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APPLICATION OF FUZZY INFERENCE FORECASTING TO THE DESIGN OF AN INTERVENTION STRATEGY FOR THE COVID-19

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Abstract-Covid-19 has had far-reaching effects, including fatalities and tremendous economic devastation. Attempts by countries to slow down its spread by implementing various restrictions and lockdowns have met with variable degrees of success. By analyzing data on fatalities and economic impact, this study hopes to recommend the best course of action for coping with a pandemic. The economy would collapse under the weight of a total lockdown until vaccination, while more cases of Covid-19 would emerge in the absence of any controls. Accordingly, a dynamic model is required to provide an appropriate approach in light of the current economic and health status. This work describes a method that uses a systems dynamics model to assess mortality and healthcare facilities, and a fuzzy inference system to choose next-period tactics according to established guidelines. We calculated GDP by adding together spending at all levels of government, investment, consumer spending, and business investment. During a pandemic, the hybrid framework that was created is an attempt to find a happy medium between maintaining public health and maintaining economic stability. After the fuzzy rules and membership functions have been established, the model may be used to make choices about restrictive policy after the parameters have been filled in.

Keywords-Covid-19, intervention measures, FIS, membership function

1. Introduction- Coronavirus is spread when an exposed person breathes in infected droplets from an infected person who is sneezing, coughing, or exhaling. The vast majority of patients who contract the COVID-19 pandemic will recover without any medical intervention at all (81%-86%). Nearly 110 million people have now been confirmed to have COVID-19 infection worldwide, and the disease has already claimed the lives of over 2.4 million people. On March 20, 2020, the global total of active cases was registered as 33,139, while the global total of deaths was recorded as 4.5 million, both according to world metres. In the United States, Brazil, India, Russia, Mexico, and Peru, the highest COVID-19-related mortality tolls were around 0.5, 0.59, 0.45, 0.25, and 0.18 million.

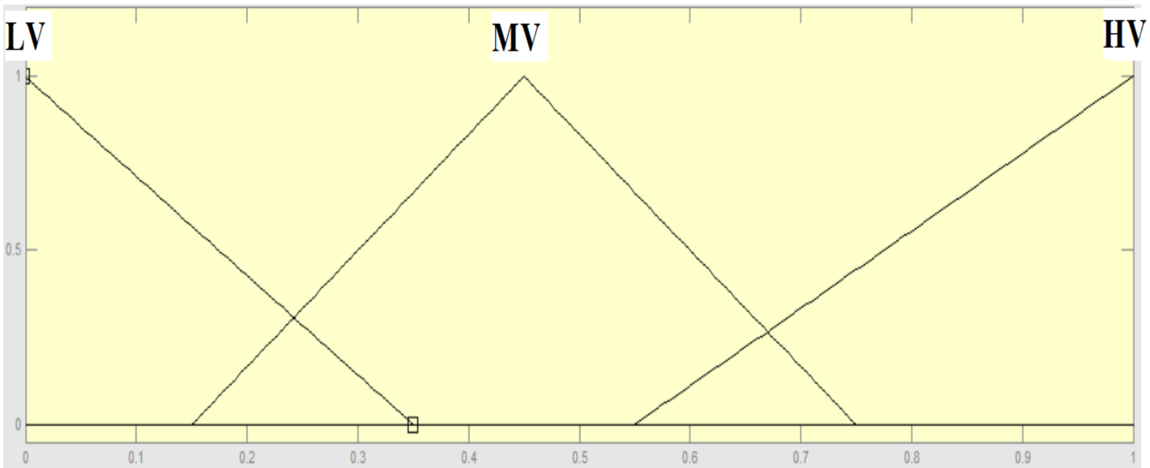
In 2011, Kharal and Ahmad used real-world illustrations and data to probe the issue of image retention in fuzzy and soft collections. In their definition of "intuitionistic fuzzy soft sets," Bashir and Salleh (2013) established the thought of mappings among image fuzzy soft sets, intuitionistic fuzzy soft sets. In 2014, Alkhazaleh et al. created the notions of a mapping on classes, classifying collections of neutrosophic soft sets into single-valued neutrosophic classes. Since its inception by Sulaiman et al. (2014), the concept of mappings in excess of compilations of multifunctional fuzzy soft sets has been widely adopted. To diagnose COVID-19, Dhiman and Sharma (2020) proposed a fuzzy inference system that takes six input factors into account, including ethanol, ambient temperature, body temperature, breath shortness, cough, and cold symptoms, and divides the output factor into three linguistic categories that correspond to the severity of infection. Coronaviruses can live on inanimate surfaces for a long time, as summarised by Kampf et al. (2020), and this work demonstrates inactivation of coronaviruses by biocidal agent by suspension and carrier testing. Through sensitivity analysis of various embedded parameters, Mnganga and Zachariah (2020) were able to calculate the sensitivity index of each parameter. Ropiak (2020) improved the process of knowledge extraction by combining deep learning techniques with rough set-based granular computing. This allowed for more accurate information to be gleaned. The idea of a coefficient of association between various hesitant fuzzy sets was characterized and utilized by Liu et al. (2021) for the purpose of medical diagnosis. In their research on the main diagnosis of COVID-19, Shatnawi et al. (2021) developed an intelligent fuzzy inference system. Tien Ly (2021) came up with the idea of using an ANFIS to make a prediction regarding the total number of COVID-19 cases in the UK. The model is educated via an artificial neural network in conjunction with a fuzzy logic framework. This allows for the model to be taught using previously gathered data. Stiegelmeier and Bressan (2021) gave a hazy approach about the manner in which intervention techniques such as lockdown assist in preventing the severe COVID-19 epidemic from spreading further. Using an unique Deep Interval Type-2 Fuzzy LSTM (Long-short term memory) model, Safari et al. (2021) predicted the number of new cases, the number of recovered cases, and the mortality rate for the COVID-19 outbreak across short and long periods of time. Using a fuzzy methodology and Fuzzy Logic in Covid-19, Pawar et al. (2022) built a Fuzzy Inference System for pattern detection and categorization. Gude (2022) introduced a hybrid methodology that included a partition model for simulating the spread of Covid-19 and a fuzzy inference system for developing the restriction strategy. Together, these two components made up the hybrid. This model would be utilized in order to devise the strategy for the restriction. Shyamsunder et al. (2023) A new fractional mathematical model to study the impact of vaccination on COVID-19 outbreaks.

2. Input and output variables and their meaning:

Table 1: Definitions of input and output variables

Input variable						Output variable	
Vaccinations		Deaths		GDP		Restrictions	
Low	LV	Low	LD	Low	LGDP	Low	LR
Medium	MV	Medium	MD	Medium	MGDP	Medium	MR
High	HV	High	HD	High	HGDP	High	HR

Figure 1: Input membership function for vaccination



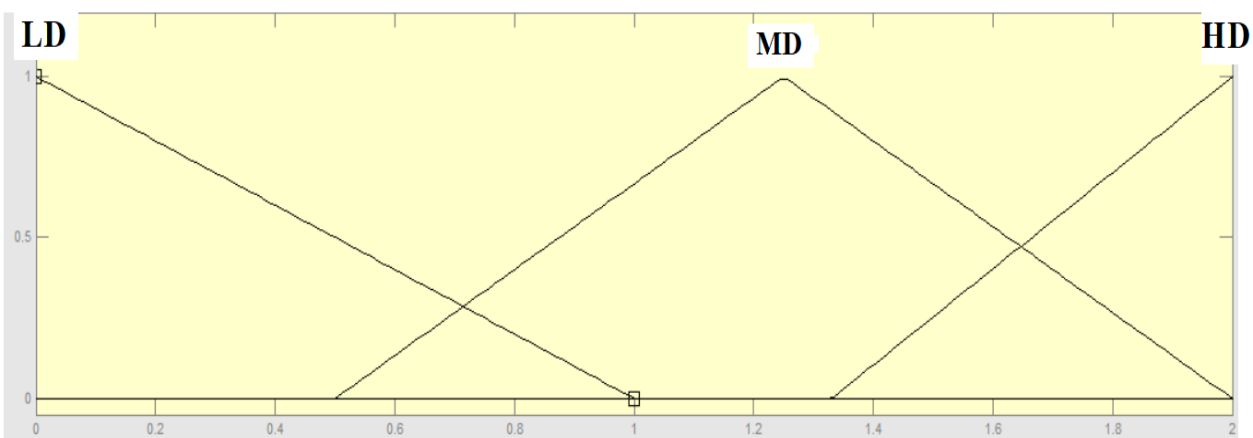
Vaccinations (input variable 1)

$\mu_{LV} = -2.857x + 1 \quad 0 \le x \le 0.35$

$$\mu_{MV} = \begin{matrix} 3.3x - 0.5 & 0.15 \le x \le 0.45 \\ -3.33x + 2.5 & 0.45 < x \le 0.75 \end{matrix}$$

$\mu_{HV} = 2.22x - 1.2 \quad 0.55 \le x \le 1$

Figure 2: Input membership function for deaths



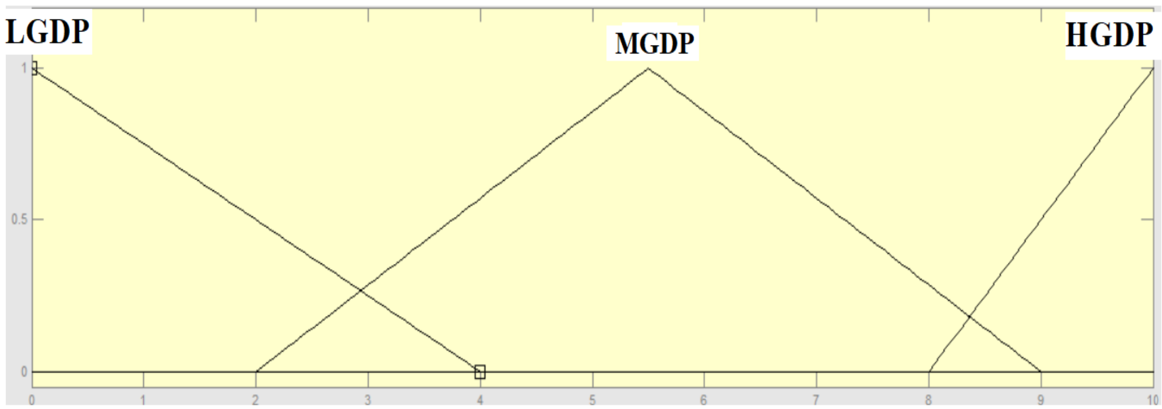
Deaths (input variable 2)

$\mu_{LD} = -x + 1 \quad 0 \le x \le 1$

$$\mu_{MD} = \begin{matrix} 1.3x - 0.66 & 0.5 \le x \le 1.25 \\ -1.3x + 2.6 & 1.25 < x \le 2 \end{matrix}$$

$\mu_{HD} = 1.4925x - 1.98 \quad x \ge 1.33$

Figure 3: Input membership function for GDP



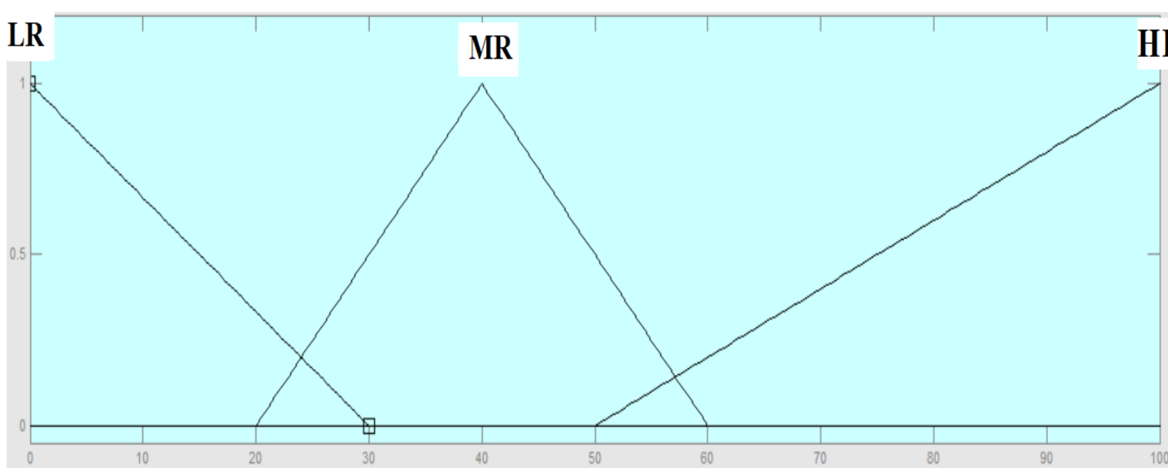
GDP (input variable 3)

$$\mu_{LGDP} = -0.25x + 1 \quad 0 \le x \le 4$$

$$\mu_{MGDP} = \begin{matrix} 0.2857x - 0.571 & 2 \le x \le 5.5 \\ -0.1183x + 1.065 & 5.5 < x \le 9 \end{matrix}$$

$$\mu_{HGDP} = 0.5x - 4 \quad x \ge 8$$

Figure 4: Output membership function for restriction



Restriction (Output variable)

$$\mu_{LR} = -0.033x + 1 \quad 0 \le x \le 30$$

$$\mu_{MR} = \begin{matrix} 0.05x - 1 & 20 \le x \le 40 \\ -0.05x + 3 & 40 < x \le 60 \end{matrix}$$

$$\mu_{HR} = 0.125x - 0.25 \quad 50 < x \le 100$$

3. Rule base of the model: It was determined that the inference engine will make use of ten different fuzzy rules. The course of action that should be taken is decided upon based on the value of the output variable. When the degree of confidence is low, the fuzzy output (restriction) corresponds to the decision to apply no restrictions; when the level of confidence is medium, it corresponds to a restriction; and when the level of confidence is high, it corresponds to a lockdown.

Table 2: Rules for FIS based COVID-19 Model

Rules	*Vaccinations*	*Deaths*	*GDP*	*Restrictions*
1		*High*	*High*	*High*
2	*Low*			*High*
3		*Low*		*Low*
4	*High*			*Low*
5		*High*	*Medium*	*Medium*
6	*Medium*	*Low*		*Low*
7	*High*		*High*	*Low*
8			*Medium*	*Low*
9	*High*	*High*		*Medium*
10	*low*	*Low*	*Low*	*Low*

4. Evaluation of output (Restrictions):

Figure 5: Inputs for low restrictions in %

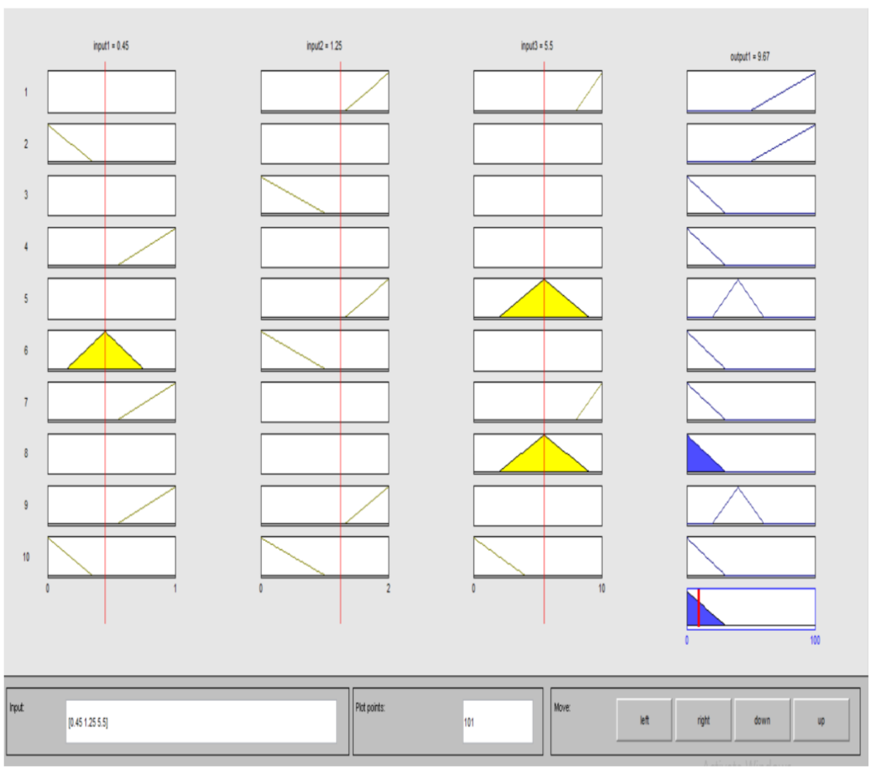


Figure 6: Inputs for Medium restrictions in %

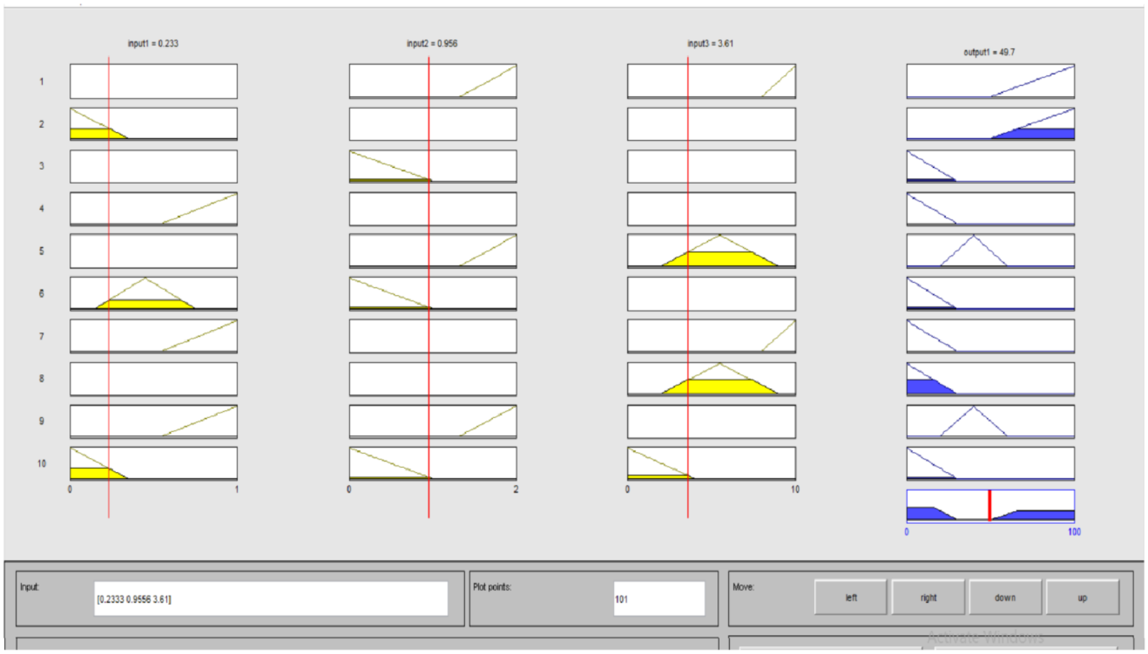


Figure 7: Inputs for high restrictions in %

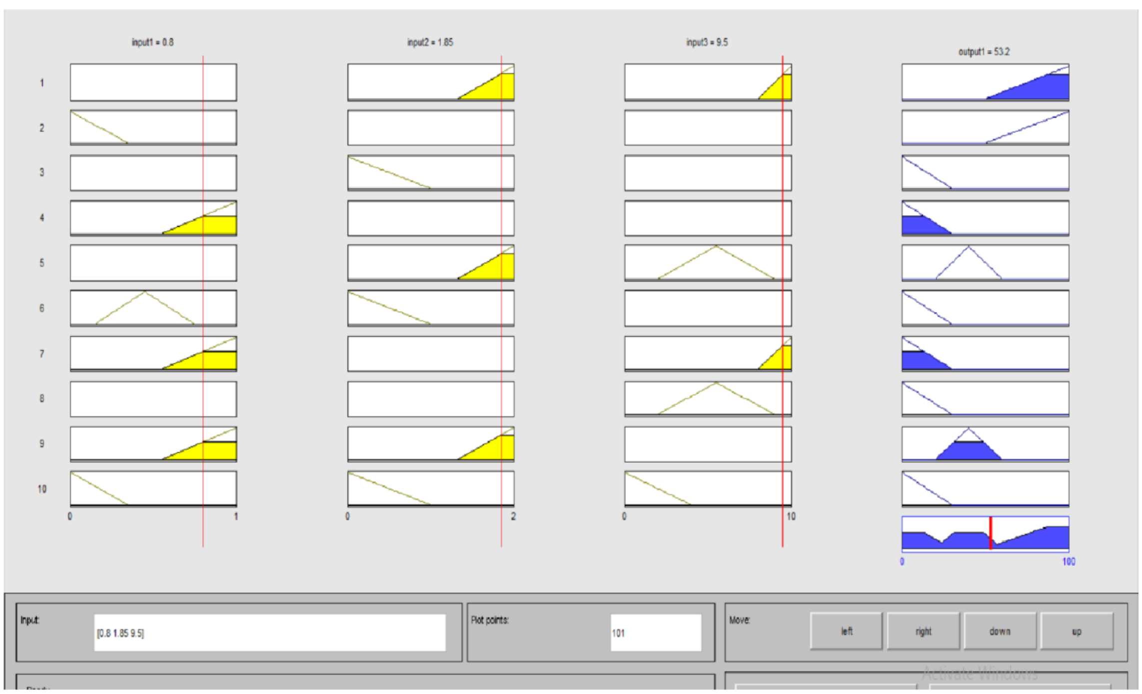


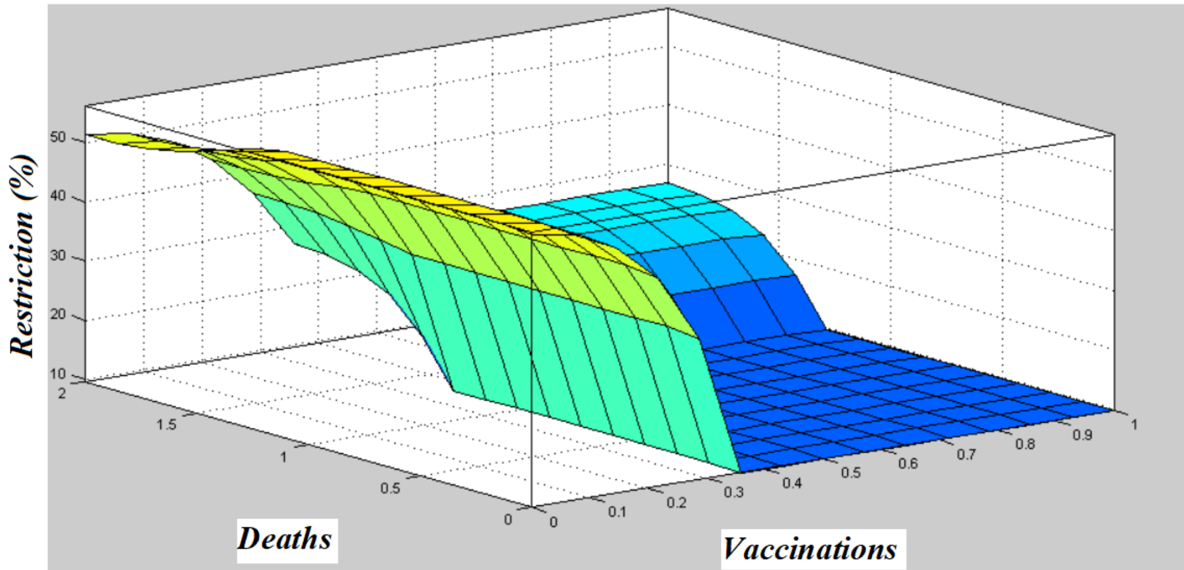
Table 3: Simulation Results regarding the restrictions as output variable and vaccinations, deaths and GDP as input variables

S.No.	Vaccinations	Deaths	GDP	Restriction (%)
1	0.5	1	5	9.88
2	0.8	0.5	4.05	10.9
3	0.8	1.36	5.2	12.6
4	0.224	0.778	2.1	60.3
5	0.122	1.04	6.57	54.9
6	0.953	0.547	5.11	9.79
7	0.633	1.08	7.19	11.3
8	0.291	0.547	4.54	34
9	0.567	1.34	7.72	13.7
10	0.469	1.62	5.42	23.8
11	0.229	0.938	7.15	48.5
12	0.162	1.26	8.38	67.7
13	0.211	1.68	9.36	81
14	0.0467	1.89	9.62	83.4
15	0.362	1.08	9.27	50
16	0.504	0.929	2.81	13.1
17	0.682	1.23	7.32	11.5
18	0.318	0.973	3.12	34.8
19	0.691	1.55	6.04	22.5
20	0.98	1.41	0.376	16.2
21	0.15	0.25	1.5	52.1
22	0.45	1.25	5.5	9.67
23	0.8	1.85	9.5	53.2
24	0.2333	0.9556	3.61	49.7
25	0.331	1.23	7.46	24.6

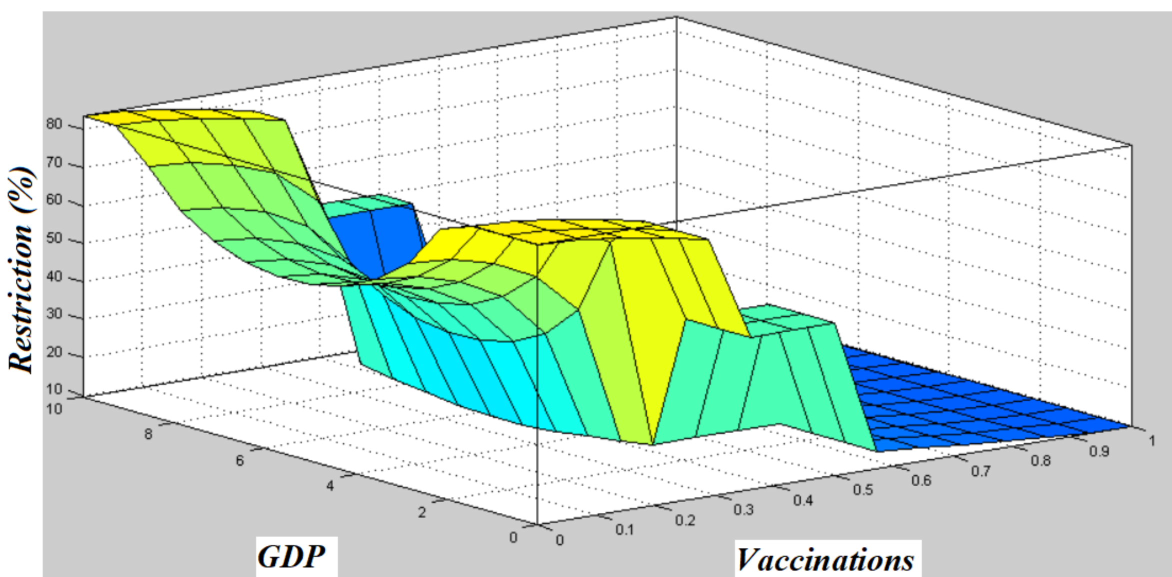
Figure (5) shows that a moderate level of vaccines, mortality, and GDP corresponds to a small percentage of restrictions. It can be shown in figure (6) that if the vaccination rate is low, the death rate is medium, and the GDP is medium, then the proportion of limitations will be in the middle. Figure (7) analyses the correlation between vaccination rates, mortality rates, and GDP and finds that higher values for all three predict a greater percentage of limitations. Therefore, the suggested inference method may help countries keep their intervention measures in place in the COVID-19 setting.

5. Surface plots in input and output variables:

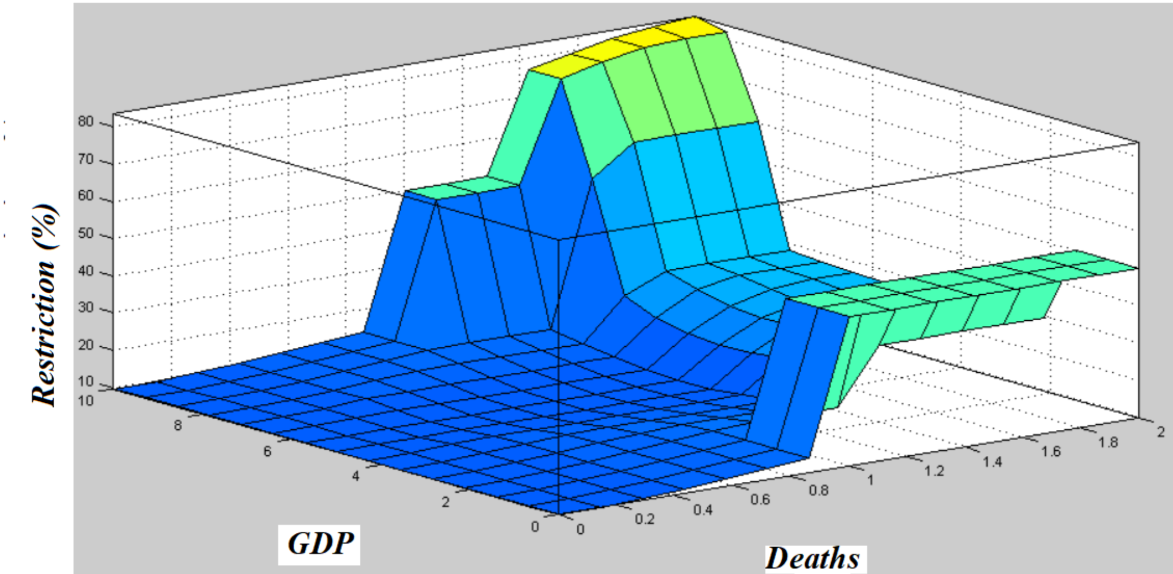
Graph 1: Surface plot of restrictions for input variables (vaccinations and deaths)



Graph 2: Surface plot of restrictions for input variables (vaccinations and GDP)



Graph 3: Surface plot of restrictions for input variables (Deaths and GDP)



6. Concluding Remarks- With the help of a fuzzy inference system, a framework was presented in this research for deciding on restrictive policies. The final integrated model seeks to strike a healthy middle ground between financial and social concerns. A lenient approach may lead to an increase in infections, while an overly stringent one could hurt the economy. A dynamic model is required to recommend the appropriate level of control. The simulation findings show that, compared to a complete lockdown policy, the model maintains the economy growing and has fewer deaths than the no restrictions approach. Employing this method, businesses can create a flexible pandemic management system in the workplace that will increase output while decreasing vulnerability to outbreaks. Adding characteristics like social distance and a propensity to adhere to safety protocols can help refine the model even further. This methodology provides the data necessary to assess GDP in every country or region.

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