the other three groups. We strive to see which class the user will be placed in and whether or not the change of class makes sense. For this purpose, four scenarios are defined as follows:



a. Membership functions of input variables for normal group



b. Membership functions of input variables for slightly sensitive and sensitive groups



c. Membership functions of input variables for very sensitive group

Fig. 3. Membership functions of input variables.

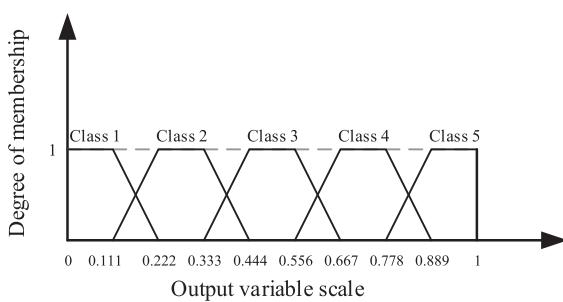
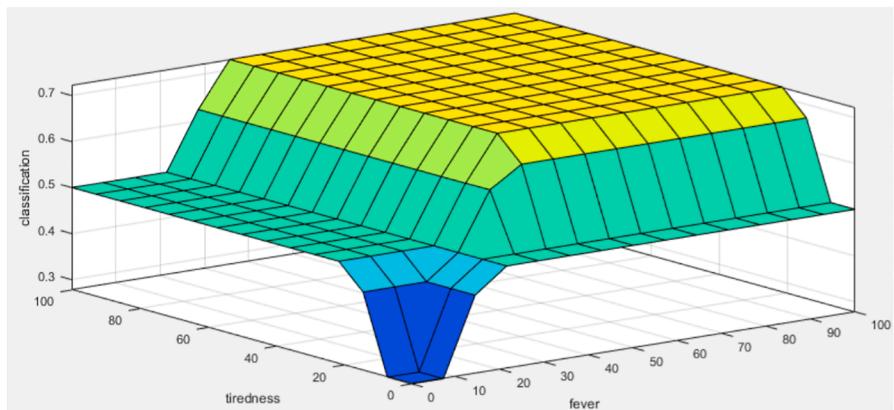
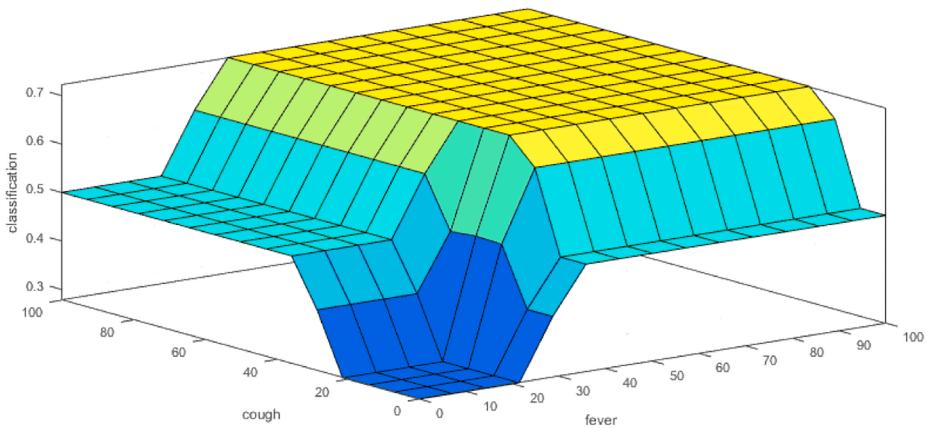


Fig. 4. Membership functions of output variables.

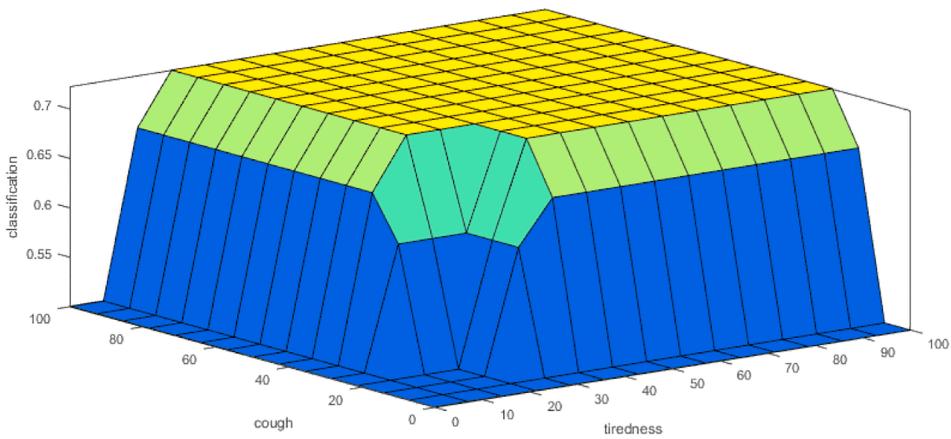
- **Scenario 1:** In this scenario, it is assumed that user 1 does not belong to the very sensitive group and belongs to one of the other three groups. When user 1 is grouped in the very sensitive group, it would belong to class 4. The user is expected to fall into class 4 or a lower one if it is placed in other groups. This is so because the membership functions of input variables in the very sensitive



a. Relationship between fever, tiredness and classification

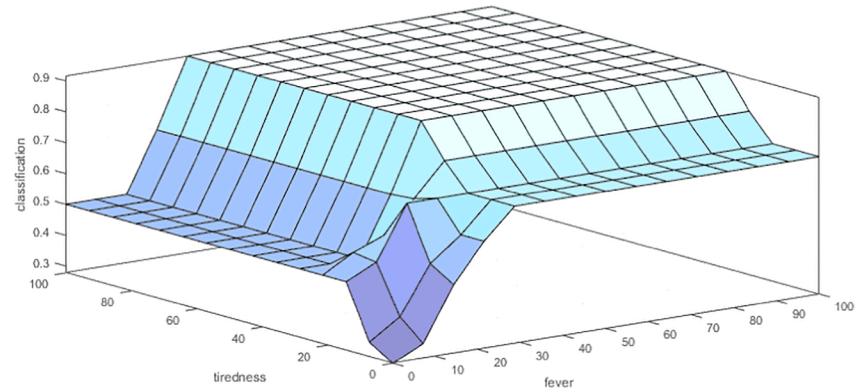


b. Relationship between fever, dry cough and classification

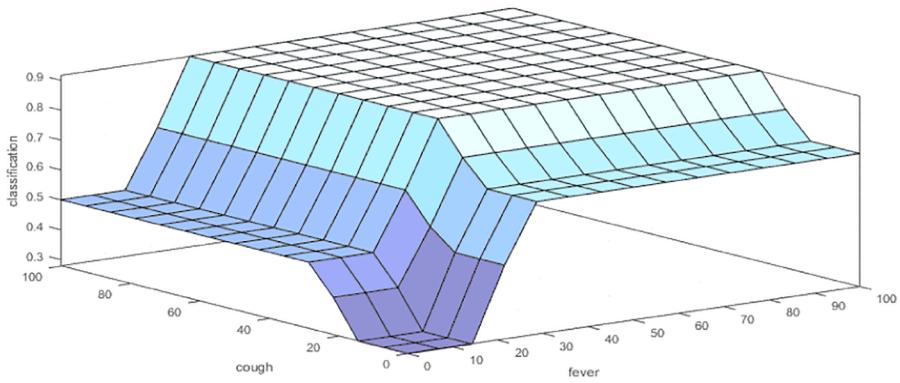


c. Relationship between tiredness, dry cough and classification

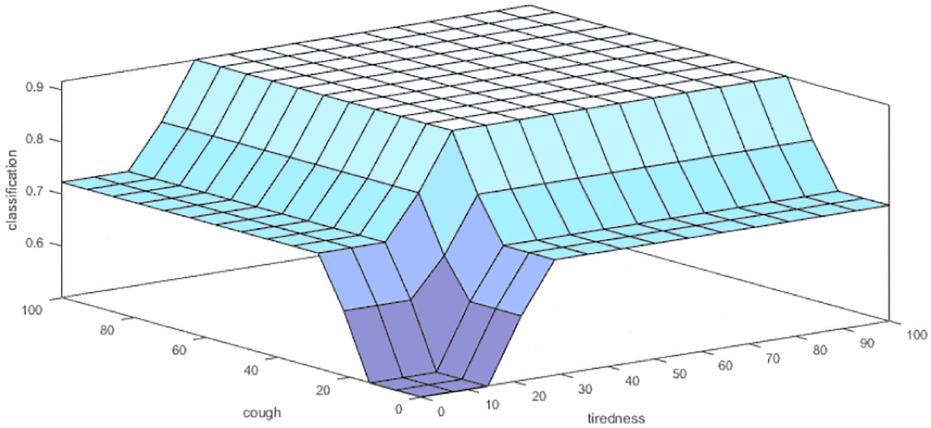
Fig. 5. Fuzzy inference rules for normal group.



a. Relationship between fever, tiredness and classification



b. Relationship between fever, dry cough and classification

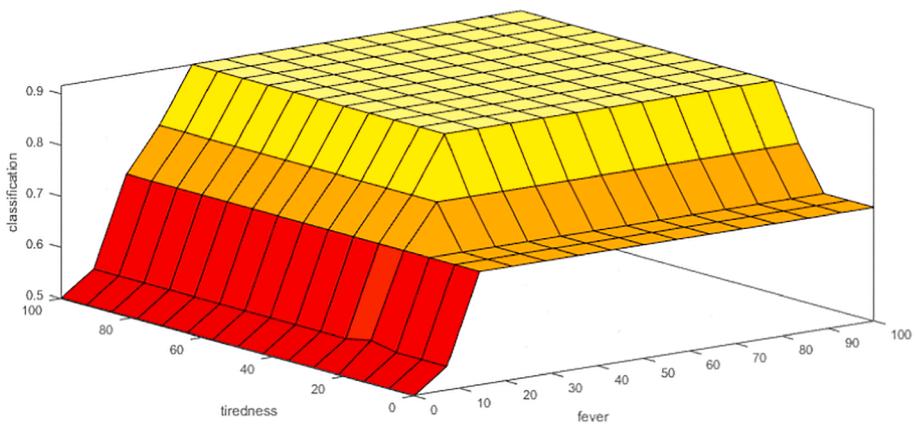


c. Relationship between tiredness, dry cough and classification

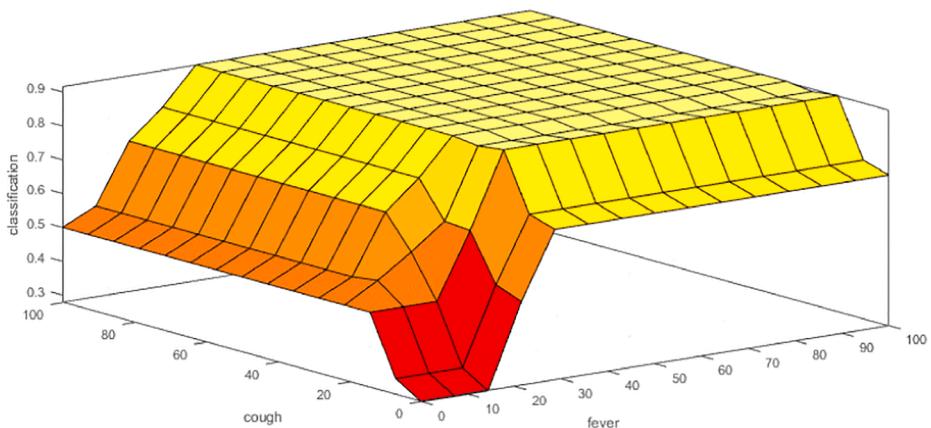
**Fig. 6.** Fuzzy inference rules for slightly sensitive group.

group are denser with a higher slope than those in the other groups. On the other hand, the fuzzy inference rules have been considered more cautious for the very sensitive group. In Table 3, the output value and classification of each user are shown.

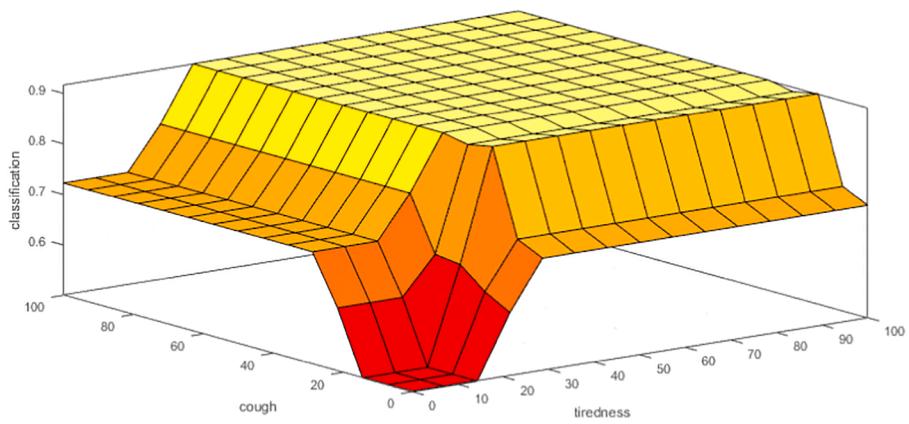
As it can be seen in Table 3, the obtained results are consistent with the claim made here; therefore, the performance of the proposed model is confirmed.



a. Relationship between fever, tiredness and classification

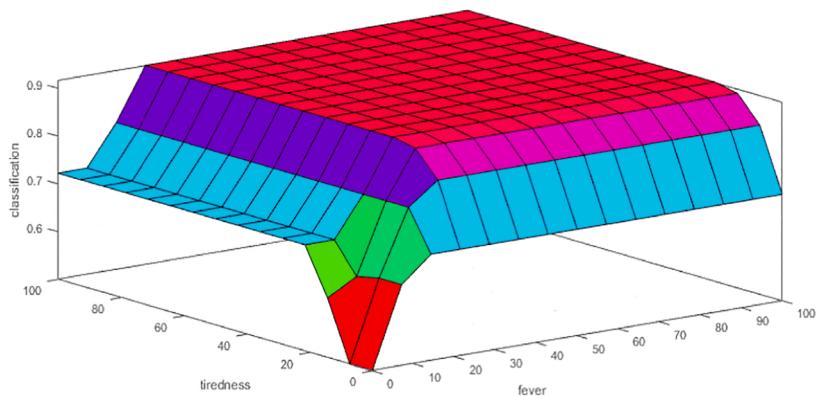


b. Relationship between fever, dry cough and classification

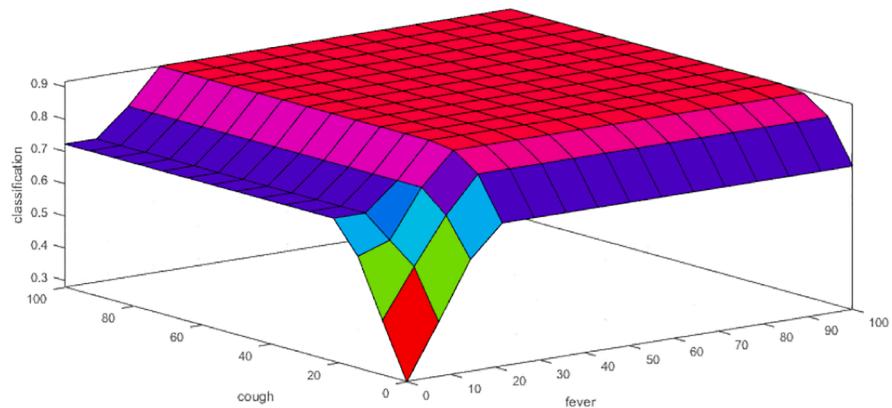


c. Relationship between tiredness, dry cough and classification

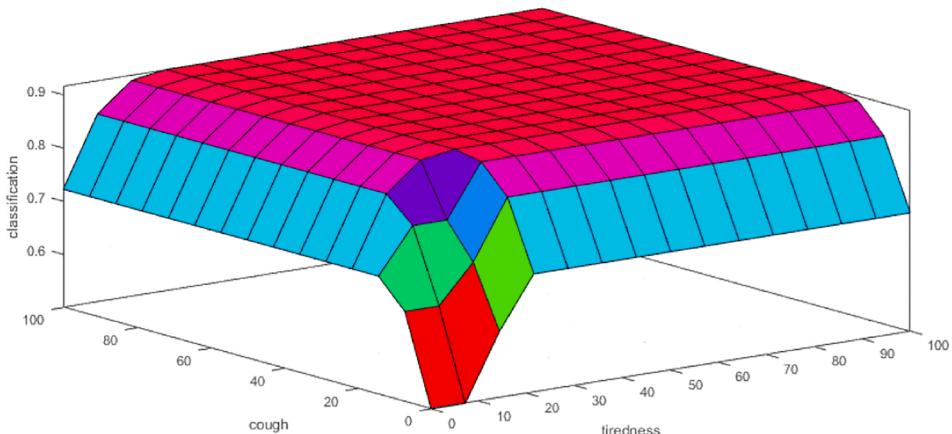
Fig. 7. Fuzzy inference rules for sensitive group.



a. Relationship between fever, tiredness and classification



b. Relationship between fever, dry cough and classification



c. Relationship between tiredness, dry cough and classification

Fig. 8. Fuzzy inference rules for very sensitive group.

**Table 1**

Responses to Questions by Each User.

	User 1	User 2	User 3	User 4
How many hours do you have a fever?	8	12	20	24
How many hours do you have a tiredness?	3	18	24	16
How many hours do you have a dry cough?	15	12	20	32

**Table 2**

Value of the output variable obtained from FIS for each user.

	User 1	User 2	User 3	User 4
Output value	0.662	0.51	0.509	0.502

**Table 3**

Performance of the proposed approach if user 1 belongs to different groups.

	Output value	class
If user 1 belongs to very sensitive group	0.662	4
If user 1 belongs to sensitive group	0.356	2
If user 1 belongs to slightly sensitive group	0.356	2
If user 1 belongs to normal group	0.262	2

**Table 4**

Performance of the proposed approach if user 2 belongs to different groups.

	Output value	class
If user 2 belongs to very sensitive group	0.722	4
If user 2 belongs to sensitive group	0.51	3
If user 2 belongs to slightly sensitive group	0.51	3
If user 2 belongs to normal group	0.317	2

**Table 5**

Performance of the proposed approach if user 3 belongs to different groups.

	Output value	class
If user 3 belongs to very sensitive group	0.916	5
If user 3 belongs to sensitive group	0.633	4
If user 3 belongs to slightly sensitive group	0.509	3
If user 3 belongs to normal group	0.5	3

- Scenario 2: In this scenario, it is assumed that if user 2 belongs to any of the very sensitive, slightly sensitive, or normal groups, the classes this user belongs to will differ. The output value and classification of this scenario are presented in [Table 4](#).

The results of this scenario are also in line with the logical expectations and reflect the accuracy of the proposed approach performance.

- Scenario 3: In this scenario, the performance of the proposed approach is measured when user 3 belongs to one of the groups other than the slightly sensitive group. In [Table 5](#), the results of this scenario are presented.

**Table 6**

Performance of the proposed approach when user 4 belonging to different groups.

	Output value	class
If user 4 belongs to very sensitive group	0.916	5
If user 4 belongs to sensitive group	0.722	4
If user 4 belongs to slightly sensitive group	0.722	4
If user 4 belongs to normal group	0.502	3

The results obtained from this scenario also show that the model follows a reasonable trend and its performance is confirmed.

- **Scenario 4:** In this scenario, it is assumed that user 4 does not belong to the normal group and belongs to one of the other three groups. If this user belonged to the normal group, it would be placed in class 3. This user is expected to be placed in classes 3, 4, or 5 if it belongs to other groups. However, if a different result is obtained, it would indicate the inaccurate performance of the proposed approach. In Table 6, the results of this scenario are shown.

The results of this scenario and the other three scenarios illustrate the soundness and proper performance of the proposed approach. Since people above 60 years of age and those with heart disease, diabetes, or high blood pressure have a poor immune system, they are more vulnerable to COVID-19 and should be given more attention. Thus, the fuzzy inference rules and membership functions are defined for different groups in accordance with their vulnerability, which is clearly observed in the four proposed scenarios. In Scenario 3, for example, if user 3 belongs to the very sensitive group and COVID-19 test result is positive, he/she should be hospitalized and placed under intensive care. However, if the same user belongs to the sensitive group, he/she will be hospitalized but does not require intensive care. On the other hand, if he/she belongs to the slightly sensitive or normal groups, there is no need for his/her hospitalization, and he/she should spend his/her illness period in quarantine at home. Therefore, the results show that the proposed approach follows logical patterns and its performance is confirmed.

## 6. Conclusion

In this paper, a practical decision support system was proposed to classify community members and, accordingly, manage the demand and control the epidemic outbreaks in the healthcare supply chain. In the proposed approach, users are first grouped according to two criteria, age range and pre-existing diseases (such as diabetes, heart problems, or high blood pressure). These users are then classified using FIS. It should be mentioned that the three criteria of fever, tiredness, and dry cough have been used to classify users and different membership functions of these variables have been considered for various groups. Finally, the proposed approach was validated using data pertaining to the four users. These results, and the results of the sensitivity analysis process, indicate the proper and effective performance of the proposed approach.

Besides its benefits, any research may suffer from some limitations and this paper is no exception. One of the limitations of the current study is that the three symptoms of fever, tiredness, and dry cough have been considered as the criteria for the assessment of community residents. These three criteria do figure among the most common symptoms of COVID-19 infection, but other symptoms, such as diarrhea, vomiting, and the like have also been observed in some patients (Huang et al., 2020; Rothon and Byrareddy, 2020; Wang et al., 2020). In this paper, three membership functions have been considered for input variables where it is possible to promote the accuracy of the decision support system by increasing the number of membership functions. Thus, for future research, it is recommended that other criteria such as diarrhea, vomiting, etc. be added to input variables in order to design a more accurate decision support system and to increase the number of membership functions of input and output variables as well. In this paper, an expert-based approach was employed to control epidemic outbreaks. It is recommended to use the integrated data science and expert knowledge to propose an adaptive neuro-fuzzy inference system for the control of epidemic outbreaks. Moreover, the decrease of the disruptions caused by epidemic outbreaks in supply chain network design by using multi-stage/scenario-based stochastic programming model can be an interesting and practical topic to be explored in future works (Govindan et al., 2017; Fattah et al., 2018; Fattah and Govindan, 2018). In epidemic disasters, the availability of vast amounts of data is usually evident. The employment of disruptive technologies can be a useful tool in this area (Choi et al., 2020a; Choi et al., 2020b; Shen et al., 2019; Ting et al., 2020; Govindan et al., 2018). Therefore, the use of larger amounts of data and blockchain technologies (Choi, 2019; Choi et al., 2019; Koh et al., 2020) to control disruptions is another attractive and new topic that is recommended to be considered as a future scope by researchers.

## References

- Acar, M., Kaya, O., 2019. A healthcare network design model with mobile hospitals for disaster preparedness: a case study for Istanbul earthquake. *Transp. Res. Part E: Logist. Transp. Rev.* 130, 273–292.
- Ahmadi, M., Seifi, A., Tootooni, B., 2015. A humanitarian logistics model for disaster relief operation considering network failure and standard relief time: a case study on San Francisco district. *Transp. Res. Part E: Logist. Transp. Rev.* 75, 145–163.
- Altay, N., Green III, W.G., 2006. OR/MS research in disaster operations management. *Eur. J. Oper. Res.* 175 (1), 475–493.
- Amindoust, A., Ahmed, S., Saghafinia, A., Bahreininejad, A., 2012. Sustainable supplier selection: a ranking model based on fuzzy inference system. *Appl. Soft Comput.* 12 (6), 1668–1677.
- Araz, O.M., Choi, T.-M., Olson, D., Salman, F.S., 2020. Data analytics for operational risk management. *Decision Sci* forthcoming.
- Asklany, S.A., Elhelou, K., Youssef, I.K., El-Wahab, M.A., 2011. Rainfall events prediction using rule-based fuzzy inference system. *Atmos. Res.* 101 (1–2), 228–236.
- BSI, 2014. Supply Chain Impact of 2014 Ebola Outbreak. accessed on March 11, 2020. [https://www.bsigroup.com/LocalFiles/en-GB/supply-chain-solutions/resources/Whitepaper%20Ebola\\_10.14\\_7.pdf](https://www.bsigroup.com/LocalFiles/en-GB/supply-chain-solutions/resources/Whitepaper%20Ebola_10.14_7.pdf).
- Büyüktatlıkın, İ.E., des Bordes, E., Kübiş, E.Y., 2018. A new epidemics–logistics model: Insights into controlling the Ebola virus disease in West Africa. *Eur. J. Oper. Res.* 265 (3), 1046–1063.
- Calnan, M., Gadsby, E.W., Kondé, M.K., Diallo, A., Rossman, J.S., 2018. The response to and impact of the Ebola epidemic: towards an agenda for interdisciplinary research. *Int. J. Health Policy Manage.* 7 (5), 402.
- Carter, W.N., 1992. Disaster management: A disaster manager's handbook. Asian Development Bank, Book, Manila, Philipines.
- Chai, Y., Jia, L., Zhang, Z., 2009. Mamdani model based adaptive neural fuzzy inference system and its application. *Int. J. Comput. Intell.* 5 (1), 22–29.
- Choi, T.M., 2019. Blockchain-technology-supported platforms for diamond authentication and certification in luxury supply chains. *Transp. Res. Part E: Logist. Transp. Rev.* 128, 17–29.
- Choi, T.M., Wen, X., Sun, X., Chung, S.H., 2019. The mean-variance approach for global supply chain risk analysis with air logistics in the blockchain technology era.

- Transp. Res. Part E: Logist. Transp. Rev.* 127, 178–191.
- Choi, T.M., Feng, L., Li, R., 2020a. Information disclosure structure in supply chains with rental service platforms in the blockchain technology era. *Int. J. Prod. Econ.* 221, 107473. <https://doi.org/10.1016/j.ijpe.2019.08.008>.
- Choi, T.M., Guo, S., Liu, N., Shi, X., 2020b. Optimal pricing in on-demand-service-platform-operations with hired agents and risk-sensitive customers in the blockchain era. *Eur. J. Oper. Res.* 284 (3), 1031–1042.
- Choi, Tsan-Ming, 2020. Innovative “bring-service-near-your-home” operations under corona-virus (COVID-19/SARS-CoV-2) outbreak: can logistics become the messiah? *Transp. Res. Part E: Logist. Transp. Rev.* 101961. <https://doi.org/10.1016/j.tre.2020.101961>.
- Chou, J., Kuo, N.F., Peng, S.L., 2004. Potential impacts of the SARS outbreak on Taiwan's economy. *Asian Econ. Papers* 3 (1), 84–99.
- Chung, C.J., Hsieh, Y.Y., Lin, H.C., 2019. Fuzzy inference system for modeling the environmental risk map of air pollutants in Taiwan. *J. Environ. Manage.* 246, 808–820.
- Fattah, M., Govindan, K., 2018. A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk: a real-life case study. *Transp. Res. Part E: Logist. Transp. Rev.* 118, 534–567.
- Fattah, M., Govindan, K., Keyvanshokooh, E., 2018. A multi-stage stochastic program for supply chain network redesign problem with price-dependent uncertain demands. *Comput. Oper. Res.* 100.
- Galindo, G., Batta, R., 2013. Review of recent developments in OR/MS research in disaster operations management. *Eur. J. Oper. Res.* 230 (2), 201–211.
- Goldschmidt, K.H., Kumar, S., 2016. Humanitarian operations and crisis/disaster management: a retrospective review of the literature and framework for development. *Int. J. Disaster Risk Reduct.* 20, 1–13.
- Govindan, K., Fattah, M., Keyvanshokooh, E., 2017. Supply chain network design under uncertainty: A comprehensive review and future research directions. *Eur. J. Oper. Res.* 263 (1), 108–141.
- Govindan, K., Cheng, T.C.E., Mishra, N., Shukla, N., 2018. Big data analytics and application for logistics and supply chain management. *Transp. Res. Part E: Logist. Transp. Rev.* 114, 343–349.
- Hamdan, B., Diabat, A., 2020. Robust design of blood supply chains under risk of disruptions using Lagrangian relaxation. *Transp. Res. Part E: Logist. Transp. Rev.* 134, 101764.
- He, Y., Liu, N., 2015. Methodology of emergency medical logistics for public health emergencies. *Transp. Res. Part E: Logist. Transp. Rev.* 79, 178–200.
- Hossain, M.N., Paul, S.K., 2018. Vulnerability factors and effectiveness of disaster mitigation measures in the Bangladesh coast. *Earth Syst. Environ.* 2 (1), 55–65.
- Hosseini-Motlagh, S.M., Nouri-Harzvili, M., Choi, T.M., Ebrahimi, S., 2019. Reverse supply chain systems optimization with dual channel and demand disruptions: sustainability, CSR investment and pricing coordination. *Inf. Sci.* 503, 606–634.
- Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., Cheng, Z., 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet* 395 (10223), 497–506.
- Ilbahar, E., Karaslan, A., Cebi, S., Kahraman, C., 2018. A novel approach to risk assessment for occupational health and safety using Pythagorean fuzzy AHP & fuzzy inference system. *Saf. Sci.* 103, 124–136.
- Ivanov, D., 2020. Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transp. Res. Part E: Logist. Transp. Rev.* 136, 101922.
- Jain, N., Singh, A.R., 2020. Sustainable supplier selection under must-be criteria through Fuzzy inference system. *J. Cleaner Prod.* 248, 119275.
- Jain, N., Singh, A.R., Upadhyay, R.K., 2020. Sustainable supplier selection under attractive criteria through FIS and integrated fuzzy MCDM techniques. *Int. J. Sustainable Eng.* 1–22. <https://doi.org/10.1080/19397038.2020.1737751>.
- Johanis, D., 2007. How Toronto Pearson International Airport applied lessons from SARS to develop a pandemic response plan. *J. Bus. Cont. Emerg. Plan.* 1 (4), 356–368.
- Kaur, H., Singh, S.P., 2019. Sustainable procurement and logistics for disaster resilient supply chain. *Ann. Oper. Res.* 283 (1), 309–354.
- Khajeh, A., Modarress, H., 2010. Prediction of solubility of gases in polystyrene by adaptive neuro-fuzzy inference system and radial basis function neural network. *Expert Syst. Appl.* 37 (4), 3070–3074.
- Koh, L., Dolgui, A., Sarkis, J., 2020. Blockchain in transport and logistics – paradigms and transitions. *Int. J. Prod. Res.* 58 (7), 2054–2062.
- Kilci, F., Kara, B.Y., Bozkaya, B., 2015. Locating temporary shelter areas after an earthquake: a case for Turkey. *Eur. J. Oper. Res.* 243 (1), 323–332.
- Lin, K.P., Ho, H.P., Hung, K.C., Pai, P.F., 2012. Combining fuzzy weight average with fuzzy inference system for material substitution selection in electric industry. *Comput. Ind. Eng.* 62 (4), 1034–1045.
- Loree, N., Aros-Vera, F., 2018. Points of distribution location and inventory management model for Post-Disaster Humanitarian Logistics. *Transp. Res. Part E: Logist. Transp. Rev.* 116, 1–24.
- Mamdani, E.H., Assilian, S., 1993. An experiment in linguistic synthesis with a fuzzy logic controller. In: *Readings in Fuzzy Sets for Intelligent Systems*. Morgan Kaufmann, pp. 283–289.
- Nazari, S., Fallah, M., Kazemipoor, H., Salehipour, A., 2018. A fuzzy inference-fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases. *Expert Syst. Appl.* 95, 261–271.
- Oruc, B.E., Kara, B.Y., 2018. Post-disaster assessment routing problem. *Transp. Res. Part B: Methodol.* 116, 76–102.
- Pourjavad, E., Mayorga, R.V., 2019. A comparative study and measuring performance of manufacturing systems with Mamdani fuzzy inference system. *J. Intell. Manuf.* 30 (3), 1085–1097.
- PrasannaVenkatesan, S., Goh, M., 2016. Multi-objective supplier selection and order allocation under disruption risk. *Transp. Res. Part E: Logist. Transp. Rev.* 95, 124–142.
- Rezaei-Malek, M., Tavakkoli-Moghaddam, R., Cheikhrouhou, N., Taheri-Moghaddam, A., 2016. An approximation approach to a trade-off among efficiency, efficacy, and balance for relief pre-positioning in disaster management. *Transp. Res. Part E: Logist. Transp. Rev.* 93, 485–509.
- Rothon, H.A., Bayareddy, S.N., 2020. The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. *J. Autoimmun.*, 102433.
- Sarma, D., Das, A., Bera, U.K., Hezam, I.M., 2019. Redistribution for cost minimization in disaster management under uncertainty with trapezoidal neutrosophic number. *Comput. Ind.* 109, 226–238.
- Shahparvari, S., Chhetri, P., Abbasi, B., Abareshi, A., 2016. Enhancing emergency evacuation response of late evacuees: revisiting the case of Australian Black Saturday bushfire. *Transp. Res. Part E: Logist. Transp. Rev.* 93, 148–176.
- Shen, B., Choi, T.M., Chan, H.L., 2019. Selling green first or not? A Bayesian analysis with service levels and environmental impact considerations in the Big Data Era. *Technol. Forecast. Soc. Chang.* 144, 412–420.
- Sheu, J.B., 2016. Supplier hoarding, government intervention, and timing for post-disaster crop supply chain recovery. *Transp. Res. Part E: Logist. Transp. Rev.* 90, 134–160.
- Sugeno, M., 1985. *Industrial Applications of Fuzzy Control*. Elsevier, Amsterdam.
- Tavana, M., Khosrojerdi, G., Mina, H., Rahman, A., 2019. A hybrid mathematical programming model for optimal project portfolio selection using fuzzy inference system and analytic hierarchy process. *Evaluat. Prog. Plan.* 77, 101703.
- Ting, D.S.W., Carin, L., Dzau, V., et al., 2020. Digital technology and COVID-19. *Nat. Med.* 26, 459–461.
- Tomasini, Rolando, Wassenhove, Luk Van (Eds.), 2009. *Humanitarian Logistics*. Palgrave Macmillan UK, London.
- United Nations, 2020. What is the coronavirus disease (COVID-19)? Civil Society, <https://www.un.org/en/civil-society/page/coronavirus-disease-covid-19>.
- Wang, W., Tang, J., Wei, F., 2020. Updated understanding of the outbreak of 2019 novel coronavirus (2019-nCoV) in Wuhan, China. *J. Med. Virol.* 92 (4), 441–447.
- Wang, Y., Wang, J., 2019. Integrated reconfiguration of both supply and demand for evacuation planning. *Transp. Res. Part E: Logist. Transp. Rev.* 130, 82–94.
- WHO, 2020. Coronavirus disease (COVID-19) outbreak situation. 31 March 2020, <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>.
- Yan, Y., Hong, L., He, X., Ouyang, M., Peeta, S., Chen, X., 2017. Pre-disaster investment decisions for strengthening the Chinese railway system under earthquakes. *Transp. Res. Part E: Logist. Transp. Rev.* 105, 39–59.
- Zhao, T., Xu, X., Chen, Y., Liang, L., Yu, Y., Wang, K., 2020. Coordination of a fashion supply chain with demand disruptions. *Transp. Res. Part E: Logist. Transp. Rev.* 134, 101838.