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Optimal Control Policies to Address the Pandemic Health-Economy Dilemma

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Outline

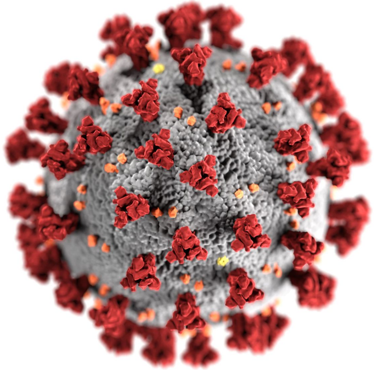
1. Background & Contribution
2. Proposed Model and Objective
3. Multi-Objective Optimization Problem
4. Experiment Setup and Simulation Results
5. Strategy Discussion
6. Conclusion

Health-Economy-Dilemma during a Pandemic

- Non-Pharmaceutical Interventions (NPIs) are used to avoid virus spreading
- NPIs shock social and economic behavior
- Multi-objective optimization algorithms can find a trade-off between
    - containing the pandemic
    - maintaining a stable economy

Related works, e.g.:

1. Yousefpour et. al suggest using EAs to optimize control policies, based on strategic goals
2. Miralles et. al. use Deep Learning and GAs to optimize the best sequence of government actions



A. Yousefpour, H. Jahanshahi, and S. Bekiros, “Optimal policies for control of the novel coronavirus (covid-19),” Chaos, Solitons & Fractals, p. 109883, 2020.
Luis Miralles-Pechuán, Fernando Jiménez, Hiram Ponce, and L. Martínez-Villaseñor. 2020. “A Methodology Based on Deep Q-Learning/Genetic Algorithms for Optimizing COVID-19 Pandemic Government Actions”, Proceedings of the 29th ACM International Conference on Information & Knowledge Management (CIKM '20), 2020.

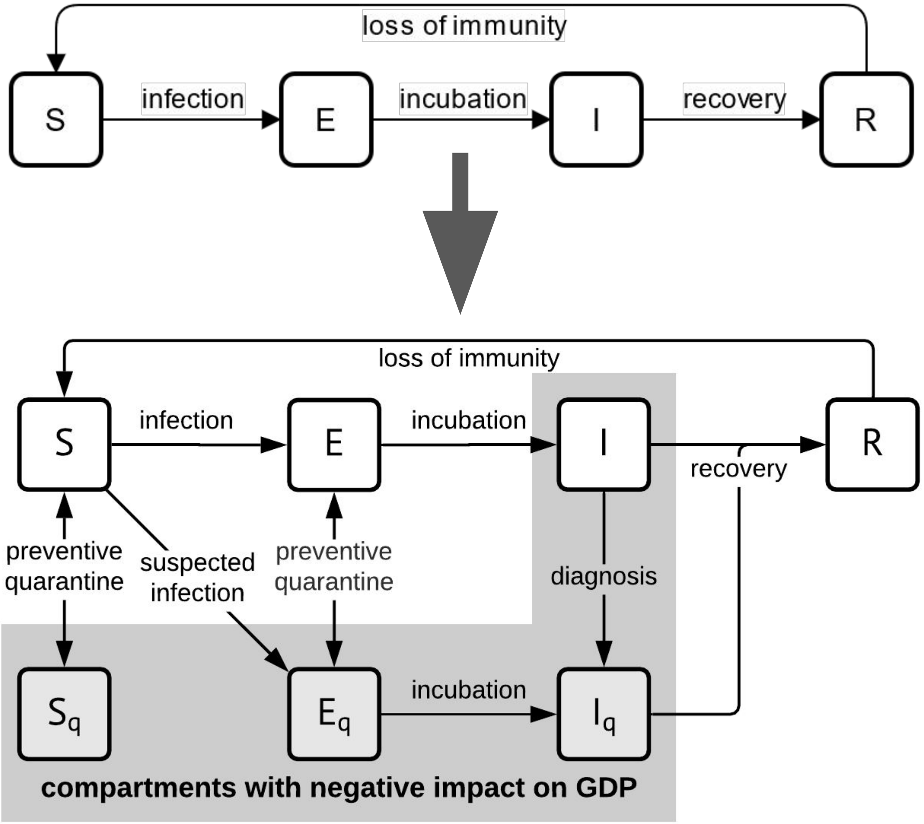
Our Contributions

1. **Extending the basic SEIR** pandemic spread model
    a. Integrating policies
    b. Integrating economy
2. Using multi-objective evolutionary algorithms (MOEAs) to **optimize the policies**
    a. Minimize the maximum number of infections
    b. Minimize the maximum damage on GDP growth
    c. Optimize the policies' trigger times
3. Identifying **optimal strategies for Decision-Makers**
    a. Baseline: No interventions
    b. Focus on health
    c. Focus on economy
    d. Trade-off strategy

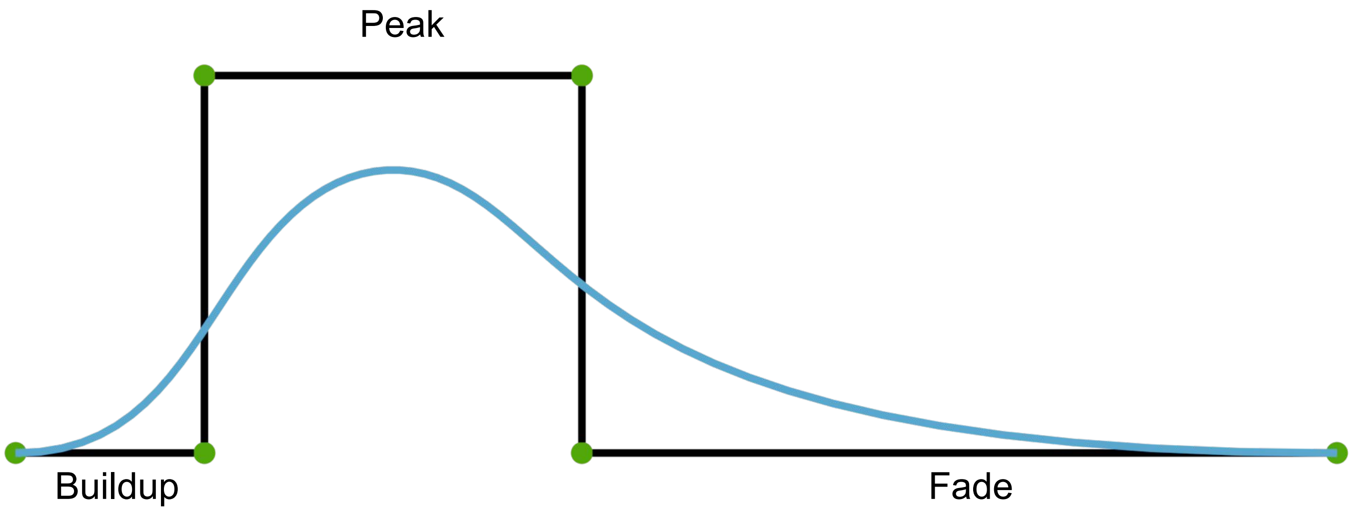
The extended SEIR model

Our extensions:

1. Quarantine compartments
2. Economic compartment
3. Linking health and economy
4. Adding control policies



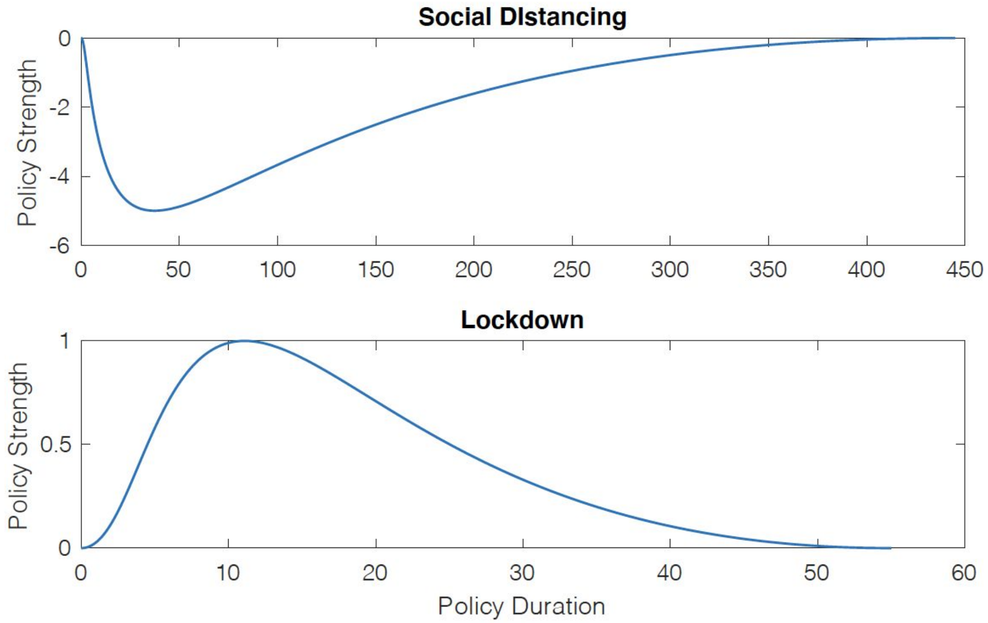
Modeling of Control Policies



- Influence curve of the policies is modeled by a bezier curve
- Total Duration = Buildup + Peak + Fade
- Curve is scaled to match amplitude
- Trigger time decides when policy starts → We only optimize this

Implemented Policies

- **“Social distancing”**, reducing *contact rate*
- **“Lockdown”**, increasing *preventive quarantine rate*



We optimize the trigger times for these two policies

Multi-Objective Optimization Problem (MOP)

MOP involves more than one objective function that are to be minimized or maximized simultaneously under certain constraints

The solution of MOP is a set of Pareto-optimal solutions that define the best trade-off between the objectives

In this paper we minimize two objectives ($min(f_1, f_2)$):

- **Health Objective (f_1):** Minimize the maximum number of infections

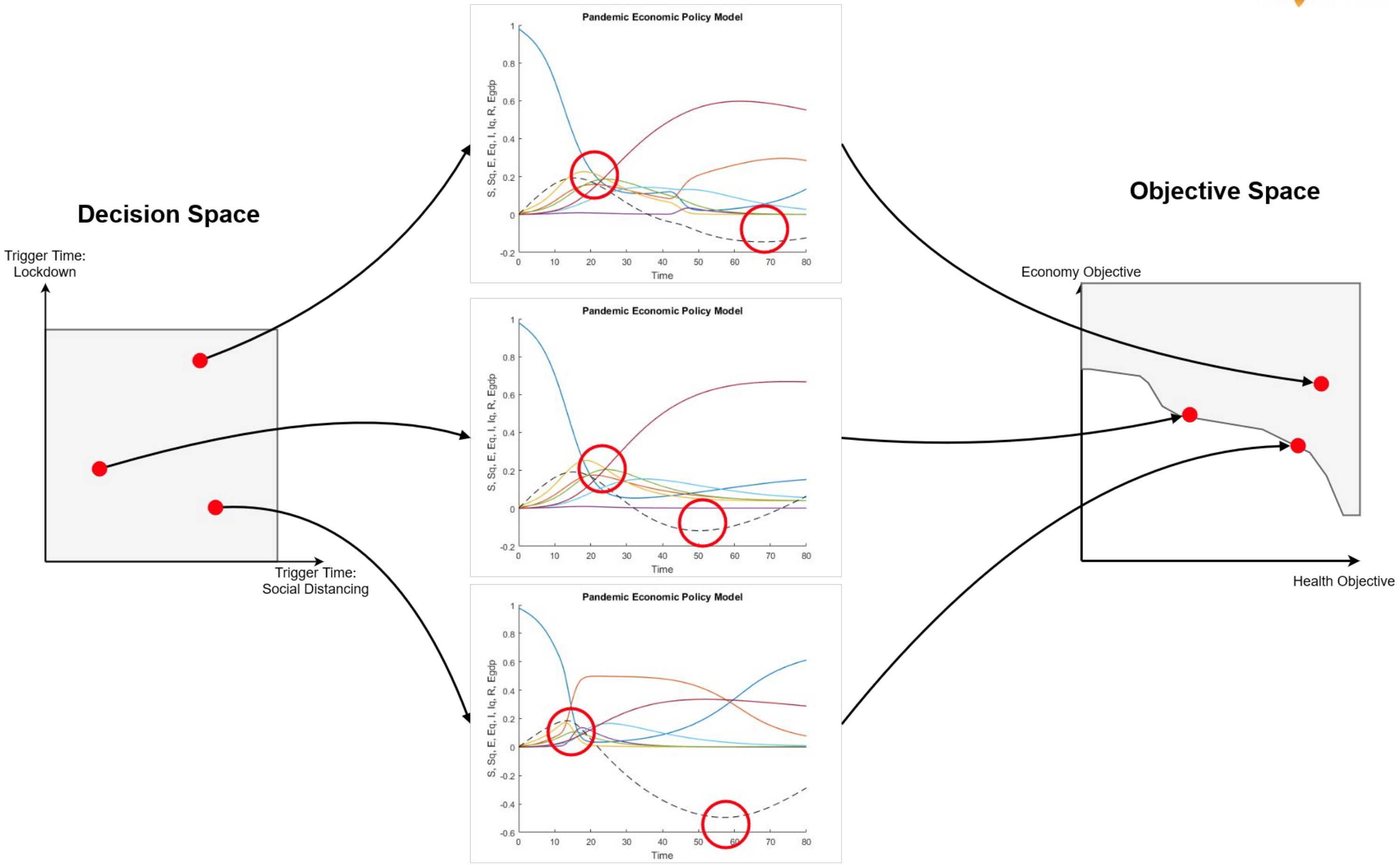
$$f_1(\mathbf{t}) = \max_{\mathbf{t}}(E(t,\mathbf{t}) + E_q(t,\mathbf{t}) + I(t,\mathbf{t}) + I_q(t,\mathbf{t}))$$

- **Economy Objective (f_2):** Minimize the maximum damage on GDP

$$f_2(\mathbf{t}) = -\min_{\mathbf{t}} GDP(t,\mathbf{t})$$

t = time, $\mathbf{t}$ = decision vector

Multi-Objective Optimization Problem (MOP)



Decision Space

Trigger Time: Lockdown

Trigger Time: Social Distancing

Objective Space

Economy Objective

Health Objective

Traditional Versus Modern MOO techniques

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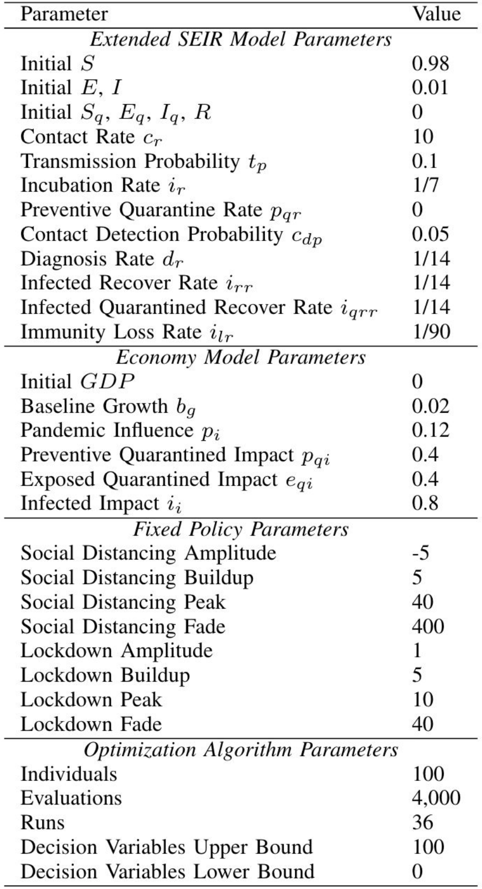
- Difficult to set weight vectors to obtain Pareto-optimal solutions in desired region
- Require knowledge of Minimum and maximum objective values
- Requires sequential runs
- Examples
  - Weighted Sum Method
  - Boundary Intersection Approach
  - Ɛ - Constraint Method

- Simple and robust in implementation.
- Can be extended to any kind of objective spaces
- Operate over a set of candidate solutions
- A single-run approach
- Examples
  - NSGA II
  - NSGA III
  - MOEA/D

Experiment Setup

- 4 Algorithms
  - NSGA-II, NSGA-III, MOEA/D, MOPSO
  - Running via the PlatEMO framework
  - 4,000 evaluations, 100 Individuals, 36 runs
- Simulated time span: 0 - 300 time units [roughly days]
- Decision variables lower bound: 0
- Decision variables upper bound: 100



Parameter	Value
Extended SEIR Model Parameters	
Initial S	0.98
Initial E, I	0.01
Initial S_q, E_q, I_q, R	0
Contact Rate c_r	10
Transmission Probability t_p	0.1
Incubation Rate i_r	1/7
Preventive Quarantine Rate p_{qr}	0
Contact Detection Probability c_{dp}	0.05
Diagnosis Rate d_r	1/14
Infected Recover Rate i_{rr}	1/14
Infected Quarantined Recover Rate i_{qrr}	1/14
Immunity Loss Rate i_{lr}	1/90
Economy Model Parameters	
Initial GDP	0
Baseline Growth b_g	0.02
Pandemic Influence p_i	0.12
Preventive Quarantined Impact p_{qi}	0.4
Exposed Quarantined Impact e_{qi}	0.4
Infected Impact i_i	0.8
Fixed Policy Parameters	
Social Distancing Amplitude	-5
Social Distancing Buildup	5
Social Distancing Peak	40
Social Distancing Fade	400
Lockdown Amplitude	1
Lockdown Buildup	5
Lockdown Peak	10
Lockdown Fade	40
Optimization Algorithm Parameters	
Individuals	100
Evaluations	4,000
Runs	36
Decision Variables Upper Bound	100
Decision Variables Lower Bound	0

Parameters of Algorithms:

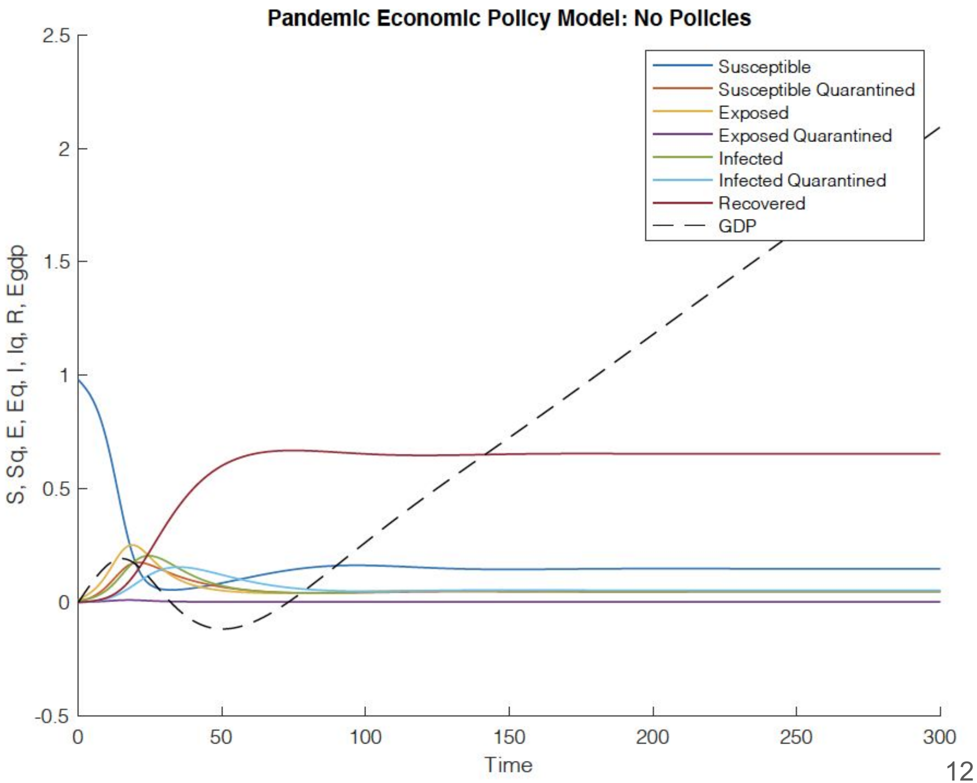
- NSGA II & NSGA III
  - Crossover and Mutation rates: $U(0,1)$
- MOPSO
  - Inertia weight: $w = 1$
  - Cognitive learning factor: $c_1 = 2$
  - Social learning factor: $c_2 = 2$
- MOEA/D
  - Weight vector: $\lambda = 1$

Ye Tian, Ran Cheng, Xingyi Zhang, and Yaochu Jin, PlatEMO: A MATLAB Platform for Evolutionary Multi-Objective Optimization [Educational Forum], IEEE Computational Intelligence Magazine, 2017, 12(4): 73-87

Baseline: No active policies / no optimization

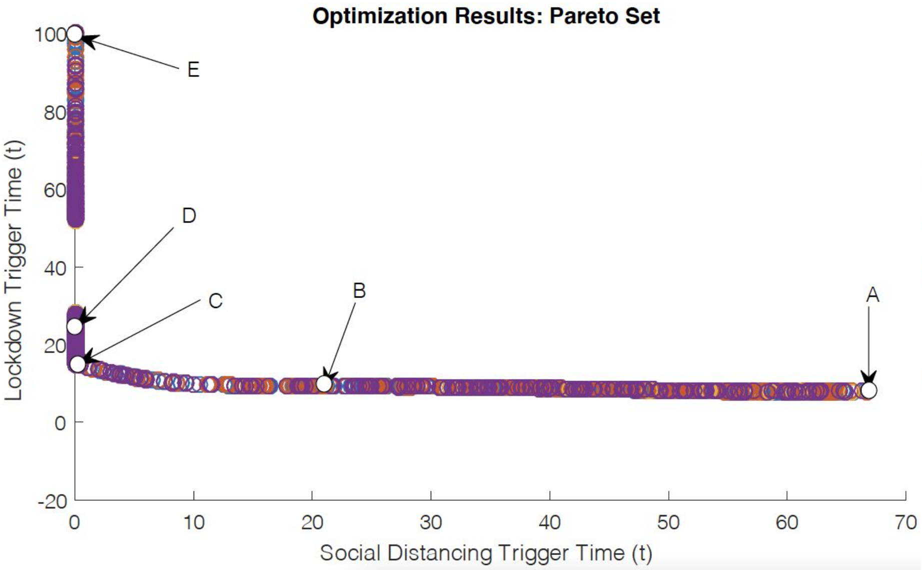
The simulation shows:

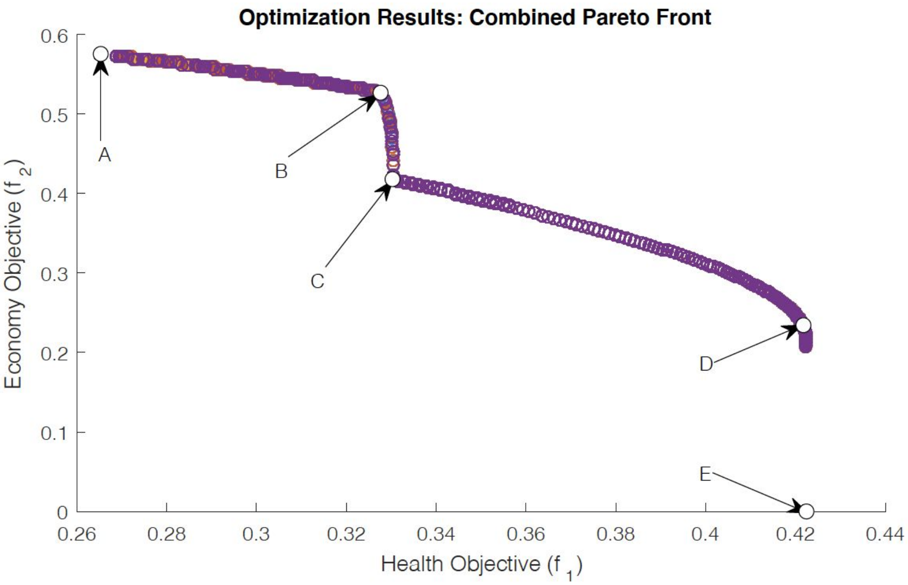
1. A single wave
2. Many early infections
3. A minor decline of the ***GDP***
4. Objectives:
   a. Peak of infections: f_1 = 0.5403
   b. Peak of GDP decline below zero: f_2 = 0.1178



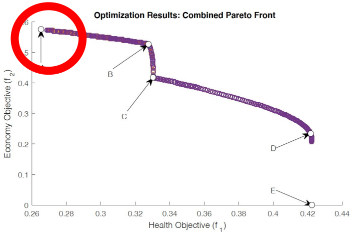
Results [combination of the results of all Algorithms]

We identify several optimal strategies from the Pareto front (A, B, C, D, and E) and analyze in the next slides:





Strategy A: Minimize impact on health

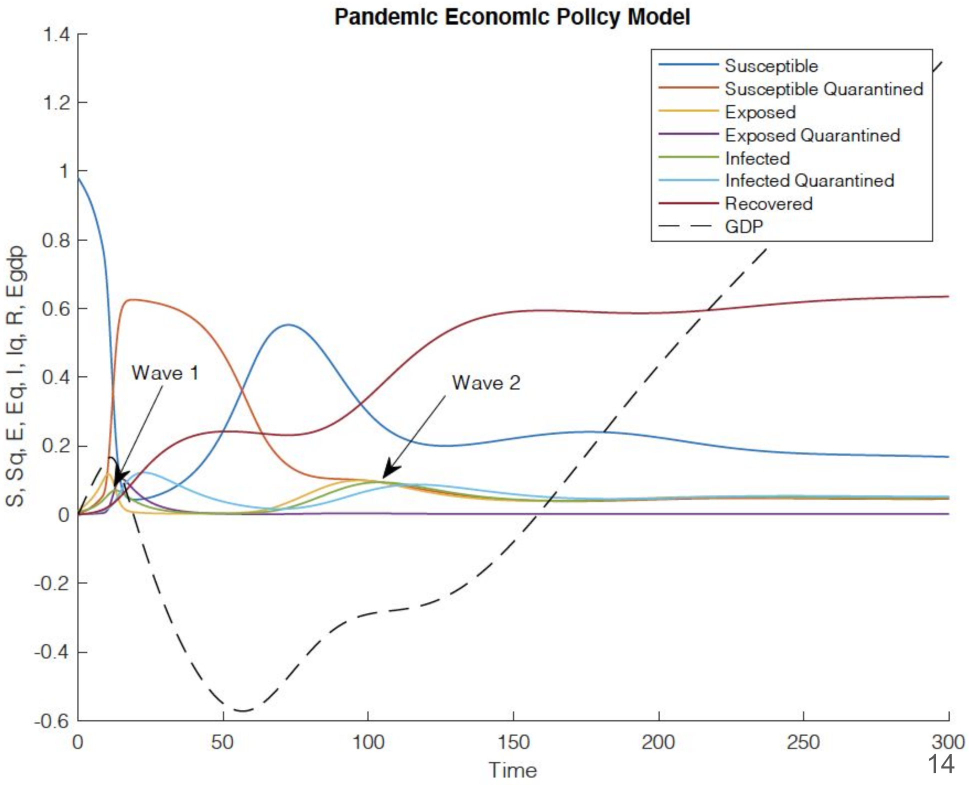


Triggering times of ...

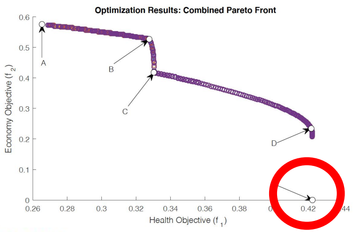
- Lockdown: t = 8.00247
- Social distancing: t = 66.8182

Objectives:

- A maximum of 26.5% (f_1 = 0.2650) individuals are infected simultaneously
- The GDP growth declines significantly (f_2 = 0.5752)



Strategy B: Focus on Economy

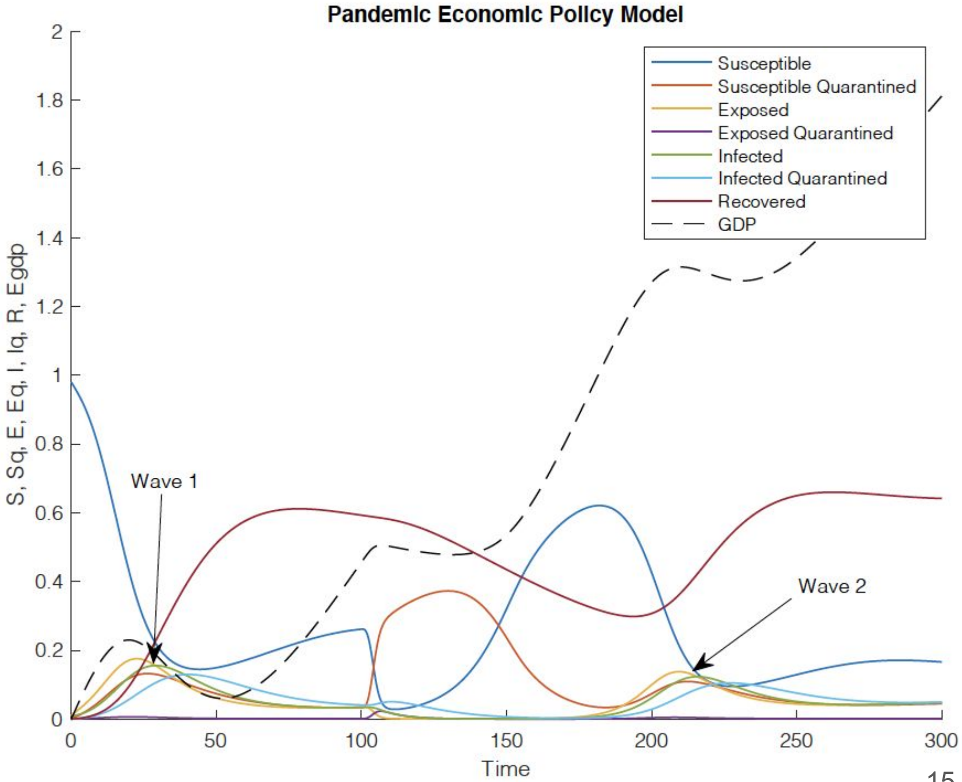


Triggering times of ...

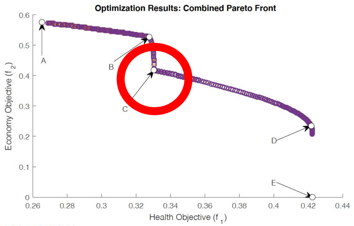
- Lockdown: t = 100
- Social distancing: t = 0.09506

Objectives:

- 42.23% of individuals are infected simultaneously (f_1 = 0.4223)
- The GDP won't worsen (f_2 = 0)



Strategy C: Trade-off Strategy

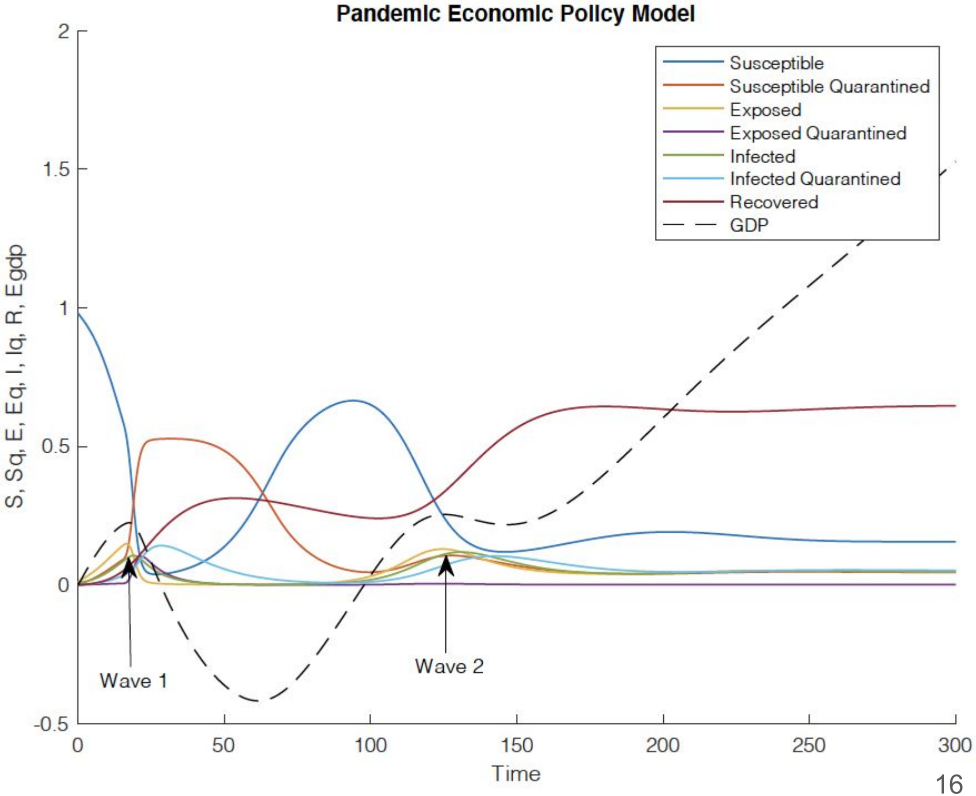


Triggering times of …

- Lockdown: t = 15.0575
- Social distancing: t = 0.0584

Objectives:

- 33.06% of individuals are at most infected simultaneously (f_1 = 0.3306)
- GDP has an early decline peak (f_2 = 0.4181)



Conclusion

- This works models the **impact of NPI policies on economic growth and virus spreading**
- We present **a bi-objective optimization problem** with **conflicting health and economy objectives**.
- Using MOEAs to find **Pareto-optimal trigger times** for social distancing and lockdown.
- Future Work: Refine compartments, objectives, and policies

Our observations support the idea that new infection waves are inevitable if NPIs are dropped before herd immunity is achieved.

In the absence of efficient treatment or vaccination, NPIs therefore need to be employed continuously.