

Fuzzy Modelling of Clinical and Epidemiological Factors for COVID-19

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Abstract

During this pandemic outbreak of COVID-19, the whole world is getting severely affected in respect of population health and economy. This novel virus has brought the whole world including the most developed countries to a standstill in a very short span like never before. The prime reason for this unexpected outburst of COVID-19 is lack of effective medicine and lack of proper understanding of the influencing factors. Here, authors aim to find the effect of epidemiological factors that influence its spread using a fuzzy approach. For the same, a total of 9 factors have been considered which are classified into *Risk* and *Preventive* factors. This fuzzy model supports to understand and evaluate the impact of these factors on the spread of COVID-19. Also, the model establishes a basis for understanding the effect of risk factors on preventive factors and vice versa. It is worth mentioning that this is the first attempt to analyze the effect of Clinical and Epidemiological factors with respect to COVID-19 using a fuzzy approach.

1. Introduction

The first case of pneumonia of unidentified cause was confirmed to the WHO (World Health Organization), China on December 2019. Since then, the epidemic of this virus became a matter of severe concern and within 1 month, the outbreak was declared an international public health emergency on 30 January 2020. Also, WHO coined a name for new coronavirus disease: COVID-19 and declared it a pandemic on 11th March 2020. The emergence of the novel coronavirus (SARS-CoV-2) infection (COVID-19) had raised a wave of shock and concern around the world as on 1st May 2020, there have been 3,181, 642 cases and 2,24, 301 deaths affecting 215 countries and territories[1]. These numbers are expected to rise significantly in future as there is no successful vaccine or antiviral strategy available against the disease. Preventive measures like lockdown remain the only viable strategy to stop the viral transmission. In the midst of this global pandemic accurate and timely information about the origin and epidemiological characteristics can prove to be a probable solution to contain this virus. Due to elevated transmissibility of these emerging infectious diseases of zoonotic origin, identifying the drivers and spatial diffusion is a great challenge. Efficient integration of tools like epidemiology, fuzzy approach and bioinformatics can provide solutions to these complex situations.

COVID-19's first case was associated with direct access to Wuhan's Huanan Seafood Wholesale Market, and from there the animal-to-human transmission was believed to be the main source of disease spread. Subsequent cases, however, were not found to be linked to the same exposure, and thus symptomatic human-to-human transmission was identified as the key cause of COVID-19 spread. At the same time, pre-symptomatic and asymptomatic transmission for the spread of the disease is equally likely [2].

Several demographic factors, including gender, age, and blood type, have previously been classified as risk factors for infection but the biostatistics studies have not been adequately advanced to examine complex associations between several variables until recently. With the emergence of fuzzy logic and genetic algorithms applications, computers can now find correlations between variables and find out the most promising ones.

The manuscript works on the broad classification of factors involved in the spread of COVID-19 as risk and preventive factors. A fuzzy model based on Mamdani approach is presented to model the inter-relationship and dependency of the factors. Three fuzzy models are presented; First based on the mapping of various factors on the risk evaluation; second based on the preventive factors mapping. The final model is the mapping of the risk and preventive factors to evaluate the susceptibility index.

The manuscript is organized as follows: After Introduction in section 1, section 2 covers the related work to COVID-19 domain. Section 3 describes the factors taken for the fuzzy modelling approach. Section 4 presents the proposal model. Section 5 presents the results and discussion of various factors on the susceptibility index, with conclusion given at the end.

2. Related Work

Researchers and health professionals have been fascinated by the spread of this epidemic virus. The pattern of unprecedented and unmatched spread of COVID-19 needs to be understood in order to devise efficient preventive mechanisms to curb its spread. The prime challenge for completely understanding the pattern of its spread is its short span. Hence, intensive study is being carried out by researchers to assimilate its epidemic nature which aids in accurately forecasting the increase in infected people. This section briefly discusses the recent studies related to the forecast of its outbreak.

Authors in [3] aim to elucidate coronavirus transmission at different stages by using Gaussian distribution. For the same, authors simulate the model considering the data related to the Hubei epidemic situation. Authors claim that the gap between model's predicted values and actual value is quite small. Thus, the proposed model can lay the basis for epidemic prevention and control in the affected countries. Another prediction model is proposed by Zifeng Yang et.al [4]. In this study, authors use the Susceptible-Exposed-Infectious-Removed (SEIR)

model on migration data (before and after January 23). Additionally, authors used the most updated epidemiological data related to COVID-19 to understand epidemic curve. Further, artificial intelligence (AI) is also integrated with SEIR and this modified SEIR model is trained using 2003 SARS data. This modified SEIR epidemiological model also included some additional parameters apart from those considered for Ebola virus analysis in 2018. Authors guarantee that this dynamic SEIR model efficiently predicts the epidemic peaks and sizes.

Authors in [5] proposed a classifier model that uses a neural network to understand how a patient responds to the treatment. For the same, this model uses related data from February 20, 2020 to March 9, 2020 related to recovered patients and dead patients. The proposed model uses seven different variables namely country, region, infection reason, confirmation date, birth year, sex and group. The proposed classifier model aims to find the most effective variables to determine fatality or recovery. This model establishes three most influencing variables viz. infection reason, confirmation date and region that strongly predicts the future state of patient. Thus, the proposed NN based model helps to envisage the status of COVID-19 patients. The transmission trend of epidemic is also studied by Yichi Li et.al [6]. This understanding enables to devise short term prevention programs that helps in devising various control measures to limit further propagation of this virus. For the same, authors present a dynamic model for epidemic and a time series model for short-term forecasting of transmission of COVID-19. Authors claim to achieve accurate prediction of the forecasting.

Work by Joel Hellewell et.al [7] further assisted the belief that contact tracing and isolation of infected cases is effective to control the spread of this contagious disease. Authors concluded this by using a stochastic transmission mode that ascertains the effectiveness of isolation and contact tracing. This model works by finding the number of primary infected people generated and secondary infected people that helps in finding the reproduction number (R_0). R_0 is a crucial factor as it indicates the number of people who get infected by an infected person. If R_0 goes above 1 then the rate of infection grows exponentially. However, if R_0 remains below 1, then the rate of infection may decay exponentially [8]. Vitaly Volpert et al. [8] used the data analytics to R_0 can be controlled by restricting the contact between individuals through a quarantine model. However, it also claims that the mere quarantine method is not sufficient to curb its spread thus new strict measures need to be considered. Authors in [9] claim that R_0 is in the expected range of 1.4-3.9 for India. This claim is made by comparing data of India with several other countries in the US. Exponential and classic susceptible-infected- recovered (SIR) models are used to perform predictions (both long-term and short-term). This model predicts that equilibrium is achieved in India by May 2020. Authors also mention that this estimation stands invalid if community transmission takes place in India as this prediction is made considering sophisticated levels of social distancing.

Melanie Bannister et al. [10] considered the influence of environmental factors on the spread of COVID-19 and presented an interesting fact that mentions the impact of temperature on its spread in Europe. The study states that higher temperature diminishes the proliferation of this virus. Similarly authors in Jianyun Lu et.al [11] studied the relationship of outbreak with ventilation. Here, authors concluded that droplet transmission is enhanced in an airconditioned environment as it persists longer in the air. Moreover, the direction of air flow is also an important factor in this regard. Apart from environmental factors, research also attempts to understand the relation of physical health. A such attempt is made to understand the impact of existing health conditions (including hypertension ,diabetes and other respiratory disease)of the infected person by [12] Authors in [12] present an analysis based on review of different databases i.e. PubMed, EMBASE and Web of Science to assess the prevalence of comorbidities in the COVID-19 patients. This study claims that the existing conditions add more risk to severe patients over non-severe patients.

3. Related Epidemiological And Clinical Factors

This section discusses the various epidemiological and clinical factors that have been considered to understand the spread of pandemic coronavirus. The contributing factors have been classified into risk and protective factors. Risk factors represent environmental and some other factors which are beyond human control. Examples of risk factors are age, humidity, and temperature etc. However, protective factors are under human control and thus can be adjusted in response to requirement. Few examples of protective factors are personal hygiene, social distancing etc.

I. VIRULENCY

Coronavirus (CoVs) is an unparalleled damaging virus for human, livestock, gastrointestinal, hepatic, infecting respiratory, and central nervous system [13]. During the 2002 SARS outbreak and 2012 MERS outbreak, the likelihood of transmission of CoVs from animals to humans was already confirmed [14]. Prior to 2019, there were only few CoVs that could infect respiratory system in human viz. HCoV-229E, HCoV-OC43, HCoV- NL63 and HKU1. These viruses could trigger only mild upper respiratory disease in normal conditions although it could also lead to serious infection under extreme circumstances. SARS-CoV and MERS-CoV are other similar viruses which can infect lower respiratory tract and cause severe respiratory syndrome [13][15].

This recent virus COVID-19 has been unanimously accepted to be the most severe virus till date as its spread is quite fast and uncertain. According to the recent guidelines by Chinese health authorities' [16] three are major transmission modes for COVID-19: 1) transmission through droplets, 2) transmission of aerosols and finally 3) transmission by contacts. Apart from these, digestive system is also considered to be a possible transmission mode for COVID-19. The distance covered by these droplets is normally limited to 2 meters. Nevertheless, this airborne transmission also takes place with much smaller droplets that can float and travel longer distance[17]. Moreover, these airborne droplets remains in environment for hours and even days under particular environmental conditions [18].

II. Host Defense Potential

Clinically, SARS-CoV-2 or any similar virus triggers the immunity system to work in two stages. Initially, it requires an immunological response to eradicate the virus during the incubation stage and thus prevent its progression to severe stages. These two stages are clinically known as anti-sera or pegylated IFN α . For the same, health of the host should be in good general health. Additionally, it also necessitates a favorable genetic history as it elicits adaptive antiviral immunity for the growth of an endogenous defensive immune response at the incubation and non-severe stages.

Genetic differences in the immune response to pathogens are believed to respond to human variations. However, when a defensive immune response is compromised, virus spreads and massive tissue destruction starts particularly in intestines and kidneys leading to severe viral infections [19] [20]. Thus, immune insufficiency or misdirection leads to viral replication and hence damages tissue. By study, it is evident that Immune insufficiency or misdirection can increase viral replication and cause damage to tissues [21].

III. Underlying Health Conditions

Health of an individual plays an important factor considering in susceptibility of COVID-19. It appeared prematurely in the COVID-19 epidemic that infants or healthy people are safe from this virus, but later it was understood that it could be just because they were unlikely to have visited the Wuhan wet market. Another reason for the same could also be that they were more probable to have asymptomatic or benign infection and therefore implausible to have been screened for it. Nevertheless, COVID-19 affected infants (1 month old). Also no cases of negative child outcomes have been reported for COVID-19 positive moms pregnancy [15].

IV. Atmospheric Temperature and Humidity

According to a research, it is claimed that high temperature and humidity can reduce the spread of coronavirus. This claim is in agreement the similar claim for spread of Influenza [22]. At the same time, it is also too early to make any strong claim based on the small historical data of not more than 4 months. Primarily, this claim is based on the strong belief that the coronavirus primarily transmits through respiratory droplets [23]. For the same, the behavior of coronavirus at different temperatures and humidity is being studied intensively. According to the study in [24], authors claim using linear regression framework that high humidity and high temperature lead to reduction in transmission of COVID-19. Authors also claim that each 1⁰ Celsius increase in temperature and 1% increase in humidity results in reduction of daily reproductive value by 0.0225 and 0.0158, respectively.

Similar study for SARS coronavirus in [23] revealed that the SARS coronavirus can retain for 5 days at temperatures of 22–25°C and relative humidity of 40–50% . However, the virus is lost at higher temperature (>38°C) and relatively higher humidity (>95%). Hence, it is evident that low temperature and low humidity environmental conditions favors expediting the virus spread.

V. Airflow and Ventilation

During the intensive study of contributing factors responsible for the spread of coronavirus, a shocking conclusion was drawn while understanding the outbreak of the virus in a southern chinese city of Guangzhou [11]. In this incident, it was noticed that the direction of droplet transmission was consistent with airflow direction. This incidence sidelined the prevalent opinion about its spread by giving an eye opening result that coronavirus can also ride on currents created by air-conditioning. Resultantly, HVAC (Heating, Ventilation and Air Conditioning Systems) engineer's society itself made an official statement that airborne transmission of COVID-19 is most likely that leads to implementation of necessary changes in the building ventilation. Authors in [25] also attempted to establish the transmission mechanism of this virus. In the study, authors in [25] conclude that HVAC, if not implemented correctly, may enhance and expedite the spread of the virus. Hence, a major shift is mandated to prevent virus spread by implementing structural changes to buildings and HVAC systems.

VI. Personal Hygiene factors

It is quite evident since the explosion of COVID-19 that this virus transmits through physical contact. Hence, the spread of this virus may be controlled by maintaining sophisticated hygiene standards. Relation between personal hygiene and virus spread has already been

established by authors in [26]. Moreover, the evidence of hand hygiene in preventing nosocomial infections was demonstrated as early as 1847. However, standard personal hygiene is not limited to hand hygiene only. It also considers safe waste management, respiratory hygiene, environmental cleaning and sterilization of patient-care equipment etc. [27]. For COVID-19, maintaining personal hygiene is most crucial as it spreads through air droplets of infected people. Hence, it is of paramount importance that the patient must cover their nose and mouth while coughing or sneezing [28].

VII. Social Distance

As the novel COVID-19 outbreak continues to proliferate around the globe, healthcare experts and government officials strongly advise individuals and families to position space between themselves and others. The idea of social distancing seems to have gone from emergency healthcare preparedness and mitigation jargon to a household expression till a proven vaccine is available. As COVID-19 is known to spread through human-to-human transmission, the transmission is known to affect contacts within 6 feet radius. The virus can be transmitted airborne and stay on objects for as many as three hours; hence social distancing is considered to be the viable and easiest solution to contain this virus.

VIII. Population Density

Another most important factor in analysing the susceptibility of the virus is population density. COVID-19 has taken hold and struck hard in different places of the world. For instance, largely dense cities, like New York, London, with the huge inflows of tourists, and hugely dense residential areas, industrial centers like Wuhan, Italy, Detroit have shown the spread of the epidemic exponentially. At the same time, its many other factors along with population density such as population size, age, education, level, work culture, also play prominent roles in the spread of epidemics.

4. Proposed Model

The literature survey shows that to ensure the susceptibility of a subject, a number of epidemiological and clinical factors need be considered and their collaborative effect has to be ensured. For the same, authors propose a fuzzy inference model in this section.

4.1 Objective

An integrated analytical approach is essentially required to model the inter-relationship and dependency of the factors. Hence, a model needs to be designed to analyse the impact of various influencing factors.

4.2 Proposal

The proposed model employs a fuzzy expert system based on Mamdani-fuzzy inference [29] system for predicting the susceptibility of the subject based on various epidemiological and clinical factors as discussed in the previous section. Here, authors attempt to give a brief introduction to the employed fuzzy expert system.

4.3 Fuzzy Expert System

Fuzzy logic is a mathematical tool to predict unknown and multi-factorial issues. Fuzzy expert system is illustrated through a block diagram as shown in following Fig. 1 containing various blocks.

The description of basic blocks is as follows: The process begins by feeding crisp values of input parameters to the fuzzifier module for fuzzification.

Fuzzifier Module: This module transforms the crisp inputs into linguistic variables and their corresponding memberships.

Fuzzy/Crisp mapping module: This module contains the mathematical details for converting a crisp value to its corresponding fuzzy set and associated membership value and vice versa.

Knowledge Base: This module contains a library of conditional rules in „IF-THEN“ form.

Inference Engine: - It refers to the knowledge base and selects the relevant rules to be fired. The selected rules are placed in the conflict set and fired one by one. The inference engine used in our case is that of Mamdani – type.

Defuzzification Module: - This module converts the obtained crisp value using any of the chosen defuzzification methods.

Characteristics of Mamdani-based fuzzy inference system are presented in Table 1.

Table 1: Characteristics of fuzzy inference system Mamdani Model

Operation	Operator	Role	Formula
Sum (OR)	MAX	T-conorm	$\mu_C(x) = \max(\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x)$
Subscription (AND)	MIN	T-norm	$\mu_C(x) = \min(\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x)$
Implication	MIN	T-norm	$\max(\min(\mu_A(x), \mu_B(x)))$
Aggregation	MAX	T-conorm	
Defuzzification	Centroid		$COA = Z = \frac{\int z \mu(z) dz}{\int \mu(z) dz}$

4.4 Proposed Model based on Mamdani based FES

The proposed model is implemented in MATLAB-R2013b. This model is based on a hierarchy of 3 FES where risk value and prevention value are calculated through the base FES and the results are fed into the inherited FES, which results into the susceptibility level determination as shown in Fig 2.

4.4.1 FES Implementation for Risk Value

Fuzzy pattern to calculate risk value is shown in Fig 3 where 5 major risk factors are considered as input to the FES. Each factor is an aggregate of multiple related risk factors like Immunity covers age, Current health position and other related health factors; similarly, atmosphere temperature also includes humidity and related factors.

These factors have their different range of variations like Virulency is scaled on a Likert Scale (0-10), Immunity is also scaled on Likert Scale (0-10), Atmospheric Temperature variate from 0-45 Degree Celsius, Population density variate from 0-1000 people/ KM² (2 or 3) and Ventilation variate from 0-50 CFM as shown in table 2 and crisp value of these variations are fuzzified into 2 or 3 linguistic variables low, medium and high etc as per the context. As per the variation of each input factors into different membership functions, total rules formed are 162. On these rules, input value of these 5 parameters are mapped and risk value is calculated by Centre of Area (Centroid).

The membership functions and the input range for each input parameter is represented in following table 2.

Table 2: Fuzzy classification of input and output for Risk variables

Parameters		Membership functions		
		L	M	H
Virulency		Contagious [0 0 4]	More Contagious [3 5 7]	Most Contagious [6 10 10]
	Immunity	Adaptive [0 0 6]	Innate [5 10 10]	
Input	Temperature	Cold [0 0 20]	Mild [15 22 30]	Hot [22 45 45]
	Population Density	Sparse [0 0 300]	Moderate [200 350 600]	Dense [450 1000 1000]
	Ventilation	Suffocated [0 0 25]	Moderate [18 28 40]	Airy [30 50 50]
Output	Risk Value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

Design of FES1 is done using fuzzy tool of MATLAB as shown in Fig 4 where a fis file of the type Mamdani is created and all the 5 factors are created as input variable and output is a single variable named, Risk Value. All 162 rules are designed in the rule base as shown in Table 3. These rules are If- Then conditions with logical operators as AND, OR and NOT.

Table 3: Rule Base for FES1

Inputs				Output	
Virulency	Immunity	Temperature	Population Density	Ventilation	Risk Value
Contagious	Adaptive	Cold	Sparse	Suffocated	Medium
Contagious	Adaptive	Cold	Sparse	Moderate	Low
Contagious	Adaptive	Cold	Sparse	Airy	Low
Contagious	Adaptive	Cold	Moderate	Suffocated	Medium
Contagious	Adaptive	Cold	Moderate	Moderate	Medium
Contagious	Adaptive	Cold	Moderate	Airy	Low
Contagious	Adaptive	Cold	Dense	Suffocated	Medium
Contagious	Adaptive	Cold	Dense	Moderate	Medium
Contagious	Adaptive	Cold	Dense	Airy	Low
:	:	:	:	:	:
:	:	:	:	:	:
Most Contagious	Innate	Hot	Dense	Airy	Medium

4.4.2 FES Implementation for Prevention Value

Following Fig. 5 illustrates the Fuzzy pattern to calculate prevention value which takes 2 input parameters (Social distancing and personal hygiene) and gives 1 output parameter (prevention value). Here, the input parameter, Social distancing ranges from 0-12 feet and personal hygiene has its value on a Likert scale (0-10) and output variable Prevention Value has its value on a Likert scale (0-10) which has been classified into 3 different ranges thus giving 9 rules altogether. All these rules aggregate the values of two input parameters to evaluate the value of prevention value.

The ranges of input and output variables for the above fuzzy pattern is given in following Table 4.

Table 4: Fuzzy classification of input and output variables for prevention value:

Parameters	Membership functions			
	L	M	H	
Input	Social distancing	Inadequate [0 0 5]	Adequate [4 6 8]	Dispersed [7 9 12]
	Personal Hygiene	Unhygienic [0 0 4]	Requisite [3 5 7]	Sophisticated [6 10 10]
Output	Prevention Value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

Similar to FES1, FES2 is also designed using fuzzy tool of MATLAB that uses social distancing and personal hygiene as input variable and give prevention value as output. The rule base in FES2 uses 9 rules comprising of If- Then conditions with logical operators as shown in Table 4 above. The snapshot of FES2 to calculate prevention value is illustrated in following Fig 6. The rule base is also demonstrated in Table 5.

Table 5: Rule Base for FES2

Inputs		Output
Social Distancing	Personal Hygiene	Prevention Value
Inadequate	Unhygiene	Low
Inadequate	Requisite	Low
Inadequate	Sophisticated	Medium
Adequate	Unhygiene	Low
Adequate	Requisite	Medium
Adequate	Sophisticated	High
Dispersed	Unhygiene	Medium
Dispersed	Requisite	High
Dispersed	Sophisticated	High

4.4.3 Fuzzy model implementation for Susceptibility Index

Following Fig. 7 illustrates the Fuzzy pattern to calculate susceptibility index by using 2 input parameters viz. risk value and prevention value and gives 1 output parameter susceptibility index.

The corresponding Rule Base is demonstrated in following Table 6.

Table 6: Rule Base for FES3

Inputs		Output
Risk Value	Prevention Value	Susceptibility
Low	Low	Medium
Low	Medium	Low
Low	High	Low
Medium	Low	High
Medium	Medium	Medium
Medium	High	Low
High	Low	High
High	Medium	High
High	High	Medium

5. Result And Discussion

Following section demonstrates the results obtained from FES implementation of Risk factors, prevention factors, and the Susceptibility Index. A comprehensive discussion of the results section wise is presented here:

5.1 Impact of Risk Factors on Susceptibility Index

The output of FES1 i.e. Risk Value (Low, Medium and High) is converted to Crisp value by Fuzzifier and mapped on Likert scale (0-10) as in Fig. 8. Different values of Virulency, Immunity, atmospheric_temperature, population_density, and ventilation is adjusted to get different values of risk values.

As can be seen from Fig. 8, highest value of Risk_value i.e. 8.41 is obtained when virulency =8.68, immunity=3.5, Atmospheric_temperature=nearly 8.9 Degree Celsius, Population_density=802 people per KM2 and Ventilation=8.02 CFM.

Surface view of FES1 results is shown in Fig. 9, where 2 input parameters can be taken into account at a time; similarly impact of other parameters can be seen in surface view.

5.2 Impact of Preventive Factors on Susceptibility Index

The output of FES2 i.e Low, Medium and High are the fuzzy results of prevention value which is converted to Crisp value using Fuzzifier and further mapped on Likert scale (0-10). Result of the same is illustrated in following Fig. 10 which demonstrates that when social_distancing is 8.08 and personal_hygiene is 5, then the obtained prevention value is 8.5 (High).

Surface view of FES2 results is represented in Fig. 11 which represents prevention value for the 2 input parameters viz. social_distancing and personal_hygiene.

5.3. Outcome of Susceptibility Index

The susceptibility index is evaluated from the optimal combination of risk factors and preventive factors. Fig. 12 demonstrates a particular case, when the risk value is 2.29 and prevention_value is 4.88, the susceptibility index becomes 1.59 (less susceptible).

Fig. 13 demonstrates the surface view of FES3 which represent susceptibility_index for 2 input parameters viz. risk_value and prevention_value. 3D demonstration of the results depicts that as the value of risk factors goes higher (i.e. above 4 units) and the preventive values, stay lower (i.e. below 4 units), susceptibility index reaches the value of >8 units. An optimal combination of risk and preventive factors will help us to keep the susceptibility index to minimum.

6. Conclusion

The manuscript proposes a Mamdani based Fuzzy inference model to determine and analyse the impact of various clinical and epidemiological factors on the susceptibility index of COVID-19. In the proposed model, the factors are broadly classified as risk and preventive factors. Risk factors evaluated are virulency, immunity, temperature, population density, and ventilation. Similarly, preventive factors like social distancing and personal hygiene are considered. Finally, susceptibility index is evaluated from the inferences of risk and

preventive values. From the results, it is evident that if a host has higher risk_value, it should maintain highest prevention (social distancing and hygiene) to have lower susceptibility. The model gives promising results and thus can be successfully implemented to evaluate impact of various factors on the spread of COVID-19. The proposed model can also be extended further to incorporate additional stochastic factors.

Declarations

We do not have any competing interest

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Figures

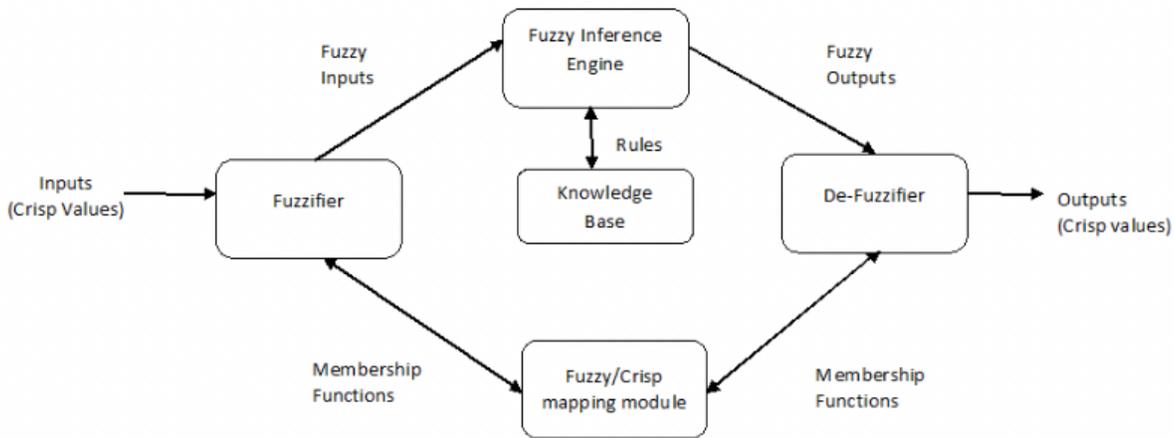


Figure 1

Block diagram of Fuzzy Expert system

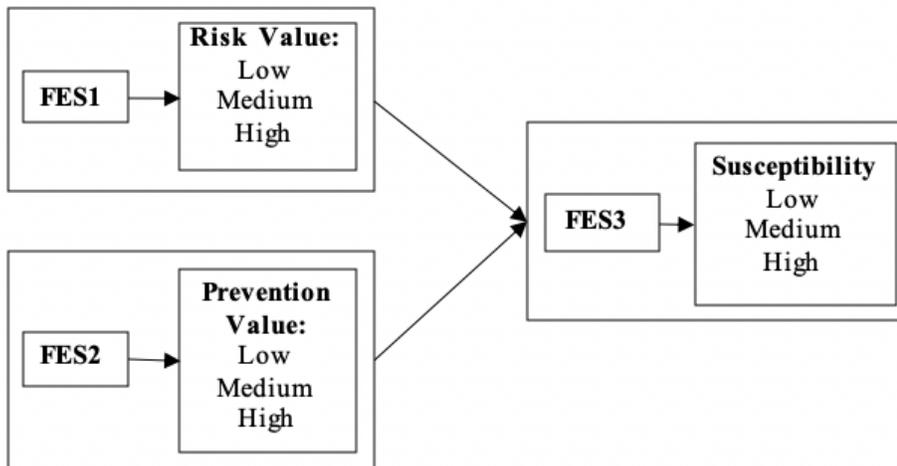


Figure 2

Hierarchy of FES in the Proposed Model

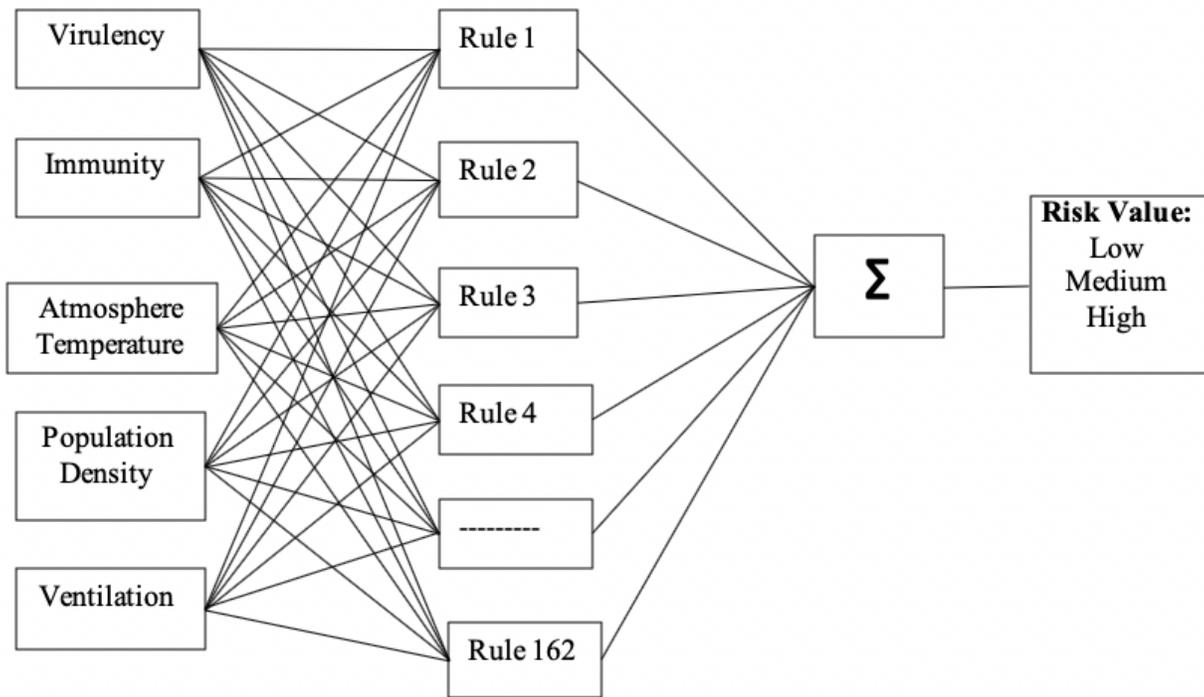


Figure 3

Fuzzy pattern to calculate Risk Value

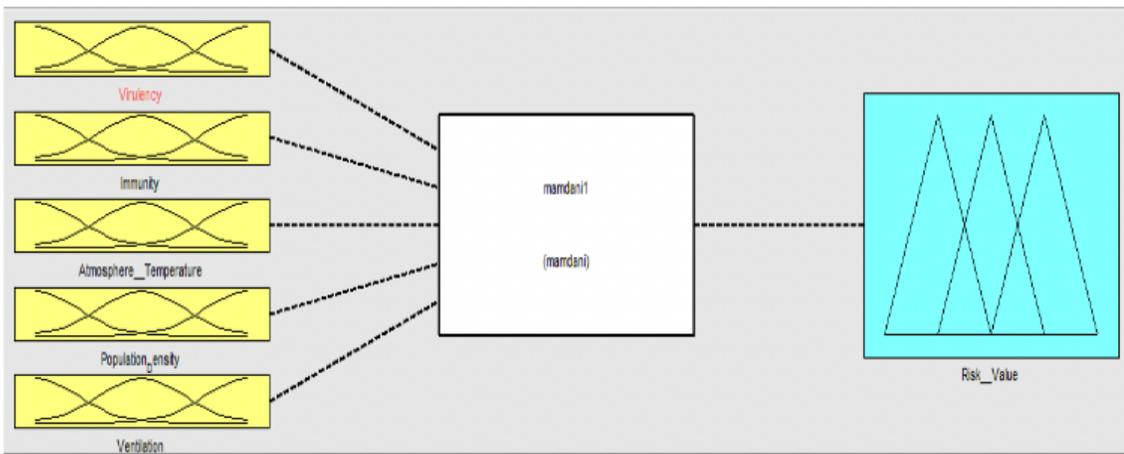


Figure 4

Snapshot of FES1 to Calculate Risk Value

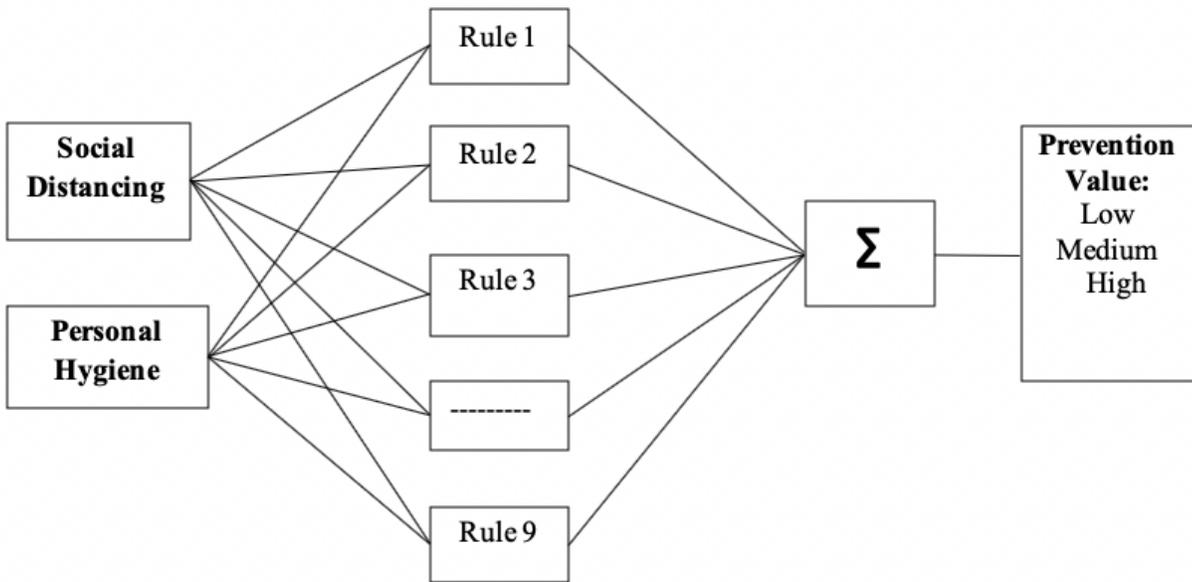


Figure 5

Fuzzy pattern to calculate Prevention value

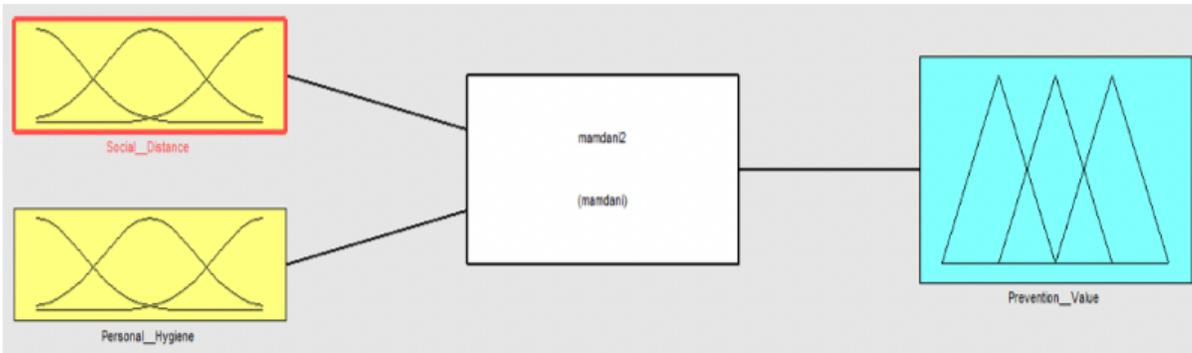


Figure 6

Snapshot of FES1 to Calculate Prevention Value

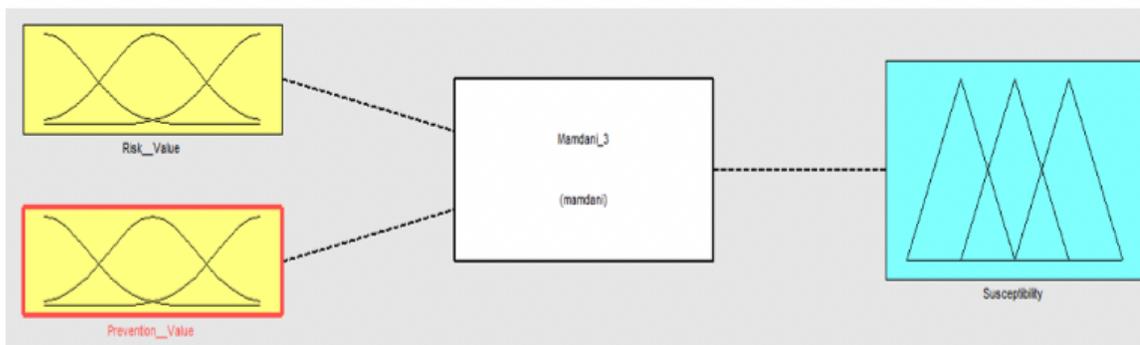


Figure 7

Snapshot of FES3 to Calculate Susceptibility Value

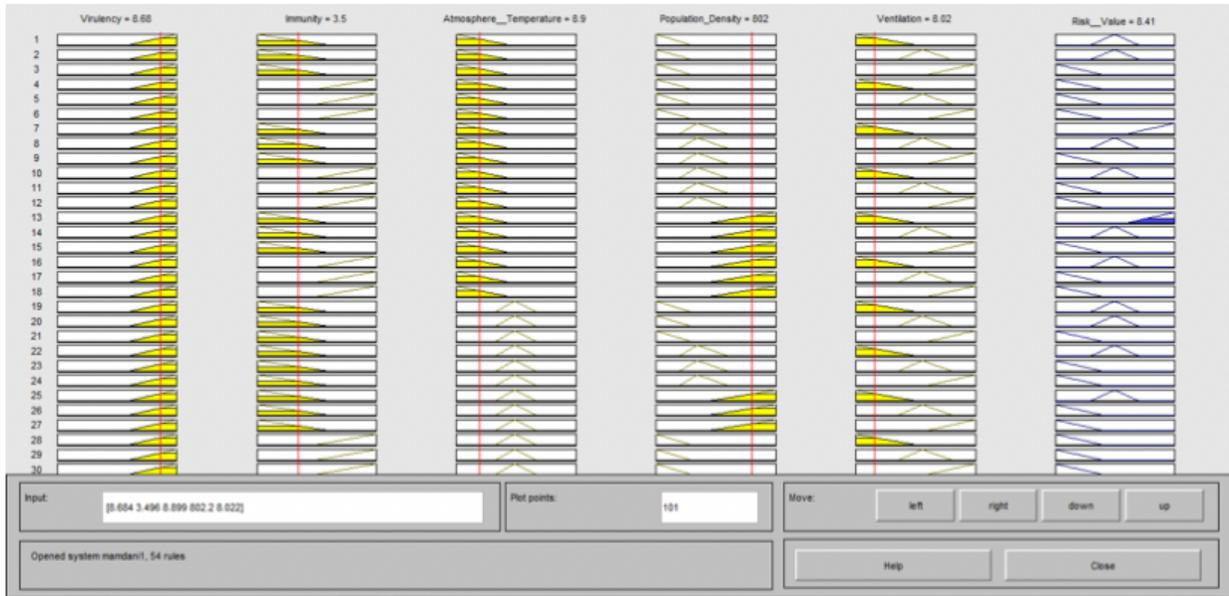


Figure 8

Snapshot of Rule Base for FES1

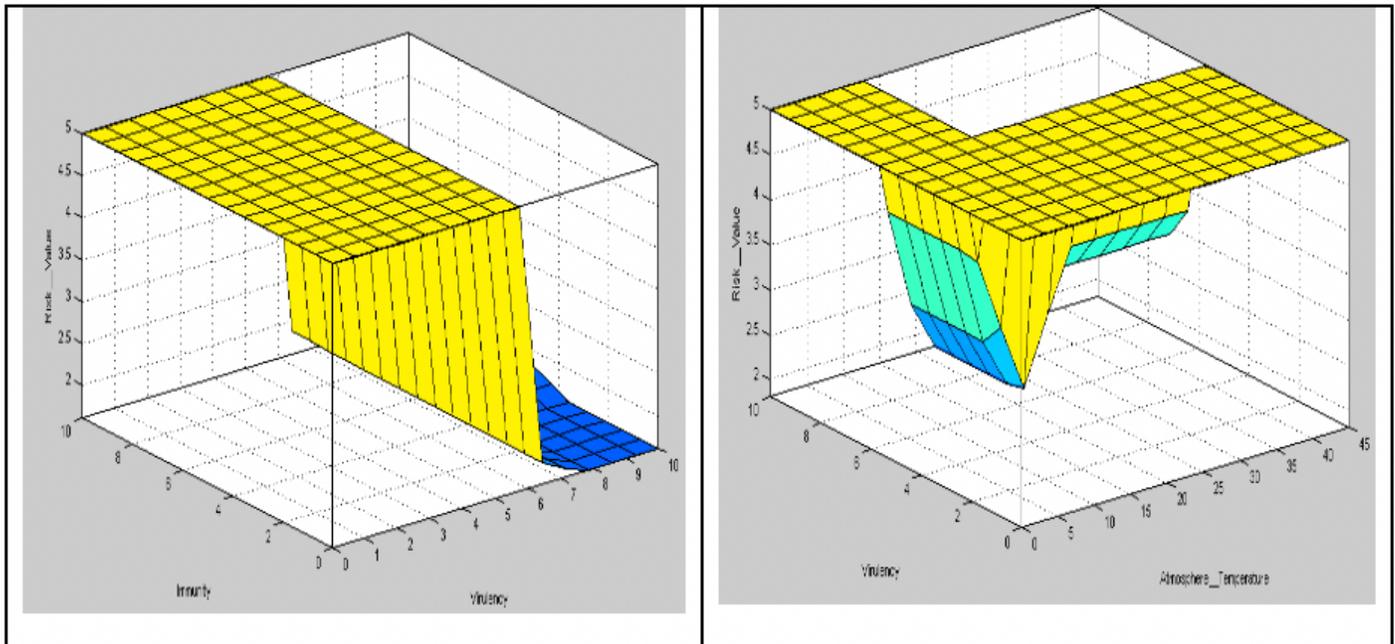


Figure 9

3-D Surface view of the FES1 Results

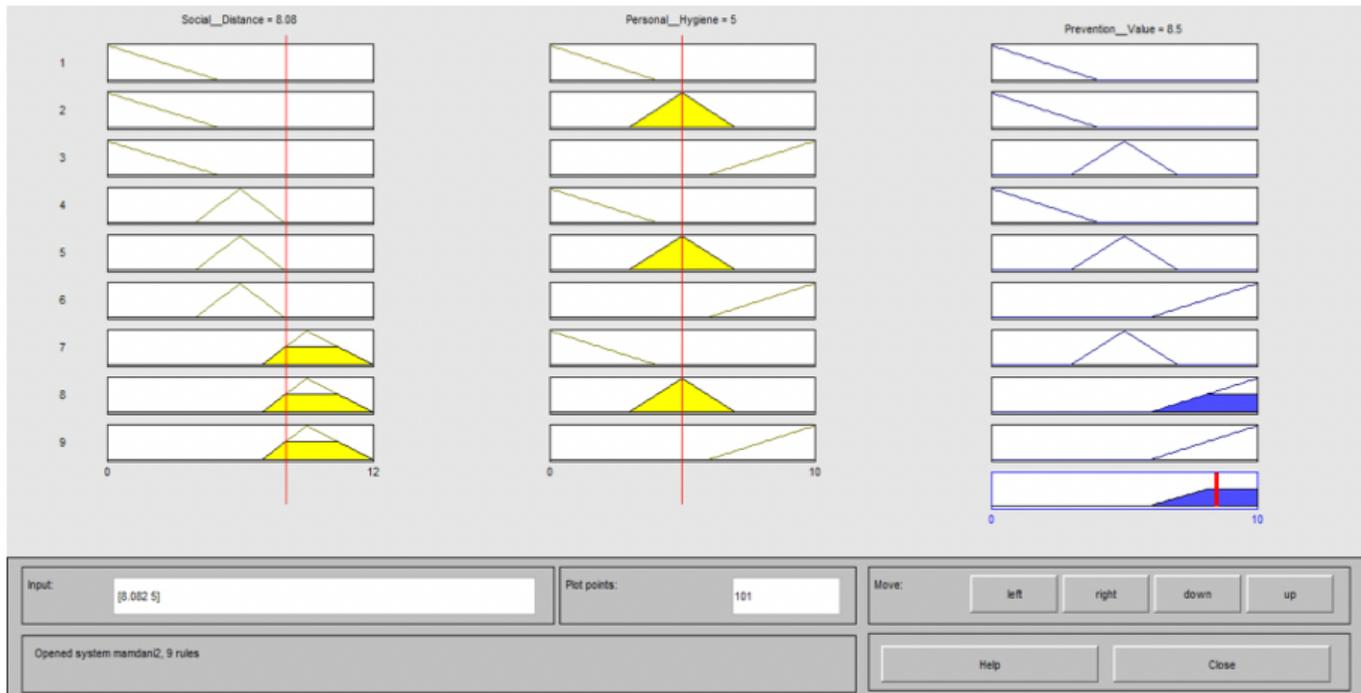


Figure 10

Snapshot of Rule Base for FES2

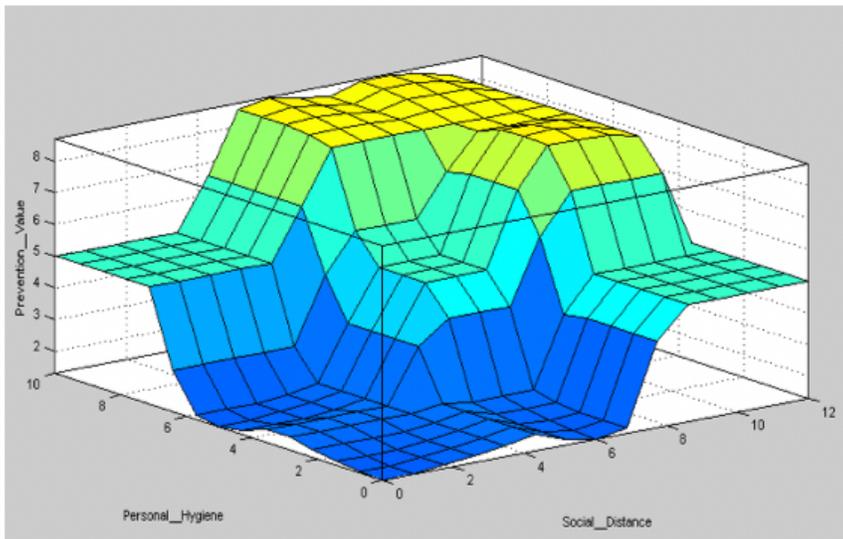


Figure 11

3-D Surface View of the FES2 Results

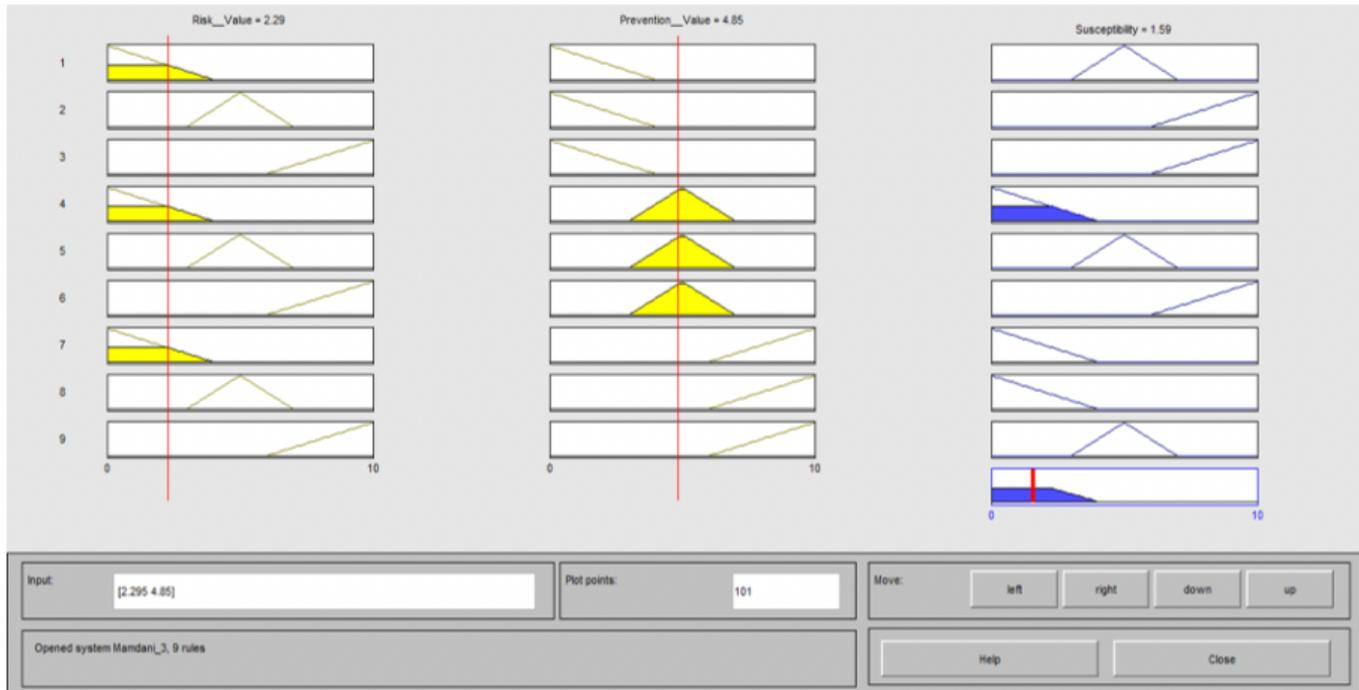


Figure 12

Snapshot of rule base for FES3

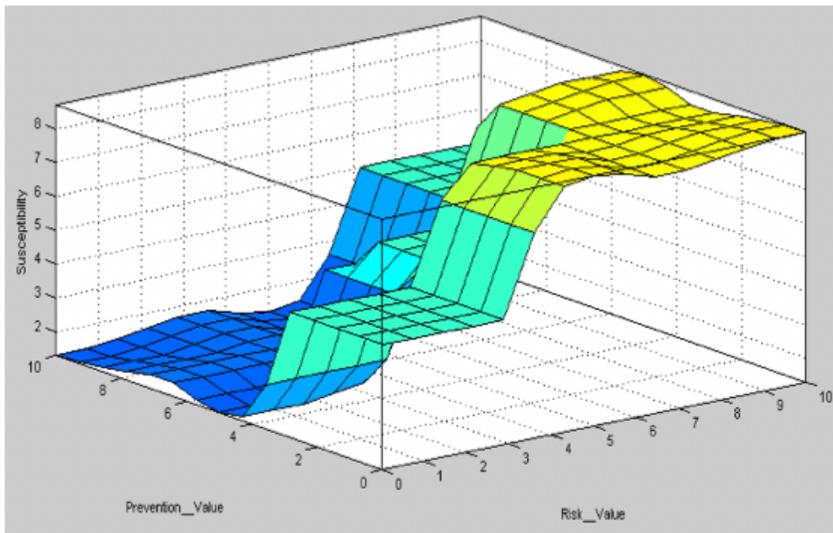


Figure 13

3-D Surface View of the FES3 Results