### Lecture 9: Full Calibration of SIR Models

#### Radu Balan

#### Department of Mathematics, NWC University of Maryland, College Park, MD

Version: February 27, 2024

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへで

## SIR Model Calibration

Recall the model:

$$\begin{array}{rcl} \frac{dS}{dt} &=& -\beta S \frac{I}{N} \ , \ S(0) \\ \frac{dI}{dt} &=& \beta S \frac{I}{N} - \alpha I \ , \ I(0) \\ \frac{dR}{dt} &=& \alpha I \ , \ R(0) \end{array}$$

with the sub-compartments  $X(t) = (1 - \gamma)R(t)$  for "recovered" and  $Y(t) = \gamma R(t)$  for deaths.

Before making useful predictions (testing), the model has to be calibrated. Last time we analyzed estimators for  $\gamma$  from the time series of *cumulative detected infections*, { $V(0), \dots, V(T_{max})$ }, and the time series of *cumulative deaths*, { $Y(0), \dots, Y(T_{max})$ }. The idea was to minimize over  $\tau \ge 0, \gamma \in [0, 1]$  the norm  $||Y(\cdot + \tau) - \gamma V||_p$ , scaled by the number of terms in each sum. Now we integrate these estimators into a scheme that performs full calibration of the SIR model.

Radu Balan (UMD)

## Optimization based on Forward Model Simulation

Pre-processing steps

**Step 1:**  $t_0$ . First detect the onset of infections, and reset the time origin to match this starting time  $t_0$ .

**Step 2:** I(t). The time series of cumulative detected infections  $\{V(0), \dots, V(T_{max})\}$  should be turned into a rate of infections. The daily rate may not be relevant to infection transmissions. Instead use a time window to convert the cumulative count into a rate:

$$I(t) = V(t + t_0 + \tau_0) - V(t + t_0 - \tau_0)$$
,  $t = 0, 1, 2, \cdots, T_{max}$ 

where  $\tau_0 > 0$  is chosen so that  $\tau_0$  accounts for average infection period. For Covid-19 it is somewhere between 5 days and 10 days. A possible value is  $\tau_0 = 7$ . Thus I(t) measures the number of invections in a 2-week period centered around t.

**Step 3:**  $Y_{measured}$ . Align the time series of cumulative death with the onset time  $t_0$ :

$$Y_{measured}(t)=Y(t+t_0)~,~t=0,1,2,\cdots,T_{max}.$$

## Optimization based on Forward Model Simulation The Meta Loop

A natural choice for initial conditions is given by: S(0) = N and R(0) = 0, where we assumed  $I(0) \ll N$ :

$$\begin{cases} \frac{dS_{sim}}{dt} = -\beta S_{sim} \frac{I_{sim}}{N} , S_{sim}(0) = N \\ \frac{dI_{sim}}{dt} = \beta S_{sim} \frac{I_{sim}}{N} - \alpha I , I_{sim}(0) = I(0) > 0 \\ \frac{dR_{sim}}{dt} = \alpha I_{sim} , R_{sim}(0) = 0 \\ Y_{sim} = \gamma R_{sim} \end{cases}$$

At this point, the parameters that need to be estimated are:  $\{\alpha, \beta, \gamma\}$ . The Forward Model based calibration works like this:

1. Construct a search set  $\Omega$  of the "free" parameters  $(\alpha, \beta)$ 

2. For each pair  $(\alpha, \beta) \in \Omega$ : (i) run the forward SIR model using an Euler scheme that produces  $(S_{sim}, I_{sim}, R_{sim})$ . (ii) Fit  $\hat{\gamma}$  to match the observed time series  $Y_{measured}$ . (iii) Fit  $\hat{\rho}$  that measures the undercounting factor in detected infections *I*. (iv) Compute the value of the objective function  $J_{\rho}(\alpha, \beta, \hat{\gamma}, \hat{\rho})$ .

3. Select  $(\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\rho})$  that minimize  $J_{\rho}$ .

# Optimization based on Forward Model Simulation

Details: The objective function

The objective function  $J_p$  is chosen to measure residuals  $I - \rho I_{sim}$  and  $Y_{measured} - Y_{sim}$ . Fix cost coefficients  $c_I$  and  $c_Y$ . For  $1 \le p < \infty$  define

$$J_{p}(\alpha,\beta,\gamma,\rho) = c_{I} \sum_{t=0}^{T_{max}} |I(t) - \rho I_{sim}(t)|^{p} + c_{Y} \sum_{t=0}^{T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)|^{p}$$

For  $p = \infty$  define

$$J_{\infty}(\alpha, \beta, \gamma, \rho) = c_{I} \max_{0 \le t \le T_{max}} |I(t) - \rho I_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le t \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{measured}(t) - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_{sim}(t)| + c_{Y} \max_{0 \le T_{max}} |Y_{max} - \gamma R_$$

Typical choices:  $p = 1, 2, \infty$  and  $(c_I, c_Y) = (0, 1)$  (if the cumulative detected infections are unreliable) or  $(c_I, c_Y) = (1, 1)$  (if detected infections is a reliable measure).

Radu Balan (UMD)

#### The Calibration Algorithm for SIR Models Algorithm (Meta-Algorithm for SIR Calibration)

Inputs: Time series  $\{V(0), \dots, V(T)\}$ ,  $\{Y(0), \dots, Y(T)\}$ . Parameters:  $V_{min}$  (default,  $\overline{V_{min}} = 5$ ),  $\tau_0$  (default,  $\tau_0 = 7$ ), N = Population,  $p \in [1, \infty]$  (default, p = 2),  $c_l, c_Y > 0$ . Search set  $\Omega$ .

**1** Detect the onset of the infection  $t_0$  as the first time so that  $V(t_0) \ge V_{min}$ , reset the time origin, and create the time series of infection rates  $I(t) = V(t + t_0 + \tau_0) - V(t + t_0 - \tau_0)$ , and aligned cumulative death  $Y_{measured}(t) = Y(t + t_0), \ 0 \le t \le T_{max}$ .

#### **2** For each $(\alpha, \beta) \in \Omega$ repeat:

• Simulate a SIR model with parameters  $(\alpha, \beta)$  and initial condition  $S_{sim}(0) = N$ ,  $I_{sim}(0) = I(0)$ ,  $R_{sim}(0) = 0$ , and obtain daily time series  $(S_{sim}, I_{sim}, R_{sim})$ .

**2** Solve 
$$\hat{\gamma} = \operatorname{argmin}_{\gamma} \| Y_{\text{measured}} - \gamma R_{\text{sim}} \|_{p}$$
.

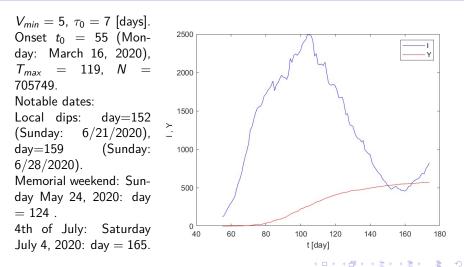
3 Solve 
$$\hat{\rho} = \operatorname{argmin}_{\rho} \|I - \rho I_{sim}\|_{\rho}$$

**3** Compute the objective function  $J = J_p(\alpha, \beta, \hat{\gamma}, \hat{\rho})$ .

**3** Determine the minimum and the minimizer of J. Outputs: Estimated  $\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\rho}$  and minimum value  $J_{min}$ .

# Numerical results (1)

Analysis of DC data for 2020



Radu Balan (UMD)

### Numerical results (2) Analysis of DC data for 2020. p = 1, $c_I = 0$ , $c_Y = 1$

3000

#### Results: $\hat{\alpha} = 0.5, \ \hat{\beta} = 0.62,$

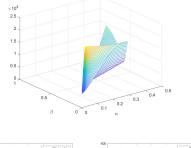
$$\hat{R_0} = 1.24$$
,

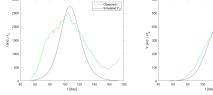
 $\hat{\gamma} = 0.21\%$ .

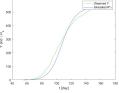
$$\hat{
ho} = 19\%$$

 $J_{optim} = 2690.$ 

#### J=J(alpha.beta.gamma=0.002104.rho=0.192764) for cl=0.000000, cY=1.000000







MATH 420: SIR Calibration

 $\times 10^{6}$ 

## Numerical results (3) Analysis of DC data for 2020. p = 2, $c_l = 0$ , $c_Y = 1$

#### J=J(alpha,beta,gamma=0.001950,rho=0.183072) for cl=0.000000, cY=1.000000

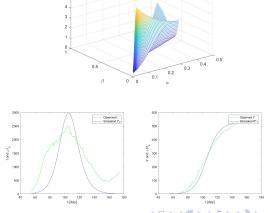
Results:  $\hat{\alpha} = 0.49, \ \hat{\beta} = 0.617$ 

 $\hat{R_{0}} = 1.26$ ,

 $\hat{\gamma} = 0.195\%.$ 

 $\hat{
ho}=18\%$ 

 $J_{optim} = 89365.$ 



MATH 420: SIR Calibration

### Numerical results (4) Analysis of DC data for 2020. $p = \infty$ , $c_I = 0$ , $c_Y = 1$

#### J=J(alpha,beta,gamma=0.001944,rho=0.220337) for cl=0.000000, cY=1.000000

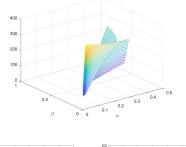
Results:  $\hat{\alpha} = 0.5$ ,  $\hat{\beta} = 0.63$ ,

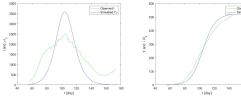
 $\hat{R_0} = 1.26$ ,

 $\hat{\gamma} = 0.19\%.$ 

 $\hat{
ho} = 22\%$ 

 $J_{optim} = 44.98.$ 





MATH 420: SIR Calibration

### Numerical results (5) Analysis of DC data for 2020. p = 1, $c_l = 1$ , $c_Y = 1$

# Results: $\hat{\alpha} = 0.5, \ \hat{\beta} = 0.61,$

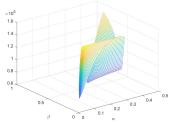
$$\hat{R_0} = 1.22$$
,

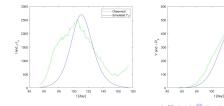
 $\hat{\gamma} = 0.23\%$ .

$$\hat{
ho} = 22\%$$

 $J_{optim} = 67250.$ 

#### J=J(alpha,beta,gamma=0.002310,rho=0.218467) for cl=1.000000, cY=1.000000







MATH 420: SIR Calibration

### Numerical results (6) Analysis of DC data for 2020. p = 2, $c_l = 1$ , $c_Y = 1$

#### Results: $\hat{\alpha} = 0.5, \ \hat{\beta} = 0.62$

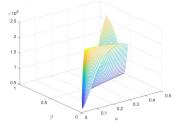
$$\hat{R_0} = 1.24$$
,

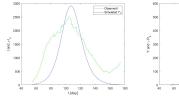
 $\hat{\gamma} = 0.21\%$ .

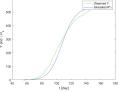
 $\hat{
ho} = 20\%$ 

 $J_{optim} = 48340173.$ 

#### J=J(alpha,beta,gamma=0.002109,rho=0.204360) for cl=1.000000, cY=1.000000







MATH 420: SIR Calibration

# Numerical results (7)

#### Analysis of DC data for 2020. $p = \infty$ , $c_l = 1$ , $c_Y = 1$

# Results: $\hat{\alpha} = 0.5$ , $\hat{\beta} = 0.64$ ,

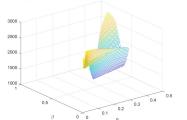
$$\hat{R_{0}} = 1.28$$
,

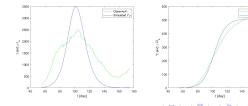
 $\hat{\gamma} = 0.18\%.$ 

 $\hat{
ho} = 19\%$ 

 $J_{optim} = 1232.$ 

#### J=J(alpha,beta,gamma=0.001789,rho=0.190301) for cl=1.000000, cY=1.000000







MATH 420: SIR Calibration

## Next Model: SEIR

The Susceptible-Exposed-Infected-Removed (SEIR) model is obtained from SIR by introducing a compartment between Susceptible and Infected of population that has been exposed to the virus but are not yet contagious:

$$\begin{cases} \frac{dS}{dt} = -\beta \frac{SI}{N} , S(0) \\ \frac{dE}{dt} = \beta \frac{SI}{N} - \delta E , E(0) \\ \frac{dI}{dt} = \delta E - \alpha I , I(0) \\ \frac{dR}{dt} = \alpha I , R(0) \end{cases}$$
(SEIR Model)

where  $\delta \ge 0$  is the rate of transition from exposed to infected. Its reciprocal  $1/\delta$  represents the *average incubation period*. If data is selected from the onset of infections, a natural initial condition is:  $R(0) = N \gg I(0)$ , R(0) = 0. The initial exposed population E(0) may be set to I(0), or can be fine tuned to fit the data. Assumin E(0) = I(0) is known, the parameters that need to be calibrated are:  $\alpha, \beta, \gamma, \delta, \rho$ .