AN AHP-BASED OPTIMAL DISTRIBUTION MODEL AND ITS APPLICATION IN COVID-19 VACCINATION

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ABSTRACT

COVID-19 is causing a large number of causalities and producing tedious healthcare management problems at a global level. During a pandemic, resource availability and optimal distribution of the resources may save lives. Due to this issue, the authors have proposed an Analytical Hierarchy Process (AHP) based optimal distribution model. The proposed distribution model advances the AHP and enhances real-time model applicability by eliminating judgmental scale errors. The model development is systematically discussed. Also, the proposed model is utilized as a state-level optimal COVID-19 vaccine distribution model with limited vaccine availability. The COVID-19 vaccine distribution model used 28 Indian states and 7 union territories as the decision elements for the vaccination problem. The state-wise preference weights were calculated using the geometric mean AHP analysis method. The optimal state-level distribution of the COVID-19 vaccine was obtained using preference weights, vaccine availability and the fact that a patient requires exactly r vaccine doses to complete a vaccination schedule. The optimal COVID-19 vaccine distribution along with state and union territory rank, and preference weights were compiled. The obtained results found Kerala, Maharashtra, Uttarakhand, Karnataka, and West Bengal to be the most COVID-19 affected states. In the future, the authors suggest using the proposed model to design an optimal vaccine distribution strategy at the district or country level, and to design a vaccine storage/inventory model to ensure optimal use of a vaccine storage center covering nearby territories.

Keywords: COVID-19; vaccine distribution model; AHP; MCDM; risk assessment

1. Introduction

In early December 2019, the first active human COVID-19 (Corona virus disease) case was officially identified in Wuhan city, Hubei province, China (WHO situation report–94). On January 30, 2020, the World Health Organization (WHO) declared COVID-19 with its exponential rate of increase and zoonotic nature, an international public health emergency (WHO situation report –11). On February 18, 2021, only 1 year and 3 months after first being identified, COVID-19 had infected around 110 million people worldwide. A sobering statistic shows that out of 87,769,856 cases, 2,441,043 or almost 3% have died. (Worldometer, 2020). Currently, this pandemic has affected 219 countries and 2 international conveyances. Many government organizations, universities, and independent institutions are investing a very large amount of money, time, and man-power in research to ensure the creation of a scientifically sound and safe treatment or vaccine for COVID-19. Vaccines can be divided into a number of different types such as live attenuated vaccines (LAV), inactivated virus vaccines, sub-unit vaccines, viral vector-based vaccines, DNA vaccines, and mRNA vaccines (Kaur & Gupta, 2020); however, they all work on the same principle of stimulating the immune response to recognize a disease-causing organism. According to the WHO (steps in vaccine development), a vaccine candidate has to clear pre-clinical studies (including studies on animals for efficiency and safety), phase-1, phase-2, phase-3, and post-marketing surveillance studies to ensure complete vaccine development.

The COVID-19 pandemic has produced a number of healthcare issues including not only finding an efficient vaccine, but determining an optimal distribution strategy as well. A pandemic response using a vaccine requires a systematic solution for vaccine i) development ii) production, and iii) distribution. For the first step, according to WHO, a number of vaccine candidates from all over the world are in various clinical stages (subdivided into phase 1, ½, 2, and 3), and some have shown promising outcomes in the human trials (WHO draft-landscape,2021). The second step of the program includes the production of a clinically sound vaccine. Since, the most advanced and cutting-edge production strategy is needed to fulfill the global requirements for COVID-19 vaccines, many alliances among various biotech companies have been formed to advance vaccine production (Lancet, 2020). The final step of the program requires an answer to the question; what is the optimal distribution plan?

The Ministry of Health and Family Welfare, in India has issued operational guidelines (2020) for phase-1 vaccine roll out, and plans to sequentially vaccinate about 10 million healthcare workers, 20 million frontline workers, and around 270 million people above 50 years of age. The phase-1 roll out (2021) of the COVISHIELD (viral vector vaccine) and COVAXIN (inactivated virus vaccine) vaccines in India started in January 16, 2021. Both COVISHIELD and COVAXIN need 2-doses to complete the vaccination schedule. Since, an inactivated virus type vaccine requires booster shots to maintain immunity (Kaur & Gupta, 2020), those receiving COVAXIN will need an additional booster dose to complete the vaccination schedule. The authors observed that the production of the COVID-19 vaccine would definitely fall short of the global requirements Hence, the need for an optimal COVID-19 vaccine distribution strategy is an expected multicriteria decision-making (MCDM) problem in the near future due to the availability constraints and multiple dose requirement of the COVID-19 vaccine.

While searching for a solution to the state-level vaccine distribution problem, the authors found a popular MCDM problem-solving tool known as the AHP. The AHP methodology was introduced by T.L Saaty (1977, 1990, 2003) to solve real-time complex MCDM problems. The application of the existing AHP model can be defined as a five-step procedure (Rosenbloom, 1997). The easy to apply systematic AHP model has a large domain of applications, including supply chain management, construction, healthcare management, safety sciences, risk assessment and many other non-mathematical fields. Recently, we have observed the presence of various mathematical theories (Mishra et al., 2020) in COVID-19 research. The AHP has been useful in solving various healthcare policy issues including a number of management issues due to the COVID-19 pandemic. Mohammed et al. (2021) applied AHP methodology to propose a convalescent plasma transfusion intelligent framework for COVID-19 patients, and Garg et al. (2020) conducted a COVID-19 risk assessment considering the ease in lockdown restrictions and population density of various activities. Moreover, Halder et al. (2020), Improt et al. (2019), Corvinet et al.(2020),and Hezametal et al. (2021) have applied the AHP to deal with various health care management issues.

The authors observed that the AHP is an efficient MCDM technique with less computational requirements than most methods that can be utilized to develop a multi-purpose distribution model resulting in significant advancements. The AHP uses Saaty's fundamental scale (Saaty, 1990) to collect pairwise comparison responses from different respondents, and to construct a pairwise comparison matrix (PCM). Therefore, the outputs are highly dependent on the data collection and human responses. Moreover, the solution strategy for a real-time distribution problem using the AHP provides no possible way to use human responses. This methodological issue can be solved by replacing the verbal scale with a well-defined mathematical expression that helps produce an unbiased PCM for the vaccination model. Therefore, the authors have developed a more dynamic AHP-based distribution model that has some significant improvements over the existing AHP model. In the present article, the authors have proposed an AHP-based multipurpose optimal distribution model. The proposed model is used to determine an optimal distribution strategy for the COVID-19 vaccine for 28 Indian states and 7 union territories (U.Ts). It can be used for limited, but varying, vaccine availability and can be generalized for large or small territorial areas. Moreover, the authors have also identified and discussed various healthcare management applications of the proposed distribution model. The work presented in this article is divided into four sections. The first section provides a general introduction to the vaccine distribution problem and the AHP procedure. In the second section, the authors have developed an AHP-based multi-purpose distribution model. The third section includes the results and discussion, in which the proposed model is applied with the COVID-19 data to provide an optimal state-level COVID-19 vaccine distribution strategy in India. In the last section, the conclusions are discussed and the future scope of the proposed model is presented to researchers and various policy makers for the use of AHP to solve heath care management issues.

2. AHP distribution model development

An ethical vaccine distribution model must be free from human bias that might favor people based on region or religion, or include possible methodological errors resulting from a human judgmental scale. However, the distribution model must be able to compile

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the heterogeneous effects of a number of factors to the degree of importance present among the decision elements. The authors have proposed an AHP-based optimal distribution model, along with required advancements, in a systematic manner as given below:

1. *Hierarchy structure*: The first step in this model includes identifying a finite number of decision elements, and then defining the distribution problem into a hierarchy structure of decision elements (Saaty, 1987).

2. *Decision element coefficient*(R_i): The decision element coefficient(R_i)value for the i^{th} decision element, compiling the combined effect of various heterogeneous factors, is defined as

$$R_i = \sum_j w_j * factor_j$$

   where $\sum_j w_j = 1$, and w_j represents a justified weight assigned to the j^{th} factor. The general computation formula R_i is designed to include the effect of a finitely large number of important factors for the problem into the model. The proposed strategy for addressing a large number of factors, including those accountable for small but significant preference variation, may help improve the real-time applicability of the model.

3. *Pairwise comparison matrix (PCM)*: The proposed model uses the mathematical function, $f: S \rightarrow R_+$ defined over the set S of all possible pairs of decision element coefficients to the set $R_+$of positive real numbers, such that

$$f\left(R_i,\, R_j\right) = f_{ij} = {R_i}\big/{R_j} \quad \forall\, i \text{ and } j.$$

   for pairwise comparison of decision elements to construct the required PCM $\left[f_{ij}\right]_{l\times l}$. Mathematically, the pairwise comparison function f,with $f_{ij}.f_{jk} = \frac{R_i}{R_j}.\frac{R_j}{R_k} = \frac{R_i}{R_k} = f_{ik}$ ensures perfect consistency (Saaty, 2003) of the PCM that eliminates any potential conflict over the selection of a particular AHP analysis method. Also, replacing the linguistic judgment scale from a well-defined mathematical function f, leads to the elimination of human bias.

4. *Preference weights*(v_i) *and ranking*: The preference weight values(v_i) can be calculated using the suitable AHP analysis method. However, the model provides a complete choice for selecting a suitable AHP analysis method; the authors used the geometric mean method (GMM)(Crawford & Williams, 1985) to calculate the preference weight values(v_i).

The presented model can be utilized as an efficient AHP-based MCDM problem solving tool and as a multipurpose optimal distribution model. Further, the model is designed to calculate an optimal state-level distribution strategy for COVID-19 vaccines. The additional steps required to develop an optimal state-level distribution model are given below.

5. *Optimal vaccine distribution*: The optimal vaccine distribution for the i^{th} state with total vaccine availability V, and the fact that a patient requires exactly r vaccine doses along with ensuring state-wise homogeneity is defined as $r.\left\lfloor \frac{V.v_i}{r} \right\rfloor$; where, $\lfloor \quad \rfloor$ is greatest integer function. The vaccine distribution formula uses the greatest integer function to obtain distribution optimality by avoiding state-level redundant overlapping of vaccine doses (i.e. vaccine doses left that are not sufficient for single patient treatment).

3. Results and discussion

The proposed vaccine distribution model is explained as a five-step procedure. Since COVID-19 is transmitted via human contact (Chan et al., 2020), it is commonly thought that highly populated countries will suffer the worst from COVID-19. Therefore, the authors have utilized this distribution model to create an optimal vaccine distribution strategy for the world's second most populated (1.39 billion) and seventh largest country, India) (Population of India, 2021). The proposed model was applied for all states and U.Ts, excluding Lakshadweep, to determine an optimal vaccine distribution strategy for the COVID-19 vaccine using the reported COVID-19 data as of January 15, 2021(Covid19india, 2021). For the first step, the model used 28 Indian states and 7 U.Ts as decision elements for the problem. The hierarchy structure of the state-level optimal vaccine distribution problem was defined by placing all 35 decision elements as alternatives of the study at the second hierarchy layer, and the problem to select a state or U.T receiving the largest vaccine lot was placed at the first hierarchy layer (Figure1).

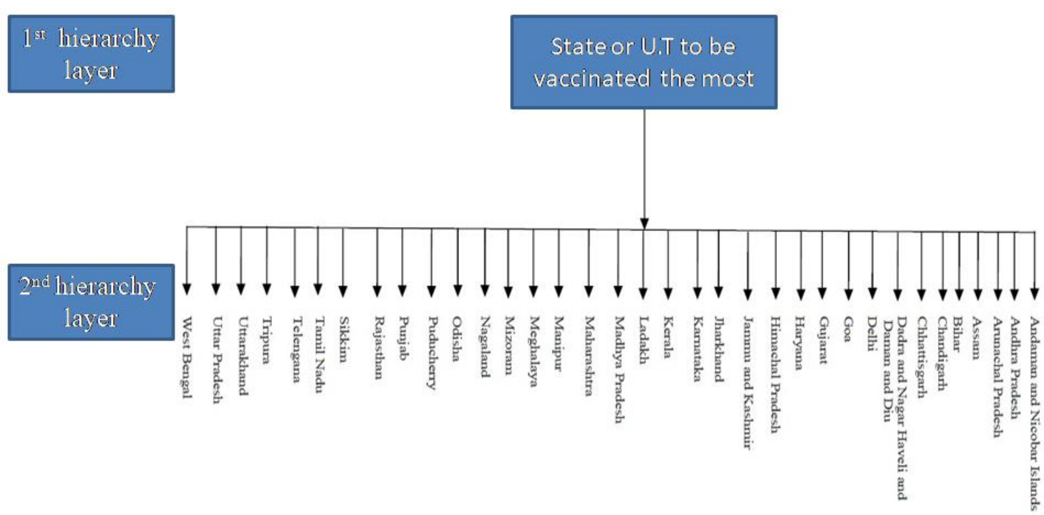

Figure 1 Hierarchy structure of the vaccine distribution problem

The authors observed that for a country like India, that covers a large territorial area and is sub-divided into a number of states and union territories (U.T) that differ from each other in size, population, density, health care facilities and medical staff availability etc., it is important to consider a measure of healthcare efficiency heterogeneity among the states/U.Ts. Since the lack of healthcare facilities and medical staff availability during the pandemic resulted in a higher number of deaths, these figures along with the number of active COVID-19 cases are considered critical factors for a vaccination model to a degree of significance to calculate the risk coefficient value relating to a state/U.T. For the second step in formulating an optimal COVID-19 vaccine distribution model, the authors calculated the state risk coefficient (R_i), considering the number of active COVID-19 cases(a_i), and the number of deaths(d_i) reported in the i^{th} state/U.T. The model application utilized two key factors for this problem, but it can also be generalized for future studies using several other factors such as the strength of the healthcare system and front line workers, pregnant women, condition of infected people, and population of senior citizens (individuals age >= 50). The globally reported 3% death rate influenced the authors to assign a weight of 0.03 to the number of deaths and 0.97 to the other factor, i.e., $\mathrm{R_i} = 0.97 * a_i + 0.03 * d_i$. Also, all 28 states and 7 U.Ts in India were listed from 1 to 35 in alphabetical order with the number of active COVID-19 cases(a_i), number of deaths(d_i) reported as of January 15,2021 (Covid19india, 2021), and the calculated state risk coefficient (R_i) in Table1.

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Table 1
State-wise reported COVID-19 data (Covid19india, 2021) and calculated $\mathbf{R_i}$ value

S.no (i)	State/Union territory	Active (a_i)	Death (d_i)	State Risk coefficient (R_i)	S.no (i)	State/Union territory	Active (a_i)	Death (d_i)	State Risk coefficient (R_i)
1	Andaman and Nicobar Islands	22	62	23.2	19	Madhya Pradesh	6957	3746	6860.67
2	Andhra Pradesh	2199	7139	2347.2	20	Maharashtra	52152	50336	52097.5
3	Arunachal Pradesh	64	56	63.76	21	Manipur	436	365	433.87
4	Assam	1616	1066	1599.5	22	Meghalaya	161	144	160.49
5	Bihar	3981	1449	3905.04	23	Mizoram	89	9	86.6
6	Chandigarh	266	330	267.92	24	Nagaland	104	88	103.52
7	Chhattisgarh	6923	3544	6821.63	25	Odisha	1910	1951	1911.23
8	Dadra and Nagar Haveli and Daman and Diu	11	2	10.73	26	Puducherry	294	640	304.38
9	Delhi	2795	10732	3033.11	27	Punjab	2739	5485	2821.38
10	Goa	866	753	862.61	28	Rajasthan	5608	2744	5522.08
11	Gujarat	6750	4360	6678.3	29	Sikkim	163	130	162.01
12	Haryana	2184	2979	2207.85	30	Tamil Nadu	6299	12251	6477.56
13	Himachal Pradesh	767	951	772.52	31	Telengana	4442	1574	4355.96
14	Jammu and Kashmir	1428	1920	1442.76	32	Tripura	45	387	55.26
15	Jharkhand	1289	1049	1281.8	33	Uttarakhand	9581	8558	9550.31
16	Karnataka	8790	12158	8891.04	34	Uttar Pradesh	2406	1602	2381.88
17	Kerala	67492	3416	65569.7	35	West Bengal	7223	10026	7307.09
18	Ladakh	104	128	104.72					

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Table 2
Optimal COVID-19 vaccine distribution for $\boldsymbol{r = 2, 3 \ and \ V = 1.5, 2, 2.5 \ and \ 4.5}$ (in Lakh) with state preference weight and rank

S.No		Preference weight		Optimal vaccine distribution with $r = 2$ and				Optimal vaccine distribution with $r = 3$ and			
(i)	State or Union Territory	(v_i)	Rank	$V = 1.5$ lakh	$V = 2$ lakh	$V = 2.5$ lakh	$V = 4.5$ lakh	$V = 1.5$ lakh	$V = 2$ lakh	$V = 2.5$ lakh	$V = 4.5$ lakh
1	Andaman and Nicobar Islands	0.000112362	34	16	22	28	50	15	21	27	48
2	Andhra Pradesh	0.01136795	16	1704	2272	2840	5114	1704	2271	2841	5115
3	Arunachal Pradesh	0.000308802	32	46	60	76	138	45	60	75	138
4	Assam	0.007746692	19	1162	1548	1936	3486	1161	1548	1935	3486
5	Bihar	0.018912875	12	2836	3782	4728	8510	2835	3780	4728	8508
6	Chandigarh	0.001297589	26	194	258	324	582	192	258	324	582
7	Chhattisgarh	0.033038492	7	4954	6606	8258	14866	4953	6606	8259	14865
8	Dadra and Nagar Haveli and Daman and Diu	0.000051967	35	6	10	12	22	6	9	12	21
9	Delhi	0.014689947	13	2202	2936	3672	6610	2202	2937	3672	6609
10	Goa	0.004177789	22	626	834	1044	1880	624	834	1044	1878
11	Gujarat	0.032344317	8	4850	6468	8086	14554	4851	6468	8085	14553
12	Haryana	0.010693051	17	1602	2138	2672	4810	1602	2136	2673	4809
13	Himachal Pradesh	0.003741466	23	560	748	934	1682	561	747	933	1683
14	Jammu and Kashmir	0.00698757	20	1048	1396	1746	3144	1047	1395	1746	3144
15	Jharkhand	0.006208009	21	930	1240	1552	2792	930	1239	1551	2793
16	Karnataka	0.043061051	4	6458	8612	10764	19376	6459	8610	10764	19377
17	Kerala	0.317567018	1	47634	63512	79390	142904	47634	63513	79389	142905
18	Ladakh	0.00050718	29	76	100	126	228	75	99	126	228
19	Madhya Pradesh	0.033227571	6	4984	6644	8306	14952	4983	6645	8304	14952
20	Maharashtra	0.252318511	2	37846	50462	63078	113542	37845	50463	63078	113541
21	Manipur	0.002101318	24	314	420	524	944	315	420	525	945
22	Meghalaya	0.000777285	28	116	154	194	348	114	153	192	348
23	Mizoram	0.000419421	31	62	82	104	188	60	81	102	186
24	Nagaland	0.000501368	30	74	100	124	224	75	99	123	225
25	Odisha	0.009256462	18	1388	1850	2314	4164	1386	1851	2313	4164
26	Puducherry	0.001474172	25	220	294	368	662	219	294	366	663
27	Punjab	0.013664497	14	2048	2732	3416	6148	2049	2730	3414	6147

28	Rajasthan	0.026744517	10	4010	5348	6686	12034	4011	5346	6684	12033
29	Sikkim	0.000784646	27	116	156	196	352	117	156	195	351
30	Tamil Nadu	0.031372094	9	4704	6274	7842	14116	4704	6273	7842	14115
31	Telengana	0.021096769	11	3164	4218	5274	9492	3162	4218	5274	9492
32	Tripura	0.000267635	33	40	52	66	120	39	51	66	120
33	Uttarakhand	0.046254025	3	6938	9250	11562	20814	6936	9249	11562	20814
34	Uttar Pradesh	0.011535912	15	1730	2306	2882	5190	1728	2307	2883	5190
35	West Bengal	0.03538967	5	5308	7076	8846	15924	5307	7077	8847	15924

For the third step, the authors performed the pair wise comparison by $f_{ij} = {}^{R_i}\!/_{R_j}$ for every possible pair (i, j); i, j =1,2…35 using the calculated R_i value. The computational work was done with Microsoft Excel and Statistical Software for Social Sciences (SPSS) to formulate a 35 order PCM $[f_{ij}]$. For the fourth step, the GMM (Crawford & Williams, 1985) was applied over the PCM$[f_{ij}]$ to calculate the state and U.T preference weights (v_i).

For the fifth step, an optimal COVID-19 vaccine distribution was calculated, for $r = 2$ with $V = 1.5, 2, 2.5\ and\ 4.5 lakh$, and for $r = 3$ with$V = 1.5, 2, 2.5\ and\ 4.5\ lakh$, using the mathematical formula $r.\left\lfloor \frac{V.v_i}{r} \right\rfloor$ as mentioned in step 5. When vaccine availability fell short of the requirement, an optimal distribution model, that was capable of ensuring homogeneity among the states and U.Ts for different $V$and r values was required. It was found that the model saved a total of $34, 40, 30, 38$ and $54, 54, 46, 48$ vaccine doses from overlapping for $r = 2$ with $V = 1.5, 2, 2.5\ and\ 4.5$ lakh and $r = 3$ with $V = 1.5, 2, 2.5\ and\ 4.5$ lakh availability respectively, which are able to be reassigned. The integrated model outcomes including the optimal COVID-19 vaccine distribution for $r = 2{,}3\ and\ V = 1.5{,}2{,}2.5\ and\ 4.5\ lakh$vaccine availability and the state preference weight(v_i) are represented in Table2.

4. Conclusions

COVID-19 is one of the most lethal pandemics ever faced by humankind, and is producing a large number of tedious management problems. Because of this, the authors observed that a multipurpose distribution model that is able to compile a large number of critical factors according to the requirements of a problem under study is required to deal with this problem. In this work, the authors developed an AHP-based multi-purpose distribution model to ensure optimal drug/vaccine distribution. The proposed model used a mathematical function for pairwise comparison to construct a PCM and eliminated any possible error caused by using linguistic judgment scales. It ensures perfect consistency to avoid any conflict that results from using different AHP analysis methods. Real-time distribution optimality was achieved by mathematically embedding the fact that exactly r vaccine doses are required to complete a vaccination schedule for one patient; therefore, avoiding overlapping of vaccine doses in every state or U.T.

The proposed model was applied in a systematic manner based on reported COVID-19 data for 28 Indian states and 7 U.Ts to provide an optimal distribution of limited COVID-19 vaccine doses. The state and U.T preference weight values(v_i)were calculated using the geometric mean AHP analysis method (Crawford & Williams, 1985) and are ranked from 1 to 35 for a greater to lesser v_i value. The computational results from the proposed model along with optimal vaccine distribution that was subject to varying vaccine availability(V) along with state-wise preference weights and ranks are shown in Table 2.

In the future, the proposed distribution model can be used as a multipurpose MCDM tool to solve various management problems due to its methodological flexibility. The model can be applied to design optimal vaccine distribution in smaller territorial areas such as at the district level within a state/U.T by considering districts as the decision elements of the problem, or at the vaccination center level within a city by considering vaccination centers as the decision elements of the problem. The model can also be generalized from the state level to the country level. Moreover, the distribution model is flexible enough to use varying vaccine availability or vaccine production capacity, and to provide an optimal vaccine distribution in milligrams or other SI units. The authors also suggest using the proposed model to design a vaccine storage or inventory model to provide optimal use of a vaccine storage center to cover nearby territories.

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