Journal of Turkish

Operations Management

Comparison of Covid-19 vaccines under different coverage levels and delivery periods

Mustafa Demirbilek[1*]

[1]Department of Industrial Engineering, Gaziantep Islam Science and Technology University, Gaziantep
e-mail: mustafa.demirbilek@gibtu.edu.tr, ORCID No: http://orcid.org/0000-0002-1520-2882

Article Info

Article History:
Received: 19.05.2021
Revised: 10.08.2021
Accepted: 06.09.2021

Keywords:
COVID-19,
SIR Network Model,
Vaccination,
Simulation

Abstract

Ongoing COVID-19 pandemic has caused many hospitalizations, deaths, and huge economic cost worldwide for approximately one and half years. Vaccination has been the most important intervention strategy to stop infectious diseases as COVID-19. Several COVID-19 vaccines have been developed, produced, and delivered to people in several countries. These vaccines have different efficacy levels in between the first and second doses as well as after the second dose and durations to reach the maximum efficacy levels. In this study, we compared three COVID-19 vaccines, Moderna, Biontech, and Sinovac in terms of the number of infected and death people by considering their efficacy levels and durations to reach the maximum efficacy levels on SIR (Susceptible-Infected-Recovered) network model. Since it is a great problem to access enough vaccines for people worldwide, we also consider different coverage levels and delivery periods in the model. The proposed SIR network model is calibrated according to actual COVID-19 cases of six countries. Results show that Biontech is the best vaccine to decrease overall cases; however, results of Moderna and Biontech are quite close and differences between results are not statistically significant in some scenarios. Sinovac vaccines do not perform well compared to Moderna and Biontech. Moderna and Biontech vaccines reduce the number of cases by %24 compared to 17% for Sinovac under 10% coverage level whereas they reduce the number of cases by 70% compared to 58% for Sinovac under 50% coverage level.

1. Introduction

Infectious diseases such as measles, chickenpox, HIV, influenza have been dramatically affecting societies all over the world since the civilization began. For example, the bubonic plague, also called as “Black death”, caused millions of deaths, decreased the population of Europe by between 30% and 60%, and had continuously appeared till 19th century (Demirbilek, 2020). 1918 Spanish Flu, the worst disease outbreak in the last century, caused deaths between 20 and 50 million, more than causalities during WW1 (The Lancet Infectious Diseases, 2018). Recently, COVID-19 pandemic caused 142 million cases and 3.04 million deaths in the world, 4.3 million cases and 35,740 deaths in Turkey since January 2020 (Worldometer, 2021) and the numbers are notably increasing day by day.

To be able to stop or at least slow down effects of the pandemic, some intervention strategies such as vaccine, quarantine, antiviral drugs, lockdowns, etc. exist (Demirbilek, 2021a). One of the most important and common strategies is vaccination. In one hand, vaccination decreases the chance of death and hospitalization for individuals significantly. On the other hand, vaccination is helpful to achieve the herd immunity for societies in a short time (Couch, 1999). 107 vaccine candidates have been developed so far for ongoing COVID-19 pandemic while only 14 of them have been approved by several authorities (COVID-19 Vaccine Tracker, 2021). Pfizer Biontech, Astra Zeneca, Moderna, Sinovac, Sputnik can be shown as examples for important COVID-19 vaccines that have been produced and delivered large quantities in many countries. Although companies have been spending incredible amount of effort to test, produce, and deliver vaccines, the number of vaccines is still insufficient to be able to inoculate the most vulnerable group of people and achieve herd immunity (Fig. 1).

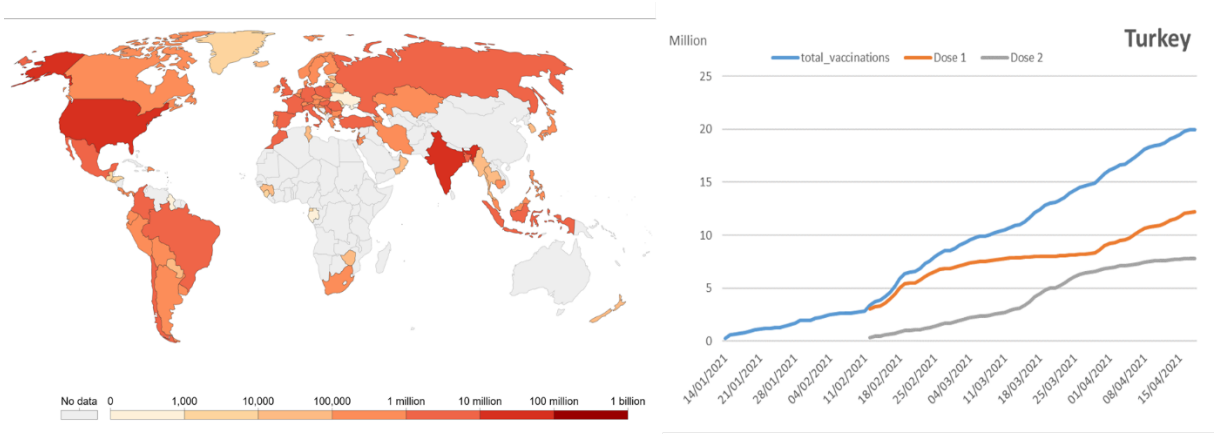

Figure 1. The total number of people that have been fully vaccinated (Our World in Data, 2021) (at the left) and the number of vaccines delivered in Turkey between January 14 and April 15 (T.C. Sağlık Bakanlığı Covid-19 Aşısı Bilgilendirme Platformu, 2021)

Each vaccine has different efficacy level, side effects, price, durations to reach the maximum efficacy level, storage and logistic conditions. The efficacy level or rate is simply the percentage reduction in a disease in a group of people who received a vaccination in a clinical trial. For example, 80% efficacy rate means that one person is infected over 5 vaccinated people. Since the immunity system in a body gradually responses inactivated virus in vaccine, vaccines cannot reach their full efficacy levels in bodies immediately. Particularly, if the vaccination needs more than one dose, the duration to reach the maximum effect takes longer. Therefore, overall efficacy levels and durations to reach the maximum efficacy levels are significant factors to protect individuals from being sick and to achieve herd immunity in the short time. Vaccine companies have revealed different efficacy levels and durations so far. It is important to observe effect of vaccines on the number of COVID-19 related cases based on a vary of efficacy levels and durations to reach the maximum efficacy levels. In this study, we consider three different vaccines, Sinovac, Pfizer Biontech and Moderna, with different efficacy levels and durations to evaluate their effects on the number of cases. To be able to test each vaccine, we first develop a network SIR (Susceptible-Infected-Recovered) model to mimic spread dynamics of COVID-19 pandemic. The model is calibrated based on actual COVID-19 related cases of six different countries. We also consider a vary of coverage levels, simply the proportion of the number of vaccinated people to the whole population, and delivery periods, times available vaccines are distributed. Since different features of vaccines have been revealed recently, any study that examines effects of different vaccines on the number of COVID-19 related cases have not been found in the literature. Main aims of this study are the followings:

- Comparisons of three popular vaccines, Moderna, Biontech and Sinovac in terms of total number of infected and death people during a pandemic,
- Consideration of different vaccine features such as efficacy levels between the first and second doses, maximum efficacy levels, and durations,
- Development of a new SIR Network Model mimicking real life interactions of individuals and spread of the disease,
- Calibrations of parameters in the model based on real COVID-19 cases.

Next section, the proposed model is explained. In Section 3, experimental settings and the calibration process are represented. In Section 4, results of simulations are demonstrated and discussed. We conclude our results and mention some limitations and assumptions.

2.Material and Method

2.1. SIR (Susceptible-Infected-Recovery) Compartmental Models

This model claims that individuals must present in a state, susceptible, infected, or recovered, in a specific time. All people but initially infected start in susceptible state. Whenever a susceptible person is infected, he/she moves to the infected state. Only infected people spread the disease to susceptible people. After predefined recovery time, infected people move to the recovery state or die. These people no more spread the disease or get infected. Fig. 2 shows transmission dynamics in the SIR model.

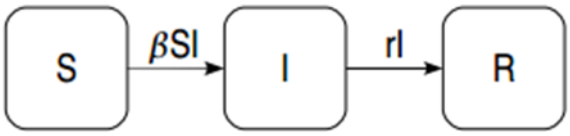

Figure 2. Transmission dynamics in the SIR model (Demirbilek, 2020)

In Figure 3, β shows the proportion of individuals moving to the infected compartment after interactions susceptible (S) people with infected (I) people whereas *r* represents the rate of recovery in a prespecified time (hour, day, etc.). The rate, β, is related to the spread speed of disease. If β is high, it means that the pandemic quickly spread as well as vanish through a population. Moreover, the recovery rate, *r*, is related to the recovery period. The longer recovery periods mean the less recovered people in a time lap (Demirbilek, 2021b).

2.2. Network Models

Network models have successfully been used in a variety of areas to inspect phenomena for which interrelationships matter (Craig et al., 2020). In economics, these cover job remitments in labour markets (Calvó-Armengol and Jackson, 2007), ways of international trade (Chaney, 2014), the diffusion of technology (Banerjee et al., 2013), and contagion in financial markets (Elliott, Golub, and Jackson, 2014). Since their suitable structure to model the pattern of transmission, network models can be adapted to model and analyse disease transmissions. Each person in the system is considered as a node and links connect people in same network. If there is no a link between two individuals, they cannot directly contact with each other and spread the disease. However, indirect links can exist if there are some nodes ensured connections between those two.

Although many studies (Walters et al., 2018; Prieto et al., 2012) related to modelling of different diseases have been conducted with SIR compartmental models, network models have been rarely employed for modelling disease purposes since the computational time is the most important obstacle to model relatively big size populations. The existing network models are mostly used for general simulation purposes via off-the-shelf-ready software and websites. FluTE (Chao et al., 2010), epiDMS (Liu et al., 2016), EpiFire (Hladish et al., 2012), FRED (Grefenstette et al., 2013), STRIDE (Kuylen et al., 2017) can be shown as examples for that software. Although this software can be very useful for researchers to observe how changing some parameters can affect some specific results, they do not allow users to configure network types, population structures, all parameters or to embed different environments such as schools, workplaces, and stores to the main frame. Although some provide open-source codes for software, they are very complex to make some modifications and to be executed in reasonable computational times. Therefore, a new flexible network model is coded in this study to consider different age groups in the population, environments such as schools, homes, and workplaces.

In this study, we consider three environments, homes, schools, and workplaces, where people are randomly assigned and connected in the fashion of random networks. Each person must be assigned to a home. Based on their ages, people will be assigned to a school or workplace. Each home, school, and workplace are consisted of a given number of people. We assume that people spend the half of their days at home (Period 1) and the other half at school or workplace (Period 2) daily. We also consider people that stay at home in whole day such as babies, unemployments and elders. Fig. 3 demonstrates the network structure of the study.

Disease transmission in our model is similar to compartmental SIR models. The first half of the day, people only contact with others in their homes. The rate of the fact that a susceptible person, *i*, is infected by *n* infected people in his/her home, r_i, is calculated as in Equation 1 (Demirbilek, 2021b).

$$r_i = 1 - p^n \quad (1)$$

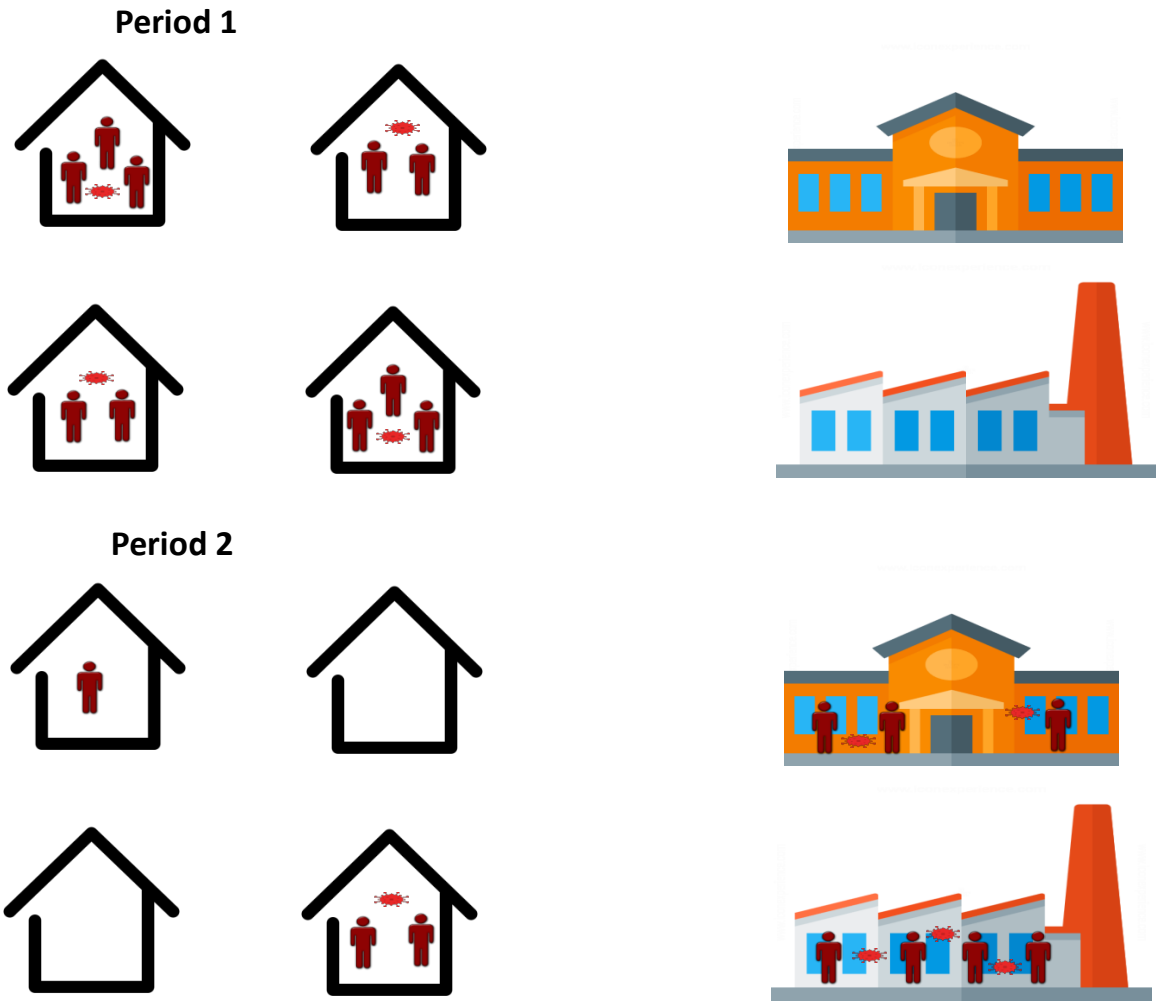

Figure 3. The network structure of this study

P is the transmission probability and assumed to be same for everyone. If r_i is equal or greater than a randomly generated number between 0 and 1, the person is infected. Vaccination directly decreases r_i with the associated efficacy rate. Note that the greater number of infected people exists in the network of a person, the more chance he/she is infected. The other half of the day, people in homes are assigned to schools or workplaces according to their ages while some people (babies, elders, and unemployment people) stay at their homes. The infected rate of each person in school, home, or workplace is calculated based on the number of sick people in their networks. Some people are infected if the calculated rate is equal or greater than randomly generated number. Same procedure is repeated in each day during the pandemic horizon. Whenever a person is infected, a recovery period is assigned to him/her. The person continues to infect people until his/her recovery period finishes. After the person is recovered, neither he/she can infect anybody nor be infected.

Algorithm 1 Pseudo code for pandemic simulation with different scenarios

```
1: Initialize Population
2: Distribute Individuals to Homes, Schools and Workplaces
3: DP ← Delivery Period                                   ▷ 30,60,120 Days
4: CL ← Coverage Level                                    ▷ 10%,30%,50%
5: Vaccine ← Vaccine Type                                 ▷ Moderna, Biontech, Sinovac
6: Trial ← Trials                                         ▷ 30
7: Day ← Set Pandemic Horizon                             ▷ 360 Days
8: DailyVaccine ← Population*CL/DP
9: for t = 1 To Trial do
10:     Initialize Infected Individuals
11:     for i = 1 To Day do
12:         if i in DP then
13:             Randomly Selected People ← DailyVaccine
14:             Set Efficacy Rate of Vaccine to Each Vaccinated Person
15:         end if
16:         Calibrate Chance of Vaccinated People to be Infected according
    to Vaccine
17:         People in Homes are Interacted and Infected
18:         Workers Move from Homes to Workplaces
19:         Students Move from Homes to Schools
20:         People in Homes, Schools, and Workplaces are Interacted and In-
    fected
21:         if i in Period of Dose 2 for Vaccine then
22:             Increase the Efficacy Rate of Vaccine for Vaccinated People
23:         end if
24:         Record Death and Infected Individuals
25:         Set Remaining Recovery Times
26:     end for
27:     Record Total Death and Infected People
28: end for
29: Print Average Number of Death and Infected People
```

Figure 4. Pseudocode for the pandemic simulation

Fig. 4 shows pseudocode for the proposed pandemic model. First two lines represent initialization of population and distribution of people to homes, schools, and workplaces. Next, the delivery period, coverage level, and vaccine type are defined for trials (Line 3-5). Each of 30 trials includes a 360-day pandemic horizon. If a day in the pandemic horizon stays in the vaccine delivery period, the number of unvaccinated and susceptible people are randomly selected and vaccinated (Line 12-15) according to the number of daily vaccines calculated division of the number of people that should be covered by the delivery period (Line 8). As represented on Fig. 3, people interact with only their home mates in the first half of the day whereas they interact with home, school and work mates in the second half of the day. Susceptible people can be infected during these interactions. However, the probability of being infected decreases with the efficacy rate of vaccine if the person is inoculated (Line 16-20). If the time of second dose comes for a person inoculated the first dose, the efficacy rate of vaccine starts to increase from the level between dose 1 and 2 to the maximum level linearly (Line 21-23). Finally, the number of cases is reported trial by trial to be able to calculate results.

3. Experimental Settings

A-year (360 days) pandemic horizon is considered in this study. The peak times fall into around middle of the pandemic. The population is divided into five different age groups, 0-4, 5-19, 20-24, 25-64, 65 and above based on 2019 demographic data, Statistic Association of Turkey. It is assumed that people in 0-4 and 65+ age groups stay at their homes in all day (two periods). All individuals aged between 5 and 19 are assumed to be students. %70 of people aged between 20 and 24 are considered as students whereas the remainings are considered as workers. %85 of people in 25-64 age group are workers and the remainings are unemployed. Note that unemployed people are assumed to stay at their homes all day long as people in 0-4 and 65+ age groups do. The attack rate, the proportion of the number of infected people to total population in a period, is calibrated according to actual COVID-19 related cases of six different countries as in Table 1.

Table 1. Calculations of attack and death rates according to populations, COVID-19 related cases and deaths of six countries (Worldometers, 2021)

Country	Population	Case	Attack Rate	Death	Death Rate
USA	331.002.651	**29.862.124**	0,090	**542.191**	0,018
Germany	83.783.942	**2.532.855**	0,030	**73.276**	0,029
UK	67.886.011	**4.234.924**	0,062	**124.987**	0,030
France	65.273.511	**3.963.165**	0,061	**89.565**	0,023
Spain	46.754.778	**3.178.442**	0,068	**71.961**	0,023
Italy	60.461.826	**3.123.368**	0,052	**100.811**	0,032
Normalized Rates	…	…	**%7,2**	…	**%2,1**

As it is mentioned before, three COVID-19 vaccines, Moderna, Pfizer-Biontech and Sinovac are compared in terms of the number of cases on the proposed model. According to studies and manufacturers, the efficacies of three vaccines between dose 1 and dose 2 and after dose 2 as well as durations to reach the proposed efficacy levels are demonstrated in Table 2.

Table 2. Data and parameters related to the model

Manufacturer	Timing of 2. Dose (Day)	Estimated Efficacy Between Dose 1 and Dose 2	Efficacy after 2. dose	Duration to Reach Full Efficacy (Day)	References
BioNTech	21	53%	95%	7	(KFF, 2021)
Moderna	28	70%	94%	14	(KFF, 2021)
SinoVac	14	25%	84%	14	(MCBU,2021;BBC, 2021)

The second column in Table 2 shows the number of days is needed for inoculation of the second dose after the first dose has been applied. For example, if a candidate is inoculated at the first time, he/she gets the second dose 21 days later for Biontech, 28 days later for Moderna, or 14 days later for Sinovac vaccines. Estimated efficacy levels between dose 1 and 2 are represented at the third column of Table 2. It is assumed that vaccines reach associated levels as soon as the first dose is applied. The fifth column demonstrates the number of days that vaccines reach the proposed highest efficacy levels. In this situation, it is assumed that vaccines gradually reach the full efficacy levels. Fig. 5 shows linear increments in efficacy levels of three vaccines after the second dose.

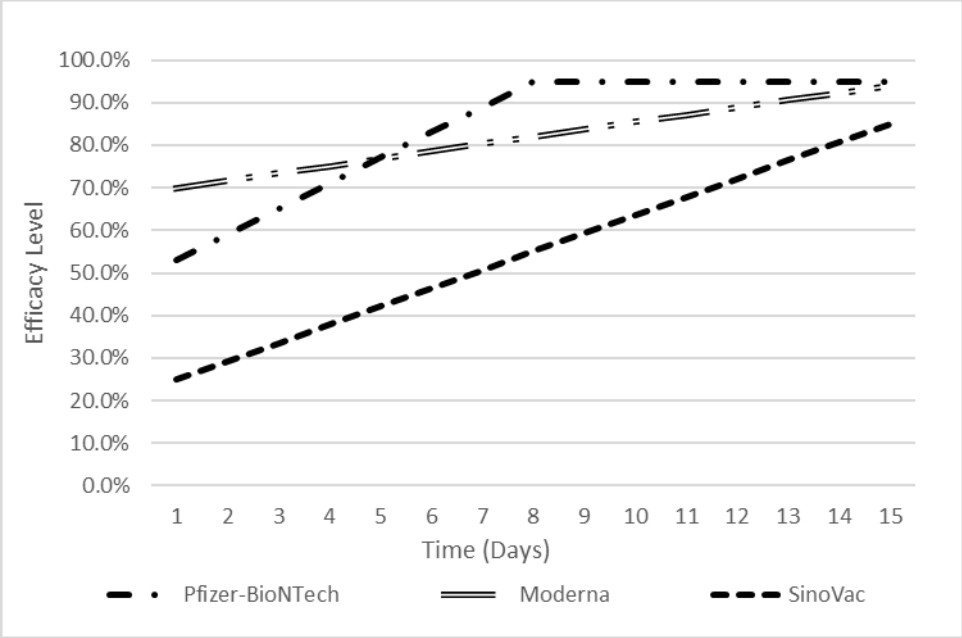

Figure 5. Linear increments in efficacy levels of three vaccines after dose 2

The calibration process is simply to set results of the model in terms of the number of cases according to real COVID-19 cases. Recovery period for each infected person is uniformly distributed between 6 and 9 days. Each simulation starts with 15 initial infected people to be able to begin the pandemic. Since it is impossible that vaccines become available at the beginning of pandemic, distribution of vaccines starts 30 days after the pandemic has begun in this study. We consider three scenarios about distribution times of vaccination. Vaccines can be distributed during 30, 60, and 120 days once the distribution starts (Day 30). It is assumed that the equal number of vaccines are delivered in each day during the distribution horizon. Three different coverage levels, 10%, 30%, and 50%, are taken into consideration. Table 3 shows all data and parameters related to the model.

Finally, since many stochastic parameters such as the recovery period, home/school/workplace sizes, infection possibility, etc. exist in this study, we conduct 30 trials to test each scenario to be able to observe if results are statistically significant. An independent sample t-test is conducted for each scenario and the associated p-value is provided. The model is coded in Python programming language. All tests are made in a PC with Intel i5 7200U 2.5 GHz CPU and 8 GB Ram.

Table 3. Data and parameters related to the model

Attack Rate	7.2%	**Coverage Level (%)**	10,30,50
Death Rate	2.1%	**Distribution Time (Day)**	30,60,120
Population (million)	1	**Pandemic Duration (Day)**	360
Initial Infectious	15	**Starting of Vaccination**	Day 30
Recovery Period (day)	Uniform (6,9)	**School Size (person)**	Uniform (290,310)
House Size (person)	Uniform (1,7)	**Workplace Size (person)**	Uniform (50,100)

4. Results

Table 4, 5 and 6 represent the number of cases for different COVID-19 vaccines and coverage levels according to three different distribution times, 30, 60, and 120 days, respectively. Furthermore, the associated p-value resulted by the independent sample t test is provided for each comparison of two vaccines. For example, in Table 4, the difference between results of Moderna and Biontech under 10% coverage level is not statistically significant since the associated p value (1.0E-01) is greater than the threshold value, 0.05, considered for all tests.

Table 4 shows the number of cases under the 30-day distribution time. First, it is obvious that the coverage levels significantly affect the number of cases. No matter what COVID-19 vaccine is distributed, the number of infected and death individuals decrease more than 60% if the half of the population are inoculated compared to only 10% of the population are. Under all coverage levels, Biontech vaccine seems the best in terms of decreasing the number of cases. However, results of Biontech and Moderna vaccines are quite close. Only under 30% coverage level, the difference between results of Moderna and Biontech is statistically meaningful. On the other hand, the number of cases resulted by Sinovac vaccine are significantly greater than results of Moderna and Biontech. The cases after Sinovac vaccines are delivered are almost 10% more than deliveries of Moderna and Biontech vaccines under 10% coverage level. Under 30% coverage level, the number of cases increases by around 25% whereas the cases rise by roughly 40% under 50% coverage level if Sinovac vaccines are delivered for 30 days instead of Moderna and Sinovac. Notice that differences between all results are statistically significant as seen in Table 4. In this study, it is assumed that no vaccinated person dies due to COVID-19 no matter what vaccine type he/she gets inoculated. Although same number of shots are delivered for three different vaccines, Moderna and Biontech vaccines reduce the number of deaths by approximately 25% compared to Sinovac under 50% coverage level. It means that vaccines with higher efficacy rates provide the herd immunity faster and unvaccinated people harm less from negative effect of the disease.

Table 4. The number of cases for different COVID-19 vaccines and coverage levels for 30-day distribution times and p-values resulted by the independent t tests for comparisons of vaccines

				Independent Sample T-Test			
Coverage Level	**Vaccines**	**Infected**	**Death**	**Biontech**	**Moderna**	**Sinovac**	**Baseline**
10%	Baseline	**74,937**	**1,764**	3.5E-24	3.2E-23	2.4E-17	…
	Biontech	**56,117**	**1,318**	…	1.0E-01	1.6E-07	3.5E-24
	Moderna	**57,201**	**1,301**	1.0E-01	…	9.1E-06	3.2E-23
	Sinovac	**61,346**	**1,377**	1.6E-07	9.1E-06	…	2.4E-17
30%	Biontech	**32,875**	**737**	…	7.8E-03	5.6E-17	3.7E-44
	Moderna	**34,369**	**738**	7.8E-03	…	2.3E-15	2.2E-44
	Sinovac	**40,960**	**826**	5.6E-17	2.3E-15	…	1.2E-38
50%	Biontech	**22,179**	**458**	…	6.0E-02	6.4E-26	2.3E-51
	Moderna	**22,796**	**464**	6.0E-02	…	2.1E-25	2.3E-51
	Sinovac	**31,510**	**557**	6.4E-26	2.1E-25	…	1.6E-45

Table 5 represents the number of cases under the 60-day distribution time. First, compared results of the 60-day delivery to the 30-day delivery of all vaccines, the number of cases is not significantly different under 10% and 30% coverage levels. Under 50% coverage levels, the 30-day longer delivery period causes almost 10% more cases. Similarly, Biontech vaccines decrease the number of cases more compared to Sinovac and Moderna as it does in 30-day delivery time. However, differences between results of Biontech and Moderna are statistically significant in both 30% and 50% coverage levels. Both vaccines perform better compared to Sinovac in all scenarios. Notice that differences between all results are statistically significant as seen in Table 5.

Table 5. The number of cases for different COVID-19 vaccines and coverage levels for 60-day distribution times and p-values resulted by the independent t tests for comparisons of vaccines

				Independent Sample T-Test			
Coverage Level	**Vaccines**	**Infected**	**Death**	**Biontech**	**Moderna**	**Sinovac**	**Baseline**
10%	Baseline	**74,937**	**1,764**	1.4E-21	1.2E-20	9.7E-15	…
	Biontech	**57,763**	**1,325**	…	2.8E-01	3.4E-06	1.4E-21

	Moderna	**58,335**	**1,337**	2.8E-01	…	3.2E-05	1.2E-20
	Sinovac	**62,784**	**1,416**	3.4E-06	3.2E-05	…	9.7E-15
30%	Biontech	**34,899**	**768**	…	2.3E-03	1.5E-16	6.0E-44
	Moderna	**36,563**	**802**	2.3E-03	…	7.4E-12	1.7E-42
	Sinovac	**42,222**	**866**	1.5E-16	7.4E-12	…	1.4E-37
50%	Biontech	**24,555**	**515**	…	2.4E-02	4.9E-21	2.3E-49
	Moderna	**25,584**	**529**	2.4E-02	…	2.7E-20	1.5E-49
	Sinovac	**32,829**	**589**	4.9E-21	2.7E-20	…	8.7E-45

Table 6 represents the number of cases under the 120-day distribution time. Differences between results of the 60-day and 120-day delivery periods do not seem significant whereas differences between results of the 30-day and 120-day delivery periods vary 5% to %32 for 10% and 50% coverage levels respectively. Moderna vaccines provide the best results in terms of cases under 50% coverage level whereas Biontech vaccines decrease the number of cases more under other coverage levels. As results in shorter delivery periods, Sinovac vaccines perform worse than Moderna and Biontech vaccines. Even relatively longer delivery period and lower coverage level, Sinovac vaccines reduce deaths by 17% and infected by 11%.

Table 6. The number of cases for different COVID-19 vaccines and coverage levels for 120-day distribution times and p-values resulted by the independent t tests for comparisons of vaccines

				Independent Sample T-Test			
Coverage Level	**Vaccines**	**Infected**	**Death**	**Biontech**	**Moderna**	**Sinovac**	**Baseline**
10%	Baseline	**74,937**	**1,764**	7.5E-22	1.0E-16	3.3E-13	…
	Biontech	**59,105**	**1,364**	…	3.0E-03	1.4E-07	7.5E-22
	Moderna	**61,553**	**1,426**	3.0E-03	…	6.7E-03	1.0E-16
	Sinovac	**64,112**	**1,468**	1.4E-07	6.7E-03	…	3.3E-13
30%	Biontech	**39,449**	**885**	…	3.3E-02	2.4E-13	2.1E-40
	Moderna	**40,756**	**888**	3.3E-02	…	3.2E-09	1.7E-38
	Sinovac	**46,015**	**959**	2.4E-13	3.2E-09	…	2.1E-34
50%	Biontech	**29,966**	**640**	…	8.5E-03	2.7E-18	5.2E-47
	Moderna	**28,768**	**606**	8.5E-03	…	1.5E-21	9.8E-48
	Sinovac	**36,942**	**699**	2.7E-18	1.5E-21	…	4.4E-42

5.Conclusions

Infectious diseases have been affecting societies and causing millions of infected, deaths, and huge economic cost since the beginning of humankind. Ongoing COVID-19 pandemic has caused a global crisis and the number of infected and death people are significantly rising every day. As helping to vanish previous pandemics, the vaccination is the most important weapon to fight against COVID-19 pandemic. However, this is not an easy task to derive right strain of virus and develop appropriate vaccines. Although almost one and half years passed after the first cases had appeared in Wuhan, China, enough vaccines have not been produced and delivered to be able to achieve herd immunities in many countries. On the other hand, some developed vaccines have different efficacy rates, side effects, prices, durations to reach the maximum efficacy levels, storage and logistic conditions. Particularly, efficacy rates (levels), the percentage reduction in a disease in a group of people who received a vaccination in a clinical trial, directly affect the number of cases. In this study, we compare three popular COVID-

19 vaccines, Moderna, Biontech, and Sinovac with different efficacy rates and durations to reach the full efficacy rates, in terms of the number of cases by considering different coverage levels and delivery periods. A stochastic network SIR model is developed to mimic spread dynamic of the pandemic and calibrated according to actual COVID-19 cases of six countries. Since there are some stochastic parameters such as recovery period, infection possibility, network structure in our model, we consider 30 trials for each scenario related to vaccines, coverage levels, and delivery periods. Associated p-values are calculated based on independent sample t-test for each comparison.

First, results show that Biontech vaccines reduce the number of cases more compared to Moderna vaccines in many scenarios even though the efficacy rate of Moderna vaccines is significantly more than Biontech between the first and second doses. Both Moderna and Biontech perform better compared to Sinovac. When the coverage level increases 10% to 50%, gaps between results of Sinovac and Moderna-Biontech rise sharply. Moderna and Biontech vaccines reduce the number of cases by around %24 compared to 17% for Sinovac under 10% coverage level whereas they reduce the number of cases by 70% compared to 58% for Sinovac under 50% coverage level. We consider three different delivery periods, 30, 60, and 120 days and each period starts 30 days after the beginning of the pandemic. According to results, differences between 30- and 60-day delivery periods are not significant under 10% and 30% coverage levels. However, under 50% coverage level and all scenarios for the 120-day delivery period, inclines in the number of cases vary 10% to 30%. It is concluded that shorter delivery times are quite effective on decreasing the number of cases if an intense vaccination campaign can be arranged.

There are some assumptions and simplifications in this study. First, the proposed model only covers home, work, and school environments where people interact with each other and spread the disease. However, other places such as restaurants, cafes, shopping malls, mosques, etc. where people have commonly been existing in real life. To be able to reduce the complexity of the model, we must ignore these places. Next, it is assumed that efficacy of vaccines increases linearly and stop at the predefined level. However, there is no evidence about linear inclines in efficacy rates in the literature. Moreover, efficacy levels can stay above or below the maximum efficacy levels. Finally, efficacy rates are accepted as being deterministic, same for person to person and trial to trial. However, these rates are stochastic and revealed with confidence intervals.

In future studies, researchers can focus on optimization methods to delivery limited number of vaccines to people based on their ages, chronic illnesses, jobs, etc. for minimizing cases and economic cost.

Conflicts of Interest

The author declared that there is no conflict of interest.

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