ISyE 6644 - Summer 2025
Project Final Report

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Project Title: Modeling Pandemic Flu Spread Using a Deterministic SEIR Model

Contents

1 Abstract

This study implements and analyzes a deterministic SEIR (Susceptible-Exposed-Infectious-Recovered) model to investigate pandemic flu spread dynamics and evaluate the effectiveness of various public health interventions. Using MATLAB's `ode45` solver, 13 distinct scenarios were simulated in a population of 10,000 individuals over 365 days, systematically varying transmission rate (β), recovery rate (γ), and incubation rate (σ).

The baseline simulation without interventions showed 96.60% of the population infected, peaking on Day 84. Reducing β through social distancing significantly flattened the curve, with strict interventions ($\beta = 0.1$) nearly halting disease spread. Enhancing recovery rates and applying partial vaccination (60%) dropped total infections to 20.17%. In addition, dynamic scenarios showed that early policy intervention on Day 20 reduced infections to 82.25%, while a delayed, more infectious variant after Day 70 caused a second wave infecting 99.73%.

These findings highlight the need for early intervention, reduced transmission, healthcare readiness, and variant monitoring. To address current model limitations, future work may incorporate spatial dynamics, population heterogeneity, and neural network-augmented SEIR models for improved realism and policy relevance.

Background & Description of the Problem

Infectious diseases have played a pivotal role in shaping human history, profoundly influencing societies, economies, and even the trajectory of entire civilizations. From the devastating Black Death in the 14th century to the global disruptions caused by the COVID-19 pandemic, the recurring emergence and re-emergence of infectious diseases continue to pose significant challenges to public health systems worldwide [1, 2].

As globalization accelerates and human-animal-environment interactions intensify, the risk of emerging zoonotic diseases and pandemics has also increased. In response, understanding the mechanisms behind disease transmission and evaluating effective intervention strategies have become central goals in public health. Mathematical modeling has emerged as an indispensable tool in this context, offering a structured framework to simulate disease dynamics and inform evidence-based decisions [3, 4].

Among various modeling approaches, compartmental models, such as SIR and its extensions, have proven especially influential due to their simplicity, interpretability, and ability to capture key epidemiological dynamics. While the classic SIR model is effective for diseases with direct transmission and short incubation periods, it falls short in capturing latent stages of infection. The SEIR model, by introducing an "Exposed" compartment to represent individuals who have been infected but are not yet infectious, addresses this gap and more accurately models diseases with incubation periods, such as influenza, SARS, and COVID-19 [5, 6, 7].

In particular, the SEIR model has been used to evaluate the timing and intensity of non-pharmaceutical interventions (NPIs) such as mobility restrictions and mask mandates, and to simulate hypothetical control scenarios under various parameter configurations [8, 9, 10]. This flexibility has made it a foundational tool in public health decision-making, both in academic research and real-time government response dashboards [11].

This project builds upon this rich modeling tradition by implementing multiple SEIR-based simulation scenarios in `MATLAB`. Using `ode45`, a widely used solver for differential equations [12], we explore the effects of parameter changes, such as reduced transmission rate, increased recovery rate, dynamic intervention policies, and vaccination, on the progression of an epidemic. Our aim is to not only replicate realistic epidemic curves but also to highlight how modeling choices and assumptions directly influence the outcomes.

2 Mathematical Model

The SEIR model is a compartmental model that divides the total population into four mutually exclusive categories:

- **S(t)**: Susceptible individuals who can contract the disease
- **E(t)**: Exposed individuals who have been infected but are not yet infectious
- **I(t)**: Infectious individuals who can transmit the disease
- **R(t)**: Recovered individuals who are no longer infectious

We assume a closed population without births, unrelated deaths, or migration. Therefore, the total population N remains constant throughout the simulations:

$$N = S(t) + E(t) + I(t) + R(t)$$

2.1 Differential Equations

The dynamics of the SEIR model are described by the following system of ordinary differential equations:

$$\begin{aligned}
\frac{dS}{dt} &= -\beta \frac{SI}{N} \\
\frac{dE}{dt} &= \beta \frac{SI}{N} - \sigma E \\
\frac{dI}{dt} &= \sigma E - \gamma I \\
\frac{dR}{dt} &= \gamma I
\end{aligned}$$

Each term describes the rate of change in the population compartments as shown in Figure 1:

- First term represents the rate at which susceptible individuals become exposed. The negative sign indicates a decrease in the susceptible population as they get exposed to the virus. The more people are susceptible and infectious, the faster the disease spreads.
- Second term reflects two opposing effects on the exposed population: increase due to new infections from susceptible individuals and decrease as exposed individuals become infectious
- Third term is the rate of change of infectious individuals.
- The last term tracks the growth of the recovered population.

Figure 1: SEIR Model

2.2 Model Parameters

- β **(Transmission Rate):** The transmission rate β shows how rapidly a disease spreads in the population. It can be decomposed into two components:

$$\beta = c \cdot p$$

  - c: The average number of contacts per person per day (contact rate)
  - p: The probability of transmission per contact with an infectious individual

  *The β depends on social behavior and interaction patterns. For example, implementing social distancing policies reduces c, while mask usage or improved hygiene may reduce p.

- σ **(Incubation Rate):** Rate at which individuals in the *Exposed* compartment become infectious. It is the reciprocal of the average latent period:

$$\sigma = \frac{1}{D_E}$$

  where D_E is the average duration (in days) of the incubation period. For example, if the average incubation period is 5 days, then $\sigma = \frac{1}{5} = 0.2$.

- γ **(Recovery Rate):** This is the rate at which individuals in the *Infectious* compartment recover and move to the *Recovered* compartment. It is the reciprocal of the average infectious period:

$$\gamma = \frac{1}{D_I}$$

  where D_I is the average number of days an individual remains infectious. For instance, if the average infectious period is 7 days, then $\gamma = \frac{1}{7} \approx 0.143$.

2.3 Model Assumptions

- Homogeneous mixing is assumed (everyone is equally likely to interact)
- Parameters β, σ, and γ are constant during the simulation
- No reinfection is allowed; once recovered, individuals stay in the R compartment

3 Implementation

The SEIR model was implemented in **MATLAB R2025a**, a widely used numerical computing platform particularly effective for solving ordinary differential equations (ODEs). MATLAB's `ode45` solver was implemented to solve the SEIR model across various epidemic scenarios.

3.1 Overview of the Code Structure

The implementation is divided into three main function:

- **seir_all_scenarios**: This is the main driver function. It iterates over a set of predefined scenarios, solves the ODEs, plots the results, saves the figures, and reports key outcome metrics such as peak infections and total infected ratio.
- **seir_ode_static**: This defines SEIR differential equations assuming constant parameters (β, σ, γ).
- **seir_ode_timevariant**: This handles dynamic scenarios where β and σ change over time (e.g., policy interventions or variant emergence).

3.2 Parameter Initialization

Each scenario in `seir_all_scenarios` defines:

- β: Transmission rate
- σ: Incubation rate (inverse of latent period)
- γ: Recovery rate (inverse of infectious period)
- N: Total population (fixed at 10,000)
- S_0: Initial susceptible population (possibly reduced due to vaccination)
- E_0, I_0, R_0: Initial exposed, infectious, and recovered individuals

The time span was set as `[0, 365]` days to simulate one year.

3.3 ODE Solvers

For static scenarios (e.g., fixed β and σ), we used:

```
[t, y] = ode45(@(t, y) seir_ode_static(t, y, beta, sigma, gamma, N), tspan, y0);
```

For dynamic scenarios (Scenario 6 and 7), we used:

```
[t, y] = ode45(@(t, y) seir_ode_timevariant(t, y, scenario_id), tspan, y0);
```

3.4 Differential Equations

In both solvers, the SEIR system is defined as:

$$\begin{aligned}
\frac{dS}{dt} &= -\beta \frac{SI}{N} \\
\frac{dE}{dt} &= \beta \frac{SI}{N} - \sigma E \\
\frac{dI}{dt} &= \sigma E - \gamma I \\
\frac{dR}{dt} &= \gamma I
\end{aligned}$$

Time-varying $\beta(t)$ and $\sigma(t)$ were implemented using `seir_ode_timevariant` for relevant scenarios.

3.5 Visualization and Output

Each simulation produces a time-series plot of $S(t)$, $E(t)$, $I(t)$, and $R(t)$ compartments, which is saved as a PNG file under the `SEIR_Output` directory.

3.6 Outcome Metrics

The simulation computes and prints the following for each scenario:

- **Peak Day**: The day when the number of infectious individuals reaches maximum.
- **Peak Infections ($I_{\max}$)**: The maximum number of simultaneous infections.
- **Total Infected Ratio**: Final recovered population $R(t = 365)$ divided by N.

3.7 Execution Environment

All simulations were performed on a standard laptop (Intel Core i5, 8GB RAM).

4 Experimental Scenarios & Results

To investigate the effectiveness of various intervention strategies and disease dynamics, we explore several simulation scenarios based on modifications to the SEIR model parameters. The baseline simulation assumes no intervention, with static parameters.

4.1 Scenario 0: Baseline Simulation (No Intervention)

Parameters:

- Population: $N = 10,000$
- Initial Infectious: $I_0 = 1$
- $\beta = 0.5$, $\sigma = 1/5$, $\gamma = 1/7$

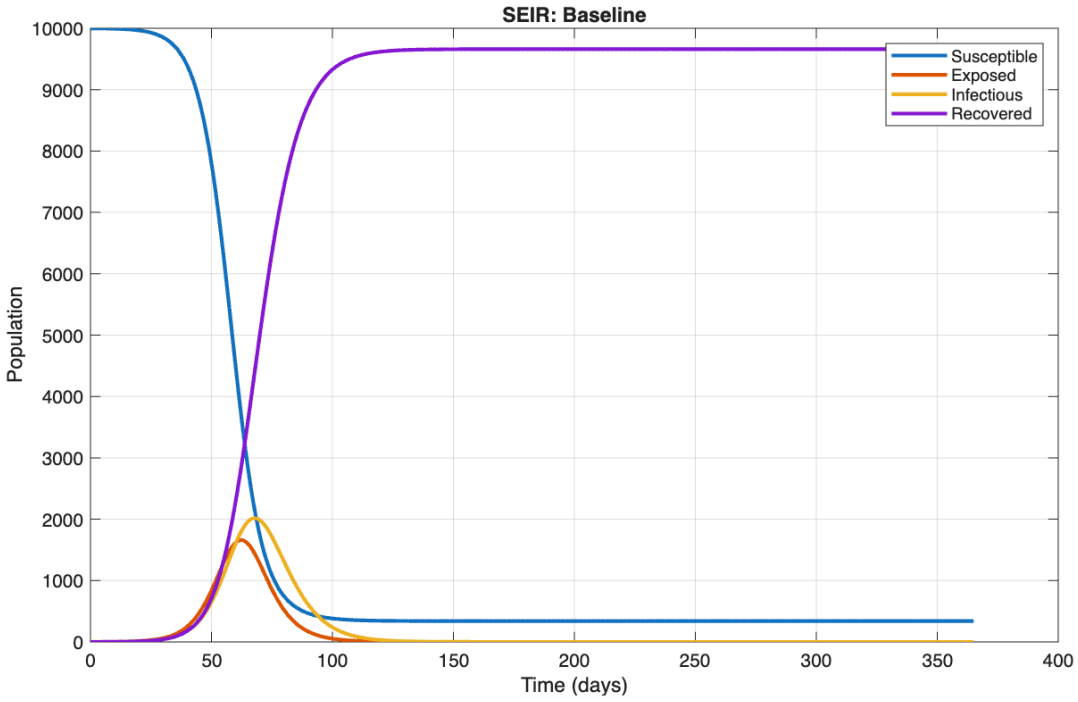

Figure 2: SEIR Simulation: Baseline Scenario (No Intervention)

4.2 Scenario 1: Reduced Transmission Rate (β)

This scenario simulates the impact of social distancing, mask-wearing, or lockdown policies that reduce the disease transmission rate. We simulate the SEIR model under:

- $\beta = 0.25$ (Moderate intervention), $\beta = 0.1$ (Strict lockdown)

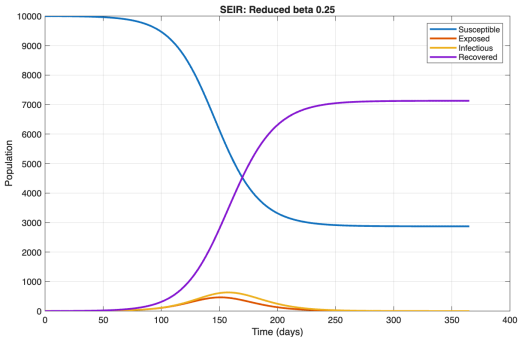

Figure 3: Reduced beta 0.25

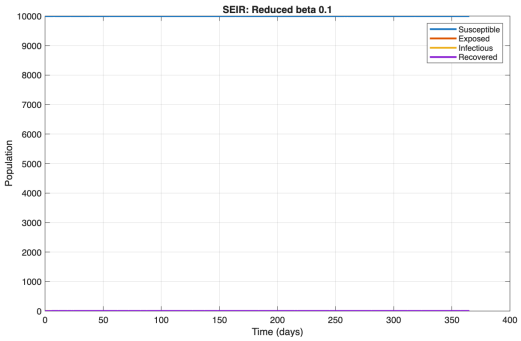

Figure 4: Reduced beta 0.1

4.3 Scenario 2: Increased Recovery Rate (γ)

This experiment models the effect of improved healthcare infrastructure or early treatment strategies that reduce the infectious period:

- $\gamma = \frac{1}{5}$ (Faster recovery), $\gamma = \frac{1}{3}$ (Highly effective treatment)

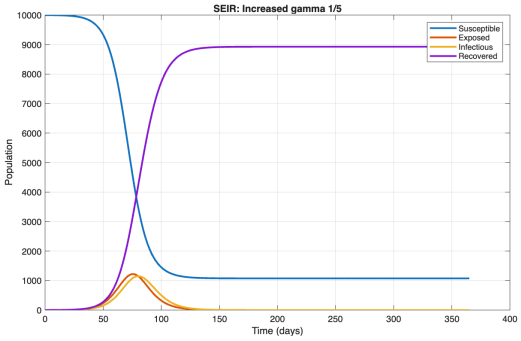

Figure 5: Increased gamma 1/5

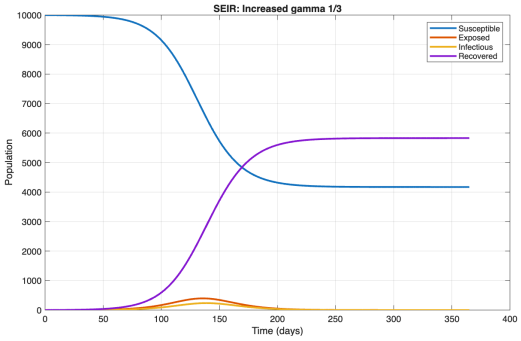

Figure 6: Increased gamma 1/3

4.4 Scenario 3: Shorter or Longer Incubation Period (σ)

This scenario reflects mutations in the virus that affect how quickly individuals become infectious:

- $\sigma = \frac{1}{3}$ (Shorter incubation), $\sigma = \frac{1}{7}$ (Longer incubation)

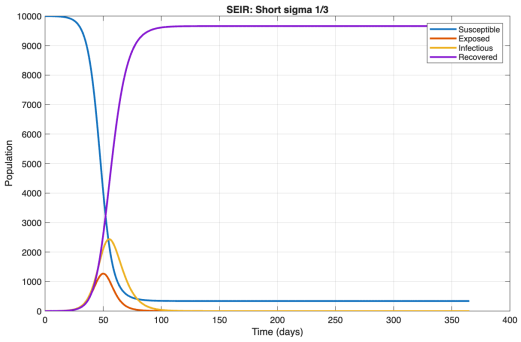

Figure 7: Shorter incubation sigma 1/3

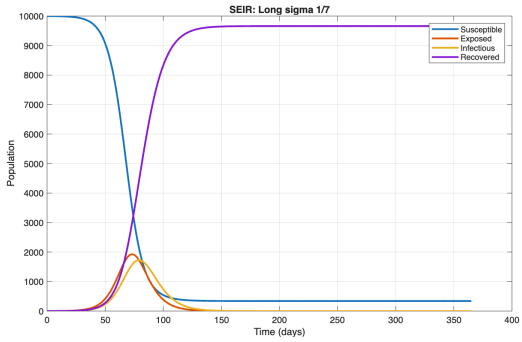

Figure 8: Longer incubation sigma 1/7

4.5 Scenario 4: Partial Vaccination (Reduced S_0)

We simulate pre-existing immunity in a portion of the population due to vaccination:

- $S_0 = 70\%$ of N (30% vaccinated), $S_0 = 40\%$ of N (60% vaccinated)

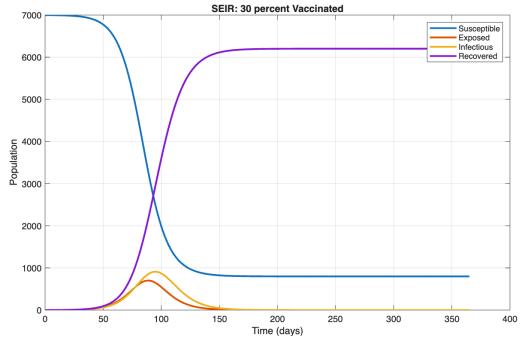

Figure 9: 30% Vaccinated

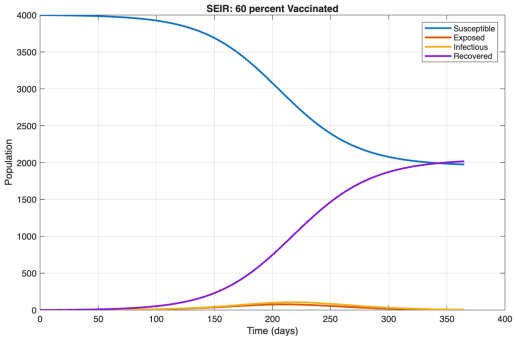

Figure 10: 60% Vaccinated

4.6 Scenario 5: Different Initial Infections

We vary the number of initially infected individuals to assess the effect of early containment:

- $I_0 = 10$, $I_0 = 100$

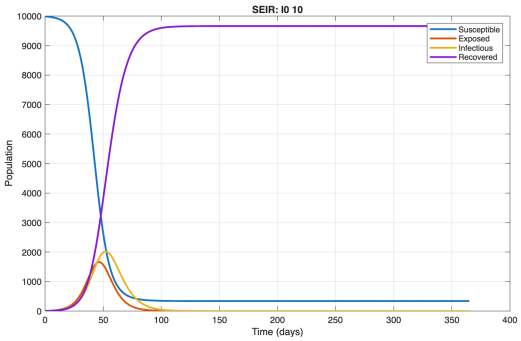

Figure 11: Initial Infectious Individuals: $I_0 = 10$

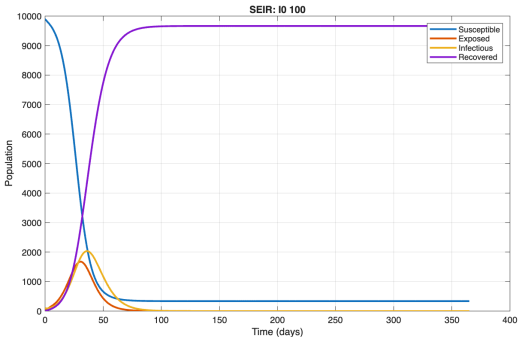

Figure 12: Initial Infectious Individuals: $I_0 = 100$

4.7 Scenario 6: Time-Based Policy Intervention (Dynamic β)

In this scenario, a government intervention such as lockdown is introduced on Day 20. The transmission rate $\beta(t)$ decreases from 0.5 to 0.3 after Day 20, modeling a relatively strong and early intervention policy.

$$\beta(t) = \begin{cases} 0.5 & \text{if } t < 20 \\ 0.3 & \text{if } t \geq 20 \end{cases}$$

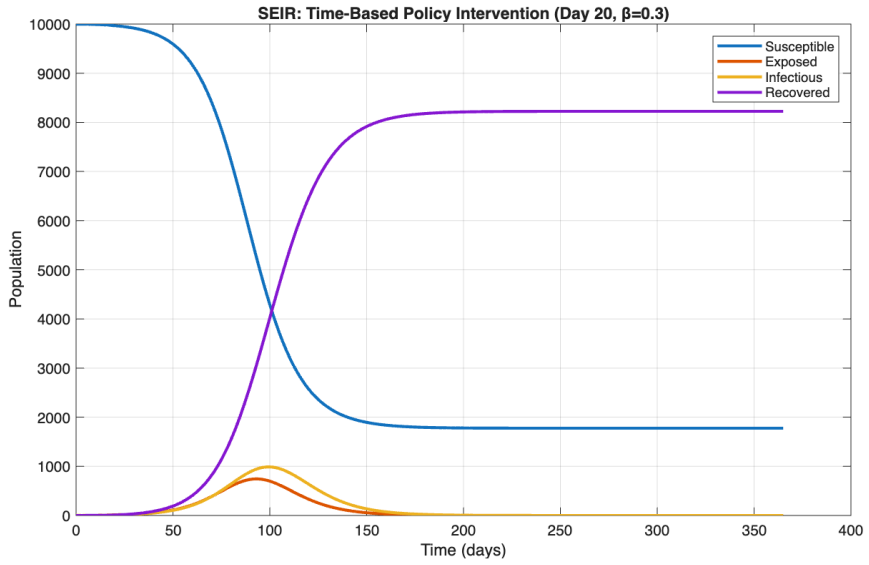

Figure 13: Time-Based Policy Intervention

4.8 Scenario 7: Delayed Variant Emergence (More Extreme)

In this scenario, we simulate a delayed but highly contagious variant emerging after 70 days. This mimics real-world situations in which a second wave, driven by a more transmissible strain, follows an initial period of controlled spread.

$$\beta(t) = \begin{cases} 0.5 & \text{if } t < 70 \\ 1.2 & \text{if } t \geq 70 \end{cases} \qquad \sigma(t) = \begin{cases} \frac{1}{5} & \text{if } t < 70 \\ \frac{1}{2} & \text{if } t \geq 70 \end{cases}$$

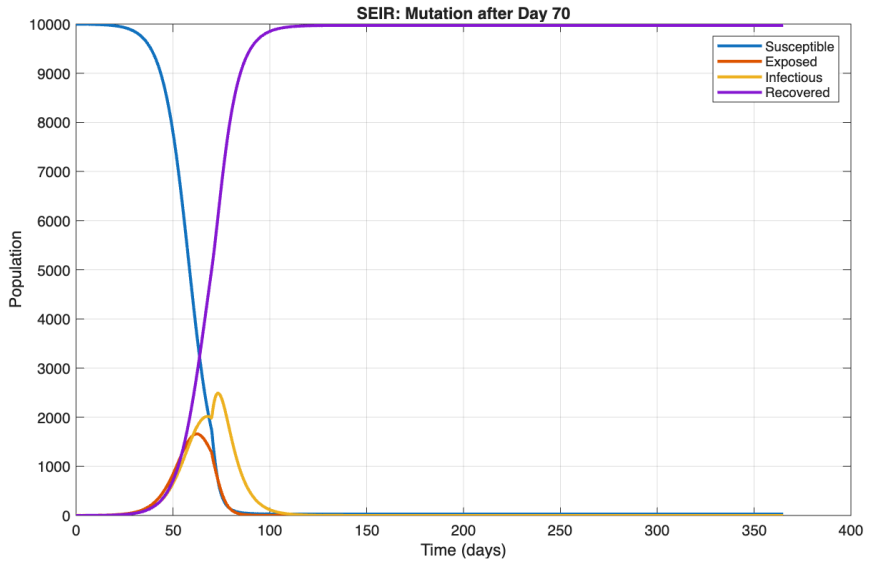

Figure 14: Extreme variant emergence on Day 70

4.9 Summary Table of Scenarios

Scenario	Description	Parameters
0: Baseline	No intervention	$\beta = 0.5$, $\sigma = \frac{1}{5}$, $\gamma = \frac{1}{7}$
1: Reduced Transmission	Models the effect of social distancing or lockdown	$\beta = 0.25,\ 0.1$
2: Increased Recovery	Faster recovery due to improved treatment or healthcare access	$\gamma = \frac{1}{5},\ \frac{1}{3}$
3: Modified Incubation Period	Reflects viral mutation affecting incubation	$\sigma = \frac{1}{3},\ \frac{1}{7}$
4: Partial Vaccination	Pre-existing immunity through vaccination coverage	$S_0 = 70\%N,\ 40\%N$
5: Varying Initial Infections	Tests impact of early containment	$I_0 = 10,\ 100$
6: Time-Based Policy Intervention	Early lockdown on Day 20 reduces β	$\beta(t) = 0.5 \to 0.3$ at $t = 20$
7: Delayed Variant Emergence	Highly infectious variant emerges at Day 70	$\beta(t) = 0.5 \to 1.2$, $\sigma(t) = \frac{1}{5} \to \frac{1}{2}$ at $t = 70$

Table 1: Summary of SEIR Simulation Scenarios and Modified Parameters

5 Main Findings and Analysis

To understand the dynamics of infectious disease transmission under various conditions, we simulated 13 SEIR model scenarios and compared them using two key metrics:

- **Infection Peak Timing (Day)** – The day on which the infectious population (I) reaches its maximum.
- **Total Infected Ratio (%)** – The percentage of the population that transitions from susceptible to recovered (R/N).

Scenario	Peak Day	Peak Infectious (I)	Total Infected (%)
Baseline	84	2016	96.60
Reduced $\beta = 0.25$	115	631	71.27
Reduced $\beta = 0.1$	1	1	0.03
Increased $\gamma = 1/5$	90	1148	89.27
Increased $\gamma = 1/3$	137	236	58.29
Short $\sigma = 1/3$	88	2436	96.60
Long $\sigma = 1/7$	82	1726	96.60
30% Vaccinated	92	909	62.01
60% Vaccinated	135	106	20.17
$I_0 = 10$	81	2019	96.60
$I_0 = 100$	75	2032	96.64
Policy Intervention (Day 20, $\beta = 0.3$)	113	988	82.25
Mutation After Day 70	96	2488	99.73

Table 2: Comparison of infection peak timing and total infected ratio across SEIR scenarios

The baseline scenario serves as the reference point against which other interventions are evaluated.

5.1 Scenario 0: Baseline Simulation (No Intervention)

In the baseline scenario, where no interventions such as vaccination, social distancing, or policy changes are implemented, the simulation shows that the infection peaks relatively early on Day 84, with approximately 2,016 individuals simultaneously infected as shown in Figure 2. Total 96.60% of the population ultimately becomes infected.

5.2 Scenario 1: Reduced Transmission Rate (β)

This scenario explores the impact of reducing the transmission rate to simulate the effects of public health interventions such as social distancing or partial lockdowns.

When β is reduced to 0.25, the infection peak is delayed to Day 115, with a significantly lower peak of 631 simultaneous infections. The total infected population drops to 71.27%. This demonstrates that even moderate interventions can substantially flatten and delay the epidemic curve. An even more extreme case, where β is reduced to 0.1, simulates strict lockdowns and high public compliance. In this case, the infection peaks on Day 1 with only 1 infected individual, and the total infected population remains negligible at 0.03%. These results, illustrated in Figures 3 and 4, highlight the crucial role of reducing transmission in epidemic control.

5.3 Scenario 2: Increased Recovery Rate (γ)

This scenario investigates the effects of increasing the recovery rate γ, which shortens the infectious period and represents scenarios such as improved treatment, faster diagnosis, etc.

When γ is increased to $\frac{1}{5}$, the infection peaks on Day 90 with 1,148 simultaneous infections, and the total proportion of the population infected is 89.27%. This moderate increase in recovery speed slightly reduces both the infection peak and overall spread. In more extreme change, with $\gamma = \frac{1}{3}$, the peak is further delayed to Day 137, and the number of simultaneous infections drops to 236. The total infected proportion also decreases significantly to 58.29%. Figures 5 and 6 illustrate these outcomes.

5.4 Scenario 3: Shorter or Longer Incubation Period (σ)

This scenario explores the effects of changing the incubation rate σ, which determines how quickly exposed individuals become infectious. A shorter incubation period means that individuals reach to the infectious stage more rapidly, whereas a longer incubation period slows down this progression.

With $\sigma = 1/3$, the simulation shows a peak on Day 88 with 2,436 infectious individuals and a total infected proportion of 96.60%. This result demonstrates that even without increasing the transmission rate β, faster progression to the infectious state leads to a more rapid and severe outbreak. In contrast, increasing the incubation period to $\sigma = 1/7$ results in a peak on Day 82 with 1,726 infectious individuals, but the total infected proportion remains high at 96.60%. The outbreak progresses slightly more slowly, and the peak is somewhat flatter and earlier than the baseline scenario. Figures 7 and 8 show difference in incubation periods.

5.5 Scenario 4: Partial Vaccination (Reduced S_0)

This scenario investigates the impact of partial vaccination coverage by reducing the initial susceptible population. Specifically, we compare two cases: 30% vaccinated and 60% vaccinated at the beginning of the simulation.

In the case of 30% vaccination coverage, the peak of infection occurs on Day 92 with approximately 909 infectious individuals, and a total of 62.01% of the population becomes infected. Although the peak is significantly lower than the baseline, group immunity is not reached. This suggests that while partial vaccination can flatten the curve, it may not be sufficient to prevent a large-scale outbreak. In contrast, with 60% vaccination coverage, the outbreak is largely contained. The peak is dramatically reduced to only 106 infectious individuals on Day 135, and the total infected population is only 20.17%.

Figures 9 and 10 show the comparative infection dynamics for 30% and 60% vaccination coverage, respectively. As the vaccination rate increases, both the infection peak and the total number of infected individuals decrease significantly.

5.6 Scenario 5: Different Initial Infections

In this scenario, we investigate how the initial number of infections (I_0) impacts the outbreak dynamics. Two cases are compared: $I_0 = 10$ and $I_0 = 100$. As shown in Figures 11 and 12, increasing the initial number of infected individuals leads to a slightly earlier and higher infection peak. Specifically, the $I_0 = 10$ scenario peaks on Day 81 with 2,019 infections, while $I_0 = 100$ peaks on Day 75 with 2,032 infections. However, the total infected population remains nearly the same in both cases, indicating that the initial seeding size influences the spreading speed but not its eventual magnitude.

5.7 Scenario 6: Time-Based Policy Intervention (Dynamic β)

This scenario simulates the effect of a time-based government intervention, such as a lockdown implemented on Day 20, by reducing the transmission rate β from 0.5 to 0.3. The result, shown in Figure 13, demonstrates a reduction in the infection peak and overall infection compared to the baseline scenario. The infection peaks on Day 113 with 988 simultaneous cases, and a total of 82.25% of the population becomes infected. This highlights the importance of timely interventions, even without changing recovery or incubation rates, modifying contact behavior early can significantly reduce the healthcare burden.

5.8 Scenario 7: Delayed Variant Emergence (More Extreme)

This scenario models the emergence of a highly infectious variant after a prolonged period of relatively stable transmission. Specifically, on Day 70, the transmission rate β increases from 0.5 to 1.2, and the incubation rate σ increases from 1/5 to 1/2.

The result, shown in Figure 14, is a delayed but extremely sharp second wave. The infection peaks on Day 96 with 2,488 simultaneous infections, and the total infected proportion reaches 99.73% of the population. This highlights the critical need for continuous surveillance and rapid response mechanisms to emerging variants, even when initial outbreak dynamics appear under control.

6 Discussion and Conclusion

This project demonstrates the power of the SEIR model for understanding the spread of infectious diseases and evaluating the potential impact of public health interventions [3, 4]. Through systematic simulation of multiple scenarios, we identified several key insights that inform evidence-based epidemic response strategies.

Our analysis shows that early and aggressive reduction in the transmission rate (β) represents the most effective intervention strategy. Reducing β from 0.5 to 0.25 decreased total infections from 96.60% to 71.27%, while extreme reductions to 0.1 eliminating disease spread. This finding underscores the critical importance of implementing social distancing measures, lockdowns, and other transmission-reducing interventions early in an epidemic's spread, consistent with findings from COVID-19 modeling studies [8, 9].

Improved healthcare capacity, modeled through increased recovery rates (γ), also demonstrated significant benefits. Increasing γ from 1/7 to 1/3 reduced total infections to 58.29% and substantially flattened the epidemic curve. This highlights the value of investing in treatment protocols, healthcare infrastructure, and early diagnosis capabilities.

Vaccination coverage emerged as a particularly powerful intervention, with 60% pre-epidemic vaccination reducing total infections to only 20.17% of the population. This result emphasizes the importance of maintaining high vaccination rates to achieve community-level protection and prevent outbreaks.

The dynamic scenarios show the importance of intervention timing and the risks of delayed response. Early policy intervention on Day 20 reduced total infections to 82.25%, while delayed variant emergence after Day 70 resulted in second waves affecting 99.73% of the population. These findings highlight the need for continuous surveillance systems, rapid response capabilities, and the maintenance of intervention measures even during periods of apparent control, as demonstrated in real-world applications during the COVID-19 pandemic [10, 13].

The SEIR model provides valuable insights into epidemic dynamics and serves as an effective tool for policy evaluation [5, 14]. However, our analysis has limitations that future research should address. The model assumes homogeneous mixing within the population, ignores demographic diversity, and does not account for stochastic effects that can significantly influence disease spread in smaller populations or during early outbreak phases. Advanced modeling approaches, including neural network-enhanced SEIR models [15] and multi-feature extensions [7], represent promising directions for future research that could overcome these limitations.

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