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► **To cite this version:**

Vignesh Dhanapal, Subhash C. Sarin. Distribution of Vaccines During a Pandemic (Covid-19). IFIP International Conference on Advances in Production Management Systems (APMS), Sep 2021, Nantes, France. pp.39-48, 10.1007/978-3-030-85910-7_5 . hal-03806537

HAL Id: hal-03806537

<https://inria.hal.science/hal-03806537v1>

Submitted on 7 Oct 2022

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Distribution of Vaccines During a Pandemic (Covid-19)

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Abstract. Covid-19 has affected the lives of people in different ways. A number of models are available in the literature to study the dynamics of a pandemic. However, there are very few models that study the impact of vaccine distribution among different population groups. In this paper, we use a modified epidemiological model which incorporates relationships between different populations to incorporate the impact of vaccine distribution and present results for different vaccine distribution strategies. We have presented how a sharing-based vaccine distribution strategy could be implemented in the face of the spread of the virus. The main finding of our work is that an effective vaccine distribution may differ depending upon the level of interactions among different population groups and a sharing-based vaccine distribution strategy is the most effective strategy.

Keywords: Pandemic, Epidemiological model, Covid-19, Population groups.

1 Introduction, Background, and Problem Statement

Covid-19, also known as Coronavirus, was first reported in December 2019 [1]. Slowly over time, the virus infections spread worldwide, and the number of cases grew very rapidly. Many people lost their lives and there was scarcity of information about how to control or stop its spread. Hospitals and other medical facilities were overwhelmed with the number of cases and they lacked resources like respirators, PPEs, healthcare workers and hospital beds. The normal life as we know it got disrupted and the livelihood of a vast number of people worldwide was challenged.

Lockdowns and other measures were implemented to slow down the spread. People were made to stay at home and many businesses were closed. Slowly, more medical centers opened, and the spread rate reduced. More resources like PPEs, respirators and hospital beds became available. As more resources became available, some of the important questions which arose were who/which region needs these resources the most, how many of the resources are needed and what will be the future impact of the actions/strategies implemented.

Different pandemics have devastated humankind over the course of history [2] starting from the earliest recorded pandemic that occurred during the Peloponnesian war around 430 B.C [3]. So, when the Covid-19 pandemic surfaced, it was not something completely new. But what makes it different is a higher population size and global travel that it impacted, thereby making it challenging to predict the progress of the pandemic and in making decisions to control its progress.

There have been many different types of forecasting models developed to predict the progress of pandemics. One of the most popular and earliest models is the epidemiological model developed in the year 1927 by Kermack & McKendrick [4]. There have been many additions to this fundamental model over time. After the outbreak of Covid-19, several versions of the epidemiological model have been employed to address the situation [5-13]. A number of recent studies have used deep learning techniques to predict progress of the Covid-19 pandemic [14,15]. However, there have not been reported works devoted to the use of epidemiological models that study the impact of progression of virus in one group to that in the other, and accordingly, determine effective strategies for the distribution of vaccines in order to mitigate the spread of virus. We have addressed this problem in this paper.

Also, we discuss the different vaccine distribution strategies and their impact in the face of the pandemic. The factors affecting the implementation of different strategies are also discussed. The best strategy for controlling the pandemic globally is suggested.

2 Methodology

This study uses a modified version of the Epidemiological model, which is one of the popular models used to study and predict the progress of pandemics. Epidemiological models are mathematical models which are effective in simulating the spread of many communicable diseases and have been used extensively for the recent Covid-19 research [5-13]. The model consists of multiple compartments with each representing a stage in the progression of the disease. A person moves across different compartments based on requisite transition rates or probabilities. At any point in time, the spread of a pandemic can be represented by the number of people in each compartment. Different models based on the number of compartments can be constructed.

One of the popular models is the SIR (susceptible-infectious-removed) model. Depending on the intensity of the disease, an individual may move to the susceptible compartment again if they do not develop immunity after the first infection. The SIR model has three compartments namely Susceptible (S), Infectious (I) and Recovered (R). Initially, a person starts in the Susceptible compartment (S) and is not yet infected. Once infected, they move to the Infected compartment (I) at a rate called the disease transmission rate β . Then, they either recover or do not survive and move to the

Recovered compartment (R) at a rate called the recovery rate γ . Our primary objective is to track and reduce the number of infected cases. The number of fatalities is proportional to the number of infections. Hence, a reduction in the number of infections will reduce number of fatalities as well. Therefore, we just keep track of the number of infections. If needed, we can further split the R compartment into Recovered and Non-survived compartments and track them separately. The impact resulting from getting the vaccine can be incorporated into the epidemiological model. A person in the Susceptible compartment after getting vaccinated directly moves to the Recovered compartment and cannot get infected. For our study, the effectiveness of the vaccines is assumed to be 100%. Thus, administering, say, v number of vaccines at time t moves v persons from the Susceptible compartment to the Recovered compartment, thereby, reducing the number of people who could further get infected. The dynamics of the model is shown in Figure 1.

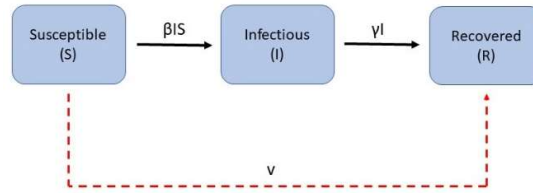


Fig. 1. An epidemiological model including impact resulting from getting a vaccine

The dynamics of movement between different compartments and the differential equations of the model are given below.

$$dS/dt = -\beta IS - v \quad (1)$$

$$dI/dt = \beta IS - \gamma I \quad (2)$$

$$dR/dt = \gamma I + v \quad (3)$$

We can study different population groups separately in order to determine progression of the virus in specific groups. For this study, we consider two groups namely, General population and Healthcare worker population. Each group will entail a separate model with its compartments and transition probabilities. The number of infections and recoveries can be found in each period for both the models. The effect of the pandemic on total population is then the sum of outcomes of both the models.

The above method considers both the population groups to be independent and the progression of the virus in one group not to impact that in the other. Such a method is pertinent to study a situation in which the groups represent regions with no interactions among them because of lockdown. However, we also consider the situation in which the progression of the virus in one group impacts that in the other. Consider the two population groups described above with each group represented by its own model and parameters. Let the ratio of the number of infected healthcare workers to

the total number of healthcare population be represented by θ . Also, the number of infections in the healthcare population affects the progress of virus in the general population, because of their essential interactions with general population through activities like testing, caring for the elderly in nursing homes and the patients admitted to the hospital, and for providing consultation to infected persons quarantining at home. This interaction is captured in the model by using a (modification) function that modifies the parameters of the general population model depending on the spread of virus in the healthcare population. The modification function, $f(\theta) = \exp(\theta * K)$ is defined using θ and a constant K . The β and γ parameters of the general population model are modified as follows:

$$\text{Modified } \beta = \beta * f(\theta) \quad (4)$$

$$\text{Modified } \gamma = \gamma / f(\theta) \quad (5)$$

With this modification, the spread of the virus in the healthcare population model (HPM) affects the parameters of the general population model (GPM) and thereby, the general population model itself. An exponential function was chosen for $f(\theta)$ as the impact of the number of infections on the total population is not linear and an exponential function form was found to give the best fit. The constant K can be used to fine tune the model depending on the subtle variations present in the region to which the populations belong. The different parameters of the model could be tuned to the actual data to obtain the best fit. We can use this modified model to evaluate various scenarios and make decisions pertaining to vaccine distribution among different populations, timing of vaccinations, and the sequence in which the vaccinations are given to different populations. Some of the scenarios and their results are discussed in the following sections.

3 Data

Besides the data on general population, we also needed data on the daily number of infected cases among healthcare population for our study. After searching over several available data sources, the Wisconsin state health department was found to provide this data and hence was chosen. Milwaukee county was chosen as it is the most populous county in the state of Wisconsin [16]. The information regarding total population and number of healthcare workers is taken from the datausa website [17]. Data from the Dane county and Waukesha county were used to evaluate different vaccines distribution strategies [16].

4 Results

The different scenarios considered, and their results are discussed in detail in this section. The parameters of the individual population models (healthcare population and general population) are fitted by tuning them to give the best fit with the actual data. Also, our studies showed that parameter tuning with the most recent data makes

the model more reactive and accurate in its prediction. The fitted graphs for different population groups are shown in Figure 2.

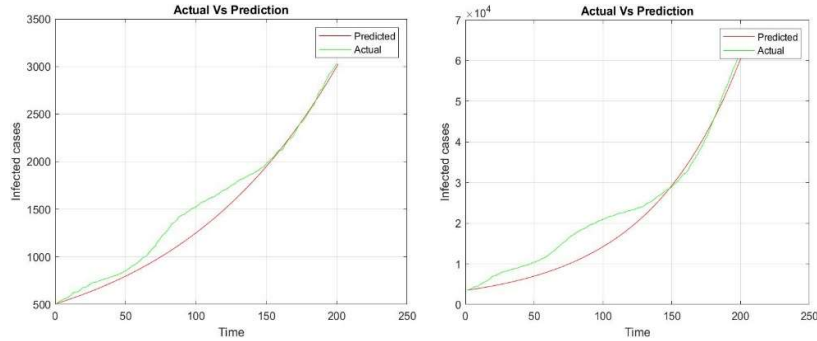


Fig. 2. Fitted model for healthcare population (left) and that for general population (right), that show actual vs predicted number of infected cases.

We studied several scenarios based on the following:

1. Number of vaccines, 2. Time of vaccination, 3. Ratio of vaccine distribution among populations, 4. Sequence of vaccination, 5. Vaccination times for multiple vaccinations, 6. Independent population groups

4.1 Number of Vaccines

In this scenario, the effect of varying the number of vaccines is studied. The model parameters and vaccination introduction time ($t=10$) are kept the same. The vaccines are allocated fully to one of the population groups. The different iterations (number of vaccines) tried were 5000, 10000, 25000, 50000 and 100000. The results show that the reduction in the number of infections increases with increment in the number of vaccines. The difference in infected cases due to different number of vaccines is non-decreasing in time. The differences vary among the population groups because of their different parameters.

4.2 Time of Vaccination

In this scenario, the effect of varying the time of vaccination is studied. The model parameters and vaccine quantity ($n=10$) are kept the same. The vaccines are allocated fully to one of the population groups. The different iterations (vaccination time) tried are 10, 25, 50, 100 and 150. As expected, the reduction in the number of infections is higher, when the vaccines are introduced earlier. The differences vary among the population groups because of their different parameters.

4.3 Ratio of Vaccine Distribution among Populations

In this scenario, the effect of varying the ratio of distribution of vaccines among different populations is studied. The model parameters and time of vaccination ($t=10$) are kept the same. The total number of vaccines available is 25,000, and they are distributed among the population groups. The different iterations (vaccine distribution ratios, healthcare:general) are 0:100, 25:75, 50:50, 75:25 and 100:0. The results show that the reduction in the number of infections is higher when a higher percentage of vaccines is introduced to the healthcare population. Also, note that, the difference in reduction becomes gradually lower with an increased percentage of vaccines being allocated to the healthcare population. Thus, it implies that we should prefer to vaccinate the healthcare population first; however, for overall effectiveness, it would be better to shift towards vaccinating the other populations instead of using all the vaccines on one population.

4.4 Sequence of Vaccination

In this scenario, the effect of the sequence in which different populations are vaccinated is studied. The vaccines are introduced at two points in time, and the number of vaccines introduced is 10,000 each time. Two different combinations of time periods are considered, and the sequence of vaccinations is varied. The model parameters are kept the same. The different iterations (healthcare vaccination time, general vaccination time) are: (50,10), (10,50), (100,10) and (10,100).

Results show that the reduction in the number of infections is higher when the healthcare population is vaccinated first in the sequence and then the general population. It was observed that vaccinating the healthcare population first would allow longer time before vaccinating the other population when compared to vaccinating general population first. Thus, we can conclude that we should prefer to vaccinate the healthcare population first in a sequence and doing so would allow us more time to delay the next vaccination.

4.5 Vaccination Times for Multiple Vaccinations

In this scenario, the effect of the time of vaccination when vaccinating multiple times is studied. The model parameters are kept the same, and the total number of vaccines to be used is 20,000. The vaccinations are done twice, and iterations consider vaccines to be fully allocated to one of the population groups. The results show that vaccinating a higher quantity during the first period allows us to delay the second vaccination period. Also, moving the first vaccination period by a period p early allows us to delay the second vaccination period by a value more than p . Hence, we can use this model to evaluate different vaccination time and quantity combinations while making vaccine distribution decisions.

4.6 Independent Population Groups

In this scenario, the effect of varying the ratio of distribution of vaccines among different populations, which are considered to be independent, is studied. The model parameters and the time of vaccination ($t=10$) are kept the same. The total number of vaccines to be used is 20,000. The different iterations (vaccine distribution ratios-healthcare:general) are 0:100, 25:75, 50:50, 75:25 and 100:0. The results show that the reduction in the number of infections is higher when higher percentage of vaccines are introduced to the general population. This observation is exactly opposite to the case of Section 4.3. This is because the general population is significantly larger in size than the healthcare population and a small amount of vaccinations in that population reduces infections by a relatively large number. On the other hand, the healthcare population is smaller in size and the maximum possible reduction in number of cases it can produce is significantly lower than that for the other population group. Also, because the groups are independently administering vaccines, the healthcare population would reduce the number of infections in that group and would not have any impact on the other group. This clearly shows incorporating the relationships between different population groups and the type and scale of relationship makes a significant difference in the decisions made. Moreover, it shows that in case the population groups considered have the least interactions between them, then it will be more effective to distribute vaccines to a larger group first because it would result in greater reductions in infections. Thus, extending this analysis to global level, at the height of pandemic spread, when the countries are essentially locked down, the distribution of vaccines to most populous places first would result in maximum reduction in infections.

5 Sharing-Based Distribution of vaccines

Appropriate steps have been taken to ensure a rapid scale-up of production of vaccines and other supplies. However, it should be noted that there is still a number of countries where the supply of vaccines is way lower than the demand. This uneven availability and inaccess to supplies are major contributors to the struggle in the face of the pandemic. One main reason for this is the hoarding of vaccines and other supplies by a few countries making it less accessible to other countries [18]. [19-22] present the statistics regarding vaccine procurement and reasons for the hoarding. As expected, these countries have procured high volumes of vaccines and a major share of manufacturing happens in these countries as well. It is prudent for a country to have sufficient supplies to vaccinate everyone in its population. However, amassing excessive inventories would leave vaccines away from communities where it can directly help in impeding the spread of the virus. Some of these countries have either procured or had confirmed orders of the vaccines more than enough to vaccinate the entire population. In some cases, this amount had been more than twice the population of those countries only to realize later that this excess inventory may not be needed, and then, starting to redistribute a portion to other nations. However, this delay

slowed the global response against the pandemic and a greater impact could have been achieved if the vaccines were made accessible to the needed communities earlier. Having a better and timely redistribution and sharing of vaccines both domestically and internationally to ensure optimal demand-supply dynamics would significantly enhance the impact of vaccinations. To illustrate this, we carried out experiments on the available dataset. Two counties in Wisconsin- Dane and Waukesha were considered and models were fitted to simulate the actual disease dynamics. The total number of vaccinations available per day for both the counties was considered as 500 and vaccinations began on the 10th day and continued till the end of the simulation period (200th day). The total number of infected cases in both the counties was observed at the end of the simulation period. The scenarios tested are shown in Table 1. In the second and sixth scenario, all the vaccines were allocated to the Dane county and Waukesha county respectively. While in Scenarios 3 to 5 this allocation was varied as shown. Scenario 1 is just the base case in which no vaccine is introduced. The last column shows the number of infected cases.

Table 1. Scenarios of experiments on different vaccination strategies in Dane and Waukesha counties in Wisconsin

Scenario Number	Number of vaccinations/day in Dane County	Number of vaccinations/day in Waukesha County	Total number of Infected cases
1	0	0	51811
2	500	0	43101
3	400	100	42289
4	250	250	42680
5	100	400	44500
6	0	500	42309

Note that, Scenarios 2-6 are better and give a smaller number of infected cases as expected when compared with the number of infected cases for Scenario 1. Scenario 3 results in the least total number of infected cases across both the counties. This shows that an appropriate sharing of vaccinations between different regions (Scenario 3) gives a better impact (reduced number of infections) as compared with allocating all the vaccines to one region (Scenario 2 & 6). As the spread of virus is dynamic, ideally the sharing of vaccines should also be implemented dynamically. Note that an equal sharing of vaccines (Scenario 4) does not necessarily give a better result.

A question arises as to the implementation of a sharing-based distribution of vaccines. The availability of capacity globally to produce vaccines is well known. Utilization of this capacity would not only enable effective logistics and global distribution of vaccines, but also, would increase the number of vaccines available. However, it demands sharing of patents and requisite materials.

6 Conclusion

In this paper, we have used an epidemiological model to study the impact of different vaccine distribution strategies pertaining to vaccination distribution, vaccinating in multiple stages, and controlling interactions between different groups. This study was carried out with two population groups. Some of the important conclusions from the study are:

- Higher quantities of vaccines and early vaccination produces the best impact.
- Healthcare population should be given a higher priority in administering vaccines and distribution ratio of vaccines.
- It would be more effective to vaccinate a proportion of one group first and then move to the other group instead of trying to completely vaccinate one group before moving to the other.
- The type and scale of relationship between different population groups makes a significant impact on the type of decisions made.
- The strategies for vaccine distribution are different depending upon the level of interaction between population groups.

We also evaluated different vaccine distribution strategies for the maximum impact in controlling the pandemic. The best strategy was found to be sharing of vaccines among different communities. Maintaining a global centralized inventory and distribution system, making vaccine patents accessible to manufacturers in order to enable utilization of available production capacity, and ensuring a free movement of raw materials and products are some of the essential steps needed to enhance the distribution of vaccines and their timely availability in the face of the spread of the virus.

The proposed model could be used to make decisions at both global and local levels. Some ideas for future work include incorporation of additional compartments, population groups, and different relationship functions in the proposed model. Moreover, an overarching optimization model could be formulated to make decisions in view of specified objectives and constraints.

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