A fuzzy logic scheme based on spread rate and population for pandemic vaccine allocation

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ABSTRACT

This paper deals with a novel decision-making scheme for inferring the allocation of vaccines to the provincial health care authorities by the central health care authority of a country in pandemic scenarios. This novel scheme utilizes a fuzzy logic-based inference scheme that utilizes the spread rate and population of a province as inputs to infer the vaccination rate. The proposed scheme is evaluated on the coronavirus disease (COVID-19) data from six southern states of India during the first week of October 2020, collected from the database maintained by the Government of India. The findings demonstrate that the suggested plan, which takes population and spread rate into account, makes sure that enough vaccination doses are distributed to the provinces with a larger spread rate with a higher priority, and that immunizations are not delayed in provinces with controlled spread rates. Also, in due course, all territories will appropriately distribute enough vaccine supply to control the spread. Therefore, this plan strengthens the efforts to control the pandemic outbreaks by ensuring the proper and balanced delivery of vaccines in a timely, efficient, and objective manner.

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1. INTRODUCTION

Pandemics have always resulted in broad-based morbidity and chaos in economies globally [1]. They created a worldwide health emergency, causing geographical and cultural barriers. There is still a long way to go until the coronavirus disease (COVID-19) pandemic is contained, and in the days ahead, new pandemics are predicted to spread [2]–[10]. One of the best and most efficient ways to shield people from pandemics is through vaccination [7]–[14]. Therefore, in the history of public wellness, global efforts to create vaccinations to fend off pandemics have been unparalleled. The allocation criteria will widen as the production of vaccines ramps up and new products are approved, ultimately allowing for the widespread use of vaccines. When there is a pandemic, officials struggle to properly coordinate the distribution of vaccines to various locations. Ensuring the timely, efficient, and impartial distribution of enough vaccines will be a formidable task [3], [13], [14].

The World Health Organization (WHO) recommended that during the COVID-19 pandemic, vaccine doses be distributed proportionately to the population of each province. This is the commonly used method of distributing vaccines from a nation's central health care system to provincial health care systems [2]. An allocation scheme considering only population as its basis appears to be voicing moral concern for equality and may be regarded as the most politically diplomatic solution. Nevertheless, it presupposes that equality entails treating all provinces equally rather than fairly addressing their various levels of need. It is highly likely that states with similar populations will experience varying degrees of pandemic illness severity and rates of dissemination. It is unfair to distribute vaccine doses solely on the basis of population. For instance, allocating antiretrovirals for the human immunodeficiency virus (HIV) based on population rather than severity in terms of actual HIV cases would be irrational and unjust [5]. In summary, there are two drawbacks to the population-based method. Smaller provinces receive fewer vaccination doses and may experience an acute vaccine shortage, which could lead to super spread if those areas have greater spread rates. Conversely, more vaccine doses are allotted to provinces with larger populations, which may result in vaccine doses being delayed due to negligent vaccination due to a false sense of security brought on by a lower rate of vaccination. Therefore, a reasonable and equitable distribution of vaccines ought to adapt to the varying rates of pandemic transmission among various areas [13]–[16].

Not much has been done to take the spread rate into account when deciding how to distribute vaccinations. A method that took the spread rate into account was put forth in [5], where the fair priority scheme was created. This approach considers the premise that provinces with greater rates of transmission should be prioritized more. This approach has the drawback of ignoring the province's population when determining vaccination rates because it solely considers the spread rate. Additionally, it ignores the natural justice principle, which states that each province should receive the appropriate amount of vaccine shots to stop the spread of disease and prevent it from spiraling out of control. For instance, even in highly populated provinces, this algorithm computes a lower vaccination rate if the spread of the province is slowing down at a faster rate. This could lead to unchecked spread in populated regions with slower rates of spread, and eventually those areas might become hotspots. Furthermore, even with a province having a smaller population, a greater vaccination rate will be calculated if the province is expanding at a faster rate. Due to an abundant supply for a smaller population, this could delay vaccinations. This scheme's disadvantage renders it unreasonable and unfair.

In this study, we present a novel scheme to determine the vaccination rate of the provinces taking into account both spread rate and population equally. The spread rate is determined by calculating the average rate of increase or decline of new cases in the provinces week wise. The number of doses to be distributed to the provinces is represented by the immunization rate. The relationship between the inputs and the output, however, is not well-defined by formal regulations or exact mathematical models; rather, some guidelines based on approximative reasoning. An appropriate method for adding approximative reasoning into practical algorithms is fuzzy logic [17]–[27]. Therefore, we provide a fuzzy logic decision-making system that determines the vaccination rate by taking the population and spread rate into account. This innovative plan makes sure that enough supply of vaccines is distributed to the provinces, which prioritizes a higher rate of spread and that vaccines are not wasted in the provinces with a lower rate of spread. Additionally, all provinces eventually receive an adequate number of vaccination shots to stop the spread. This strengthens the effort to stop the sudden spread of pandemics and guarantees the provinces receive the available vaccination doses in an effective and efficient manner.

Here is how the rest of this paper is organized. A fuzzy logic technique for estimating vaccination rate based on population and spread rate is shown in Section 2. The findings and discussion are presented in Section 3. The study is concluded in Section 4.

2. METHOD

The two input parameters, spread rate ‘S’ (the average of the rate of rise or fall of new cases week wise) and population ‘P’ are scaled into the normalized range [0,1]. The population of the province with the largest population is chosen as the scaling factor of the input ‘Population’, and the highest of the magnitude of the spread rate across all provinces is chosen as the scaling factor of the input “Spread rate”. Hence, the fuzzy interface engine takes two inputs: the normalized population and the normalized spread rate. The vaccination rate ‘V’, normalized within the interval [0,1] is the output.

2.1. Fuzzification

The normalized inputs are fuzzified using the fuzzy sets as indicated in Figures 1 and 2. The fuzzy sets of the input spread rate ‘S’ are negative big (NB), negative medium (NM), negative small (NS), zero (Z), positive small (PS), positive medium (PM), and positive big (PB) and those of input population ‘P’ are very low (VL), low (L), medium (M), high (H), and very high (VH). The fuzzy sets of the output Vaccination Rate ‘V’ are very low (VL), low (L), medium (M), high (H), and very high (VH) as shown in Figure 3.

2.2. Rule base

Approximate reasoning is used to create the fuzzy inference system's rule foundation. The rule base has rules of the form “If population is very high and the spread rate is positive big, then the vaccination rate is very high”. The rule base derived is presented in Table 1. The mapping between the inputs and the output is shown in Figure 4.

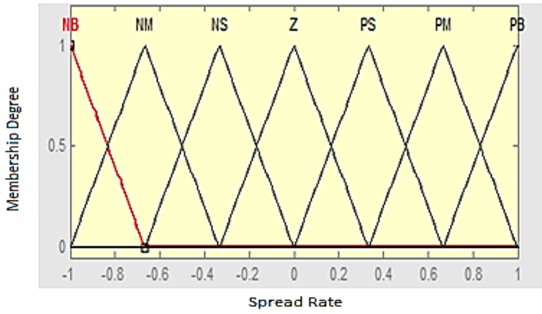
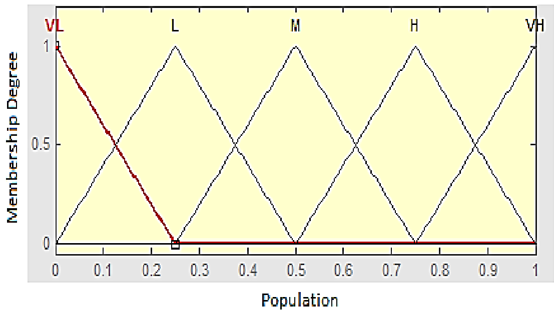


Figure 1. Spread rate ‘S’



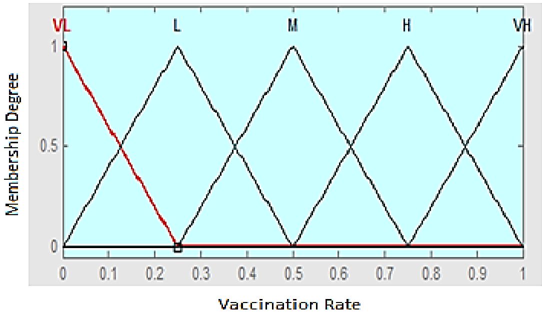


Figure 2. Population ‘P’ Figure 3. Vaccination rate ‘V’

Table 1. Fuzzy rules

Population	Spread rate				
	VL	L	M	H	VH
NB	VL	VL	VL	VL	VL
NM	VL	VL	VL	VL	L
NS	VL	VL	VL	L	M
Z	VL	VL	L	M	H
PS	VL	L	M	H	VH
PM	L	M	H	VH	VH
PB	M	H	VH	VH	VH

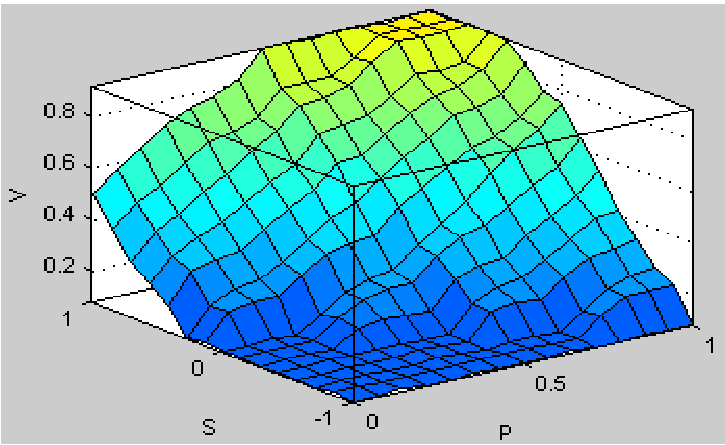


Figure 4. The mapping between inputs and output

2.3. Fuzzy implication

Mamdani type of implication is considered in this inference model. In the Mamdani implication type, each rule has an antecedent part consisting of a compound statement of fuzzy sets of inputs using connective “and” and a consequent part consisting of a fuzzy output [24]. For instance, in this inference model, one rule has the form “If the population is VH and the spread rate is PB, then the vaccination rate is VH”. The connective between the inputs in these rules is the “and” logic. Hence, the operator “min” is applied to the membership values to obtain the truth value of the rule. This value is then applied to the fuzzy set “VH” of the output. The fuzzy outputs of the different rules are then combined into a single fuzzy output using the “max” aggregator [25]–[27].

2.4. Defuzzification

The fuzzy output of the fuzzy implication is defuzzified using the center of area defuzzification method. The center of area defuzzification calculates the center of area of the fuzzy output using (1). The center of area method is selected because of the advantage of generating highly smooth and precise output [24].

$$y^* = \frac{\int \mu_C(y).y dy}{\int \mu_C(y)\, dy} \tag{1}$$

Here, y^* holds the defuzzified value of the fuzzy output variable y, $\int \mu_C\,(y)$ holds the membership function of the combined single fuzzy output.

3. RESULTS AND DISCUSSION

The population data from the database of the Reserve Bank of India (RBI) and the COVID-19 data of the first week of October 2020 from the Government of India database for six southern province states of India were used to verify the proposed scheme. The vaccination rates of the considered territories computed by the proposed inference system are shown in Figure 5 to Figure 10. The vaccination rates inferred by the proposed scheme are respectively 0.856, 0.917, 0.279, 0.333, 0.276, and 0.0863 for Kerala, Tamil Nadu, Karnataka, Telangana, Andhra Pradesh and Puducherry.

The vaccination rate estimated by the suggested technique, which is based on both the spread rate and population, is translated to a percentage of the supply of vaccine doses and studied in comparison with two standard schemes: the one that is based just on population and the other that is based just on spread rate. The comparison is presented in Table 2. The proposed scheme suggests a higher vaccination rate of 31.16% in the state of Kerala with a comparatively medium population (normalized value of 0.463) and a comparatively very higher increasing spread rate (normalized value of 1). In contrast, the scheme which is based on just population suggests a vaccination rate of 13.23% (medium) considering the comparatively medium population, and the scheme which is based on just spread rate suggests a rate of 30.77% (very high) considering the fact that the maximum spread rate is reported in Kerala. The inference in the case of Tamil Nadu is a vaccination rate of 33.38%, considering the very high population of the state (normalized value of 1) and a comparatively smaller rate of increase of the spread (normalized value of 0.4). In contrast, the scheme based on just population infers a vaccination rate of 28.58% (very higher) considering the fact that Tamil Nadu is the state with the largest population among the states considered in this study, and the scheme based on spread rate alone infers a rate of 21.54% (medium) because of the medium rate of the increase of the spread. The inference of vaccination rate in the case of Karnataka is 10.16% (lower) as the population of Karnataka is higher (normalized value of 0.847) and the spread is decreasing at a medium rate (normalized rate of -0.6). In contrast, the conventional scheme based on population alone infers a vaccination rate of 24.21% (higher) due to the state's higher population, and the method based on spread rate alone infers a vaccination rate of 6.15% (lower) considering the fact that the spread is decreasing at a medium rate. The inference in the case of Telangana is a vaccination rate of 12.12% (lower) considering the medium population (normalized value of 0.485) and the fact that the spread is increasing at a lower rate (normalized value of 0.1). In contrast, the scheme based on population alone infers a rate of 13.86% (medium) considering the medium population of the state, and the scheme based on spread rate infers a rate of 16.92% (medium) considering the lower rate of increasing of spread at 0.1. The inference in the case of Andhra Pradesh is 10.05% vaccination rate considering the higher population of the state (normalized value of 0.687) and fact that the spread is decreasing at a lower rate of (normalized value of -0.3), the scheme based on population alone infers a rate of 19.63% (higher) because of a higher population, and the scheme based on spread rate alone infers a rate of 10.77% (lower) considering the fact that the spread is decreasing at a lower rate. The inference in the case of Puducherry is a rate of 3.14% (very low) considering the very low population of the state (normalized value of 0.017) and the fact that the spread is decreasing at a very lower rate of (normalized value of -0.1). In contrast, the scheme based on population alone infers a vaccination rate of 0.49% (very low) due to Puducherry's extremely low population, while the scheme based on spread rate alone infers a rate of 13.85% (medium) due to the fact that the spread is decreasing at a very slower rate.

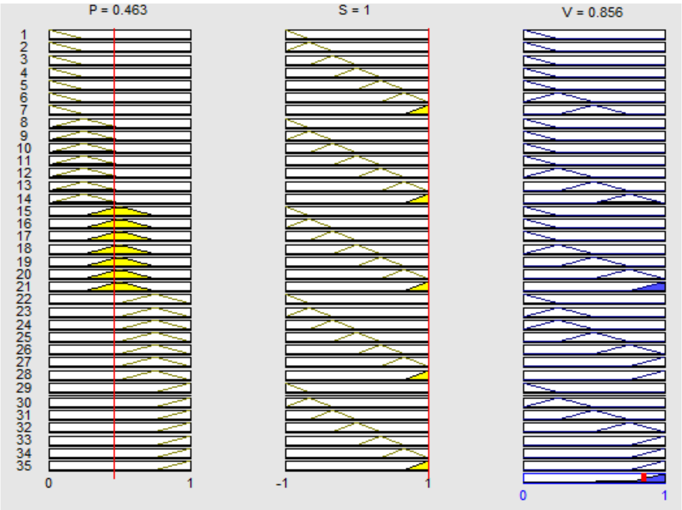


Figure 5. Inference computation: Kerala

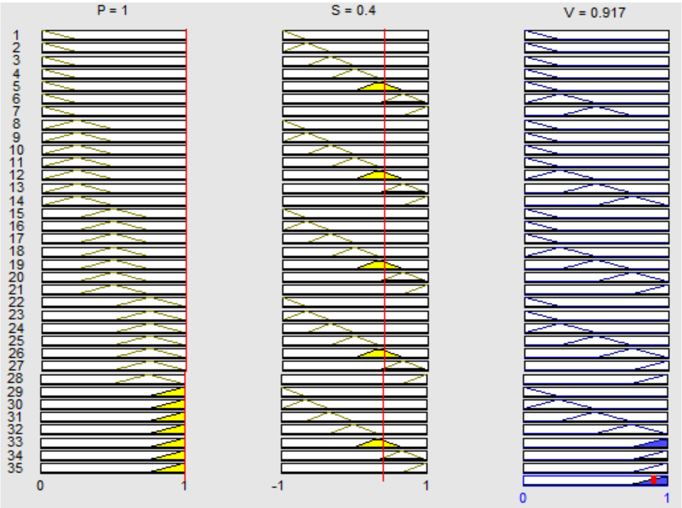


Figure 6. Inference computation: Tamil Nadu

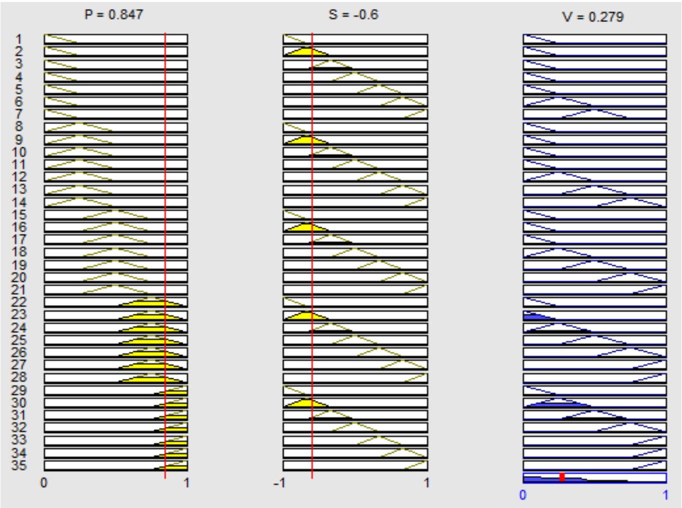


Figure 7. Inference computation: Karnataka

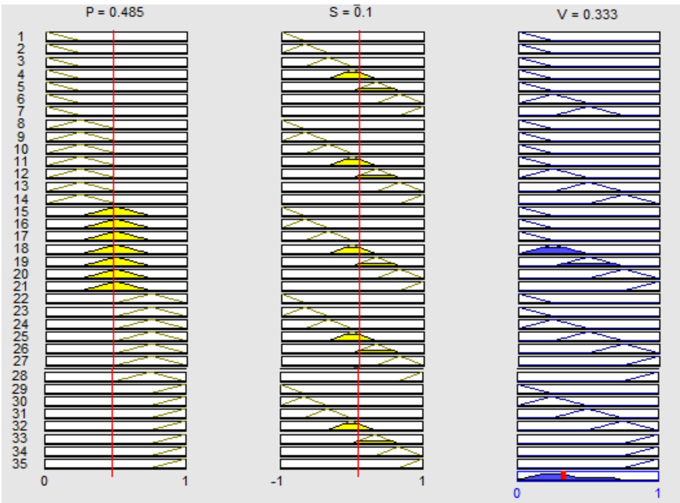


Figure 8. Inference computation: Telangana

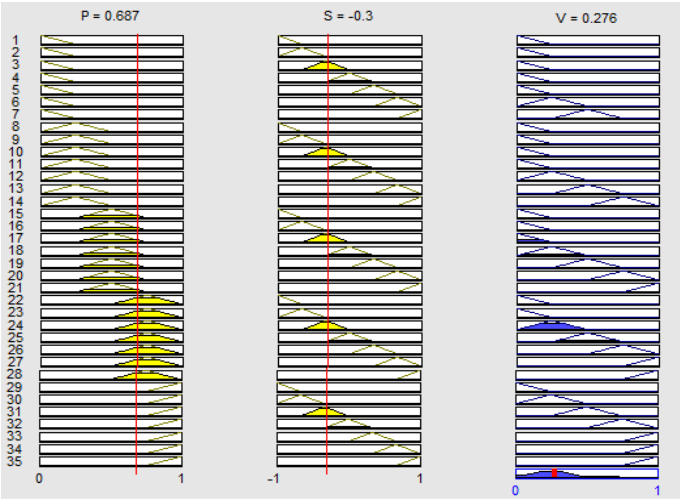


Figure 9. Inference computation: Andhra Pradesh

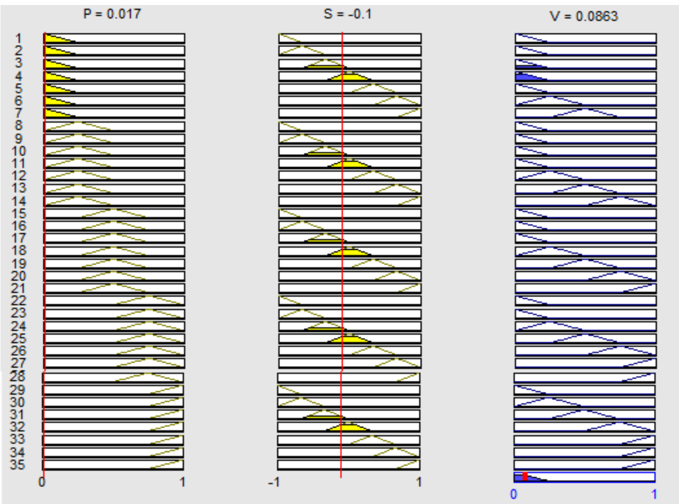


Figure 10. Inference computation: Puducherry

Table 2. Vaccination rate

Provincial State	Allocation of vaccine doses (%)		
	Scheme based on spread rate and population	Population-base scheme	spread rate-based scheme
Kerala	31.16	13.23	30.77
Tamil Nadu	33.38	28.58	21.54
Karnataka	10.16	24.21	6.15
Telangana	12.12	13.86	16.92
Andhra Pradesh	10.05	19.63	10.77
Puducherry	3.14	0.49	13.85

The comparison demonstrates how the population-based approach determines immunization rate based only on population. As a result, regions with smaller populations receive fewer vaccination doses and may experience a vaccine deficit, which could lead to super spreading if those provinces have a greater rate of transmission. In a similar vein, provinces with larger populations receive bigger doses of vaccinations and may waste them owing to vaccination-related noncompliance brought on by a false sense of security brought on by a lower rate of dissemination. The second method, which is based only on the spread rate alone, infer the vaccination rate purely based on the spread rate. Therefore, even in cases when a province's population is quite high, this method infers a lower vaccination rate if the province's spread is falling at a faster rate. In some populated provinces with a lower spread rate, this could lead to uncontrolled spread, and eventually those areas could turn into hotspots. Furthermore, even in cases when a province has a relatively small population, a greater vaccination rate will be implied if the state is spreading at a faster rate. The excess supply for a lower population could result in vaccine waste. The suggested fuzzy logic approach infers the vaccination rate allotted to the local authorities of various provinces by accounting for both population and spread rate. This innovative plan guarantees that sufficient vaccination doses are distributed to the areas that have a greater priority for vaccine transmission and that vaccinations are not delayed in provinces where the rate of spread is under control. Additionally, all provinces eventually receive an adequate number of vaccination shots to stop the spread. This strengthens the effort to stop the sudden spread of pandemics and guarantees the provinces receive the available vaccination doses in an effective and efficient manner.

4. CONCLUSION

This study proposes a novel fuzzy logic approach for a country's central health care system to distribute vaccines to its regional health care systems. The proposed scheme considers the spread rate and population in the process of the inference of the vaccination rate of the provinces. The scheme is assessed using COVID-19 data that was gathered from the Government of India's database during the first week of October 2020 in six southern province states. The outcomes are contrasted with the existing inference schemes, two of which are based solely on spread rate and population. The findings indicate that vaccinations are not held up in territories where the spread rate is under control, and that enough doses of vaccines are distributed to the provinces with priority on greater spread rates. Additionally, all provinces eventually receive an adequate number of vaccination shots to stop the spread. Therefore, the suggested scheme strengthens the effort to combat pandemics by guaranteeing the prompt, efficient, and impartial distribution of vaccines.

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