Avrupa Bilim ve Teknoloji Dergisi
Sayı 23, S. 62-69, Nisan 2021

Araştırma Makalesi

www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
No. 23, pp. 62-69, April 2021

Research Article

The Effect of School/Workplace Closure Based Scenarios on COVID-19 Spread

Mustafa Demirbilek[1*]

[1*] Gaziantep Islam Science Technology University, Faculty of Engineering ve Natural Sciences, Department of Industrial Engineering (ORCID: 0000-0002-1520-2882)
mustafa.demirbilek@gibtu.edu.tr

(First received 18 December 2020 and in final form 12 March 2021)

(**DOI:** 10.31590/ejosat.842793)

ATIF/REFERENCE: Demirbilek, M. (2021). The Effect of School/Workplace Closure Based Scenarios on COVID-19 Spread. *European Journal of Science and Technology*, (23), 62-69.

Abstract

Contagious diseases have wreaked havoc on human communities since ancient times. Ongoing COVID-19 pandemic has caused millions of incidents and deaths so far and continues to affect all over the world in the near future. One of ways to stop and slow down a pandemic in absent from proper and effective drugs and vaccines is workplace/school closures limiting people interactions and spread of the disease. In this study, we consider workplace/school closures as an intervention strategy to observe the effect on overall incidents and deaths. Six scenarios, covering workplace and school closures together or separately and applications in different times during the pandemic, are tested for the SIR (Susceptible-Infectious-Recovery) network model where people can interact with others in their homes, schools, and workplaces daily. People in the model are divided into five age groups. Each individual is assigned to a home and school or workplace with a given probability regarding to his/her age. People contact with others in their networks (school, workplace, and home) every day and can be infected with a given probability if they interact with sick people. We calibrate sickness probability according to the attack rate derived from COVID-19 related data of six countries. Results show that applying any of intervention strategies as soon as the pandemic begins makes huge differences in terms of overall cases compared to applying them around the peak times. Overall cases decrease by 40% and 65% for the high attack rate (10%) and COVID-19 related attack rate (3.2%) when workplace/school closures are applied 2 weeks after the pandemic has started. Moreover, results imply that even closing schools and workplaces in two weeks does not stop the spread of diseases completely based on recovery times uniformly distributed between 6 and 9 days.

Keywords: COVID-19, Workplace/School Closures, SIR Network Models, Simulation

Okul ve İş Yeri Kapatmalara Dayalı Senaryoların COVID-19 Yayılımına Etkileri

Öz

Bulaşıcı hastalıklar eski zamanlardan beri insanlığa büyük zararlar vermişlerdir. Devam etmekte olan COVID-19 salgını şimdiye kadar milyonlarca insanın hasta olmasına ve ölmesine yol açmıştır ve yakın gelecekte de etkisini göstermeye devam edecektir. Etkili ilaç ve aşıların yokluğunda, bulaşıcı hastalıkları yavaşlatmanın ve durdurmanın yollarından biri de, kişiler arasındaki etkileşimlerin kısıtlanmasını ve hastalığın yayılmasını engelleyen okul/iş yeri kapatma yöntemidir. Bu çalışmada, toplam hasta ve vaka sayılarına etkilerini görmek için bir müdahale yöntemi olan okul/iş yeri kapatmayı göz önüne aldık. Okul ve iş yerlerinin salgının farklı zamanlarında, ayrı ayrı veya birlikte kapatılmasını içeren altı farklı senaryo, kişilerin okul, iş yeri ve evlerindeki insanlarla günlük etkileşim içinde olduğu SIR (Korumasız-Hasta-İyileşmiş) Ağ (Network) modeli için test edilmiştir. Sistemdeki kişiler yaşlarına göre beş farklı gruba bölünmüş ve bir ev, iş yeri veya okula atanmışlardır. Kişiler günlük olarak, kendi ağlarındaki (ev, iş yeri veya okul) diğer kişilerle etkileşime girip, belirli bir olasılıkla hasta kişilerden enfekte olabilmektedirler. Hastalık bulaştırma olasılığı altı farklı ülkenin COVID-19 istatistiklerinden yararlanılarak hesaplanmıştır. Sonuçlara bakıldığından hangi senaryo olursa olsun, salgın başlangıcında uygulandığında, salgının zirve yaptığı zamanlarda uygulanmasına göre, hasta ve ölüm sayısını düşürmesi bakımından

[*] Corresponding Author: mustafa.demirbilek@gibtu.edu.tr

çok daha etkili olduğu görülmüştür. Salgın başladıktan iki hafta sonra uygulanan kapatma, toplam vakaları COVID-19 salgın şiddetinde (%3,2) %65 ve daha yüksek salgın şiddetinde (%10) %40 oranında azaltmıştır. Dahası 2 haftalık okul/iş yeri kapatılmasının, 6 ve 9 gün arasında düzgün dağılım gösteren iyileşme zamanları baz alındığında salgını tamamen durduramadığı gözlenmiştir.

Anahtar Kelimeler: COVID-19, Okul/İş Yeri Kapatılması, SIR Ağ Modelleri, Benzetim

1. Introduction

Infectious diseases have dramatically effected societies and caused a huge amount of infected and death people and economic costs for centuries. Epidemics occur year by year while pandemics appear irregularly and cause high number of deaths and hospitalizations. 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). The other example is, 1918 Spanish Flu, the worst infectious disease outbreak in the last century, caused deaths between 20 and 50 million, more than causalities during WW1 (Webby & Webster, 2003; McConnell, 2002).

On December 30, 2019, a cluster of patients with pneumonia of obscure etiology was monitored in Wuhan, China, and reported to the World Health Organization (WHO). By January 2, 2020, the full genome of a new coronavirus (SARS-CoV-2) had been sequenced just over a week later, the sequence had been printed and the Chinese National Health Commission warned of its potential danger. The virus was initially defined as "novel coronavirus 2019" (2019-nCoV) by the WHO – but, on February 11, 2020, was given the official name of SARS-CoV-2 by the International Committee on Taxonomy of Viruses (The COVID-19 Pandemic: A Summary, 2020). As shown in Fig. 1, COVID-19 pandemic caused 56 million cases and 1.46 million deaths in the world, 421,000 cases and 11,740 deaths in Turkey since then (Worldometers.info, 2020).

Figure 1. COVID-19 cumulative cases dashboard in December 2020 (Dong & Gardner 2020).

There are some intervention strategies such as vaccination, school/workplace closures, quarantine, etc. to slow down or stop spreading of diseases. To be able to understand effects of any intervention strategy, researchers and decision makers must first model and analyse transmission dynamics of the disease. SIR (Susceptible-Infected-Recovery) compartmental models have been commonly used to model and analyse contagious diseases since Kermack and McKendrick (1927) developed. Compartmental models are methods for the mathematical modelling of infectious diseases. Each compartment represents a division of the population and individuals in a compartment show similar characteristics. In each time interval, a number of people move to the next compartment with corresponding rates. The main assumption of this model is that people in each compartment mix uniformly and randomly with each other (Demirbilek, 2020). However, people generally have narrower environments where interacting with less people daily in homes, schools, or workplaces. Therefore, the model that considers limited relationships and contacts among people is more realistic compared to compartmental SIR models.

Network models have successfully been employed in many fields to study phenomena for which interrelationships matter (Craig et al., 2020). In economics, these include job referrals in labour markets (Calvó-Armengol and Jackson, 2007), patterns of international trade (Chaney, 2014), 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. Fig. 2 simply illustrates the difference between compartmental and network SIR models.

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, intervention strategies explained in next sections.

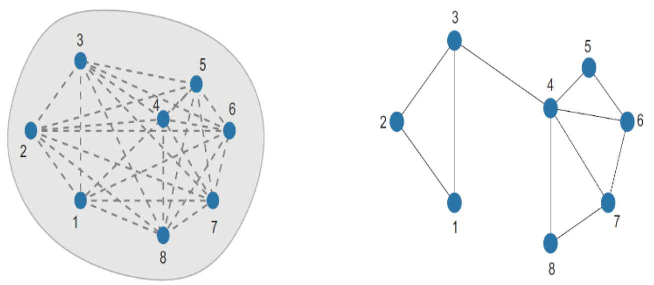

Figure 2. Illustration of social interactions in compartmental models (on the left) and network models (on the right) (Craig et al., 2020)

Main purpose of the study is to examine the effect of school/workplace closures, an intervention strategy many governments have applied to stop or slow down spread of COVID-19 nowadays. We construct a network SIR model where people can interact with others in their homes, schools, and workplaces daily. People in the model are divided into five age groups. Each individual is assigned to a home and school or workplace with a given probability regarding to his/her age. People can contact and spread the disease with a given probability to their family members in the half of the day. In the other half of the day, people interact with their colleagues and schoolmates and spread the disease. Each home, school, and workplace are consisted of a given number of people and their numbers change according to the size of population. We create some scenarios such as only schools or only workplaces closures for a given number of weeks and schools/workplaces closures at the same time. Results under no closures are compared with results of different scenarios and we elaborate our inferences about results.

The next section, we explain SIR compartmental and network models, and experimental settings. In Section 3, the proposed scenarios are tested and results are discussed. In the last section, we conclude our study and discuss about 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 neither spread the disease nor get infected. Fig. 3 shows transmission dynamics in the SIR model.

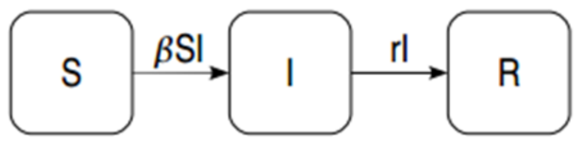

Figure 3. Transmission dynamics in the SIR model.

In Fig. 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.

2.2. Network Models

Although network models are commonly employed in epidemiology, they were initially used in social science to model spread of ideas and innovations. Similarly, spread of an infectious disease through a population has same framework; however, epidemiologists use different terms such as nodes, edges instead of actors and relations in social science. Random, lattice, small world, spatial are the most common network types used in different models. In random networks, the spatial position of nodes is not relevant and connections among nodes are assigned arbitrarily (Keeling and Eames, 2005). In lattice networks, nodes are assigned on a systematic grid of points in two or three dimensions and only neighbour nodes interact with each other. Small world networks are constructed to eliminate long path length problem in lattice models, and lower-level clustering problem in random mixed models (Watts and Strogatz, 1998). Finally, in spatial networks, nodes are set in a specific area and the relation between two nodes is established with a probability related to their separation determined by an interaction kernel (Keeling and Eames, 2005; Watts and Strogatz, 1998).

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 individual 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 homes (Epoch 1) and the other half at schools or workplaces (Epoch 2) daily. We also consider people that stay at home in whole day such as babies, unemployments and elders. Fig. 4 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.

$$r_i = 1 - p^n \tag{1}$$

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 gets sick. 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.

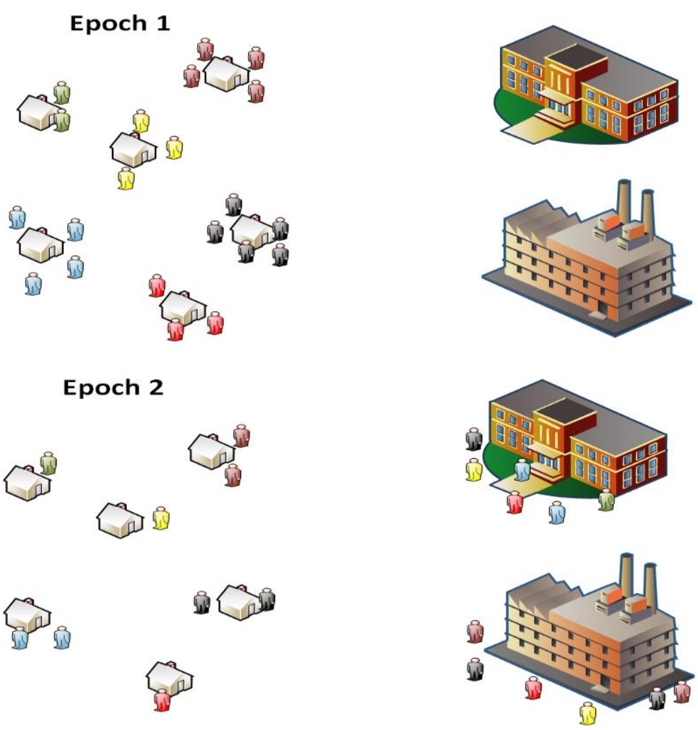

Figure 4. The network structure of this study

2.3. Experimental Settings

We consider 120-day-pandemic period and the peak of the pandemic falls into the middle of the period. Attack rates, the percantages of infected individuals at the end of a pandemic to susceptible individuals at the beginning, and the number of deaths under no-vaccination scenario are calibrated according to attack rates COVID-19 as shown Table 1. Six countries` populations, cases, deaths data are used for the calibration process. Population is divided into five different age groups, 0-4, 5-19, 20-24, 25-59, and 60+. Individuals between 0 and 4, and 60+ are assumed to stay their homes in the whole day. People between 5 and 19 are considered as school age children and each is assigned to a school. 70% of individuals between 20 and 24 are considered as university students and the remaining are assumed to be employees. Finally, 85% of people between 25 and 59 are employees and the remaining are assumed to be unemployed. The number of people assigned to each age group are derived from demographic data of the Statistics Association of Turkey, 2019. Transmission probability, P, is calibrated according to normalized attack rates in Table 1. Recovery time for each person is uniformly distributed between 6 and 9 days. We start the pandemic with 15 infected people. Table 2 shows related data in the simulation.

We consider six different scenarios for workplace/school closures. We model workplace and school closures together and separately. The half of scenarios are related to the timing of closures. We assume that workplaces/school closures are applied for two weeks and eight weeks after the pandemic has started. Each closure continues two weeks. Students and workers stay in their homes during this time. In this condition, interactions between family members increase by two times. Note that we consider only full closures in this study where everybody in schools and workplaces must stay at their homes. Although the number of infected and death people is carefully recorded in many countries thanks to their developed surveillance systems, the number of cases can be more than revealed since some infected people recover without visiting any hospital and some death cases are diagnosed with different illnesses. Therefore, we also consider 10% attack rate beside attack and death rates derived from actual cases.

Fig. 5 shows pseudo codes for the pandemic simulation with different scenarios in this study.

```
Algorithm 1 Pseudo code for pandemic simulation with different scenarios
1: Initialize Population
2: Distribute Individuals to Homes, Schools and Workplaces
3: Scenario ← Set Number of Scenarios                          ▷ 6 Scenarios
4: Trial ← Set Number of Trials                                ▷ 30 Trials
5: Day ← Set Pandemic Horizon                                  ▷ 120 Days
6: for s = 1 To Scenario do
7:     for t = 1 To Trial do
8:         Initialize Infected Individuals
9:         for i = 1 To Day do
10:            People in Homes are Interacted and Infected
11:            if i in Closure Horizon for Scenario[s] then
12:                People in Schools and/or Workplaces stay at homes accord-
   ing to Scenario[s]
13:                People in Homes are Interacted and Infected
14:            else
15:                Workers Move from Homes to Workplaces
16:                Students Move from Homes to Schools
17:                People in Homes, Schools, and Workplaces are Interacted
   and Infected
18:            end if
19:            Record Death and Infected Individuals
20:            Set Remaining Recovery Times
21:        end for
22:        Record Total Death, Infected People and Places
23:    end for
24:    Print Average Number of Death, Infected People and Places
25: end for
```

Figure 5. Pseudo codes for pandemic simulation with different scenarios.

As it is represented, we initialize the population by considering age groups at the beginning. After that, individuals are distributed to homes, schools, and workplaces created continuously according to predefined distributions as Line 2. We set the number of closures scenarios, trials for independent t tests, and pandemic horizon (Line 3-5). Next, each trial starts with the initial infected people (Line 8) after the scenario is defined. In each day of the trial, individuals in homes are interacted and infected at the first half of the day (Line 10). If the current day is in a closure day, only students or workers or both must stay at their homes and they have only interactions with their relatives at homes (Line 11-13). If not, they go to schools and workplaces and interact with their collegues (Line 14-17). In each day, the data of new infected and death people are collected as in Line 19. Moreover, previously assigned recovery days decrease by 1 for infected people. After the trial finishes, the algorithm records total number of infected and death individuals, and the percantages of infected places as in Line 22. As soon as all trials are executed, the algorithm prints average results and moves to the next scenario.

Since there are many stochastic parameters such as the recovery period, home/school/workplace sizes, being infected, etc. in this study, we make 30 trials to test each scenario to be able to understand whether results are statistically meaningful. We conduct an independent sample t-test for each scenario and provide associated p-value. The model is coded in Python programming language. All tests are conducted in a PC with Intel i5 7200U 2.5 GHz CPU and 8 GB Ram.

Table 1. Calculations of attack and death rates according to populations, COVID-19 related cases and deaths of six countries (Worldometers.info, 2020).

Country	Population	Case	Attack Rate	Death	Death Rate
USA	331,002,651	13,249,447	0.040	269,597	0.020
Germany	83,783,942	1,005,307	0.012	15,767	0.016
UK	67,886,011	1,574,562	0.023	57,031	0.036
France	65,273,511	2,183,660	0.033	50,957	0.023
Spain	46,754,778	1,637,844	0.035	44,374	0.027
Italy	60,461,826	1,509,875	0.025	52,850	0.035
Normalized Rates	…	…	**0.032**	…	**0.024**

Table 2. Simulation settings and scenarios.

Attack Rate	0.032, 0.1	**Workplace Size (person)**	Uniform (50,100)
Death Rate	0.024	**Scenario 1**	Only school closure in 2. week
Population (million)	1	**Scenario 2**	Only workplace closure in 2. week
Initial Infectious	15	**Scenario 3**	School/workplace closure in 2. week
Recovery Period (day)	Uniform (6,9)	**Scenario 4**	Only school closure in 8. week
House Size (person)	Uniform (1,7)	**Scenario 5**	Only workplace closure in 8. week
School Size (person)	Uniform (290,310)	**Scenario 6**	School/workplace closure in 8. week
Closure (week)	2	**Baseline**	Do nothing (No closure)

3. Results and Discussion

Table 3 shows the number of infected and death people, and percentages of infected houses and schools under different scenarios based on COVID-19 attack and death rates. Baseline scenario represents the number of cases under no intervention strategy. P-values denote whether results of scenarios are statistically meaningful compared to the Baseline scenario. We set the threshold value as 0.05 to test p-values. If p-values are less than the threshold value, we accept the alternative hypothesis, the difference between results is statistically significant. The first three scenarios show results of applied intervention strategies two weeks after the pandemic has started whereas the last three scenarios demonstrate results of applied intervention strategies eight weeks after the pandemic has started. Since we consider a 120-day pandemic period, the last three scenarios are applied around the peak time of the pandemic. Results clearly represent that the number of cases significantly decrease if any intervention strategy is applied as soon as the pandemic has begun. The number of cases resulted from the two-week school closure eight weeks after the pandemic started (Scenario 4) is not statistically different than results of the Baseline scenario. School and workplace closure (Scenario 6) around the peak time of the pandemic decrease the number of infected people by 20% and death people by 18% whereas the number of overall cases goes down by 65% if closures are applied two weeks after the pandemic started (Scenario 3). The other important issue is that the closure of workplaces seems more useful than the closure of schools in terms of decreasing overall cases. However, many studies show that vaccinating schoolchildren helps to prevent overall incidents during epidemics and pandemics (Tsuzuki et al., 2019; Medlock and Galvani, 2009; Kawai et al., 2011; Glasser et al., 2010) since schoolchildren are the most responsible for transmission, and their parents can be considered as bridges to spread disease to the rest of the population. In this study, workplaces are considered as relatively small networks compared to schools. As we mentioned, each workplace consists of between 50 and 100 people whereas each school consists of between 290 and 310 children. We generate around 5.380 workplaces and 956 schools for a-million population. As a result, we cut more connections among people in different networks when the workplace closures are applied. Furthermore, we consider that schools are serving children that live in same area. Thus, when the disease starts to spread in a school, mostly children and parents that live in same area are affected and the possibility of spreading the rest of network (other homes, schools, workplaces) is relatively low. Finally, when we test the opposite situation (workplace consists of between 290 and 310 people whereas each school consists of between 50 and 100 children), it is observed that school closures significantly decrease the number of cases compared to workplace closures.

Table 4 shows the number of infected and death people, and percentages of infected houses and schools under different scenarios based on 10% attack rate and associated death rates. Results show similar pattern with COVID-19 calibrated results. Applied any intervention strategy two weeks after the pandemic has started reduces the overall cases much more than applied those eight weeks after it has started. However, comparing to COVID-19 based results, declines in terms of the percentage are relatively low. For example, the number of overall cases decreases by 65% whereas it decreases only by 40% in Scenario 3 when we observe more aggressive attack rate (0.1). Similarly, Scenario 6 provides 20% less cases under the COVID-19 based attack rate while cases only reduce by 17% under the 10% attack rate. Workplace closures work better than school closures as previous results. The number of infected houses, workplaces, and schools proportionally increases in higher attack rate. However, percentage inclines for COVID-19 calibrated attack rate are higher. Note that all differences between results are statistically significant.

Table 3. The number of infected and death people, and percentages of infected houses, workplaces, and schools under different scenarios based on COVID-19 attack and death rates.

Scenario	Infected	p-value	Death	House	School	Workplace
Baseline	**35.158**	…	**824**	4,46%	4,81%	4,70%
1	**28.109**	6,51E-07	**659**	3,57%	4,31%	3,79%
2	**21.323**	2,51E-15	**503**	2,90%	3,37%	3,37%
3	**12.407**	5,61E-27	**291**	1,73%	2,70%	2,11%
4	**33.459**	8,86E-02	**792**	4,25%	4,69%	4,48%
5	**31.418**	3,78E-04	**743**	4,07%	4,49%	4,39%
6	**28.337**	1,91E-07	**672**	3,66%	4,26%	4,01%

Table 4. The number of infected and death people, and percentages of infected houses, workplaces, and schools under different scenarios based on the 10% attack rate and associated death rate.

Scenario	Infected	p-value	Death	House	School	Workplace
Baseline	**98.863**	…	**2.316**	11,70%	12,59%	12,48%
1	**86.405**	4,66E-04	**2.032**	10,20%	11,45%	10,92%
2	**69.902**	7,12E-11	**1.665**	8,34%	9,08%	9,14%
3	**59.898**	5,42E-17	**1.409**	7,10%	8,27%	7,81%
4	**92.473**	4,38E-02	**2.161**	10,92%	11,95%	11,64%
5	**88.130**	1,04E-04	**2.075**	10,44%	11,27%	11,23%
6	**81.379**	8,43E-07	**1.909**	9,61%	10,63%	10,36%

4. Conclusions and Recommendations

As many infectious diseases, COVID-19 has dramatic effect on people all over the world. Although almost more than a year has passed since the first cases has appeared, thousands of people are still being infected and dying every day. There are some intervention strategies such as vaccinations, antiviral drugs, quarantine, workplace and school closures to be able to stop or slow down spread of infectious diseases. Unfortunately, scientists have not been developed 100% effective antiviral drugs and vaccines against COVID-19 so far in despite of their enormous and invaluable efforts. Therefore, workplace and school closures have been applied by many governments all over the world to stop and slow down the progression of COVID-19. In this study, we also consider school/workplace closures as an intervention strategy to observe how applications of workplace and school closures together or separately and different times during the pandemic effect on results. To be able to achieve that, we test 6 scenarios that consider school and workplace closures separately or together and applications of closures in two different time periods, two and eight weeks after the pandemic started. On the other hand, we proposed a network SIR model to mimic spread of COVID-19 on the population by considering five age groups based on the demographic structure of Turkey.

We considered a-million population size and 120-day pandemic period for the simulation. People contact with others in their networks (school, workplace, and home) every day and can be infected with a given probability if they interact with sick people. If they are infected, they start to spread the disease to others in their networks until they recover or die. We calibrate sickness probability according to the attack rate derived from COVID-19 related data of six countries. Since the cases in the countries are observed after some precautions have been already applied, the higher attack rate is also taken into consideration when testing scenarios. Results show that applying any of intervention strategies as soon as the pandemic begins makes huge differences in terms of overall cases compared to applying them around the peak times. Overall cases decrease by 40% and 65% for the high attack rate and COVID-19 related attack rate when workplace/school closures are applied 2 weeks after the pandemic has started. These rates decrease to 17% and 20% when we apply closures around in eighth week. Furthermore, closures of workplaces seem to decrease overall cases much more than closures of schools. The reason is that workplaces in this study are defined much smaller than schools in terms of the number of individuals and the number of workplaces is several times higher than the number of schools. Therefore, people in workplaces can contact with more people in different networks directly or indirectly and closures of workplaces significantly limit interactions among people and decrease overall cases more than school closures. When we repeat same tests for larger workplaces and smaller schools, it is observed that school closures decrease overall cases much more than workplace closures. Finally, results imply that even closing schools and workplaces in two weeks does not stop the spread of diseases completely based on recovery times uniformly distributed between 6 and 9 days. Obviously, people can interact with family members more during closures and continue to spread disease in their homes. After closures finish, new infected individuals start to spread diseases in workplaces or schools again.

Some limitations and assumptions exist in this study. First, infectious probability is assumed same for each person independent of his/her age even though the possibility of being sick can highly change according to ages, chronical illnesses, even jobs of people in real life. However, since COVID-19 pandemic is still ongoing and related data are relatively insufficient and unreliable, we use overall attack rates to calibrate sickness probabilities. We assume that people can contact with other people only in their workplaces, homes, and schools. However, people have interactions in other places such as public transportations, restaurants, shopping malls, etc. Since network models are complex systems and need high computational times to run simulations, we ignore other places and interactions not to make the model even more sophisticate. Finally, we assume that infected people continue to contact with as many people as they contact before they are infected.

In this study, we consider only effect of school/workplace closures on the number of infected and death people during a pandemic. In future research, other intervention methods, vaccinations and antiviral drugs, can be considered beside of school/workplace closures and some optimization methods can be applied to select the best strategy or strategies to be able to minimize the number of cases and related economic costs.

References

Calvó-Armengol, Antoni, and Matthew O. Jackson (2007). "Networks in Labour Markets: Wage and Employment Dynamics and Inequality." Journal of Economic Theory, 132(1): 27–46.

Chaney, T. (2014). "The Network Structure of International Trade." American Economic Review, 104(11): 3600–3634.

Chao, D.L., Halloran, M.E., Obenchain, V.J. and Longini Jr, I.M., (2010). FluTE, a publicly available stochastic influenza epidemic simulation model. PLoS computational biology, 6(1), 1–8.

Craig, B. R., Phelan, T., Siedlarek, J. P., & Steinberg, J. (2020). Improving Epidemic Modelling with Networks. Economic Commentary, (2020-23).

Demirbilek, M. (2020). YAYsim: Salgın Modelleme ve Karar Destek Sistemi. Bilecik Şeyh Edebali Üniversitesi Fen Bilimleri Dergisi, 7 (1), 104-112.

Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. The Lancet infectious diseases, 20(5), 533-534.

Elliott, Matthew, Benjamin Golub, and Matthew O. Jackson (2014). "Financial Networks and Contagion." American Economic Review, 104(10): 3115–3153.

Glasser, J., Taneri, D., Feng, Z., Chuang, J. H., Tll, P., Thompson, W., ...& Alexander, J. (2010). Evaluation of targeted inuenza vaccination strategies via population modeling. PloS one, 5(9), e12777.

Grefenstette, J.J., Brown, S.T., Rosenfeld, R., DePasse, J., Stone, N.T., Cooley, P.C., Wheaton, W.D., Fyshe, A., Galloway, D.D., Sriram, A. and Guclu, H., (2013). FRED (A Framework for Reconstructing Epidemic Dynamics): an open-source software system for modeling infectious diseases and control strategies using census-based populations. BMC public health, 13 (1), 940.

Hladish, T., Melamud, E., Barrera, L.A., Galvani, A. and Meyers, L.A., (2012). EpiFire: An open source C++ library and application for contact network epidemiology. BMC bioinformatics, 13(1), 76.

Kawai, S., Nanri, S., Ban, E., Inokuchi, M., Tanaka, T., Tokumura, M., ... & Sugaya, N. (2011). Inuenza vaccination of schoolchildren and inuenza outbreaks in a school. Clinical infectious diseases, 53(2), 130-136.

Keeling, M. J., & Eames, K. T. (2005). Networks and epidemic models. Journal of the Royal Society Interface, 2(4), 295-307.

Kermack, W. O. and McKendrick, A. G. (1927). A Contribution to the Mathematical Theory of Epidemics. Proc. R. Soc. A Math. Phys. Eng. Sci., 115(772), 700–721.

Kuylen, E., Stijven, S., Broeckhove, J. and Willem, L., (2017). Social Contact Patterns in an Individual-based Simulator for the Transmission of Infectious Diseases (Stride). In ICCS, January, 2438-2442.

Liu, S., Poccia, S., Candan, K.S., Chowell, G. and Sapino, M.L., (2016). epiDMS: data management and analytics for decision-making from epidemic spread simulation ensembles. The Journal of infectious diseases, 214, 427-432.

McConnell, J. (2002). Ready for the next influenza pandemic? The Lancet, 359(9312), 1133.

Medlock, J., & Galvani, A. P. (2009). Optimizing inuenza vaccine distribution. Science, 325(5948), 1705-1708.

Prieto, D. M., Das, T. K., Savachkin, A. A., Uribe, A., Izurieta, R., and Malavade, S. (2012). A systematic review to identify areas of enhancements of pandemic simulation models for operational use at provincial and local levels," BMC Public Health, 12(1), 251.

The COVID-19 Pandemic: A Summary, https://thepathologist.com/subspecialties/the-covid-19-pandemic-a-summary, 1 December 2020.

Tsuzuki, S., Baguelin, M., Pebody, R., & van Leeuwen, E. (2019). Modelling the optimal target age group for seasonal inuenza vaccination in Japan. Vaccine.

Walters, C. E., Meslé, M. M. I. and Hall, I. M. (2018). Modelling the global spread of diseases: A review of current practice and capability. Epidemics, 25, 1–8.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of small-world networks. Nature, 393(6684), 440-442.

Webby, R. J., & Webster, R. G. (2003). Are we ready for pandemic influenza? Science, 302(5650), 1519-1522.

Worldometers.info, https://www.worldometers.info/coronavirus/, 29 November 2020.