Model of Pandemic Progression

CS 752 System Dynamics Course Project Report

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Abstract

This report presents a system dynamics model to analyze pandemic situation. This Model help us to understand population dynamics, healthcare system responses, vaccination strategies, and economic impacts during a pandemic. We specially focused on understanding epidemic wave patterns and evaluating strategies for simulation-based analysis.

Contents

1 Problem Statement

The COVID-19 pandemic pushed health systems around the world to their limits—but the impact was especially intense in countries like India. With a huge population, not enough medical infrastructure, and mixed levels of public cooperation, the situation quickly became a massive challenge. Decision-makers had to act fast—rolling out lockdowns, scaling up testing, making sure hospitals didn't get overwhelmed, and trying to get people to follow hygiene and distancing rules—all while flying blind, to some extent, as the virus kept changing and surprising us.

We've leaned on traditional epidemiological models like SIR and SEIR for decades, and while they're helpful for understanding the big picture, they tend to gloss over a lot of the messy details. In real life, things like testing delays, underreported cases, how well contact tracing works, and how people change their behavior over time matter—a lot. These models often just aren't equipped to handle that level of complexity, especially when resources are limited and decisions need to be made quickly.

That's why there's a real need for something better—something that brings together how the disease actually spreads and how people and systems respond. A model that doesn't just look at theory, but one that reflects delays, bottlenecks, and feedback loops. Something flexible enough to explore "what if" scenarios, so we can better understand the potential impact of different strategies before putting them into action.

2 Introduction

The outbreak of the COVID-19 pandemic has presented an unprecedented challenge to global health systems, economies, and societies. As the virus spread rapidly across populations, decision-makers were forced to respond with limited information and under immense uncertainty. In such situations, mathematical and computational models play a crucial role in predicting disease progression, evaluating intervention strategies, and informing public health policies.

One powerful approach in this context is the use of **System Dynamics (SD) models** — a class of simulation models designed to understand complex, nonlinear systems that evolve over time. Unlike traditional compartmental models that often simplify real-world behaviors, SD models can incorporate delays, feedback loops, resource constraints, and human behavioral responses, making them particularly well-suited to model epidemics in heterogeneous and resource-limited settings like India.

One useful tool is a **computer model**. In this report, we use a model made with **system dynamics**. This type of model helps us understand how different parts of the pandemic system—like people getting infected, vaccines, hospitals, and human behavior—change over time. It uses simple rules to simulate what could happen in the real world. This helps us see how these actions affect the spread of the disease. The model also shows how waves of infection happen and what we can do to reduce them.

3 Objective of Model

1) Capture Endogenous Feedbacks

Model how infection prevalence, public awareness, and policy measures interact dynamically over time, including behavioral adaptations such as increased hygiene or "lockdown fatigue."

2) Represent Intervention Levers

Provide structured, time-varying inputs for non-pharmaceutical interventions (e.g., social distancing, mask usage, quarantine protocols, testing/-tracing capacity) to evaluate their individual and combined effects.

3) Reflect Healthcare System Constraints

Incorporate hospital and intensive-care capacity, modeling overflow effects (e.g., increased mortality or extended recovery times when capacity is exceeded).

4) Accommodate Delays and Lags

Include realistic delays for incubation, testing/reporting turnaround, contact tracing, and progression through care pathways to reflect real-world operational bottlenecks.

5) Support Scenario Analysis

Enable exploration of "what-if" scenarios—such as early versus late implementation of measures or varying degrees of public compliance—to compare outcomes in terms of cases, hospital load, and fatalities.

4 Modelling

The system dynamics model for the pandemic focuses on the **spread of infectious diseases** within a specific region (e.g., India) over a defined time horizon, typically ranging from the early outbreak phase to several months after the epidemic's peak. The model explicitly considers the following elements within its boundary:

1. **Population Dynamics:** The model incorporates a population that interacts through social networks, which can be influenced by various interventions. The system dynamics framework accounts for demographic factors, such as population age, geographic distribution, and urban/rural variations, which can affect disease spread.

2. **Disease Transmission:** The model tracks the flow of individuals between different stages of infection (e.g., exposed, symptomatic, quarantined, hospitalized, recovered, or deceased). These transitions are governed by infection rates, intervention strategies, and individual behaviors.

3. **Intervention Mechanisms:** Interventions such as testing, contact tracing, quarantine, social distancing, hygiene practices (e.g., mask usage), and lockdowns are central to the model's dynamics. The effects of these measures are modeled dynamically to assess their timing, intensity, and effectiveness in controlling the epidemic.

Model Assumptions The following assumptions are made to simplify the model and focus on key dynamics while maintaining realism:

1. **Homogeneous Mixing Assumption:** Individuals within the population are assumed to mix randomly, meaning that every individual has an equal probability of coming into contact with any other individual. While this assumption is idealized, it serves as a starting point for the model. Variations in social behavior, regional mobility, and localized outbreaks can be considered in future refinements.

2. **Exogenous Risk of Infection:** The model assumes that infection spreads through contact with individuals who are already infected. It does not consider external sources of risk such as new strains of the virus or international travel (although these could be modeled in more complex versions).

3. **Constant Rates for Disease Progression:** Disease progression times (e.g., the incubation period, duration of infectiousness, recovery times) are assumed to be constant across the population. While individual variation exists in the real world, these rates are averaged for simplicity and based on existing epidemiological data.

Limitations While the model provides a valuable tool for understanding the dynamics of a pandemic and evaluating intervention strategies, it is important to note the following limitations:

- **Simplification of Human Behavior:** The model assumes relatively uniform and predictable human behavior, which is often not the case in real-world scenarios where people may act unpredictably, especially under stress or misinformation.

- **Fixed Parameters:** Many parameters (e.g., transmission rates, healthcare capacity) are fixed based on available data, but these parameters can evolve over time due to emerging evidence or interventions.

- **Data Quality and Availability:** The accuracy of the model's predictions is heavily dependent on the quality and timeliness of the data used for calibration (e.g., reported case numbers, testing rates). Inconsistent or incomplete data can lead to biased outcomes.

5 Stocks & Their Roles

In this system dynamics model, the following stocks are critical for representing the key population groups and states related to the pandemic:

1. **Healthy Non-Vaccinated People**

   This stock includes individuals who are susceptible to infection and have not yet received a vaccine. These individuals represent the primary reservoir for infection. As the virus spreads, individuals from this group transition into the "Infected" stock. The size of this stock is crucial for understanding the potential for epidemic growth and the speed at which the disease can spread.

2. **Infected**

   This stock represents individuals who are infected with the virus, including both symptomatic and asymptomatic individuals. These individuals actively spread the disease through their interactions with healthy people. As the infected population grows, the disease transmission rate increases, which accelerates the spread of the epidemic. The dynamics of this stock are central to understanding how quickly the infection can spread in the absence of interventions such as vaccination or isolation measures.

3. **Identified Infected**

   This stock refers to individuals who have been identified as infected through testing or contact tracing. These individuals are typically isolated or quarantined to prevent further transmission to the susceptible population. The identification of infected individuals is a critical point in controlling the spread of the virus, as it allows for targeted isolation and treatment, helping to reduce the overall transmission rate.

4. **Death**

   This stock tracks the cumulative number of individuals who have died due to the virus. The death toll is a significant outcome measure, reflecting the severity of the epidemic. The number of deaths is influenced by several factors, including the effectiveness of healthcare interventions, the healthcare system's capacity, and the timing of interventions like social distancing or vaccination campaigns. Monitoring this stock helps assess the severity of the epidemic and the overall effectiveness of control measures.

5. **Recovered**

   The "Recovered" stock represents individuals who have recovered from the infection and are assumed to have gained immunity, at least temporarily. These individuals are no longer part of the susceptible population, reducing the potential for further transmission. The number of individuals who recover is crucial for assessing the progression of the epidemic, as it helps slow the rate of infection and contributes to the development of herd immunity within the population.

6. **Healthy Vaccinated People**

   This stock includes individuals who have been vaccinated and are presumed to have immunity or reduced susceptibility to severe infection. Vaccination helps protect individuals from infection, and the more people who are vaccinated, the lower the overall transmission rate. As the number of vaccinated individuals increases, the pandemic slows, and the healthcare system is less likely to become overwhelmed. The presence of this stock is essential for evaluating the long-term effectiveness of vaccination campaigns in controlling the pandemic.

By tracking these stocks, the system dynamics model can effectively represent the population's changing health status over time. The interactions between these stocks (e.g., susceptible individuals becoming infected, infected individuals being identified and isolated, or people recovering) drive the overall epidemic dynamics and provide a basis for evaluating the impact of different intervention strategies, such as vaccination or isolation measures.

6 Flows and Equations

In this section, we describe the flows governing the dynamics of the pandemic model, as well as the associated equations. Each stock in the system changes over time based on these flows. The system includes six key stocks: Healthy Non-Vaccinated People (S), Healthy Vaccinated People (V), Infected (I), Identified Infected (Q), Recovered (R), and Death (D). Below are the details of each flow and its associated equations.

Infection Flow

$$\text{Infection} = \min\left(S,\ \min\left(1000,\ I \times S \times \frac{\text{Infection\_rate}}{\max(100, N)}\right)\right),$$

$$\text{Infection\_rate} = \frac{\text{Virus\_mutation} \cdot (1 - \text{Social\_distancing})}{\text{Infection\_period}}.$$

Vaccination Flow

$$\text{Vaccination} = \begin{cases} \min\left(S,\ \min(S \cdot r_v,\ M_v)\right), & T \geq \text{Vaccination\_Start\_Time}, \\ 0, & T < \text{Vaccination\_Start\_Time}, \end{cases}$$

$$r_v = \min\left(0.05,\ \min\left(\frac{\text{Vaccine\_demand}}{\max(10, S)},\ \frac{\text{Vaccines\_available}}{\max(100, S)}\right)\right).$$

Breakthrough Infection Flow

$$\text{Breakthrough} = \min\left(V,\ \min\left(1000,\ I \times V \times (1 - \text{Vaccine\_efficacy}) \times \frac{\text{Infection\_rate}}{\max(100, N)}\right)\right).$$

Recovery (Rehabilitation) Flow

$$\text{Recovery\_rate} = \text{SMOOTH3}\left(\min\left(0.2,\ \frac{\text{Hospital\_capacity}}{\max(10, Q)} \cdot \text{Immunity} + \text{Medication}\right),\ 3\right),$$
$$\text{Rehabilitation} = \text{SMOOTH3}\left(\min(Q,\ Q \cdot \text{Recovery\_rate}),\ \text{Treatment\_Delay\_Time}\right).$$

Mortality Flow

$$\text{Mortality} = Q \cdot \text{Mortality\_Rate}.$$

Stock Equations Let $N = S + V + I + Q + R$ denote the total population (excluding deaths). Then the stock changes are:

$$\begin{aligned} \Delta S &= -\min\left(S,\ \text{Infection} + \text{Vaccination}\right), \\ \Delta V &= \min\left(\text{Discharged} + \text{Vaccination},\ N\right) - \min\left(\text{Breakthrough},\ V\right), \\ \Delta I &= \min\left(\text{Infection} + \text{Breakthrough},\ N\right) - \min\left(\text{Testing},\ I\right), \\ \Delta Q &= \text{Testing} - \min\left(Q,\ \text{Mortality} + \text{Rehabilitation}\right), \\ \Delta D &= \text{Mortality}, \\ \Delta R &= \text{Rehabilitation} - \min\left(R,\ \text{Discharged}\right). \end{aligned}$$

7 Our Pandemic Model

In this section, we present the structure of our pandemic model. The model is designed to simulate the spread of an infectious disease within a population, accounting for various factors such as vaccination, infection rates, recovery, and mortality. It captures the dynamics of six primary stocks in the system: Healthy Non-Vaccinated People, Healthy Vaccinated People, Infected, Identified Infected, Recovered, and Death. Each stock evolves over time based on several interrelated flows that describe how individuals transition between different states.

The model incorporates key parameters such as infection rates, vaccination rates, social distancing effects, and healthcare capacity, which influence the transitions of individuals between susceptible, infected, and recovered states. By simulating these dynamics, the model provides insights into how different factors affect the course of an epidemic and helps in understanding the effectiveness of various interventions, such as vaccination campaigns, social distancing, and testing.

To visualize the interactions between these stocks and flows, we provide a detailed diagram of the model's structure. This diagram highlights the flow of individuals through the different compartments (stocks) and the associated transitions.

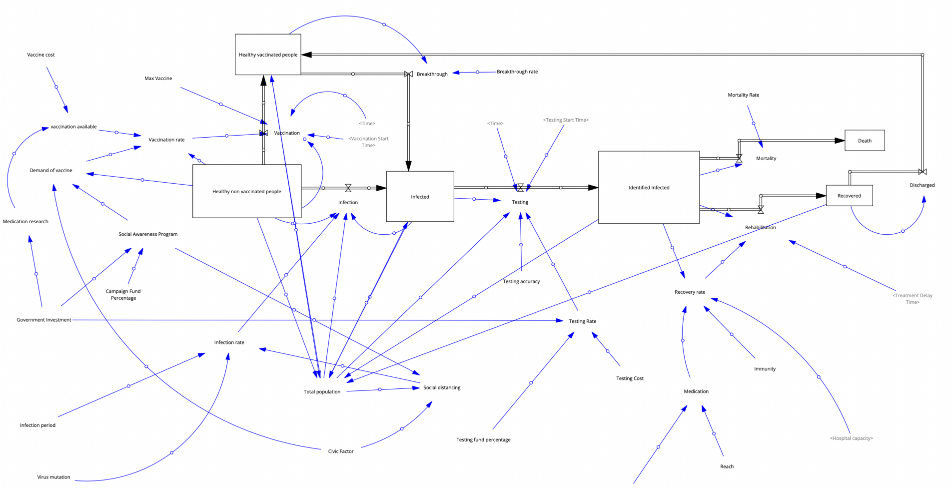

Figure 1: Comprehensive diagram of the Pandemic Model showing all stocks and flows in detail.

8 Simulation Trends

This section presents the simulation trends derived from our pandemic model. Each trend illustrates the temporal evolution of various key stocks and flows under different intervention scenarios and parameter settings. By analyzing these graphs, we gain valuable insights into the dynamics of disease spread, the effectiveness of interventions like vaccination and testing, and the impact of healthcare capacity on outcomes such as recovery and mortality.

8.1 Stocks

8.1.1 Healthy Vaccinated People

This plot shows how the number of healthy vaccinated individuals evolves over time. It reflects the impact of vaccination campaigns and breakthrough infections.

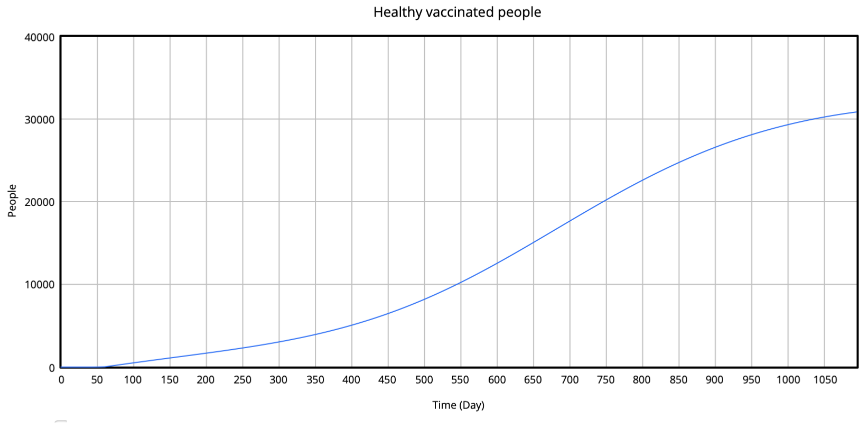

Figure 2: Trend of Healthy Vaccinated People over time.

8.1.2 Infected

This graph represents the number of individuals currently infected. It accounts for both new infections and removals due to testing.

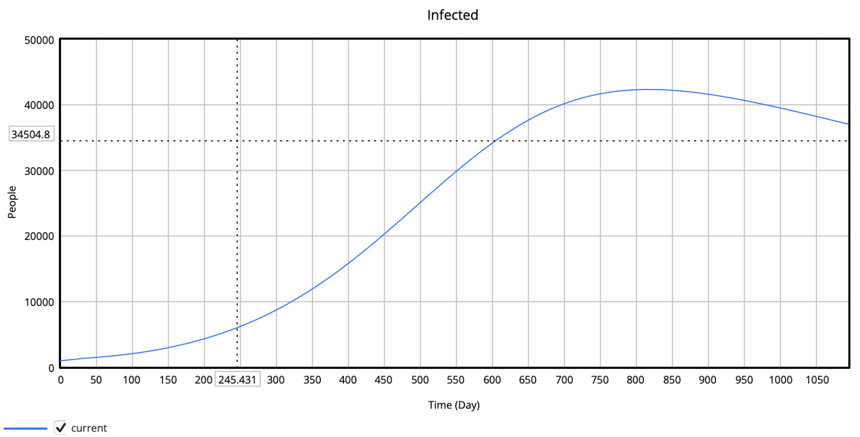

Figure 3: Trend of Infected individuals over time.

8.1.3 Recovered

This graph tracks the number of individuals who have recovered after infection. It is influenced by treatment, immunity, and medication.

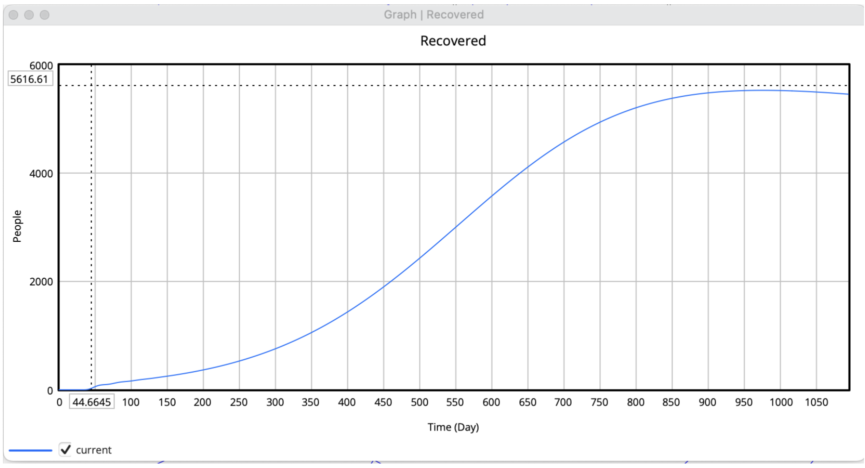

Figure 4: Trend of Recovered individuals over time.

8.1.4 Healthy Non-Vaccinated People

This trend shows the number of healthy individuals who are not vaccinated. The count decreases due to infection and vaccination.

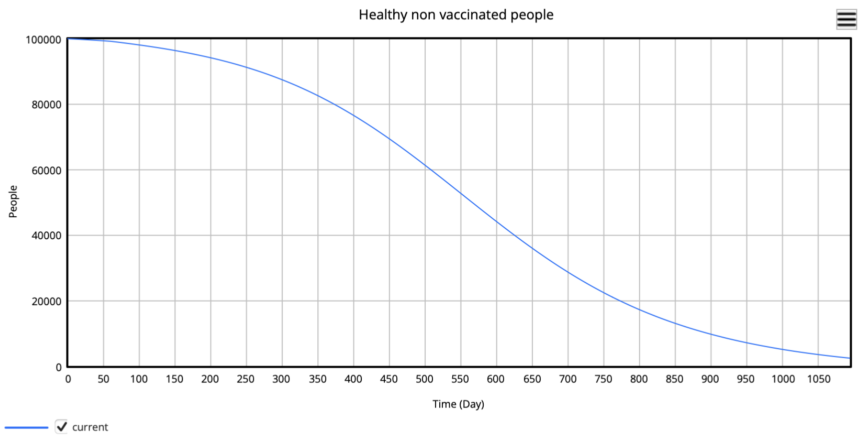

Figure 5: Trend of Healthy Non-Vaccinated People over time.

8.2 Flows

8.2.1 Vaccination

This flow represents the number of people vaccinated per unit time, constrained by vaccine availability and start time.

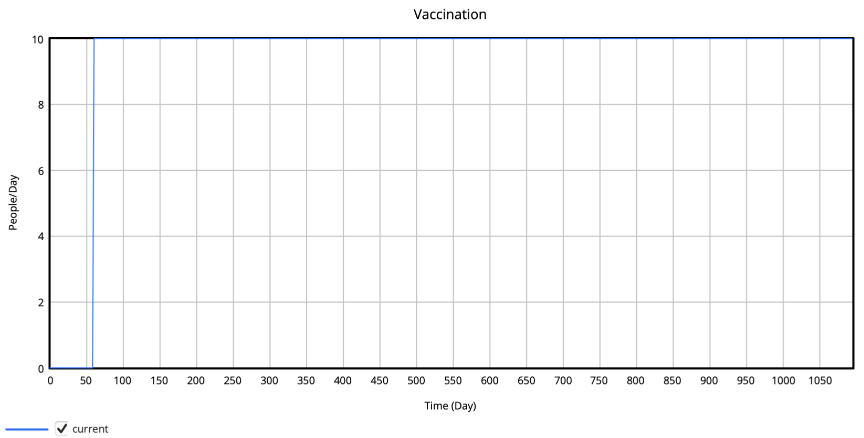

Figure 6: Trend of Vaccination Flow over time.

8.2.2 Mortality

This graph shows how many identified infected individuals die due to the disease in each time period.

Figure 7: Trend of Mortality Flow over time.

8.2.3 Testing

This trend reflects how infected individuals are detected through testing. It includes time lags and capacity effects.

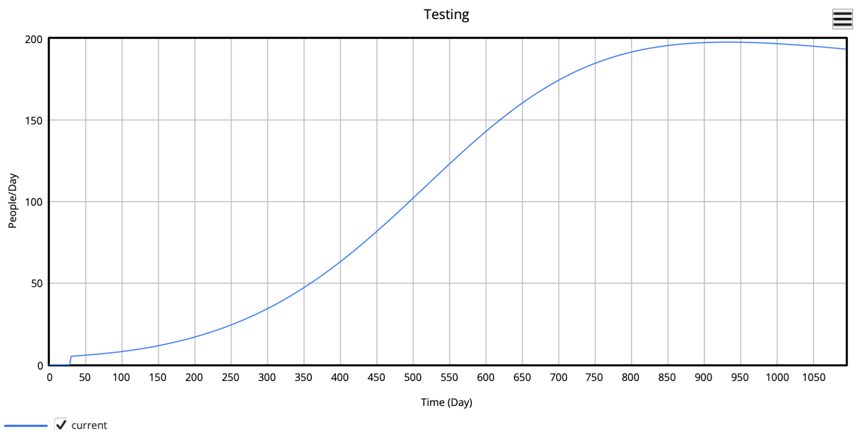

Figure 8: Trend of Testing Flow over time.

8.2.4 Infection

This flow shows how the infection rate evolves over time, influenced by contact rate, transmission probability, and susceptible population.

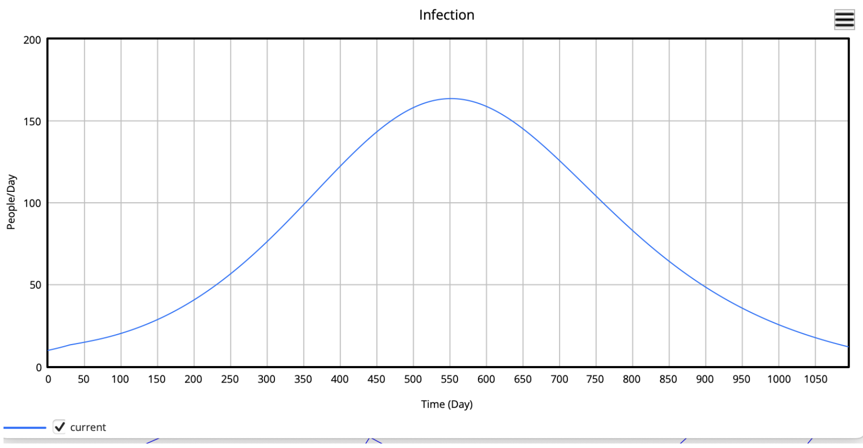

Figure 9: Trend of Infection Flow over time.

8.2.5 Total Population

This graph displays the overall population trend, factoring in births, deaths, recoveries, and new infections.

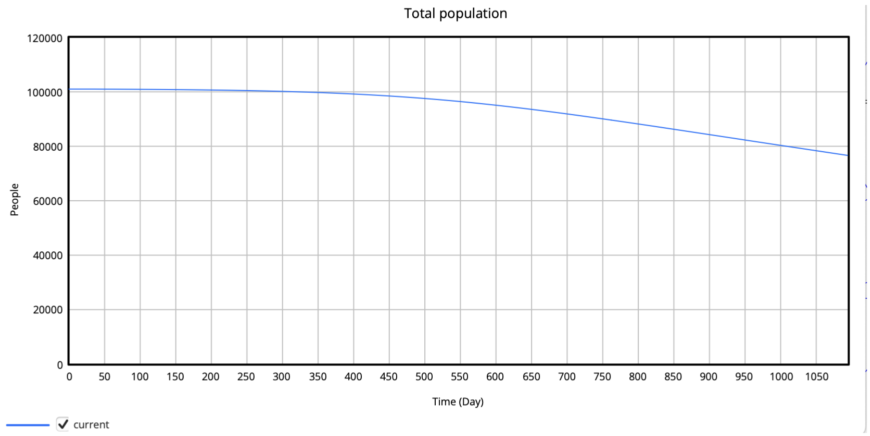

Figure 10: Trend of Total Population over time.

8.3 Comparative Analysis under Virus Mutation Rates

This subsection presents a comparative analysis of key population trends under different virus mutation rates. We focus on two core stocks — **Infected** and **Healthy Vaccinated People** — and examine how their dynamics change when the virus mutation rate is set to 0.4 and 0.8. This helps us understand the robustness of vaccination campaigns and the potential severity of outbreak under more aggressive variants.

Infected Individuals Comparison

The following plots show the number of infected individuals over time for two virus mutation rates. A higher mutation rate may increase the infection rate and challenge public health interventions.

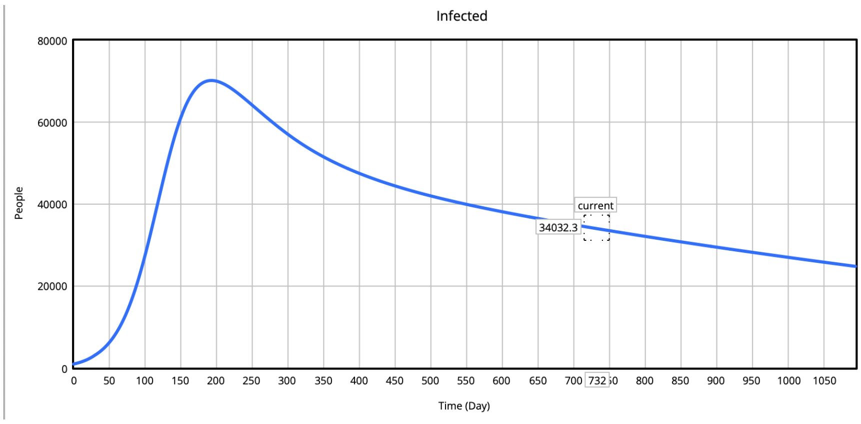

Figure 11: Infected Individuals over Time (Mutation Rate = 0.4)

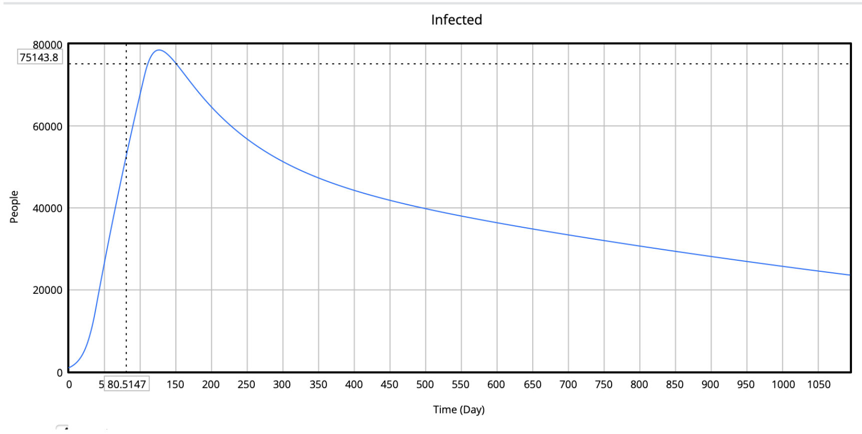

Figure 12: Infected Individuals over Time (Mutation Rate = 0.8)

Healthy Vaccinated Individuals Comparison

The following plots compare the evolution of healthy vaccinated individuals under the two mutation scenarios. A higher mutation rate may lead to more breakthrough infections, reducing the effectiveness of vaccination.

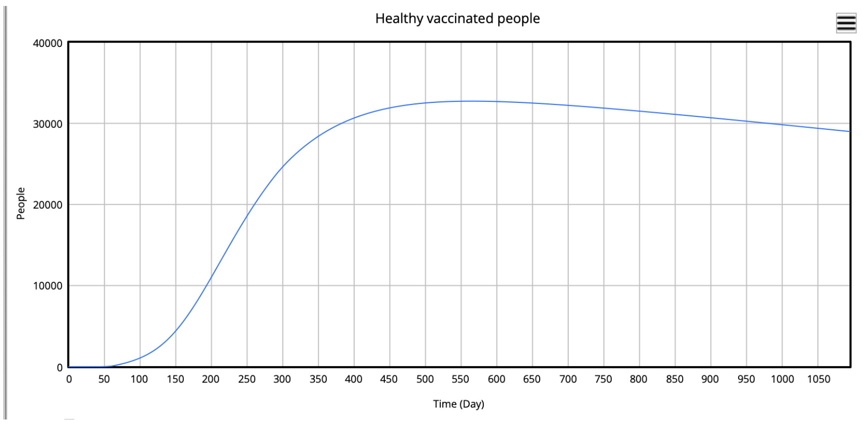

Figure 13: Healthy Vaccinated Individuals over Time (Mutation Rate = 0.4)

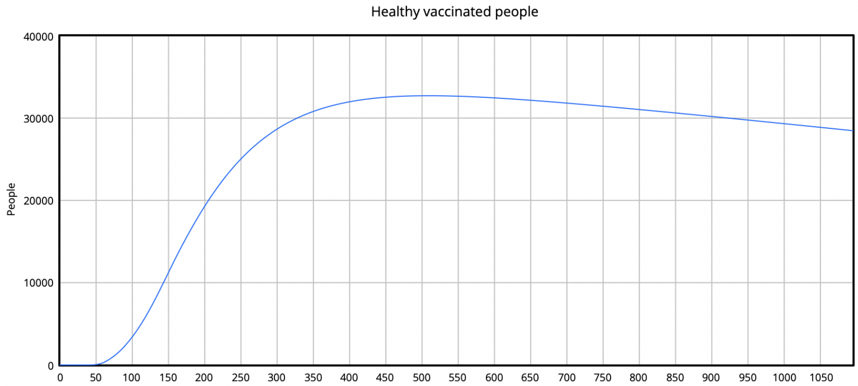

Figure 14: Healthy Vaccinated Individuals over Time (Mutation Rate = 0.8)

8.4 Combined Stock Variable Trends

In this section, we present a unified graph that visualizes the trends of all major stock variables simultaneously. This combined plot allows for a comprehensive understanding of how different segments of the population — such as infected, recovered, healthy vaccinated, and healthy non-vaccinated individuals — evolve over time in relation to each other.

Analyzing these collective dynamics helps identify peak infection periods, effectiveness of vaccination strategies, and the timeline of recovery. It also provides insights into the shifting proportions of population categories as the pandemic progresses.

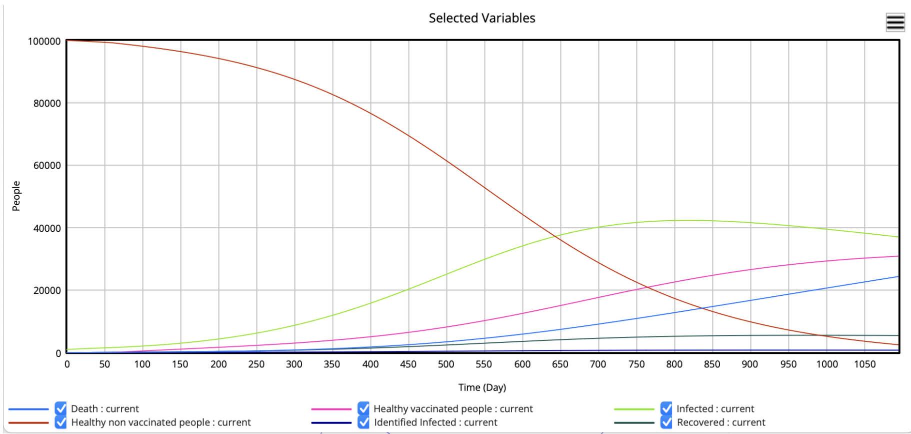

Figure 15: Combined Trends of All Stock Variables Over Time

9 Summary and the Way Forward

In this report, we developed a system dynamics-based pandemic model to simulate the spread of a contagious disease and to evaluate the effects of various intervention strategies. By integrating core epidemiological concepts with vaccination, testing, and mortality dynamics, we captured the evolution of the pandemic across multiple population groups—healthy vaccinated, healthy unvaccinated, infected, and recovered individuals.

Our simulation trends revealed several critical insights:

- Timely vaccination campaigns significantly reduce infection peaks and help stabilize the healthy population.
- Increased testing leads to earlier identification and containment of infections, curbing further transmission.
- Mortality rates fluctuate based on infection severity and healthcare capacity, underscoring the need for timely interventions.
- Virus mutations dramatically shift the infection curve, indicating the importance of surveillance and adaptability in policy response.

The comparison between scenarios with different virus mutation rates (0.4 and 0.8) demonstrated how even small changes in virus characteristics can have substantial effects on infection levels and healthcare burden. Similarly, the combined stock trends illustrated the complex and interlinked nature of pandemic dynamics.

In conclusion, system dynamics modeling is a powerful approach to pandemic analysis. By continuously refining the model and incorporating real-time data, policymakers and researchers can stay ahead of outbreaks and make informed decisions to safeguard public health.

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