



**MARMARA UNIVERSITY**  
**INSTITUTE FOR GRADUATE STUDIES**  
**IN PURE AND APPLIED SCIENCES**



# **A SYSTEM DYNAMICS MODEL OF COVID-19 PANDEMIC IN TURKEY**

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DENİZ YERİNDE

**MASTER THESIS**

Department of Industrial Engineering

**Thesis Supervisor**

Asst. Prof. Dr. Merve ER

ISTANBUL, 2024

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Deniz YERİNDE, a Master of Science student of Marmara University Institute for Graduate Studies in Pure and Applied Sciences, defended her thesis entitled “A System Dynamics Model of COVID-19 Pandemic in Turkey”, on Jan 12, 2024 and has been found to be satisfactory by the jury members.

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In the thesis study, the COVID-19 pandemic in Turkey was modelled with the system dynamics approach and the effect of the pandemic spread was examined. I hope that this model, which can be revised for all epidemics, will benefit first my country and then all humanity in combating epidemics.

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**January, 2024**

DENİZ YERİNDE

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## ÖZET

### TÜRKİYE'DEKİ COVID-19 PANDEMİSİNİN BİR SİSTEM DİNAMİĞİ MODELİ

COVID-19 pandemisi küresel olarak birçok alanda ekonomiyi, çevreyi, sağlığı ve toplumu etkilemiştir. Pandemilerin neden olduğu zararı azaltmak için hızlı bir şekilde stratejileri uygulamaya ihtiyaç vardır. Dinamik sistemlerde, salgınlara yönelik müdahalelerin etkileri ancak zaman geçtikten sonra ortaya çıkar. Bu nedenle son derece belirsiz, dinamik ve riskli bu ortamda uzmanların etkin stratejiler belirlemesine yardımcı olacak simülasyon modellerinin geliştirilmesi oldukça önemlidir. Bilim adamları, gelecekteki pandemilerin kaçınılmaz olduğunu söylüyor, bu nedenle pandemi modelleme araştırmaları büyük önem taşımaktadır. Farklı ülkelerde COVID-19 pandemisinin modellenmesi için SD metodolojisini kullanan birkaç makale var. Bu çok kritik araştırma alanına katkıda bulunmak amacıyla bu çalışma, COVID-19 pandemisinin dinamiklerini simüle etmek ve farklı senaryoları analiz etmek için bir Sistem Dinamiği (SD) modeli geliştirmektedir. Modele semptom geliştirme zamanı, bulaşma oranı, karantina politikası ve diğer önleyici müdahaleler gibi çeşitli faktörler dahil edilmiştir. İlk olarak, COVID-19 pandemisinin etkisinin ardındaki karmaşık etkileşimleri temsil etmek için bir nedensel döngü diyagramı geliştirilmiştir. Daha sonra bu model, değişkenleri matematiksel denklemlerle temsil ederek stok-akış diyagramına dönüştürülmüştür. Geliştirilen SD modeli, salgın modellemede en çok kullanılan matematiksel modellerden biri olan SEIR kompartıman modeline dayanmaktadır. Model, enfeksiyonun dört aşamasını simüle eder: Duyarlı (S), Maruz (E), Bulaşıcı (I) ve İyileşenmiş (R). Önerilen model farklı senaryolar için VENSIM yazılımında çalıştırılmıştır. Sonuçlar, hükümetlere ve sağlık uzmanlarına pandeminin yayılmasını önleme ve kontrol etme konusunda önemli iç görüler sağlamaktadır. Model Türkiye'yi baz durum olarak kullanmıştır, ancak bazı modifikasyonlarla diğer ülkelere ve farklı pandemi türlerine de uyarlanabilir.

**Anahtar kelimeler;** Kompartman Modelleri, COVID-19, Pandemi Modellemesi, Simülasyon Modellemesi, Sistem Dinamikleri

## **ABSTRACT**

### **A SYSTEM DYNAMICS MODEL OF COVID-19 PANDEMIC IN TURKEY**

COVID-19 pandemic has globally affected the economy, environment, health, and society in many areas. An urgent strategy is required to reduce the harm caused by pandemics. In dynamic systems, the effects of interventions to epidemics emerge only after time has passed. Simulation models are very helpful to help experts for identifying effective strategies in this highly uncertain, dynamic and risky environment. Scientists say that future pandemics are inevitable, hence research in pandemic modelling is of high importance. There are several papers that employ SD methodology for COVID-19 pandemic modelling in different countries. In order to contribute to this highly important research area, this study develops a System Dynamics (SD) model to simulate the dynamics of the COVID-19 pandemic and analyse different scenarios. Various factors are included in the model; e.g., time to develop symptoms, transmission rate, quarantine policy and other preventive interventions. Initially, a causal loop diagram is developed to represent the complex interactions behind the impact of the COVID-19 pandemic. Then, this model is converted to a stock-and-flow diagram by representing the variables with mathematical equations. Developed SD model is based on the SEIR compartmental model which is one of the most used mathematical models in epidemic modelling. The model simulates the four stages of infection: Susceptible (S), Exposed (E), Infectious (I), and Removed (R). Proposed model is run in VENSIM software for different scenarios. Results provide important insights for governments and health experts to prevent and control the spread of the pandemic. The model used Turkey as a base case, but the model can be applied to other countries and different types of pandemics with some modifications.

**Keywords;** Compartmental Models, COVID-19, Pandemic Modeling, Simulation Modeling, System Dynamics

## **SYMBOLS**

<b>D</b>	: Dead people
<b>E</b>	: Exposed people
<b>I</b>	: Infected people
<b>N</b>	: Total number of people in all groups (entire population)
<b>R</b>	: Recovered people
<b>R<sub>0</sub></b>	: Basic Reproduction Number
<b>S</b>	: Susceptible people
<b>β</b>	: Infection rate
<b>γ</b>	: Rate of removal or recovery that controls the transition between I and R

## **ABBREVIATIONS**

- CLD** : Causal Loop Diagram  
**SD** : System Dynamics  
**SFD** : Stock and Flow Diagram

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# 1. INTRODUCTION

Throughout the history of humanity, world has faced serious and unprecedented global health problems due to emerging infectious diseases and increased vulnerability of the population. An epidemic is an epidemic disease that occurs in a geography and affects a high proportion of the population. Pandemic is an epidemic disease that spreads over a very wide area on the surface of a continent or the world, and its effect is felt to a large extent. Some of the worst pandemics may be listed as follows: SARS, H5N1, H1N1. Epidemics not only caused significant changes in social life, but also affected economic life and brought economic troubles. The devastating effect of epidemics has once again been revealed. From health to social life, from economy to education, there are great changes in every aspect of life with coronavirus. Moreover, the SARS epidemic in the 2000s emerged in Hong Kong, the epidemic spread throughout the world in 2002 and 2003 and 775 people died. The epidemic spread rapidly to 37 countries within weeks. The cost of this disease to the world economy was approximately 40 billion dollars, the majority of this loss was experienced in tourism revenues (Lee and McKibbin, 2004).

It is significant to determine the right policies and strategies in the pandemic. For this reason, there are many methods used in the academic studies. Mathematical models are needed to predict parameters such as the spread of the epidemic, the number of deaths and recovery. Different countries have taken different and important measures to prevent the spread of the epidemic, but population density, different unknown effects of the virus, its mechanism of reaching and especially in countries with high population density such as India make it very difficult to cope with such a contagious and deadly disease. Furthermore, many different studies have been conducted to model and forecast the spread of Covid-19 and test the impact of different prevention strategies (Liu et al., 2020; Nadim et al., 2021). Compartmental models are commonly used mathematical models in epidemiology (Brauer, 2008; Massonis, 2021). Compartmental model is a very general modelling approach that is frequently used in mathematical modelling of infectious diseases. Publications combine and integrate compartmental models with other techniques to achieve their goals. The most frequently used technique is simulation (Alsinglawi et al., 2021; Qian et al., 2021). Pandemic modelling includes many unknown parameters such as incubation period, transmission rate, etc. Simulation provides the

opportunity to analyse different alternative scenarios. Different compartments are used in these simulation models to investigate the behaviour of the entire population. Even, epidemic simulators were developed by researchers (Kuzdeuov et al., 2021).

Some of the researchers strengthened their model by incorporating compartmental approach with machine learning and deep learning techniques (John et al., 2022; Aggarwal et al., 2021), Artificial Neural Network (La Gatta et al., 2021), Genetic Algorithm (Yarsky, 2021) and regression (Majumder et al., 2021) to obtain insights on key uncertainty drivers, predict the pandemic trend, and solve complex disease control optimization problems. Furthermore, artificial intelligence is used for diagnosis of the disease by using sensor data for temperature and thermographic temperature. Artificial Intelligence (AI) based detector helps to reduce the mistaken alarm (Magesh et al., 2020). Other methods that are integrated with the compartmental modelling approach in the COVID-19 literature can be listed as follows: agent-based modelling (Mellacher, 2022), big data analytics (Huynh et al., 2021), fuzzy set algorithm (Abdy et al., 2021), Markov process (Gourieroux and Jasiak, 2023) and system dynamics approaches (Kumar et al., 2021c). Decision support systems were also developed for clinical decisions, allocation of resources, lock-down management, and optimization of response strategies (Gillis et al., 2021).

System Dynamics (SD) approach has been used in epidemic modelling to design appropriate policies by examining the behaviour of the entire system rather than only predicting a specific value related to the system (Abdolhamid et al., 2022; Chen et al., 2022; Niwa et al., 2020). The aim is to investigate the behaviour of the examined system regarding certain changes and to make decisions by determining the strategies to regulate this behaviour. For this reason, it became an important tool to improve policy making and strategy development stages. SD is based on the well-known systems theory and enables modelling complex systems under different scenarios before they occur. Therefore, it is very beneficial in pandemic modelling. There are various studies that employ SD approach to analyse the transmission of the pandemic and examine the impact of various factors and health strategies on the transmission of the disease; e.g., behavioural changes, lockdowns, government campaigns, vaccinations, etc. (Vincenot and Moriya, 2011; Safarishahrjari et al., 2017; Ackere and Schulz, 2020).

Scientists warn us about the growing risk of future pandemics due to various factors such as climate change, deterioration of the balance of species in the world, increasing globalization, global distribution of food, and changes in microbes. Hence, lessons learned from COVID-19 pandemic are of vital importance (Ahmad et al., 2021). Especially insights gathered from compartmental mathematical models are very helpful in making decisions about forecasting progress of the pandemic, resource allocation, pandemic planning, effects of government and health policies. Simulation models have the potential to offer valuable insights that can shape future strategies for responding to pandemics. These forecasts hold significant potential as a tool to educate the public and minimize the risks. The aim of this thesis is to contribute to this highly important area by developing a SD model for the COVID-19 pandemic. Previous researches show that local models are more successful and practical than global pandemic models (Aslan et al., 2020). Hence, the model is developed based on the data of Turkey. First, a causal loop diagram representing the interactions between epidemiological and other factors is developed with the help of literature and published reports. Then, this model is converted to a stock-and-flow diagram by using appropriate equations and parameters. The model is based on the SEIR (Susceptible, Exposed, Infectious, and Removed) compartmental model. Developed model is run in VENSIM software for different scenarios that include different pandemic prevention strategies (e.g. lockdown, isolation). This model may be adapted for any future pandemics, and provide a basis for future researches.

The remainder of the thesis is structured as follows Section 2 presents the relevant literature under Epidemiological Modelling, Compartmental Modelling and System Dynamics Modelling of COVID-19 subheadings to provide a background about the research field. Section 3 explains the methodology and data collection stages. Section 4 presents the proposed SD model in detail and gives information about parameters and variables of the model. Section 5 gives and discusses the results of the model for different scenarios. Finally, Section 6 concludes the thesis.



## **2. LITERATURE REVIEW**

### **2.1. Epidemiological Modelling**

The world has faced different infectious disease outbreaks, epidemics, and pandemics throughout the history. Pandemic, which has taken the whole world under its effect, has left humanity in a difficult situation in many areas. Human has experienced social, economic and environmental effects such as home quarantine, being socially alienated, and new post-pandemic trends in education field and business world (Leite et al., 2020; Hurajova et al., 2022). It is very important to understand the transmission mechanism and trends of infectious diseases to develop effective policies. Mathematical models are very helpful to study dynamics of diseases from multiple perspectives such as health, economic and social.

Epidemiological models refer to the use of mathematical and computational techniques to simulate the spread and impact of infectious diseases within populations. These models are essential tools in public health and epidemiology for understanding, predicting, and managing pandemics and disease outbreaks. In essence, pandemic modelling plays a critical role in public health, helping society better prepare for, respond to, and recover from infectious disease outbreaks. All of these situations brought pandemic modelling at the forefront of academic research and government decision making. Governments have tried many preventive strategies for overcoming COVID-19 pandemic. Most of the research in this area focus on fundamental reproduction number of the epidemic and the efficiency of different treatments to decrease virus transmission (Currie et al., 2020; Khalilpourazari and Doulabi, 2021). Many different studies have been conducted to model and forecast the spread of Covid-19 and test the impact of different prevention strategies (Liu et al., 2020; Nadim et al., 2021).

Epidemiological models have been used to study different infectious diseases in the past; such as plague disease (Kermack and McKendrick, 1927), Ebola virus (Ferrández et al., 2023), H1N1 (Samsuzzoha et al., 2011), hepatitis A (Effelterre et al., 2016). In 1998, Shulgin et al. (1998) examined the pulse vaccination strategy based on the SIR epidemiology model. They investigated how it can affect the spread of infectious diseases and how it can be used in epidemiological control using the SIR model. Samsuzzoha et

al. (2011) developed a model for H1N1 influenza epidemic. They addressed the mathematical modelling of influenza epidemics, with a particular focus on situations where the transmission coefficient varies. Such models can be used to understand and control the spread of infectious diseases like influenza. Numerical studies are very helpful to understand the behaviour of infectious diseases and suggest appropriate mitigation and prevention actions. Ahmad et al. (2021) conducted a survey and published the results through sensitivity and simulation analyses on what needs to be done for future pandemics based on the findings of their study.

## **2.2. Compartmental Models**

Since ancient times, world has faced different infectious disease outbreaks, epidemics, and pandemics. Some of these epidemics and pandemics caused death of millions of people. Although the academic literature includes various studies in the modelling of these diseases, there has been a substantial growth in the academic literature after the global COVID-19 pandemic (Mac et al., 2021; Small and Cavanagh, 2020; Kumar et al., 2021a; Abdolhamid et al., 2022). Compartmental models are commonly used in mathematical modelling of infectious disease transmission (Kumar et al., 2021a; Volpato, 2021). These models divide the population into different groups called as "compartments". These epidemiological models compute the theoretical number of people for each mutually exclusive compartment within a closed population over time. The most basic compartmental model in this area is the SIR (Susceptible – Infected – Recovered) model which forms the cornerstone in the study of infectious disease dynamics (Kim and Milner, 1995). Kermack and McKendrick (1927) modelled the plague disease for the first time in 1927 using the SIR model. "Susceptible" refers to healthy individuals who have not yet been diagnosed with the disease and are open to catching it, "Infected" refers to infected/sick individuals, and "Recovered" refers to individuals who recovered or died due to the disease.

The aim of compartmental mathematical models is to identify mathematical equations that describe disease transmission and flow of individuals between different epidemiological states over time. Each state is treated as a different compartment. These

states are dependent on the disease under study. In the basic SIR model, population size is considered to be constant. Dynamics of the system is represented by a set of differential equations. In the SIR model, population is the sum of the susceptible, infected, and recovered people. The population in these three compartments change over time as the virus spreads. As more individuals become infected, S decreases and I increases. In the I compartment, either the people from the S group who get sick come and the people who recover leave. It is assumed that people who recover will become immune and will not be re-infected. Transitions between groups are determined using differential equations. The beginning and progress of the epidemic can be explained as in the following (Tang et al., 2020; Bastos et al., 2021):

- Before the start of the disease epidemic, S is equal to the whole population as no one is immune, and the number of people in groups I and R is 0 because other diseases are not considered.
- It is assumed that only 1 individual is infected at the beginning of the epidemic, and as soon as the first individual is infected, S decreases by 1 and I increase by 1.
- This first contagious individual infects other vulnerable people (before they recover or die).
- The epidemic continues dynamically as recently infected individuals infect other vulnerable people.
- As people recover from the disease or die, the number of people in the R group increases over time.

When modelling the dynamics of the epidemic, three different equations are needed to describe the rates of change in each group (Tang et al., 2020):

$$S(t) = -\frac{\beta I(t)S(t)}{N} \quad [1]$$

$$I(t) = \frac{\beta I(t)S(t)}{N} - \gamma I(t) \quad [2]$$

$$R(t) = \gamma I(t) \quad [3]$$

Where:

- $N$  is the total number of people in all groups ( $S + I + R = N$ ),
- $\beta$  is the infection rate controlling the transition between  $S$  and  $I$ ,
- $\gamma$  represents the rate of removal or recovery that controls the transition between  $I$  and  $R$ .

$R_0 = \beta/\gamma$  (Basic Reproduction Number)

$R_0$ , which is the basic reproduction number shows how many people an infected person will infect. When  $R_0 > 1$ , virus will continue to spread among susceptible people, if there are no changes in the environment or external effects. When  $R_0 < 1$ , virus will disappear inevitably.

In the academic literature, there are different variants and extensions of the basic SIR model. SI model assumes that patients who recover can become infected again. Dead factor is included in the SIRD model (Ayodele et al., 2021; Menon, 2021; Acosta-González et al., 2022; La Gatta et al., 2021; Rubio-Herrero and Wang, 2022). SEIR model considers the incubation period of the disease (Chowell, 2017; Vrabac, 2022; John et al., 2022). SEIR model emerged to separate those who were exposed to the virus but did not show symptoms (Pechlivanoglou et al., 2022; Ma et al., 2022; Alrabaiah et al., 2021). Some people have innate or vaccine immunity against certain diseases, and there is a MSIR model that expresses them with  $M$ . Over time, new compartmental models have been developed by considering various disease dynamics and additional compartments such as exposed, dead cases, maternally derived immunity, and insusceptible. Other example models include SEI (Majumder et al., 2021), SIRS (Li et al., 2022a; Lympelopoulou, 2021), MSEIR (Chen et al., 2020), SEIRV (Meng et al., 2021), SEIJR (Carpio and Pierret, 2022), SEIHR (Deressa and Duressa, 2021), SEIRD (Desai, 2021; Volpatto, 2021), SEIARD (Liu et al., 2021), SEIAQRDT (Kumari et al., 2021), SEIQRDP (Bahloul et al., 2020) and SPEIQRD (Hethcote, H., 2000; Guanghong et al., 2004). Table 2.1 summarizes some of the compartmental models used in COVID-19 literature.

Governments all over the world applied different responses to fight with the COVID-19 pandemic including partial and full lockdowns, wearing mask, online education, etc. Researchers developed various local and global compartmental models to simulate the effects of quarantine and other government strategies. Vaccines are very effective at preventing hospitalization, severe disease, and death from COVID-19. Hence, they are frequently included in mathematical models. For instance, Poonia et al. (2022) developed three SEIR models considering three different scenarios: no social distancing, social distancing and social distancing with vaccination. Reproduction number is 2.16 without social distancing and 1.3 with social distancing. Indeed, social distancing and vaccination has an important role to surpass COVID-19. In addition, Rajapaksha et al. (2021) studied SEIRV model and simulated vaccine strategies. According to their results, vaccination rate should be higher than %45 to reduce infected people as soon as possible.

**Table 2.1.** Example compartmental models developed for COVID-19 in the literature

Compartmental Model	Compartments					
	S	E	I	R	H	D
SEI (Majumder et al., 2021)	X	X	X			
SEIR (Yarsky, 2021)	X	X	X	X		
SEIHR (Deressa and Duressa, 2021)	X	X	X	X	X	
SIRD (Ayodele et al., 2021)	X		X	X		X

\* S: Susceptible, E: Exposed, I: Infected, R: Recovered, H: Hospitalized, D: Dead

### 2.3. System Dynamics Modelling of COVID-19

System dynamic (SD) models of COVID-19 are computational models created to simulate the dynamics and interactions of various factors involved in the spread and effects of the COVID-19 virus (Niwa et al., 2020; Alım and Kesen, 2023). These models are designed to understand the complex behaviour of the epidemic and guide decision-making processes. Stocks of the system that need to be resolved, dynamic variables, and

connections that provide interaction among all these system elements are particularly important for understanding how all the elements in the system are related, and how changes in one variable within the system will affect another variable in the same system. System dynamics models operate under a cause-and-effect logic in terms of their working methodology. Dynamic variables and their impact on stock variables are analysed by comprehending the entirety of the designed system and its components accurately.

There are various researches on pandemic modelling in the literature, but since the COVID-19 pandemic is fairly new, not many resources have been created yet. Since the impact of COVID-19 will be handled not only numerically but also with a holistic approach together with the implemented government policies, it will draw the attention of researchers from different domains like health sector, psychologists, statistics, mathematics, etc. This topic is still an alarming topic for the health industry and the entire society. Researches related to Covid-19 may also provide an important basis and knowledge for any possible pandemics that may occur in the future.

Within the scope of this study, the processes and methodologies related to mathematical modelling of epidemics and pandemics have been discussed up to this point. In the subsequent section, the topic will revolve around various information gathered from the literature, in accordance with the subject of application within the study's scope: System Dynamics modelling of pandemic.

Academic literature includes different SD models that include different epidemiological, social, behavioural, and financial factors (Aminullah and Erman, 2021; Chen et al., 2022; Jia et al., 2022). Appendix A summarizes some of the SD models developed for the COVID-19 pandemic in the literature. Previous research demonstrate that local models provide more successful results as the transmission of the virus and behavioural characteristics may be highly impacted from region specific properties. Niwa et al. (2020) applied SD modelling incorporating stock flow and infection modelling to describe regional population dynamics and estimate assumed region-specific transmission rates in Japan. This model demonstrated the effectiveness of inbound traveller quarantine and resident self-isolation policies and practices. The findings have shown insights that could contribute to an understanding of how social resilience to future infectious disease threats can be developed.

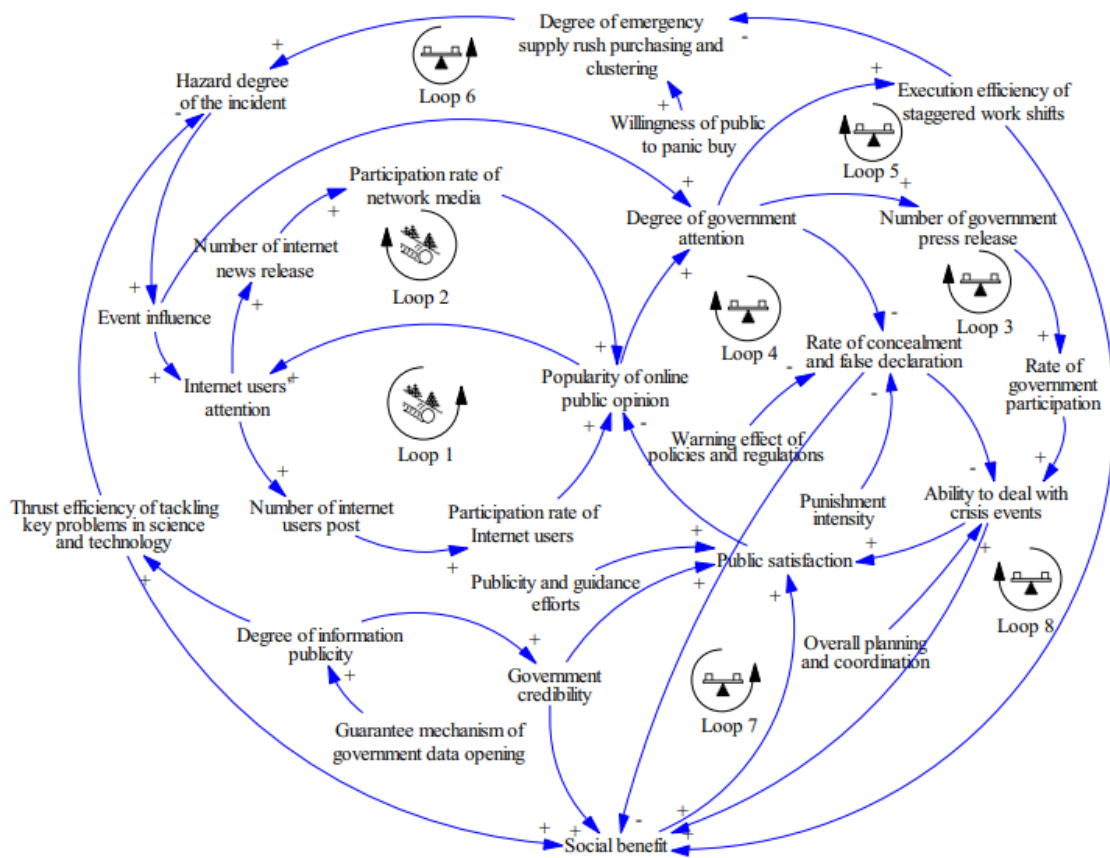
Erkayman et al. (2023) constructed a SD framework for Turkey and analysed the elements affecting the rate of COVID-19 spread. This model integrates vaccine logistics, limitations on social activities, and various social constraints. The study employed three distinct simulation models to derive outcomes related to vaccine distribution scenarios, accompanied by corresponding interpretations. Alim and Kesen (2023) built a SD model based on the SEIR compartmental model and also developed a dynamic Decision Support System (DSS) for five control strategies. They also investigated the economic impact of the pandemic along with the spread rate.

Some of the studies include the capacity and properties of the health system in the focus region. Venkateswaran and Damani (2020) developed a SD model customized for India. They included capacity of hospitals and critical care units in their model. Considering the total number of beds in hospitals, capacity of intensive care units, number of health personnel, and availability of medical supplies in SD models may provide an important perspective for the assessment of the impact of the disease on the health system and evaluation of the expected load on the current health systems.

Abdolhamid et. al. (2022) developed a SD model based on the SEIR compartmental model. The aim of the model is to assess how factors like people's behaviour, contact rates between individuals, social distancing measures, and public quarantine influence the spread of the disease in Iran. The findings highlight the importance of timely intervention policies. Applying these policies early significantly affects the outcomes of the system. Moreover, if the number of severely ill patients surpasses the capacity of intensive care units in hospitals, the mortality rate significantly rises. Effective intervention policies play a vital role in reducing infection rates, mortality, and ultimately controlling the pandemic. The study also suggested that if the proposed policies fail to work before hospital capacity is breached, the most effective strategy is to expand hospital capacity by adding suitable equipment.

Jia et al. (2022) focused on prevention and control regarding social benefit affected by public opinion, online media usage, government policies, effect of regulations, supply, etc. They developed the causal loop diagram in Figure 2.1 to reflect the interactions and feedback mechanisms within the system. They developed a stock-and-flow diagram based

on this figure and simulated several scenarios to contribute to the theoretical background about the spread and prevention of the pandemic.



Existing SD models differ in terms of the used parameters, variables, structure and assumptions of the model. Sensitivity Analysis is also applied in most of the studies to evaluate the impact of changes in key parameters and assumptions on model outputs (Sy et al., 2021). This analysis identifies the most influential factors and uncertainties in the model's predictions (Rehman et. al. 2023).

**Figure 2.1.** An example causal loop diagram developed for COVID-19 (Jia et al., 2022)

Some researchers integrated SD approach with other methods and used their hybrid approaches in epidemic modelling. Safarishahrbijari et al. (2017) developed a SD model with using particle filtering method when predicting the evolution of upcoming infectious disease outbreaks. The aim of the model is to provide strong guidance to health decision makers. Vincenot and Moriya (2011) developed a hybrid model with representation of localized outbreaks SD model and spatially detailed simulation of the transmission between populations in Individual-Based Modelling. Ackere and Schulz (2020) discussed

the challenge of eradicating measles due to parental scepticism about the recommended MMR vaccination. It emphasizes the need for a measles prevalence model that considers behavioural factors, as parental decisions are influenced by both epidemiological and behavioural factors. The model accounts for factors like vaccination coverage, disease prevalence, risk perceptions, government campaigns, and changes in disease control policies. Water scarcity is an important topic that threatens health. Wang et al. (2018) examined the environmental consequences and economic impacts of global water scarcity. A complex system model was created by combining an agent-based model and SD model that simulate the environmental and economic effects of alternative economic policies on water usage and pricing. Additionally, this designed model also considered the water transport capacity constraint, which represents the carrying capacity of certain local water resources in the region where the study was conducted.



### **3. METHODOLOGY**

#### **3.1. Overview of Research Approach**

The global COVID-19 coronavirus pandemic has led to high death rate and negatively impacted social life and economy all over the world. Identification and timely application of the most effective strategies is very important to control the pandemic. Simulation models provide a computer platform to help researchers analyse the causal relations and dynamic behaviour within a system. In this thesis, a System Dynamics (SD) model of the COVID-19 pandemic was developed to examine the relationships and dynamics of the pandemic over time. SD methodology, which is based on the well-known systems theory (See Section 3.2 for details), is chosen because of its efficiency in studying policy design and analysis (Aminullah and Erman, 2021).

SD approach has different applications in modelling infectious and non-infectious diseases such as poliovirus, obesity, diabetes, and has many advantages. Darabi and Hosseinichimeh (2020) provide a very comprehensive systematic literature review on various applications of SD modelling in health and medicine. SD models are based on the cause-effect relationships and can give more informative and helpful results than predictive models in most studies (Thiel et al., 2014). The number and variety of SD models created especially for the COVID-19 pandemic in the academic literature are few (Aminullah and Erman, 2021; Alim and Kesen, 2023). Existing SD models include various important parameters about the pandemic and the affected people; population, average time to develop symptoms, average time for critical patients to die or recover, average time to quarantine, number of cases, duration of disease, average of the transmission coefficient, period of the latency of the disease, etc. Current models vary based on the covered variables and scenarios used to investigate the transmission and control of the pandemic. For example, public opinion and awareness policies in the COVID-19 model may also be included in the model (Jia et al., 2022).

In this thesis, first a causal loop diagram (CLD) was developed to represent the entire society and the spread of COVID-19 pandemic by including different factors such as transmission of the disease, people's behaviour, contact reduction, and different policy responses to COVID 19, etc. This diagram was developed with the help of relevant

literature. Then, CLD was converted to a stock-and-flow diagram (SFD) by representing the variables and their relations by mathematical equations.

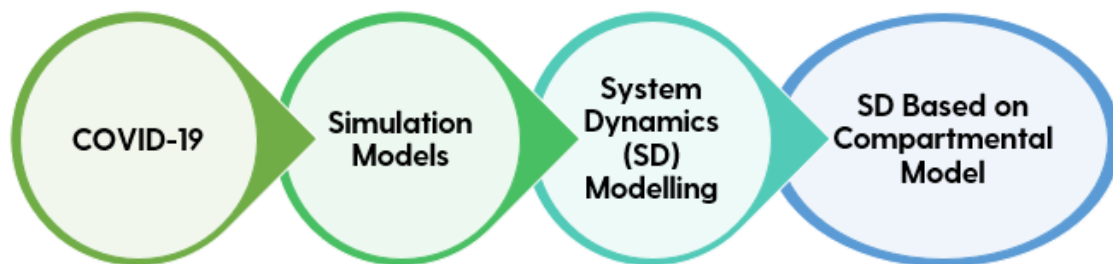
Different factors such as lockdown, isolation policies, policy duration, infection rate, and incubation time are also included in the model to simulate real-life scenarios and study the impact of different policies. The proposed SD model was run by using the Vensim software using the records in Turkey. The model was run for the period that covers the start of the pandemic and the next 60 days. Different scenarios were performed to analyse the pandemic and its impacts from various points of view; spread of disease, changing social habits of people, lock down, etc. Table 3.1 provides summary of the scenarios.

**Table 3.1.** Summary of the scenarios

<b>Scenario No</b>	<b>Explanation</b>
S1L1	Lockdown policy scenario – low level threshold to start lockdown
S1L2	Lockdown policy scenario – moderate level threshold to start lockdown
S1L3	Lockdown policy scenario – high level threshold to start lockdown
S2L1	Policy duration scenario – short term
S2L2	Policy duration scenario – medium term
S2L3	Policy duration scenario – long term
S3L1	Transmission rate – low level increase
S3L2	Transmission rate – moderate level increase
S3L3	Transmission rate – high level increase

Compartmental models are frequently used in mathematical modelling of the spread of infectious diseases (Kermack and McKedrick, 1927; Ma et al., 2022). An extension of the basic SIR model, SEIR compartmental model, was incorporated to the simulation model. SEIR model can be used in SD models by incorporating the compartmental structure into the differential equations and diagramming (Jung, 2018). SEIR model is used as the basis

of the SD model and to simulate the level of the disease's compartments under in the future. The proposed model in this thesis includes the following compartments: Susceptible, Exposed, Infected, Recovered and Dead. Simulation results provide important insights about the topics from multiple perspectives, not from a single point of view. The overview of the research approach of the thesis is presented in Figure 3.1.



**Figure 3.1.** Overview of the research

### **3.2. Systems Theory**

System theory approach is an understanding that deals with an interdisciplinary problem or phenomenon as a system. The system can be defined that consists of certain parts and has certain relations between these parts and with the external environment. Systems approach is used to represent causal relationships for simulation of the whole system relations (Bala et al., 2017). When the concept of system is considered theoretically, it has a structure with dynamic relations and forms an inseparable whole. Dynamic relations are defined as being in motion and changing over time.

Health systems are complex systems including many subsystems and entities such as health organizations, people, social factors, health equipment, and complex processes. These systems should be analysed with the systems approach, and the entire system should be evaluated in decision making processes including resource allocation, planning, and control of health institutions. Employment of the systems approach in policy design and development will contribute to industrial and organizational transformation and improvement. To give an example, Sturmberg et al. (2014) stated that administrative structures in the field of health is in transformation through the differentiation in the system perspective and predicted that self-organization will come to the forefront in today's health organizations.

### **3.3. System Dynamics**

System dynamics (SD) is a discipline that studies how a system behaves and changes over time (Schoenenberger et al., 2021; Sánchez and Serrato, 2023). This discipline includes a set of methods and concepts used to describe and analyse various systems with mathematical models. System dynamics can be applied in many fields, from physical systems to economic systems, biological systems and social systems (Ghadge et al., 2021, Er Kara et al., 2021).

In system dynamics, the behaviour of a system is often related to how variables within the system interact. These variables represent the properties of the parts that make up the system. Each variable represents a particular value or state, and changes over time by interacting with other variables.

Simulation of dynamics models based on system dynamics was created by Forrester (Sterman, 2000). SD is a continuous time simulation approach. It is used for both qualitative and quantitative modelling. SD is defined as a very useful and widely known approach for explaining the complex systems encountering in real life and understanding how it sometimes behaves in its external environment. Systems can be represented by the feedback processes among the components of the system. SD has three characteristics which are the concept of feedback loops collecting information about the system, computer simulation which is enabled to reveal the behavioural results in time of the hypothesized loops, and needing to engage with mental models which are complex, quantitative, and hard to include (Lane, 2000).

SD is based on mathematical modelling consisting of sets of equations with significant parameters (Ogata, 2014). As a whole system, it is based on the behaviour of closed loops and stocks or dynamic variables that can be intervened at any time from the outside. The stocks in the system dynamics, the dynamic variables and the connections that facilitate the interaction between the system elements provide an understanding of how the whole system and the elements in the system are related to each other, and how and to what extent the change of a variable in the system affects another variable in the same system.

SD methodology starts with the emergence of the problem; the problem is identified, limitations are set, and objectives are specified (Bala et al., 2017). Second, the system is defined by designing a relational causal loop diagram (CLD) of all the features that affect the system. CLD represent variables, interactions between them, positive or negative signs of variables and feedback loops (Er Kara et al., 2021). Afterwards, all the elements of the system are formulated mathematically in stock-and-flow diagram and the model is defined and operated in the computer environment. Applications such as Vensim and Stella are widely used. Finally, the model of the problem is tested, and the policy design and final outputs of the model are evaluated by trying different scenarios with the results obtained in the simulation.

Sensitivity analysis evaluates the sensitivity of the outputs of the system dynamics model to model parameters. This analysis allows to understand the effect of changes in the value of a given parameter on the outputs of the model. Sensitivity analysis is used to rank parameters, evaluate the effects of uncertainties, and understand the stability or sensitivity of the model (Fair et al., 2021). For example, in the COVID-19 model, susceptibility analysis can assess the impact of varying infection rate or vaccination efficacy on outcomes. Sensitivity analysis is usually done by changing the value of a parameter by small amounts and measuring the effect of these changes on model outputs. This analysis is important to increase the reliability of the model and to ensure that the parameters are set correctly. SD models notice the effect of changing parameters and the behaviour of these is significant than the numerical ones (Hekimoğlu and Barlas, 2010).

Parameter estimation and sensitivity analysis are important tools for calibrating, validating and developing system dynamics models. This step ensures the reliability and usability of the model by increasing the model's fit to real-world situations. System dynamics modelers can refine and validate their models, improve understanding of the underlying system, and assess the model's behaviour under various conditions. These techniques contribute to the robustness, reliability, and usefulness of system dynamics models for decision-making and policy analysis.

### 3.3.1. Causal Loop Diagram

A causal loop diagram (CLD) is a visual representation tool used in system dynamics, a branch of systems thinking and system dynamics methodology. It is designed to capture and illustrate the cause-and-effect relationships among variables within a system (Meadows, 2009). Causal-loop diagrams are composed of nodes, which represent variables, and also arrows, which indicate the direction and nature of the relationships between variables and aims to connect simulation variables (Binder et al., 2004; Ranganath and Rodrigues, 2008).

Connection polarities used in the SD model define the physical structure of the system in which it is used and in which direction the model operates. There are two types of feedback structures used in a system of SD modelling. Feedback loop simulates the system with positive and negative directions. Causal links indicate how changes in one variable affect another variable. There are two types of causal links (Bala et al., 2017):

**Positive Causal Link:** A positive causal link indicates a direct relationship between two variables, where an increase in one variable leads to an increase in the other, or a decrease in one variable leads to a decrease in the other. It is represented by an arrow with a plus sign (+). In the positive system, an increase in a defined variable in the system depending on the changes made by the system from the outside or by the system itself feeds itself continuously because the system wants to increase the numerical progress of the system due to its structure. In other words, the variables in a positive feedback loop in the system create a mutual effect among themselves, and as a result of this effect, they stimulate each other in the same direction, with good or bad results (Bala et al., 2017).

**Negative Causal Link:** A negative causal link indicates an inverse relationship between two variables, where an increase in one variable leads to a decrease in the other, or a decrease in one variable leads to an increase in the other. It is represented by an arrow with a minus sign (-).

Causal-loop diagrams are classified into two categories which are reinforcing (R) loops known as positive loops (+), and balance loops (B) known as negative (-) loops. As an example, the changes of birth rate will affect population but death rate effects population

in the opposite direction. Reinforcing and balancing loops are explained in the following (Sapiri et al., 2017):

**Reinforcing Loop:** A reinforcing loop (also called a positive feedback loop) reinforces the change in a system. It creates a self-reinforcing cycle, leading to exponential growth or decline. It is represented by a loop with an even number of negative (or positive) causal links.

**Balancing Loop:** A balancing loop (also called a negative feedback loop) balances the change in a system. It tends to stabilize or regulate the system. It is represented by a loop with an odd number of negative (or positive) causal links.

Terms as “goal seeking” are often used for negative feedback systems or balancing loops, which are one of the feedback elements in SD models (Kirkwood, 1998). Negative feedback systems in the systems focus on a certain numerical value, any point between the nodes or any behaviour of the variables according to the status of the parameters and variables in the system. This means that such systems used in simulation modelling always seek and focus on the precise target within the scope of their working methodologies. The complex system, which acts to reach the target in the modelled simulation, constantly needs its current output at hand, its general position or its physical condition in the model, with its efforts to achieve this target. As a result, negative feedback always brings stability or stubbornness to a system within a model.

By analysing and understanding the causal loop diagrams, policymakers, managers, and researchers can identify the key variables, feedback structures, and dynamics that influence a system. This understanding can help in formulating effective strategies for managing and improving the behaviour of complex systems.

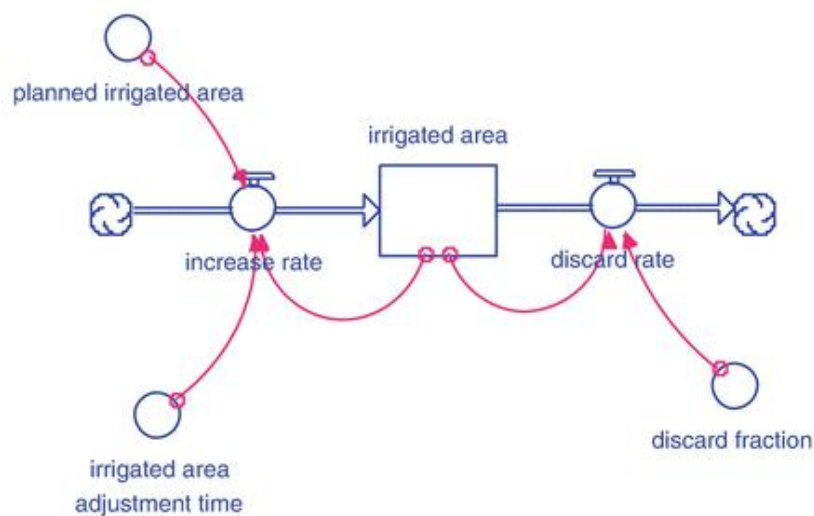
### **3.3.2. Stock-and-Flow Diagram**

A Causal Loop Diagram is converted to a Stock-and-Flow Diagram (SFD) diagram to apply the proposed model and mathematically analyse the behaviour of the system over time (Campuzano and Mula, 2021). The SFD diagram is a prototype of the system and pays attention to saving and rates of change. The connections between stocks, flows, and

converters in a stock and flow diagram indicate the relationships and dependencies within the system.

Stocks represent accumulations or quantities of a specific variable that accumulate over time. They are typically represented by rectangles or ovals in the diagram. Stocks can include physical quantities such as water levels in a reservoir, population numbers, or financial assets. Flows represent the rates of change or flow between stocks. They are usually represented by arrows in the diagram. Flows can include inflows, outflows, or other processes that affect the level of a stock. For example, in a population system, births and immigrations can be inflows, while deaths and emigrations can be outflows.

The SFD diagram shows how flows affect the levels of stocks, and how the levels of stocks influence the flows. These connections can be direct or indirect, forming feedback loops that create dynamic behaviour in the system (Senge, 2006). Stocks are where change happens. Everything that can change by increasing or decreasing can be defined as stock. While variables such as heat, energy, and speed may be easy to measure, there may be stocks in variables that are not easy to measure such as happiness, anger, and fatigue. Decreasing or increasing of stock variable influences the flow. There are factors that affect the speed of flows, and these are indicated by arrows. Figure 3.2 shows a basic example of an irrigation stock and flow diagram.



**Figure 3.2.** Stock-and-flow diagram (Bala et al., 2017)

There is one stock which is irrigated area and two flow variables which are increase rate and discard rate affected by planned irrigated area, irrigated area adjustment time and discard fraction. Irrigated area grows by increase rate and decreases by discard rate (Bala et al., 2017). To obtain further details about SFD for SD model, see Forrester (1994).

### **3.4. Input Data and Parameter Estimation**

Parameter estimation is a crucial step in system dynamics modelling. It help to calibrate model parameters and assess the robustness and reliability of the model's behaviour (Bala et al., 2017). SD models generally simulates policies and test them. Parameter estimation refers to the determination of the values of the parameters used in the SD model. These parameters represent the factors that affect the behaviour and outputs of the model. For example, in the COVID-19 model, parameters may include factors such as infection rate, transmission rate, recovery time, or vaccine efficiency.

Parameter estimation is usually performed based on available data or expert knowledge. A good parameter estimation ensures that the model accurately represents the real-world system. This can be accomplished by comparing observation data with model outputs or using optimization techniques (Rehman et al., 2023).

In this thesis, a SD model was developed to evaluate the progress of the pandemic and the impact of different health policies and strategies on the transmission of the pandemic. Past research shows that local models give better and more practical results than global models (Aslan et al., 2020). Hence, the model was simulated for Turkey. The main parameters and their values that are used in this study are given in Table 3.2 with corresponding reference(s).

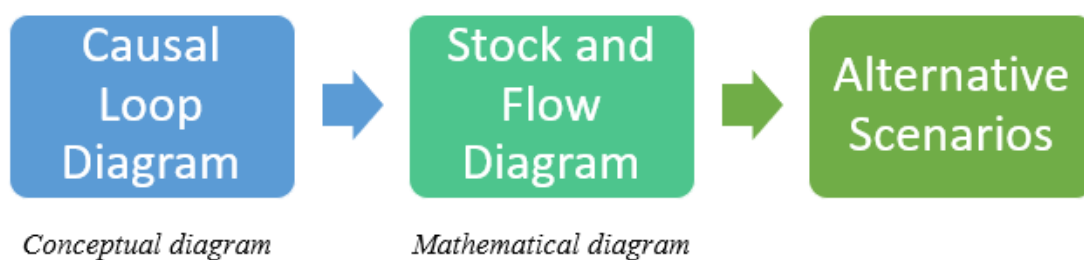
**Table 3.2.** Numerical values of parameters

<b>Parameter</b>	<b>Values</b>	<b>Reference</b>
Total population	83.614.000	TUIK (2021)
Infection duration	7 days	Cheng et. al. (2021)
Incubation time	7 days	Assumption
Fatality rate	0.0093 ~ 0.01	Alim and Kesen (2023)
Initial infected	1 person	Assumption
Infection rate	5.24	Aslan et. al. (2020)
Impact of lockdown	0.011	Aslan et. al. (2020)
Threshold for lockdown	2500 people	Assumption
Threshold for isolation	5000 people	Assumption
Policy duration	90 days	Assumption
Policy start time	1 <sup>th</sup> day	Assumption

#### 4. PROPOSED MODEL

In order to predict the spread of virus, there is a need to work with different parameters. This is such a complex system that affects many areas. When we do not work with a system approach, there may be incompleting many issues. For this reason, system dynamics approach would be the best option to investigate a holistic result and show different alternative scenarios. Especially, we can easily adapt it to other pandemics and another country. This is that the system perspective provides.

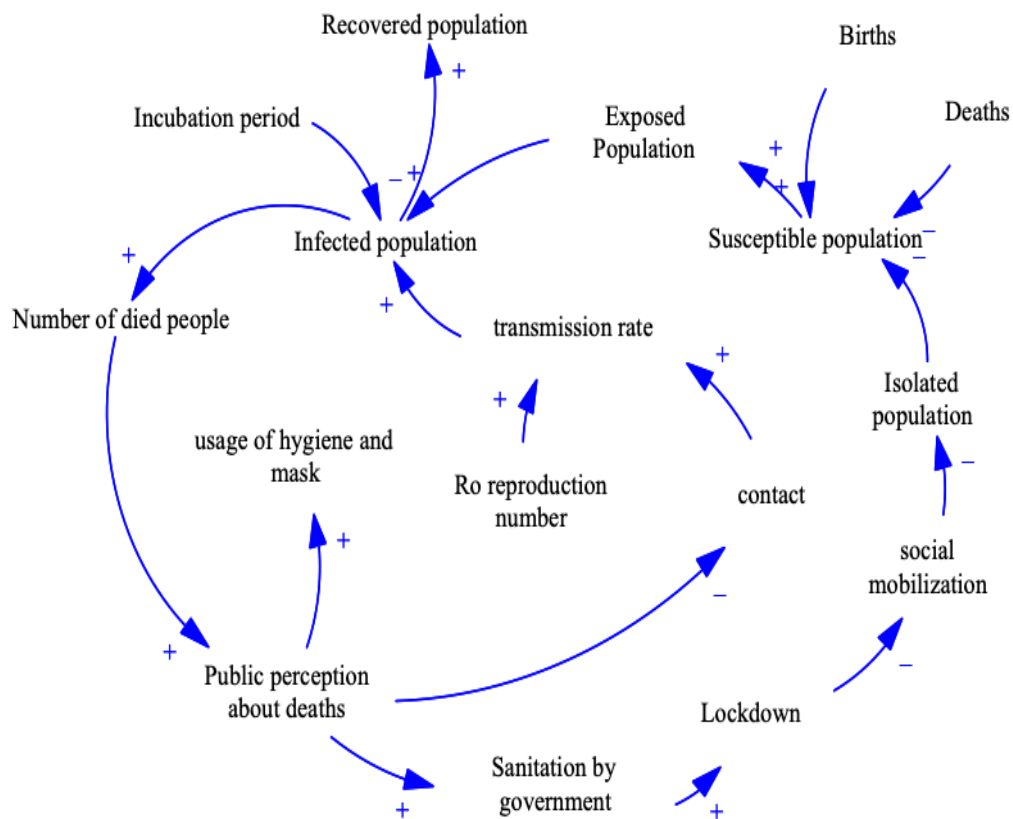
In this thesis, first a causal loop diagram (CLD) was developed to represent the entire society and the spread of COVID-19 pandemic by including different factors such as transmission of the disease, people's behaviour, contact reduction, and different policy responses, etc. Then, CLD was converted to a stock-and-flow diagram (SFD) by representing the variables and their relations by mathematical equations by using compartments. Different factors such as lockdown, isolation policies, policy duration, infection rate, and incubation time are also included in the model to simulate real-life scenarios and study the impact of different policies. The proposed SD model was run by using the Vensim software using the data in Turkey. The model was run for the period that covers the start of the pandemic and the next 60 days. Different scenarios were performed to analyse the pandemic and its impacts from various points of view. Figure 4.1 shows the flow of the proposed model.



**Figure 4.1.** The flow of the proposed model

## 4.1. Causal Loop Diagram of COVID-19

CLD is presented to show the relations of factors that affects the spread of COVID-19. Number of infected populations depends on the interrelationships between multiple parameters. In this study, a holistic study was performed that handles different factors that are effective on the COVID-19 pandemic and enables the simulation of the problem with a systems approach. The causal loop diagram, which reflects the dynamics of this study and the cause-effect relations between the factors in the proposed model, is shown in Figure 4.2.



**Figure 4.2.** Causal loop diagram of the proposed model

According to Figure 4.2., Susceptible population is affected by births and deaths. Some of the individuals get exposed to virus and become infected. Infected population can either recover or die. Some of them needs to stay in hospital. If the number of people die

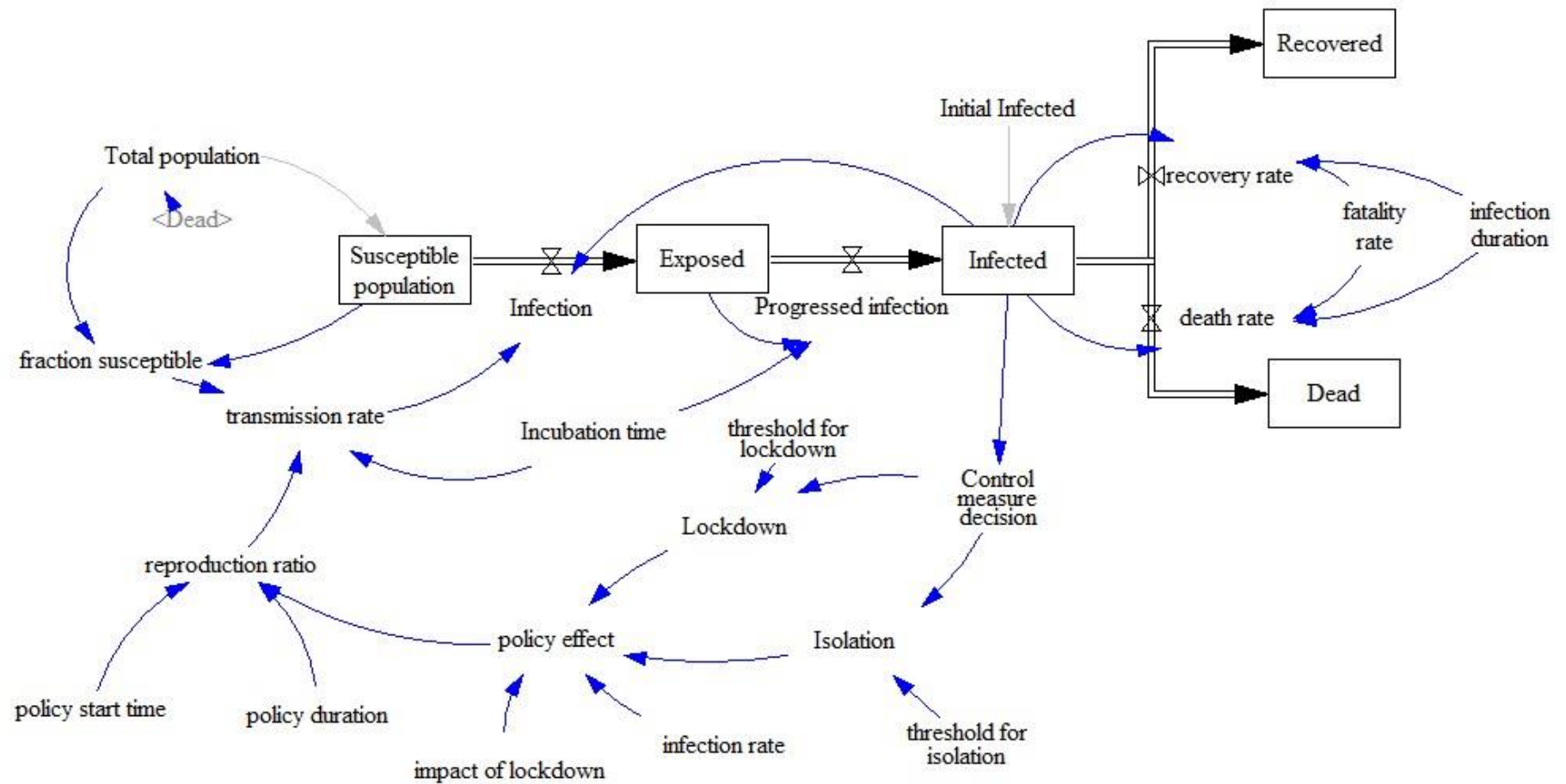
increase, then public perception about the pandemic gets high and it triggers the usage of hygiene. In this regard, governments take control about the social mobilization and lockdown. In this way, transaction of virus among population decreases. When lockdown is applied, exposed population is decreasing with a negative feedback loop because of reducing social mobilization.

## **4.2. Stock and Flow Diagram of COVID-19**

The stock and flow diagram is created in the Vensim software and given in Figure 4.3. It contains all the parameters, variables, stocks and flows required for the SD model developed to investigate how the COVID-19 epidemic virus spreads and what intervention strategies will be followed. Stock and flow diagram represent the SD model with parameters and formulations. Total population is regarded as %70 of total population because there are inactive people in the society (e.g. people above 65 age) (Alım and Kesen, 2023).

Population is divided into four categories in the model which are Susceptible, Exposed, Infected, and Recovered. Susceptible population can be exposed to virus and transmit it to the other people. In the exposed population, some people are infected with virus but symptoms of the virus are not yet observed. Number of infected people who can contact people with the potential to get the disease and transmit the disease to these people. Recovered refers to people who have gained immunity from the epidemic disease in any way. With the onset of the spread of the virus, susceptible people in the society transfer the part where the exposed people are before contagious and then either recover or die.

As the number of infected people increases, the government develops some policies and takes lockdown and/or isolation measures. As a result of these policies, we simulate the policy effect. Policy start time and policy duration variables are added to the model in order to simulate the start of the policy, its duration, and impact of these two variables on the spread of the disease. Instead of taking the reproduction coefficient of the disease as a fixed value, it has been formulated dimensionless by considering the precautions taken. The reproductive ratio of the disease increases or decreases the rate of transmission of the disease between individuals.



**Figure 4.3.** Stock and flow diagram of the proposed model

Transmission of the disease is reduced by applying isolation and lockdown policies. Occurrence of the lockdown is connected to a threshold value. Therefore, if the number of infected people becomes higher than the given limit, the government applies a lockdown. The reproduction ratio of the virus will vary according to both isolation and lockdown strategies. Hence, it will affect the transmission rate of the virus. The rate at which one person transmits the disease to another is expressed as the transmission rate.

Validation of the model is tested by using the following approaches (Ghadge et al., 2021): relevance test, consistency test, sensitivity analysis, and extreme condition test. First, the connection of the variables are tested by changing the values and examining the direction and extent of the changes in the influenced variable. Then, the SD model's behavior is compared with the real world data to check the consistency of the proposed model. Thirdly, parameters and consistency of the model's structure are assessed by changing the parameter values. Lastly, extreme cases are simulated to check the results of the proposed model. The proposed model's validation is approved.

There are some exceptions in the scope of model. One of them is to ignore new natural births and death. Other one is also that the total number of populations within this system is constant. The variables and equations are given in Appendix B.

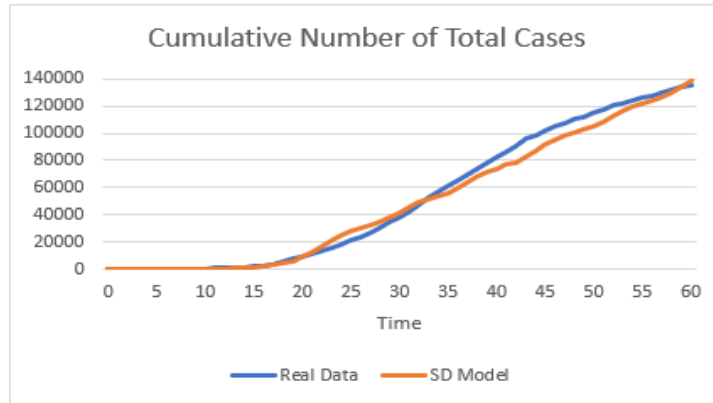


## **5. RESULTS AND DISCUSSION**

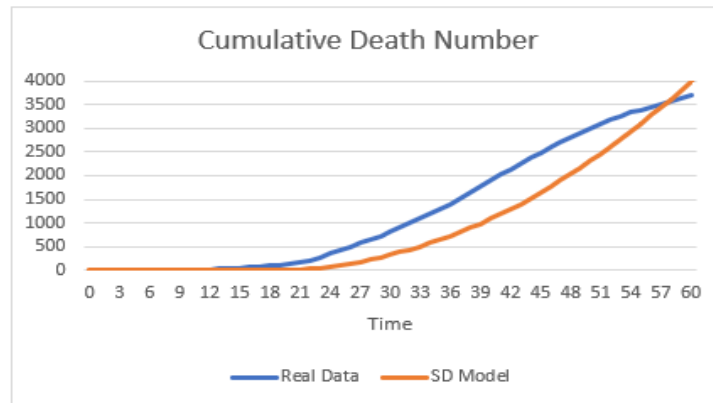
### **5.1. Results of the Basic Model**

The simulation model was run for a 60-days period starting from March 11, 2020. In Figure 5.1, real data in Turkey is compared with the output of the simulated model. X axis shows the time in days, Y axis shows the total number of COVID-19 cases cumulatively. As it is seen from the figure, the difference between the model result and the real data is very low, both in the total number of cases and in the number of deaths. However, some differences can still be observed for various reasons. One of these is that government policies are very changeable and their effects do not remain constant over time. In addition, some values in the model are used as fixed based on various sources, but the distribution in real life may vary. Additionally, the disease has progressed by changing mutations, and the transmission rate of the disease may have changed a lot during this time. Despite all of these factors, the simulation predicted the model close to reality and be a trustful platform to test different policies for pandemic management.

The trend in the SD model prediction starts to exceed the real data in the last few days of the simulation period. In the first weeks of the week, nobody was prepared for such a pandemic. However, after some time, governments started to apply new policies and initiatives such as developing test kits. Additionally people started to understand the seriousness of the pandemic and this affected the behaviour of the society. Hence, this difference is normal. The proposed model focuses on the first period of the pandemic. New variables such as number of tests, adequacy of hospitals/ hospital capacity, effectiveness of hospital care may be added to increase the accuracy of the model to simulate further periods of the pandemic.



(a)



(b)

**Figure 5.1.** Comparison of real data and output of the proposed SD model of COVID-19 in Turkey: a) cumulative number of total cases b) cumulative death number

Lastly, the difference between the real data and the results of the simulation model is higher in the total number of deaths. This is also another expected result, because there were some individuals whose death cause were identified as some factors such as multiple organ failure and couldn't be tied to coronavirus.

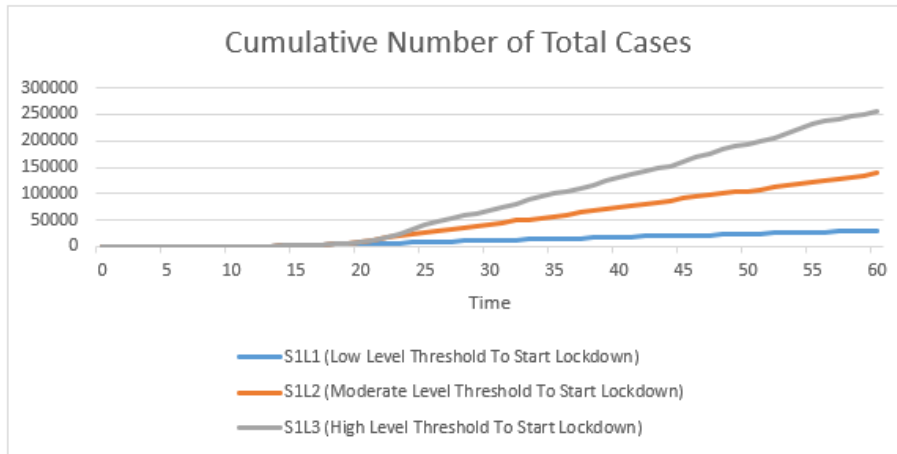
## 5.2. Alternative Scenarios

Nine different scenarios were tested under 3 different main headings below and the results were compared.

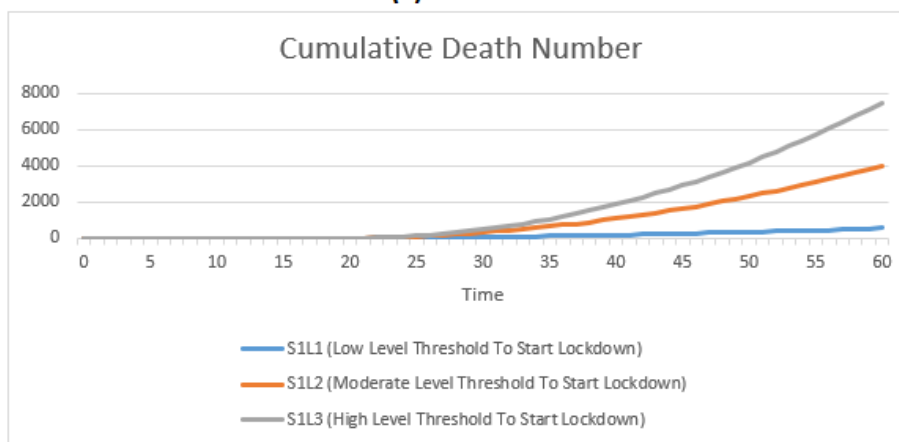
### **5.2.1. Lockdown Scenario**

Lockdown is a policy taken by the government to prevent the spread of the virus. When the number of cases began to increase, restriction such as shopping malls, schools, lockdown were implemented. In this context, when these measures were implemented, it became important in the course of the spread of the virus. Observations show that lockdown was the most effective policy to prevent the spread of the pandemic.

Lockdown was connected to the total number of COVID-19 cases. When an identified threshold level was reached, the proposed model applied a lockdown policy. In the scenarios, three different levels of threshold were identified to start the lockdown policy. S1L1 shows the scenario when a lockdown policy is implemented when the number of cases exceeds 500 people. S1L2 is the scenario in which lockdown starts when the number of cases exceeds 2500 people. S1L3 shows the scenario where lockdown is implemented when the number of cases exceed 5000 people. Three levels of lockdown policies were simulated to see what will happen if lockdown starts at different time periods. Figure 5.2 show the results of these scenarios.



(a)



(b)

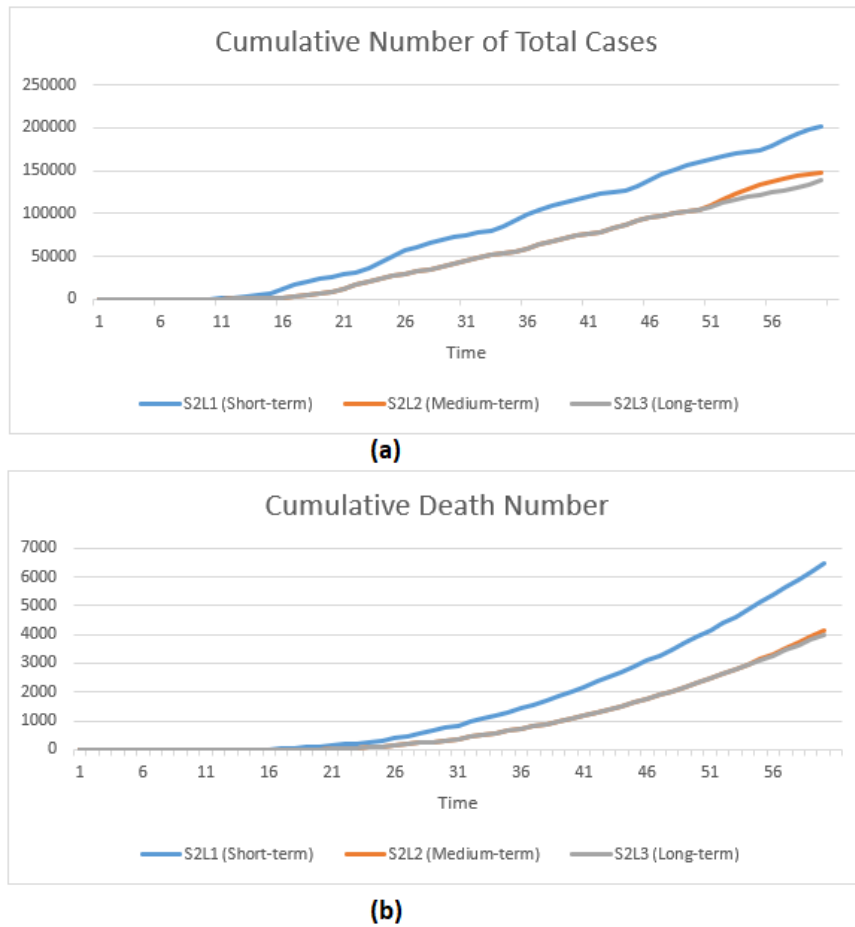
**Figure 5.2.** Lockdown Scenarios: a) cumulative number of total cases b) cumulative death number

As it is seen from Figure 5.2, the number of total cases reaches to highest levels in the high level threshold scenario (S1L3) as lockdown will start very late. This figure is important because governments can use this figure to compare these numbers with the total capacity of hospitals, and can find the best lockdown strategy based on the insights gathered from this figure.

### 5.2.2. Policy Duration Scenario

The effects of the preventive strategies taken by governments may vary. For instance, the effect of a full lockdown and a time-dependent closure are not the same. The precaution taken regarding hygiene and the closure of schools do not have the same effect. While

some policies reduce the instantaneous infection rate, others provide a sustainable reduction. For this reason, the change in the number of cases and deaths were simulated by creating 3 different scenarios. If policy duration is 1 day, S2L1; if it is 30 days, S2L2; It was concluded that if policy duration is 60, it will face the consequences of S2L3 shown in Figure 5.3.

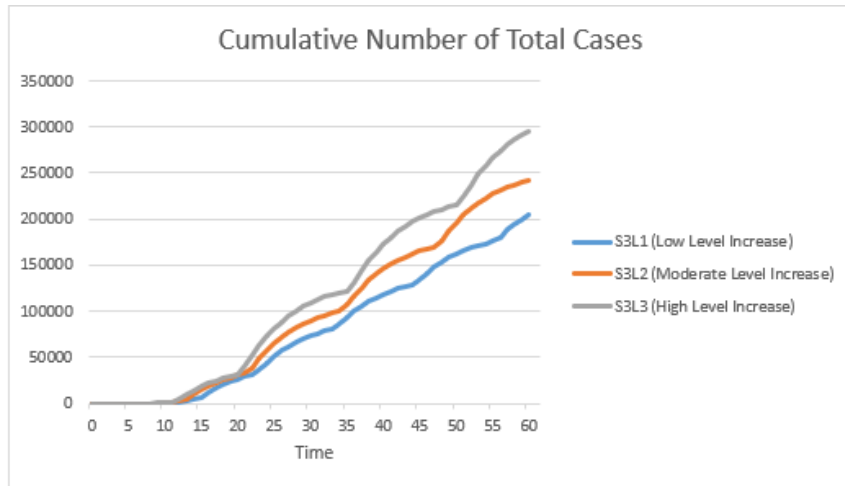


**Figure 5.3.** Policy Duration Scenarios: a) cumulative number of total cases b) cumulative death number

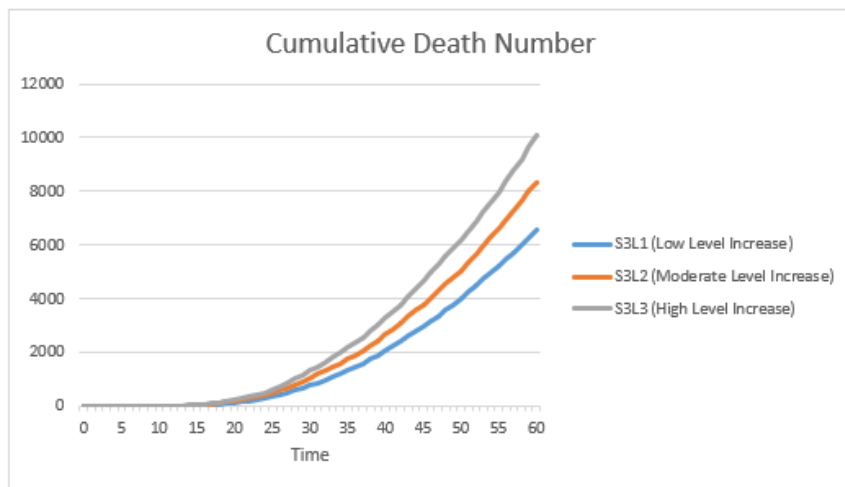
If we see the impact of the policies in the first 30 days, we expect the number of cases to increase. Or, at the extreme point, if a 1-day policy was implemented and we did not see the effect of the policy for the remaining 59 days, the number of cases would increase even more. We used 60 days in the model. Changing the policy duration affects the reproduction ratio and hence affects the number of total cases and deaths.

### 5.2.3. Transmission Rate Scenario

The virus of COVID-19 changes over time and this leads to the emergence of different variants such as delta and omicron variants. For this reason, the transmission rate of the virus may increase or decrease. The spread of the virus was simulated at an increase of transmission rate with 2, 3 and 4 times larger, respectively.



(a)



(b)

**Figure 5.4.** Transmission Rate Increase Scenarios: a) cumulative number of total cases  
b) cumulative death number

This figure provides information about the extent of the pandemic if a new variant occurs. The proposed model may also be used to simulate new diseases in the future by adapting the transmission rate and fatality rate of the new virus.

## 6. CONCLUSION

Pandemics are sudden and unexpected increases of a specific disease that spreads over several regions, countries or continents. Their affect may be catastrophic as in the COVID-19 pandemic. Scientists from different areas studied to understand, prevent and find medications for the COVID-19 pandemic. Unfortunately, all countries struggled to find effective government policies and control strategies for this new and unexpected pandemic. Social and health systems are complex and dynamic systems due to the interconnections and causal relationships among different components of the system. Based on the systems approach, this thesis proposed a System Dynamics model to provide a platform to analyse the impact of different policies and interventions on the spread of the pandemic. System Dynamics models are very helpful methods to study strategic and policy analysis.

First, a causal loop diagram was developed to represent the interlinkages among different social, behavioural and pandemic related variables, conceptually. Then, this diagram was converted to a stock-and-flow diagram by representing the relationships by mathematical equations. The input data and values of parameters were identified with the help of academic literature, health authorities, and coronavirus statistics of Turkey. Totally 9 different scenarios were executed to explore the impact of lockdown policy, duration of the policy, and transmission rate on the spread of coronavirus and mortality rates. The simulation model was run in the Vensim software. Simulation period includes 60-days by taking the first day of Covid-19 as 3/11/2020. The results of the simulation model were interpreted to evaluate the impact of different policies and interventions.

It is known that, the spread of the virus did not remain stable throughout the Covid-19 period. The fatality of the disease caused many financial and moral problems. For this reason, the government took different precautions from time to time. Lockdown and isolation were the most important of these. That's why these two factors are included in the model. If the number of infected people exceeded a certain threshold, a full lockdown or partial lockdown was implemented. At the same time, various precautions were taken to ensure isolation, considering the infection rate. Their impact on the spread of the virus was concentrated under the policy effect.

In case of lockdown, the decrease in the transmission rate of the disease was determined by various parameters, and in the absence of it, the rate of transmission was determined by various parameters due to the isolation effect. This policy effect created the reproduction coefficient of the disease. Since the reproduction coefficient of the disease depends on the policies, the start date and duration of the policy were also considered. There have been short- or long-term policies, for example, the effect of a weekend lockdown and a weekly lockdown is not the same. This change was added to simulate the spread of the virus. A detailed analysis was performed to examine how the spread of the virus will be determined by changing the parametric values in the scenarios.

SD is a powerful methodology to study policy analysis and design for outbreaks, epidemics, and pandemics. This computer-based mathematical approach may support policy developers in their decision-making process and guide to find the most effective and timely strategies. Governments and health authorities may use the proposed model as a basis to see the impact of potential interventions before implementing the policy in the actual life. For future work, the proposed SD model may be extended by including additional interventions such as different vaccinations, different lockdown scenarios, etc.

## REFERENCES

- Abdolhamid, M.A., Pishvae, M.S., Aalikhani, R., Parsanejad, M. (2022). A system dynamics approach to COVID-19 pandemic control: a case study of Iran. *Kybernetes*, 51(8). 2481-2507. doi: 10.1108/K-01-2021-0038
- Abdy, M., Side, S., Annas, S., Nur, W., Sanusi, W. (2021). An SIR epidemic model for COVID-19 spread with fuzzy parameter: the case of Indonesia. *Advances in difference equations*, 2021(1), 105. doi: 10.1186/s13662-021-03263-6
- Ackere, A.V., Schulz, P.J. (2020). Explaining vaccination decisions: A system dynamics model of the interaction between epidemiological and behavioural factor. *Socio-Economic Planning Sciences*, 71. doi: 10.1016/j.seps.2019.100750
- Acosta-González, E., Andrada-Félix, J., & Fernández-Rodríguez, F. (2022). On the evolution of the COVID-19 epidemiological parameters using only the series of deceased. A study of the Spanish outbreak using Genetic Algorithms. *Mathematics and computers in simulation*, 197, 91–104. doi: 10.1016/j.matcom.2022.02.007
- Aggarwal, L., Goswami, P., & Sachdeva, S. (2021). Multi-criterion Intelligent Decision Support system for COVID-19. *Applied soft computing*, 101. doi: 10.1016/j.asoc.2020.107056
- Ahmad, M., Akhtar, N., Jabeen, G., Irfan, M., Khalid Anser, M., Wu, H., & Işık, C. (2021). Intention-Based Critical Factors Affecting Willingness to Adopt Novel Coronavirus Prevention in Pakistan: Implications for Future Pandemics. *International journal of environmental research and public health*, 18(11), 6167. doi:10.3390/ijerph18116167
- Ak, F. (2021). A Simulation Approach For Covid-19 Pandemic Assessment Based on Vaccine Logistics, Sars-Cov-2 Variants and Spread Rate.
- Alım, M., Kesen, S.E. (2023). Investigating the effects of various control measures on economy and spread of COVID-19 in Turkey: a system dynamics approach. *Simulation*, 99(2). 113–125. doi: 10.1177/00375497221116641
- Alrabaiah, H., Arfan, M., Shah, K., Mahariq, I., Ullah, A. (2021). A comparative study of spreading of novel corona virus disease by ussing fractional order modified SEIR model. *Alexandria Engineering Journal*, 60(1), 573-585. doi: 10.1016/j.aej.2020.09.036
- Alsinglawi, B., Mubin, O., Alnajjar, F., Kheirallah, K., Elkhodr, M., Al Zobbi, M., Novoa, M., Arsalan, M., Poly, T. N., Gochoo, M., Khan, G., Dev, K. (2021). A simulated measurement for COVID-19 pandemic using the effective reproductive number on an empirical portion of population: epidemiological models. *Neural computing & applications*, 1–9. doi: 10.1007/s00521-021-06579-2
- Aminullah, E., Erman, E. (2021). Policy innovation and emergence of innovative health technology: The system dynamics modelling of early COVID-19 handling in Indonesia. *Technology in Society*, 66. doi: 10.1016/j.techsoc.2021.101682

- Aslan, I.H., Demir, M., Wise, M.M., Lenhart, S. (2020). Modeling COVID-19: Forecasting and analyzing the dynamics of the outbreaks in Hubei and Turkey.
- Ayodele, K. P., Jimoh, H., Fagbamigbe, A. F., Onakpoya, O. H. (2021) The dynamics of COVID-19 outbreak in Nigeria: A sub-national analysis, *Scientific African*, 13. doi: 10.1016/j.sciaf.2021.e00914
- Bahloul, M. A., Chahid, A., & Laleg-Kirati, T. M. (2020). Fractional-Order SEIQRDP Model for Simulating the Dynamics of COVID-19 Epidemic. *IEEE open journal of engineering in medicine and biology*, 1, 249–256. doi:10.1109/OJEMB.2020.3019758
- Bala, B. K., Arshad, F. M., Noh. K. M. (2017). *System Dynamics: Modelling and Simulation*. Singapore: Springer.
- Bastos, S.B., Morato, M.M., Cajuiro, D.O., Normey-Rico, J.E. (2021). The COVID-19 (SARS-CoV-2) uncertainty tripod in Brazil: Assessments on model-based predictions with large under-reporting. *Alexandria Engineering Journal*, 60(5), 4363-4380. doi: 10.1016/j.aej.2021.03.004
- Binder, T., Vow, A., Belyazid, S., Haraldsson, H. Svensson, M. (2004). Developing System Dynamics Models From Causal Loop Diagrams. *Proceedings of the 22<sup>nd</sup> international conference of the system dynamics society*.
- Brauer, F. (2008). Compartmental models in epidemiology. In *Mathematical epidemiology*. Springer, Berlin, Heidelberg.
- Campuzano, F. Mula, J. (2011). *Supply Chain Simulation: A System Dynamics Approach For Improving Performance*. Springer-Verlag, London.
- Carpio, A., Pierret, E. (2022). Uncertainty quantification in Covid-19 spread: Lockdown effects, *Results in physics*, 35. doi: 10.1016/j.rinp.2022.105375
- Chen, D., Yang, Y., Zhang, Y., Yu, W. (2020). Prediction of COVID-19 spread by sliding mSEIR observer, *Science China Information Sciences*, 63(12). doi:10.1007/s11432-020-3034-y
- Chen, J., Chou, S.Y., Yu, T.H.K., Rizqi, Z.U., Hang, D.T. (2022). System dynamics analysis on the effectiveness of vaccination and social mobilization policies for COVID-19 in the United States. *PLoS ONE* 17(8). doi: 10.1371/ journal.pone.0268443
- Cheng, C., Zhang, D., Dang, D., Geng, J., Zhu, P., Yuan, M., Liang, R., Yang, H., Jin, Y., Xie, J., Chen, S., Duan, G. (2021). The incubation period of COVID-19: a global meta-analysis of 53 studies and a Chinese observation study of 11 545 patients. *Infectious diseases of poverty*, 10(1), 119. doi: 10.1186/s40249-021-00901-9
- Chowell, G. (2017). Fitting dynamic models to epidemic outbreaks with quantified uncertainty: A primer for parameter uncertainty, identifiability, and forecasts, *Infectious Disease Modelling*. 2. 379– 398.

- Currie, C. S. M., Fowler, J. W., Kotiadis, K., Monks, T., Onggo, B. S., Robertson, D. A., Tako, A. A. (2020). How simulation modelling can help reduce the impact of COVID19. *Journal of Simulation*, 14(2), 83-97. doi: 10.1080/17477778.2020.1751570
- Darabi, N. Hosseinichimeh, N. (2020). System dynamics modeling in health and medicine: a systematic literature review. *System Dynamics Review*, 36(1), 29–73. doi: 10.1002/sdr.164629
- Deressa, C.T., Duressa. G.F. (2021). Investigation of the dynamics of COVID-19 with SEIHR nonsingular and nonlocal kernel fractional model. *International Journal of Modelling and Simulation*. doi: 10.1080/02286203.2021.2012636
- Desai, P.S. (2021). News Sentiment Informed Time-series Analyzing AI (SITALA) to curb the spread of COVID-19 in Houston, *Expert Systems with Applications*, 180. doi: 10.1016/j.eswa.2021.115104
- Effelterre, T.V., Marano, C., Jacobsen, K.H. (2016). Modeling the hepatitis A epidemiological transition in Thailand. *Vaccine*, 34(4), 555-562. doi: 10.1016/j.vaccine.2015.11.052.
- Er Kara, M., Ghadge, A., Bititci, U.S. (2021). Modelling the impact of climate change risk on supply chain performance. *International Journal of Production Research*, 59:24, 7317-7335. doi: 10.1080/00207543.2020.1849844
- Erkayman, B., Ak, F., & Çodur, S. (2023). A simulation approach for COVID-19 pandemic assessment based on vaccine logistics, SARS-CoV-2 variants, and spread rate. *Simulation*, 99(2), 127–135. doi:10.1177/00375497221120018
- Fair, J. M., LeClaire, R. J., Dauelsberg, L. R., Ewers, M., Pasqualini, D., Cleland, T., Rosenberger, W. (2021). Systems dynamics and the uncertainties of diagnostics, testing and contact tracing for COVID-19. *Methods (San Diego, Calif.)*, 195, 77–91. doi: 10.1016/j.ymeth.2021.03.008
- Ferrández, M.R., Ivorra, B., Redondo, J.L., Ramos, A.M., Ortigosa, P.M. (2023). A multi-objective approach to identify parameters of compartmental epidemiological models—Application to Ebola Virus Disease epidemics. *Communications in Nonlinear Science and Numerical Simulation*, 120, 107165. doi: 10.1016/j.cnsns.2023.107165
- Forrester, J. W. (1994). *System Dynamics, Systems Thinking, and Soft OR*. *System Dynamics Review* 10 (2-3), 245– 256.
- Ghadge, A., Er, M., Ivanov, D., Chaudhuri, A. (2021). Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: a system dynamics approach. *International Journal of Production Research*, 60(20), 6173-6186.
- Ghaffarzadegan, N., Rahmandad, H. (2020). Simulation-based estimation of the early spread of COVID-19 in Iran: actual versus confirmed cases. *System Dynamics Review*, 36(1), 101–129. doi: 10.1002/sdr.1655

- Gillis, M., Urban, R., Saif, A., Kamal, N., Murphy, M. (2021). A simulation–optimization framework for optimizing response strategies to epidemics. *Operations Research Perspectives*, 8. doi: 10.1016/j.orp.2021.100210
- Gourieroux, C., Jasiak, J. (2023). Time varying Markov process with partially observed aggregate data: An application to coronavirus. *Journal of econometrics*, 232(1), 35–51. doi: 10.1016/j.jeconom.2020.09.007
- Guanghong, D., Chang, L., Jianqiu, G., Ling, W., Ke, C., Di, Z. (2004). SARS epidemical forecast research in mathematical model. *Chin Sci Bull*, 49(21), 2332-2338. doi: 10.1360/04we0073
- Hekimoğlu, M., Barlas, Y. (2010). Sensitivity Analysis of System Dynamics Models by Behavior Pattern Measures. *System Dynamics Organization*, 54, 1-31.
- Hethcote, H. (2000). The Mathematics of Infectious Diseases, *SIAM Review*, 42 (4), 599–653.
- Hurajova, A., Kollárová, D., Juraj, L. (2022). Trends in education during the pandemic: modern online technologies as a tool for the sustainability of university education in the field of media and communication studies. *Heliyon*, 8(5), 2405-8440. doi: 10.1016/j.heliyon.2022.e09367
- Huynh, H.X., Lai, B.U., Duong-Trung, N., Nguyen, H.T., Phan, T.C. (2021). Modeling population dynamics for information dissemination through Facebook. *Concurrency Computation Practise and Experience*. doi: 10.1002/cpe.6333
- Jia, S., Li, Y., Fang, T. (2022). System dynamics analysis of COVID-19 prevention and control strategies. *Environmental science and pollution research international*, 29(3), 3944–3957. doi:10.1007/s11356-021-15902-2
- John, C.C., Ponnusamy, V., Krishnan, C. S., & Ra, N. (2022). A Survey on Mathematical, Machine Learning and Deep Learning Models for COVID-19 Transmission and Diagnosis. *IEEE Reviews in Biomedical Engineering*, 5, 325-340. doi: 10.1109/RBME.2021.3069213
- Jung, W.S. (2018). A System Dynamics Analysis of National R&D Performance Measurement System in Korea. *Industrial Engineering & Management Systems*, 17(4), 833-839. doi: 10.7232/iems.2018.17.4.833
- Kermack, W.O., McKendrick A.G.A. (1927). Contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, The Royal Society, 700–721.
- Khairulbahri, M. (2020). Modeling the COVID-19 Transmission in Italy: The Roles of Asymptomatic Cases, Social Distancing, and Lockdowns in the First and the Second Waves. doi: 10.2139/ssrn.3822451
- Khalilpourazari, S., Doulabi, H.H. (2021). Robust modelling and prediction of the COVID-19 pandemic in Canada. *International Journal of Production Research*. doi: 10.1080/00207543.2021.1936261

- Kim, M., Milner, F. (1995). A mathematical model of epidemics with screening and variable infectivity. *Mathematical and Computer Modelling*, 21(7), 29–42.
- Kirkwood Craig W. (1998). *System Dynamics Methods: A Quick Introduction*, College Of Business Arizona State University.
- Kumar, A., Choi, T.-M., Wamba, S.F., Gupta, S., Tan, K.H. (2021a). Infection vulnerability stratification risk modelling of COVID-19 data: a deterministic SEIR epidemic model analysis, *Annals of Operations Research*. doi: 10.1007/s10479-021-04091-3
- Kumar, A., Viswakarma, N.K., Adlakha, Mukherjee, K. (2021b). How successful have the lockdowns been in controlling the (COVID-19/SARS-CoV-2) pandemic —A simulation-based analysis.
- Kumar, A. Priya, B. And Srivastava, S.K. (2021c). Response to the COVID-19: Understanding implications of government lockdown policies. *Journal of Policy Modeling*, 43(1), 76-94. doi:10.1016/j.jpolmod.2020.09.001
- Kumari, P., Singh, H. P., Singh, S. (2021) SEIAQRDT model for the spread of novel coronavirus (COVID-19): A case study in India, *Applied intelligence* (Dordrecht, Netherlands), 51(5), 2818–2837. doi:10.1007/s10489-020-01929-4
- Kuzdeuov, A., Karabay, A., Baimukashev, D., Ibragimov, B., Varol, H. A. (2021). A Particle-Based COVID-19 Simulator With Contact Tracing and Testing. *Journal of engineering in medicine and biology*, 2, 111–117. doi: 10.1109/OJEMB.2021.3064506
- La, Gatta V., Moscato, V., Postiglione, M., & Sperli, G. (2021). An epidemiological neural network exploiting dynamic graph structured data applied to the COVID-19 outbreak. *IEEE Transactions on Big Data*, 7(1), 45-55. doi: 10.1109/TBDATA.2020.3032755
- Lane, D.C. (2000). Should System Dynamics be Described as a 'Hard' Or 'Deterministic' Systems Approach. *Systems Research and Behavioral Science*, 17, 3-22.
- Lee, J. W., W. J. McKibbin. (2004). Estimating the global economic cost of SARS. In *Learning from SARS: Preparing for the next disease outbreak: Workshop summary*. Washington, DC: The National Academies Press.
- Leite, H., Hodgkinson, I.R., Gruber, T. (2020). New development: ‘Healing at a distance’—telemedicine and COVID-19. *Public Money & Management*, 40(6), 483–485. doi: 10.1080/09540962.2020.1748855
- Li, Y., Zeng, Z., Feng, M., Kurths, J. (2022a). Protection Degree and Migration in the Stochastic SIRS Model: A Queueing System Perspective. *IEEE Transactions on Circuits and Systems I: Regular Papers*, 69(2), 771-783. doi: 10.1109/TCSI.2021.3119978
- Li, S. Ma, S., Zhang, J. (2022b). Building a system dynamics model to analyze scenarios of COVID-19 policymaking in tourism-dependent developing countries: A case study of Cambodia. *Tourism Economics*. 0(0) 1-25

- Liu, M., Thomadsen, R., Yao, S. (2020). Forecasting the spread of COVID-19 under different reopening strategies. *Scientific Reports*, 10(2036). doi: 10.1038/s41598-020-77292-8
- Liu, X. X., Fong, S. J., Dey, N., Crespo, R. G., Herrera-Viedma, E. (2021). A new SEAIRD pandemic prediction model with clinical and epidemiological data analysis on COVID-19 outbreak, *Applied intelligence*, 51(7), 4162–4198. doi: 10.1007/s10489-020-01938-3
- Lymperopoulos, I.N. (2021). #stayhome to contain Covid-19: Neuro-SIR – Neurodynamical epidemic modeling of infection patterns in social networks, *Expert Systems with Applications*, 165. doi: 10.1016/j.eswa.2020.113970
- Ma, Z., Wang, S., Lin, X., Li, X., Han, X., Wang, H., Liu, H. (2022). Modeling for COVID-19 with the contacting distance. *Nonlinear Dynamics*, 107(3), 3065-3084. doi: 10.1007/s11071-021-07107-6
- Mac, S., Mishra, S., Ximenes, R., Barrett, K., Khan, Y.A., Naimark, D.M.J., Sander, B. (2021). Modeling the coronavirus disease 2019 pandemic: A comprehensive guide of infectious disease and decision-analytic models. *Journal of clinical epidemiology*, 132, 133–141. doi: 10.1016/j.jclinepi.2020.12.002
- Magesh, S., Niveditha, V.R., Rajakumar, P.S., Radha RamMohan, S., Natrayan, L. (2020). Pervasive computing in the context of COVID-19 prediction with AI-based algorithms. *International Journal of Pervasive Computing and Communications*, 16 (5), 477-487. doi: 10.1108/IJPC-07-2020-0082
- Majumder, D., Mazumder, S., Ghosal, P. (2021) CARD Predictive Modeling and SEI Formulation: COVID-19 Statistics in India, *Journal of The Institution of Engineers (India): Series B*, 102(6), 1167–1176. doi:10.1007/s40031-021-00608-3
- Massonis, G., Banga J.R., Villaverde, A.F. (2021). Structural identifiability and observability of compartmental models of the COVID-19 pandemic. *Annual reviews in control*, 51, 441–459. doi: 10.1016/j.arcontrol.2020.12.001
- Meadows, Donella H. (2009). *Thinking in systems : a primer*. London; Sterling, VA :Earthscan
- Mellacher P. (2022). Endogenous viral mutations, evolutionary selection, and containment policy design. *Journal of economic interaction and coordination*, 17(3), 801–825. doi: 10.1007/s11403-021-00344-3
- Meng, X., Cai, Z., Si, S., Duan, D. (2021) Analysis of epidemic vaccination strategies on heterogeneous networks: Based on SEIRV model and evolutionary game. *Applied mathematics and computation*, 403. doi: 10.1016/j.amc.2021.126172
- Menon, N. (2021). Does BMI predict the early spatial variation and intensity of Covid-19 in developing countries? Evidence from India. *Economics and Human Biology*, 41. doi: 10.1016/j.ehb.2021.100990

- Nadim, S.S., Ghosh, I., Chattopadhyay, J. (2021). Short-term predictions and prevention strategies for COVID-19: A model-based study. *Applied Mathematics and Computation*. 404(126251). doi: 10.1016/j.amc.2021.126251
- Niwa, M., Hara, Y., Sengoku, S., Kodama, K. (2020). Effectiveness of Social Measures against COVID-19 Outbreaks in Selected Japanese Regions Analyzed by System Dynamic Modeling. *International journal of environmental research and public health*, 17(17), 6238. doi:/10.3390/ijerph17176238
- Ogata, K. (2014). *System Dynamics* (Ed. 4th). Harlow: Pearson.
- Pechlivanoglou, T., Li, J., Sun, J., Heidari, F., Papagelis, M. (2022). Epidemic Spreading in Trajectory Networks. *Big Data Research*, 27. doi: 10.1016/j.bdr.2021.100275
- Poonia, R.C., Saudagar, A.K.J., Altameem, A., Alkhatami, M., Khan, M.B., Hasanat, M.H.A. (2022). An Enhanced SEIR Model for Prediction of COVID-19 with Vaccination Effect. *Life*, 12, 647. doi: 10.3390/life12050647
- Qian, W., Bhowmick, S., Neill, M., Mikler, S.R., Mikler, A.R. (2021). Applying a Probabilistic Infection Model for studying contagion processes in contact networks. *Journal of Computational Science*, 54. doi: 10.1016/j.jocs.2021.101419
- Rajapaksha, R.N.U., Wijesinghe, M.S.D., Jayasooriya, S.P., Gunawardana, B.I., Weerasinghe, W.P.C. (2021). An Extended Susceptible Exposed-Infected-Recovered (SEIR) Model with Vaccination for Forecasting the COVID-19 Pandemic in Sri Lanka. doi: 10.1101/2021.06.17.21258837
- Ranganath, B.J., Rodrigues, L.L.R. (2008). *System Dynamics: Theory and Case Studies*. I K International Publishing House, New Delhi.
- Rehman, A. U., Mian, S. H., Usmani, Y. S., Abidi, M. H., Mohammed, M. K. (2023). Modeling Consequences of COVID-19 and Assessing Its Epidemiological Parameters: A System Dynamics Approach. *Healthcare*, 11(2), 260. MDPI AG. doi:10.3390/healthcare11020260
- Rubio-Herrero J., Wang Y. (2022). A flexible rolling regression framework for the identification of time-varying SIRD models. *Computers and Industrial Engineering*, 167. doi: 10.1016/j.cie.2022.108003
- Safarishahrbiari, A., Teyhouee, A., Waldner, C., Liu, J., Osgood, ND. (2017). Predictive accuracy of particle filtering in dynamic models supporting outbreak projections. *BMC Infect Dis*, 17. doi: 10.1186/s12879-017-2726-9
- Sánchez, B.J.M., & Serrato, B.R. (2023). Design Control Model in System Dynamics Through State-Space Representation. *Appl. Sci.* 13, 7154. doi: 10.3390/app13127154
- Samsuzzoha, M., Singh, M., & Lucy, D. (2011). Numerical study of a diffusive epidemic model of influenza with variable transmission coefficient. *Applied Mathematical Modelling*, 35(12), 5507-5523.
- Sapiri, H., Zulkepli, J., Ahmad, N., Abidin, N.Z., Hawari, N.N. (2017). *Introduction to System Dynamics Modelling and Vensim Software*. UUM Press.

- Schoenenberger, L., Schmid, A., Tanase, R., Beck, M., Schwaninger, M. (2021). Structural Analysis of System Dynamics Models. *Simulation Modelling Practice and Theory*, 110. doi: 10.1016/j.simpat.2021.102333
- Senge, P. (2006). *The Fifth Discipline: The art and practice of the learning organization*. Random House Books.
- Shulgin, B., Stone, L., Agur, Z. (1998). Pulse vaccination strategy in the SIR epidemic model. *Bulletin of mathematical biology*, 60(6), 1123-1148.
- Small, M., Cavanagh, D. (2020). Modelling Strong Control Measures for Epidemic Propagation With Networks-A COVID-19 Case Study. *IEEE Access*. doi: 10.1109/ACCESS.2020.3001298
- Sterman, J.D. (2000). *Business Dynamics: Systems Thinking and Modelling for a Complex World*. McGraw-Hill Higher Education, New York
- Sturmberg J. P., Martin C. M., Katerndahl D. A. (2014). Systems and Complexity Thinking in the General Practice Literature: An Integrative, Historical Narrative Review. *Annals of Family Medicine* 12(1), 66-74.
- Sy, C., Bernardo, E., Miguel, A., San Juan, J. L., Mayol, A. P., Ching, P. M., Culaba, A., Ubando, A., Mutuc, J. E. (2020). Policy Development for Pandemic Response Using System Dynamics: a Case Study on COVID-19. *Process Integration and Optimization for Sustainability*, 4(4), 497–501. doi: 10.1007/s41660-020-00130-
- Sy, C., Ching, P.M., Juan, J.L.S., et al. (2021). Systems Dynamics Modeling of Pandemic Influenza for Strategic Policy Development: a Simulation-Based Analysis of the COVID-19 Case. *Process Integration and Optimization for Sustainability*. 5, 461-474.
- Tang, L., Zhou, Y., Wang, L., Purkayastha, S., Zhang, L., He, J., Wang, F., Song, P. X. (2020). A Review of Multi-Compartment Infectious Disease Models. *International Statistical Review*, 88(2), 462–513. doi: 10.1111/insr.12402
- Thiel D, Le Hoa Vo T, Hovelaque V. (2014). Forecasts impacts on sanitary risk during a crisis: a case study. *The International Journal of Logistics Management*. 25(2), 358–378. TUIK.<https://data.tuik.gov.tr/Bulten/Index?p=Adrese-Dayali-Nufus-Kayit-Sistemi-Sonuclari-2020-37210> (2023, accessed 21 December 2023)
- Venkateswaran, J., Damani, O. (2020). Effectiveness of Testing, Tracing, Social Distancing and Hygiene in Tackling Covid-19 in India: A System Dynamics Model.
- Vincenot, C.E., Moriya, K. (2011). Impact of the topology of metapopulations on the resurgence of epidemics rendered by a new multiscale hybrid modeling approach. *Ecol Inform* 6:177–186. <https://doi.org/10.1016/j.ecoinf.2011.04.002>
- Vrabac, D., Shang, M., Butler, B., Pham, J., Stern, R., Pare, P.E. (2022). Capturing the Effects of Transportation on the Spread of COVID-19 with a Multi-Networked SEIR Model. *IEEE Control Systems Letters*, 6, 103-108. doi: 10.1109/LCSYS.2021.3050954
- Volpatto, D.T., Resende, A.C.M., dos Anjos, L., Silva, J.V.O., Dias, C.M., Almeida, R.C., Malta, S.M.C. (2021). A generalised SEIRD model with implicit social distancing

mechanism: A Bayesian approach for the identification of the spread of COVID-19 with applications in Brazil and Rio de Janeiro state, *Journal of Simulation*. doi: 10.1080/17477778.2021.1977731

Wang, H., Zhang, J., Zeng, W. (2018). Intelligent simulation of aquatic environment economic policy coupled ABM and SD models. *Science of the Total Environment*, 618, 1160-1172.

Yarsky P. (2021). Using a genetic algorithm to fit parameters of a COVID-19 SEIR model for US states. *Mathematics and computers in simulation*, 185, 687–695. doi: 10.1016/j.matcom.2021.01.02

**APPENDIX A.** System Dynamics Models of COVID-19 from selected studies

<b>Author</b>	<b>Aim of the study</b>	<b>Used Variable</b>	<b>Finding(s)</b>
Ghaffarzadegan and Rahmandad (2020)	Estimate the outbreak of COVID-19 with simulation-based approach using SEIR model	Contact rate, confirmed death rate, test coverage, total duration of illness, exposure period, fractional infectivity, public perception of recent death, seasonal effect, infectivity base value, etc.	This study compares official statistics and its estimations from many aspects that the pandemic can grow dangerously until the vaccine, through the situation in Iran early phases of disease.
Khairulbahri (2021)	Construct SEIR model in Italy regarding social distancing, lockdowns and asymptomatic policies	Behavioural risk reduction, lockdown reaction time, lockdown risk reduction, fraction of undocumented cases upon documented cases, flying rates, import time, etc.	This study found the undocumented case are %70 of documented ones in Italy. The differences among other studies that to model is estimated infected, recovered, and dead cases regarding undocumented cases.
Li et al. (2022b)	Employ a SD model to evaluate and select effective policy responses that both control the virus spread and support tourism	Number of international flights, tourists, new confirmed infection cases, rehabilitation cases, activity intensity of shopping, catering and entertainment, domestic traffic infection rate, tourist activity degree, etc.	It has been shown out of 5 different scenarios that limited number of international flights is not effective for spreading the COVID-19 and the quarantine policy is the most effective method. The second highest performance is domestic transportation bans, but this method has the worst effect on tourism in terms of income.
Ak (2021)	Predict how long it will take for herd immunity to mature	Number of infected people, number of people exposed, number of people susceptible to disease, vaccine demand, vaccine supply, recoveries, social life restrictions, communication rates, vaccine effectiveness, variant effect, social mobility, seasonal effect, international travels, etc.	Scenarios: 1) With a monthly supply of 15 million vaccines, it is estimated that the country's herd immunity will reach 70% in 161 days. 2) With a monthly supply of 30 million vaccines, it is estimated that the country's herd immunity will reach 70% in 117 days. 3) With a monthly supply of 40 million vaccines, it is estimated that the country's herd immunity will reach 70% in 98 days.

**APPENDIX A.** System Dynamics Models of COVID-19 from selected studies (cont.)

<b>Author</b>	<b>Aim of the study</b>	<b>Used Variable</b>	<b>Finding(s)</b>
Fair (2021)	Analyse uncertainty because of COVID-19 regarding biological, political, sociological and infrastructure responses to support decisions	Maximum mortality enhancement multiplier, reduction in early symptom contagion due to limited quarantine, pre-symptomatic and asymptomatic spread	Widespread testing, contacting tracing and quarantine can curtail the pandemic through identifying asymptomatic people in the population with two scenarios.
Aminullah and Erman (2021)	Examine health system with respect to policy-based innovation, creation of innovative technologies and implication to the system	Vaccine, government decisions, travel, workforce operations, public health, infectious disease, economic impact, population and etc.	Large Scale Social Restriction (LSSR) is stricter than social distancing (SD) guidelines, but not lockdown, because it gave opportunity for people to move outside their home for fulfilling essential needs. It is the main controller of COVID-19.
Sy et al. (2020)	Policy recommendation through a SD modelling approach	Quarantine effectiveness, behavioural risk, economic pressure, community quarantine measures, public health strain, active infected, infected, exposed, susceptible, deaths, population, hospital care effectiveness and etc.	Policy recommendations
Kumar et al. (2021b)	A multi-objective optimal control problem has been simulated to gauge the success of the lockdowns in India	Number of individuals hospitalized for special care, recovered individuals from hospitals, number of deceased individuals, rate of protection from infection including all actions	Cost-benefit analysis of lockdown: examine the relationship between lockdown intensity, number of deaths, and revenue loss because of pandemic.

**APPENDIX A.** System Dynamics Models of COVID-19 from selected studies (cont.)

<b>Author</b>	<b>Aim of the study</b>	<b>Used Variable</b>	<b>Finding(s)</b>
Kumar et al. (2021c)	Create a model focusing on the effects of social distancing and lockdown strategies on people and facilitate policymakers to gain insights on trajectory of COVID-19	Panic among people, behavioural change, awareness programs, susceptible population, population exposed to disease, infected population, people died, government efforts, lockdown imposition, fraction of people self-isolating, self-isolated population, etc.	5 different scenarios according to the level of intervention are discussed and they showed the comparison about the number of recovered populations, the number of died people and the number of infected populations.
Venkateswaran and Damani (2020)	Capture various disease transmission pathways, expanding significantly from the standard SEIR model	Contact rate matrices, external arrivals (as per actual data), and a few other calibrated fractions based on the reported cases of Covid-19 in India	Model shows that, even after a 49-day lockdown, some non-trivial number of infections will be left and the pandemic will resurface. Most effective actions are high rate of testing, isolating positive individuals, contact tracing, and quarantine

**APPENDIX B.** Variables in the proposed model

<b>Variables</b>	<b>Mathematical Equations</b>
Total population	$(83.614.000 * 0.7) - \text{Dead}$
Dead	INTEGER(death rate)
Death rate	Infected/Infection duration*fatality rate
Exposed	INTEGER(Infection – Progressed infection)
Fraction susceptible	Total population/Susceptible population
Infected	INTEGER(Progressed infection-death rate-recovery rate) Initial Value : Initial Infected
Infection	Transmission rate*Infected
Isolation	IF THEN ELSE(Control measure decision>threshold for isolation, Control measure decision/1000,0)
Lockdown	IF THEN ELSE(Control measure decision>threshold for lockdown,1,0)
Policy effect	IF THEN ELSE(Lockdown=1, impact of lockdown, (disease transmission rate due to isolation -Isolation)
Progressed infection	STEP(Exposed, Incubation time)
Recovered	INTEGER(recovery rate)
Recovery rate	$(\text{Infected}/\text{Infection duration}) * (1 - \text{fatality rate})$
Reproduction ratio	STEP(policy effect, policy start time) + STEP ( policy effect, policy start time + policy duration)
Susceptible population	INTEGER(-Infection) Initial value : Total population-1
Transmission rate	$(\text{reproduction ratio}/\text{incubation time}) * \text{fraction susceptible}$

## **BIOGRAPHY**

*Deniz Yerinde* holds Bachelors degree in Industrial Engineering. She was graduated from the faculty with second honors. She is working in telecommunication sector as a Data Scientist. Her main research interests include Simulation and Modeling, Data Mining Techniques, Machine Learning and Artificial Intelligence.