Agent-Based SEIRD Modelling of a Closed Community

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Abstract

We develop an agent-based *Susceptible–Exposed–Infectious–Recovered–Dead* (SEIRD) model using the modern `Mesa` 3.2 framework to analyse COVID-19 transmission in a closed population of 10 000 individuals. Model extensions include cost attribution for diagnostics, treatment, isolation and mortality. Baseline dynamics without systematic testing produced a median attack rate of 80 % and a cumulative economic loss of 93.8 m$, of which mortality accounted for 70.3 %. A factorial experiment varied (i) testing interval $\{1, 4, 7, 11, 14\}$ days and (ii) per-test sampling probability $\{0.00, 0.23, 0.45, 0.68, 0.90\}$. The optimal grid point (daily testing at 90 % coverage) reduced loss by 89.6 % to 9.8 m$; conversely, indiscriminate daily testing with 0 % diagnostic yield raised costs to 161 m$. Results highlight the non-linear trade-off between surveillance intensity and marginal benefit, providing quantitative guidance for society containment policies.

1 Introduction

Modern society poses unique challenges for epidemic control because of high population density, heterogeneous contact patterns and limited surge capacity in isolation facilities. While deterministic compartmental models capture macroscopic trends, agent-based approaches retain individual heterogeneity that is critical for evaluating targeted non-pharmaceutical interventions. Here we integrate an agent-level SEIRD transmission kernel with an explicit economic layer to quantify the cost-effectiveness of repeated reverse-transcription polymerase chain reaction (RT-PCR) screening.

2 Methods

2.1 Agent configuration

Each agent possesses a health state $s \in \{S, E, I, R, D\}$, a day-counter and Monte-Carlo contacts drawn from a discrete uniform distribution $U(3, 7)$. Parameter values (Tab. 1) approximately simulate mid-2020 wild-type SARS-CoV-2.

Agent behaviors are described by the Discrete-time Markov Process. Let $X_t \in \{S, E, I, R, D\}$ denote the health state of an arbitrary agent at the beginning of day t. Conditional on the population counts $\big(S_t, E_t, I_t, R_t, D_t\big)$, the one–step transition $P\big(X_{t+1} = j \mid X_t = i\big) = \pi_{ij}(t)$ is governed by the matrix

$$\mathbf{\Pi}(t) = \begin{pmatrix} 1-\lambda_t & \lambda_t & 0 & 0 & 0 \\ 0 & 1-\sigma & \sigma & 0 & 0 \\ 0 & 0 & 1-\gamma-\delta & \gamma & \delta \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}, \qquad \lambda_t = \beta\, c\, \frac{I_t}{N},$$

where

$$\gamma = (1 - p_{\text{death}})\gamma, \qquad \delta = p_{\text{death}}\gamma.$$

Table 1: Epidemiological and economic parameters.

Parameter	Symbol	Value
Basic infection probability per contact	β	0.15
Mean incubation period (days)	σ^{-1}	5.5
Mean infectious period (days)	γ^{-1}	14
Case-fatality probability	p_{death}	0.005
Cost per RT-PCR test (\$)	c_{test}	50
Daily treatment cost per infectious (\$)	c_{inf}	250
Daily isolation cost per case (\$)	c_{iso}	1500
Statistical value of life (\$)	c_{death}	1.2 M

2.2 Testing module

At simulation step t, if t is an end of a testing interval I_{test}, each agent is sampled with probability p_{test}. Infectious positives are *immediately* transferred to the recovered compartment (proxy for perfect isolation) and incur an isolation cost. False negatives are ignored, and specificity is assumed to be 100 %.

2.3 Experimental design

Two experimental blocks were run:

2.3.1 Baseline experiment

The baseline comprises *two* counter-factual scenarios executed under identical epidemiological parameters (Table 1):

1. **No-testing scenario (NT).** Diagnostics are disabled ($p_{\text{test}} = 0$) and infectious cases follow the natural SEIRD course.

2. **Routine-testing scenario (RT).** Default surveillance is enabled with a 7-day interval and 20 % random sampling per round ($I_{\text{test}} = 7,\ p_{\text{test}} = 0.20$).

2.3.2 Factorial grid

In order to investigate the impact of testing, multiple experiments with different combinations of the testing interval and testing probability are conducted. Specifically, $I_{\text{test}} \in \{1, 4, 7, 11, 14\}$ days, $p_{\text{test}} \in \{0.00, 0.23, 0.45, 0.68, 0.90\}$. Five stochastic replicates per cell used unique seeds; results were averaged.

3 Results

3.1 Baseline epidemic trajectory

Compared with NT, routine testing (RT) reduced cumulative loss by **29.4 %** and mortality by **58 %**. Expenditure shifted markedly: diagnostic and isolation costs jointly absorbed 29.1 % of the budget, displacing mortality from 70.3 % down to 41.7 %. The epidemic tail, however, lengthened by 46 days because early identification prevented explosive spread but allowed low-level transmission to persist (Tab. 2)

Table 2: Outcome metrics for the two baseline scenarios.

Metric	**NT (No test)**	**RT (Routine test)**
Total economic loss (M$)	93.84	66.25
- testing (%)	0.0	23.4
- medical (%)	29.7	29.3
- isolation (%)	0.0	5.7
- mortality (%)	70.3	41.7
Total deaths	55	23
Total isolations	0	7
Duration (days)	171	217

It's also shown in Fig. 1, the number of infection cases rose rapidly in the early stage and reached its peak at a similar time (50-60 days). However, compared with NT, the infection peak of RT is lower.

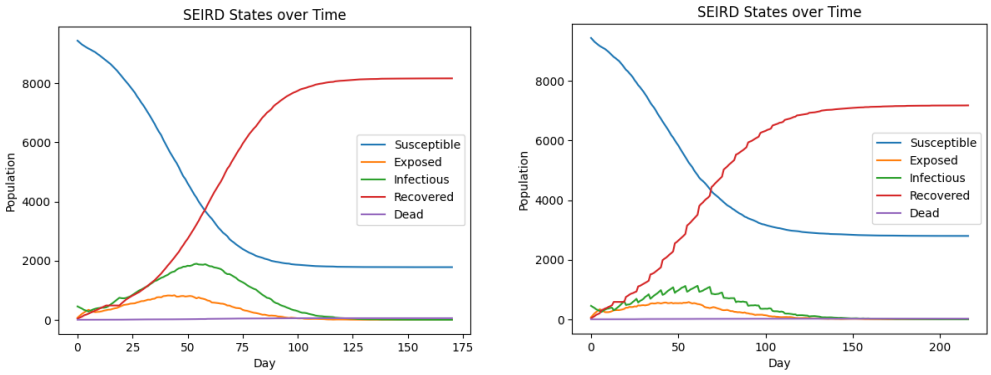

Figure 1: SEIRD states over time without systematic testing. (Left: NT, Right: RT)

3.2 Cost composition

Mortality dominated expenditure (Fig. 2), consuming 70.3 % of the 93.8 m$ loss; treatment costs contributed 29.7 %.

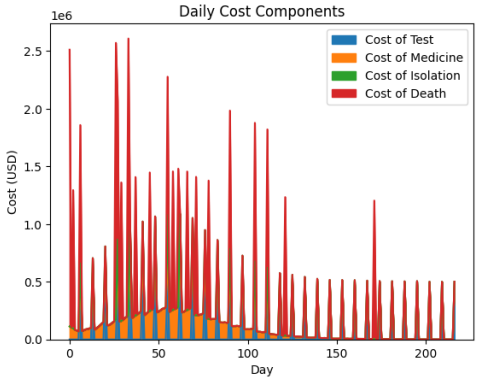

Figure 2: Daily cost components for the baseline scenario.

3.3 Impact of testing strategies

Cumulative costs across the 5×5 grid are summarised in Fig. 3. High-frequency, high-probability testing (*bottom-left*) minimised losses, whereas frequent testing with zero yield (*top-left*) was counter-productive.

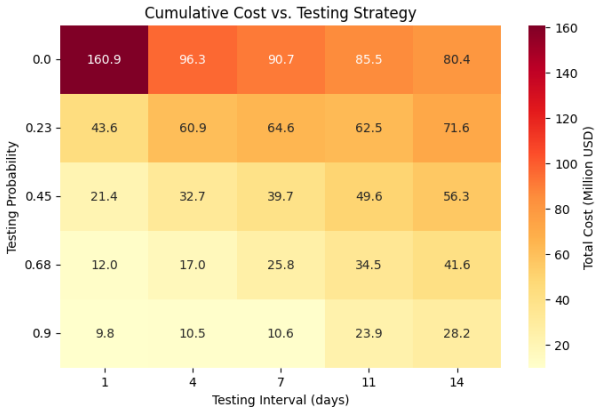

Figure 3: Mean total economic loss (in million USD) as a function of testing interval and sampling probability.

4 Discussion

The NT scenario illustrates the heavy macro-economic burden of uncontrolled outbreaks, with mortality dominating cost. Introducing even *modest* routine surveillance (20 % sampling every week) produced a cost–benefit ratio. Nonetheless, policymakers must weigh the trade-off between reduced mortality and prolonged epidemic duration, which can strain society operations. Future work should explore adaptive test frequencies, targeted sampling and partial isolation efficacy to refine these baseline insights.

The model suggests diminishing returns when extending the swab interval beyond one week once testing probability exceeds 68 %. Conversely, expensive universal screening without subsequent case finding (the $p_{\text{test}} = 0$ row) drastically inflates cost due to repeated laboratory expenditure without epidemiological benefit.

Limitations include homogeneous mixing and deterministic isolation efficacy; incorporating classroom contact networks or partial adherence would refine estimates.

5 Conclusion

A daily RT-PCR programme covering at least 90 % of the population could lower cumulative economic loss by nearly 90 %. Policy makers should balance laboratory capacity with realistic participation rates to attain maximal cost-effectiveness.