

# Interior-Point Methods for an Optimal Control Influenza Model

Paula A. Gonzalez Parra<sup>1</sup>, Sunmi Lee<sup>3</sup>,  
Leticia Velazquez<sup>1,2</sup>, Carlos Castillo-Chavez<sup>3</sup>

<sup>1</sup>Program in Computational Science, University of Texas at El Paso

<sup>2</sup>Department of Mathematical Sciences, University of Texas at El Paso

<sup>3</sup>Mathematical, Computational and Modeling Sciences Center, Arizona State University

2012 SIAM annual meeting

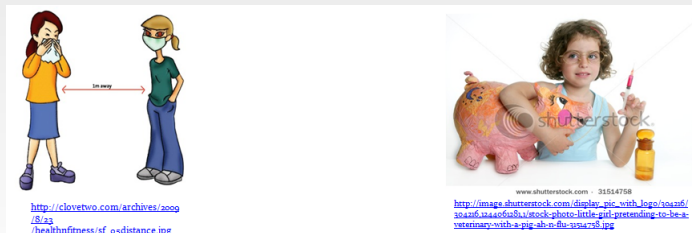
Minneapolis, MN

July 9, 2012

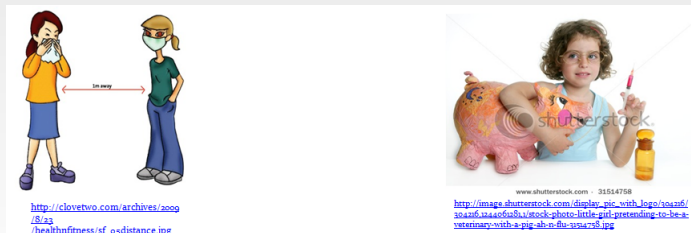


- 1 Introduction
- 2 Optimal Control Problem
- 3 Methodology
  - Pontryagin's Maximum Principle
  - Interior-Point Methods
- 4 Numerical Solution
- 5 Conclusions

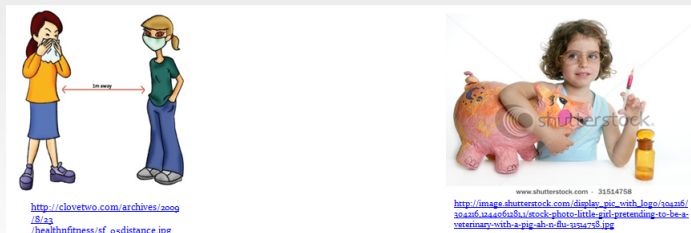
- Different continuous time approaches have been used to study single influenza outbreaks.
- The identification of optimal control strategies that involve antiviral treatment and isolation have been investigated in the continuous case.
- We formulate a discrete time model and we include **social distancing** and **treatment** as control policies.

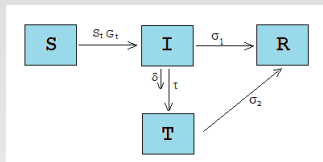


- Different continuous time approaches have been used to study single influenza outbreaks.
- The identification of optimal control strategies that involve antiviral treatment and isolation have been investigated in the continuous case.
- We formulate a discrete time model and we include **social distancing** and **treatment** as control policies.



- Different continuous time approaches have been used to study single influenza outbreaks.
- The identification of optimal control strategies that involve antiviral treatment and isolation have been investigated in the continuous case.
- We formulate a discrete time model and we include **social distancing** and **treatment** as control policies.



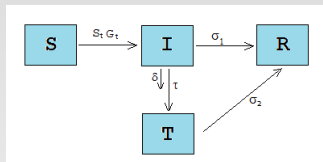


- The model is given by the system of difference equations:

$$\begin{aligned}
 S_{t+1} &= S_t(1 - G_t) \\
 I_{t+1} &= S_t G_t + (1 - \tau_t)(1 - \sigma_1)(1 - \delta)I_t \\
 T_{t+1} &= (1 - \sigma_2)T_t + \tau_t(1 - \sigma_1)(1 - \delta)I_t \\
 R_{t+1} &= R_t + \sigma_1(1 - \delta)I_t + \sigma_2 T_t
 \end{aligned} \tag{1}$$

- Where

$$G_t = \rho\gamma(1 - x_t) \frac{I_t + \epsilon T_t}{N_t}, \tag{2}$$



- The model is given by the system of difference equations:

$$\begin{aligned}
 S_{t+1} &= S_t(1 - G_t) \\
 I_{t+1} &= S_t G_t + (1 - \tau_t)(1 - \sigma_1)(1 - \delta)I_t \\
 T_{t+1} &= (1 - \sigma_2)T_t + \tau_t(1 - \sigma_1)(1 - \delta)I_t \\
 R_{t+1} &= R_t + \sigma_1(1 - \delta)I_t + \sigma_2 T_t
 \end{aligned} \tag{1}$$

- Where

$$G_t = \rho\gamma(1 - x_t)\frac{I_t + \epsilon T_t}{N_t}, \tag{2}$$

- Our goal is to minimize the number of infected individuals over a finite interval  $[0, n]$  by using a minimal effort on treatment and social distancing.
- The problem can be written as

$$\min \frac{1}{2} \sum_{t=0}^{n-1} (B_1 I_t^2 + B_2 X_t^2 + B_3 T_t^2), \quad (3)$$

subject to Model 1.



- Our goal is to minimize the number of infected individuals over a finite interval  $[0, n]$  by using a minimal effort on treatment and social distancing.
- The problem can be written as

$$\min \frac{1}{2} \sum_{t=0}^{n-1} (B_1 I_t^2 + B_2 X_t^2 + B_3 T_t^2), \quad (3)$$

subject to Model 1.

- The Hamiltonian at time  $t$  is defined as

$$H_t = \frac{1}{2} (B_1 I_t^2 + B_2 x_t^2 + B_3 \tau_t^2) + \lambda_{t+1}^i y_{t+1}^i.$$

- The necessary conditions are given by:

- The adjoint equation

$$\lambda_t^i = \frac{\partial H_t}{\partial y_t^i},$$

- The transversality condition

$$\lambda_n^i = 0,$$

- The optimality condition

$$\frac{\partial H_t}{\partial x_t} = 0 \quad \text{and} \quad \frac{\partial H_t}{\partial \tau_t} = 0.$$

- The Hamiltonian at time  $t$  is defined as

$$H_t = \frac{1}{2} (B_1 I_t^2 + B_2 x_t^2 + B_3 \tau_t^2) + \lambda_{t+1}^i y_{t+1}^i.$$

- The necessary conditions are given by:

- The adjoint equation

$$\lambda_t^i = \frac{\partial H_t}{\partial y_t^i},$$

- The transversality condition

$$\lambda_n^i = 0,$$

- The optimality condition

$$\frac{\partial H_t}{\partial x_t} = 0 \quad \text{and} \quad \frac{\partial H_t}{\partial \tau_t} = 0.$$

- The Hamiltonian at time  $t$  is defined as

$$H_t = \frac{1}{2} (B_1 I_t^2 + B_2 x_t^2 + B_3 \tau_t^2) + \lambda_{t+1}^i y_{t+1}^i.$$

- The necessary conditions are given by:
  - The adjoint equation

$$\lambda_t^i = \frac{\partial H_t}{\partial y_t^i},$$

- The transversality condition

$$\lambda_n^i = 0,$$

- The optimality condition

$$\frac{\partial H_t}{\partial x_t} = 0 \quad \text{and} \quad \frac{\partial H_t}{\partial \tau_t} = 0.$$

- The Hamiltonian at time  $t$  is defined as

$$H_t = \frac{1}{2} (B_1 I_t^2 + B_2 x_t^2 + B_3 \tau_t^2) + \lambda_{t+1}^i y_{t+1}^i.$$

- The necessary conditions are given by:

- The adjoint equation

$$\lambda_t^i = \frac{\partial H_t}{\partial y_t^i},$$

- The transversality condition

$$\lambda_n^i = 0,$$

- The optimality condition

$$\frac{\partial H_t}{\partial x_t} = 0 \quad \text{and} \quad \frac{\partial H_t}{\partial \tau_t} = 0.$$

- The Hamiltonian at time  $t$  is defined as

$$H_t = \frac{1}{2} (B_1 I_t^2 + B_2 x_t^2 + B_3 \tau_t^2) + \lambda_{t+1}^i y_{t+1}^i.$$

- The necessary conditions are given by:

- The adjoint equation

$$\lambda_t^i = \frac{\partial H_t}{\partial y_t^i},$$

- The transversality condition

$$\lambda_n^i = 0,$$

- The optimality condition

$$\frac{\partial H_t}{\partial x_t} = 0 \quad \text{and} \quad \frac{\partial H_t}{\partial \tau_t} = 0.$$

- IPM were introduced by Karmarkar in 1984 for solving linear programming problems.
- Contrary to the simplex method, IPM find an optimal solution by crossing the interior of the feasible region.
- Problem (3) is posed as a nonlinear programming problem,

$$\begin{aligned} \min \quad & f(y) \\ \text{s.t} \quad & E(y) = 0, \\ & y \geq 0 \end{aligned} \tag{4}$$

where  $\mathbf{y} = (S_1, I_1, T_1, x_0, \tau_0, \dots, S_n, I_n, T_n, x_{n-1}, \tau_{n-1})$ , and

$$f(y) = \frac{1}{2} (B_1 |\tilde{I}|^2 + B_2 |x|^2 + B_3 |\tau|^2) \tag{5}$$

- IPM were introduced by Karmarkar in 1984 for solving linear programming problems.
- Contrary to the simplex method, IPM find an optimal solution by crossing the interior of the feasible region.
- Problem (3) is posed as a nonlinear programming problem,

$$\begin{aligned} \min \quad & f(y) \\ \text{s.t} \quad & E(y) = 0, \\ & y \geq 0 \end{aligned} \tag{4}$$

where  $\mathbf{y} = (S_1, I_1, T_1, x_0, \tau_0, \dots, S_n, I_n, T_n, x_{n-1}, \tau_{n-1})$ , and

$$f(y) = \frac{1}{2} (B_1 |\tilde{I}|^2 + B_2 |x|^2 + B_3 |\tau|^2) \tag{5}$$



- IPM were introduced by Karmarkar in 1984 for solving linear programming problems.
- Contrary to the simplex method, IPM find an optimal solution by crossing the interior of the feasible region.
- Problem (3) is posed as a nonlinear programming problem,

$$\begin{aligned} \min \quad & f(y) \\ \text{s.t} \quad & E(y) = 0, \\ & y \geq 0 \end{aligned} \tag{4}$$

where  $\mathbf{y} = (S_1, I_1, T_1, x_0, \tau_0, \dots, S_n, I_n, T_n, x_{n-1}, \tau_{n-1})$ , and

$$f(y) = \frac{1}{2} (B_1 |\tilde{I}|^2 + B_2 |x|^2 + B_3 |\tau|^2) \tag{5}$$

- The Lagrangian associated to (4) is

$$L(y, w, z) = f(y) + E(y)^T w - y^T z.$$

- The perturbed KKT conditions associated with (4) can be written as

$$F = \begin{bmatrix} \nabla_y L(y, w, z) \\ E(y) \\ YZ - \mu e \end{bmatrix} = 0 \quad (6)$$

- A linesearch Newton's method is applied to the perturbed KKT conditions (6).

- The Lagrangian associated to (4) is

$$L(y, w, z) = f(y) + E(y)^T w - y^T z.$$

- The perturbed KKT conditions associated with (4) can be written as

$$F = \begin{bmatrix} \nabla_y L(y, w, z) \\ E(y) \\ YZ - \mu e \end{bmatrix} = 0 \quad (6)$$

- A linesearch Newton's method is applied to the perturbed KKT conditions (6).

- The Lagrangian associated to (4) is

$$L(y, w, z) = f(y) + E(y)^T w - y^T z.$$

- The perturbed KKT conditions associated with (4) can be written as

$$F = \begin{bmatrix} \nabla_y L(y, w, z) \\ E(y) \\ YZ - \mu e \end{bmatrix} = 0 \quad (6)$$

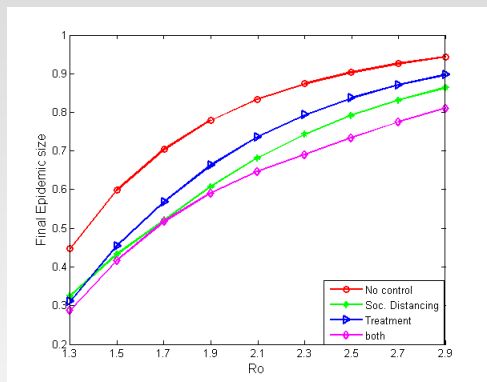
- A linesearch Newton's method is applied to the perturbed KKT conditions (6).

Table: Comparison between **Forward-Backward** and **Interior-Point methods**.

	FB		IPM	
Strategy	# of iterations	F	# of iterations	F
1	52	0.67997	11	0.68069
2	54	0.33014	10	0.33018
3	87	0.30423	23	0.30092

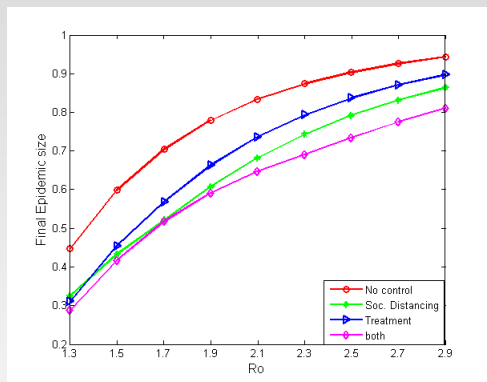
For all strategies IPM reach the solution with fewer number of iterations.

## Final epidemic size vs. $R_0$

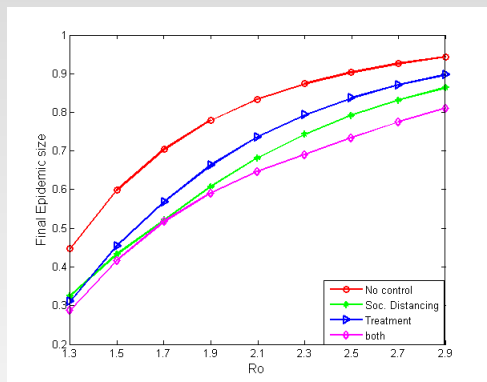


- We compare the final epidemic size for different values of  $R_0$  under each strategy.
- Strategy 3 yields the highest reduction of the final epidemic size.
- For single policies Strategy 1 has more impact in the reduction of the final epidemic size than Strategy 2

## Final epidemic size vs. $R_0$



- We compare the final epidemic size for different values of  $R_0$  under each strategy.
- Strategy 3 yields the highest reduction of the final epidemic size.
- For single policies Strategy 1 has more impact in the reduction of the final epidemic size than Strategy 2



- We compare the final epidemic size for different values of  $R_0$  under each strategy.
- Strategy 3 yields the highest reduction of the final epidemic size.
- For single policies Strategy 1 has more impact in the reduction of the final epidemic size than Strategy 2



- We want to consider the case of **limited resources**.
- An isoperimetric constraint is included

$$\sum_{t=0}^{n-1} (\tau_i(t) l_i(t)) = k, \quad (7)$$

where  $k$  represents the available number of treatment doses.

- It can be written as

$$\boldsymbol{\tau}^T \mathbf{l} = k$$

- We want to consider the case of **limited resources**.
- An isoperimetric constraint is included

$$\sum_{t=0}^{n-1} (\tau_i(t) l_i(t)) = k, \quad (7)$$

where  $k$  represents the available number of treatment doses.

- It can be written as

$$\tau^T \mathbf{l} = k$$

- We want to consider the case of **limited resources**.
- An isoperimetric constraint is included

$$\sum_{t=0}^{n-1} (\tau_i(t) l_i(t)) = k, \quad (7)$$

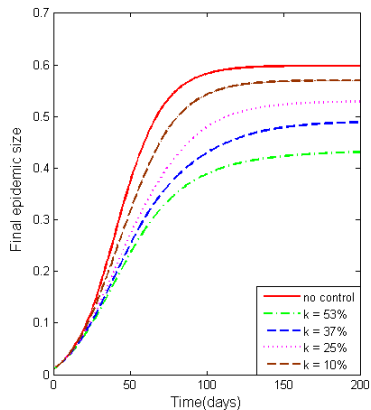
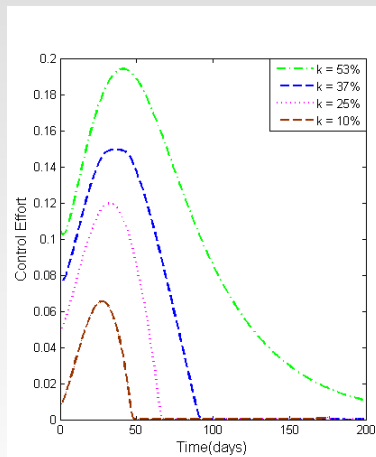
where  $k$  represents the available number of treatment doses.

- It can be written as

$$\boldsymbol{\tau}^T \mathbf{l} = k$$

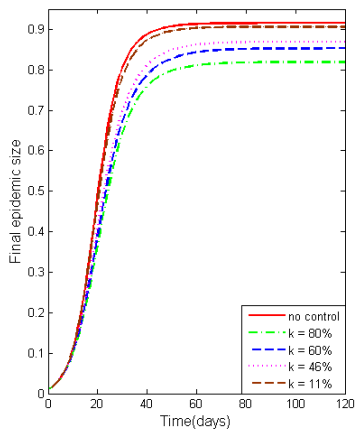
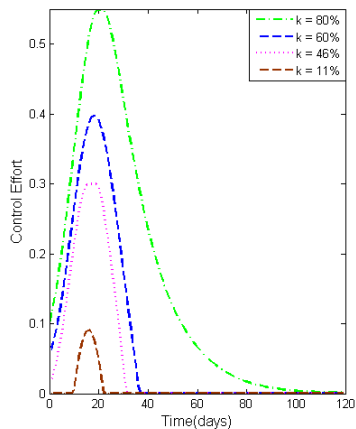
## Numerical Results, $R_0 = 1.5$

# Numerical Results, $R_0 = 1.5$



## Numerical Results, $R_0 = 2.6$

# Numerical Results, $R_0 = 2.6$



- An optimal control problem is solved by using two techniques: Forward-Backward algorithm and interior-point methods.
- Interior-point methods reach the solution with fewer number of iterations.
- The use of single and dual strategies results in reductions in the cumulative number of infected individuals.
- Under the implementation of a single policy, the social distancing strategy is more effective than the antiviral treatment when  $R_0 > 1.4$ .
- **Future Work:** Extend the model to an age-structured model and analyze how control policies should be implemented in each group.



- An optimal control problem is solved by using two techniques: Forward-Backward algorithm and interior-point methods.
- Interior-point methods reach the solution with fewer number of iterations.
- The use of single and dual strategies results in reductions in the cumulative number of infected individuals.
- Under the implementation of a single policy, the social distancing strategy is more effective than the antiviral treatment when  $R_0 > 1.4$ .
- **Future Work:** Extend the model to an age-structured model and analyze how control policies should be implemented in each group.

- An optimal control problem is solved by using two techniques: Forward-Backward algorithm and interior-point methods.
- Interior-point methods reach the solution with fewer number of iterations.
- The use of single and dual strategies results in reductions in the cumulative number of infected individuals.
- Under the implementation of a single policy, the social distancing strategy is more effective than the antiviral treatment when  $R_0 > 1.4$ .
- **Future Work:** Extend the model to an age-structured model and analyze how control policies should be implemented in each group.

- An optimal control problem is solved by using two techniques: Forward-Backward algorithm and interior-point methods.
- Interior-point methods reach the solution with fewer number of iterations.
- The use of single and dual strategies results in reductions in the cumulative number of infected individuals.
- Under the implementation of a single policy, the social distancing strategy is more effective than the antiviral treatment when  $R_0 > 1.4$ .
- **Future Work:** Extend the model to an age-structured model and analyze how control policies should be implemented in each group.

- An optimal control problem is solved by using two techniques: Forward-Backward algorithm and interior-point methods.
- Interior-point methods reach the solution with fewer number of iterations.
- The use of single and dual strategies results in reductions in the cumulative number of infected individuals.
- Under the implementation of a single policy, the social distancing strategy is more effective than the antiviral treatment when  $R_0 > 1.4$ .
- **Future Work:** Extend the model to an age-structured model and analyze how control policies should be implemented in each group.



P. Gonzalez-Parra, S. Lee, L. Velazquez, and C. Castillo-Chavez (2011)  
A note on the use of optimal control on a discrete time model of influenza dynamics.  
*Math. Biosc. & Eng.* 8, 183–197.



E. Fenichel, C. Castillo-Chavez, G. Ceddia, G. Chowell, P. Gonzalez-Parra, L. Velazquez et al. (2011)  
Adaptive human behavior in epidemiological models.  
*Proceedings of the National Academy of Sciences*, 108(15).



P. Gonzalez-Parra, L. Velazquez, M. Villalobos, and C. Castillo-Chavez (2010)  
Optimal control applied to a discrete influenza model.  
*Conference Proceedings Book of the XXXVI International Operation Research Applied to Health Services*, edited by Franco Angeli Edition



P. Gonzalez-Parra, S. Lee, L. Velazquez, and C. Castillo-Chavez (2011)  
A note on the use of optimal control on a discrete time model of influenza dynamics.  
*Math. Biosc. & Eng.* 8, 183–197.



E. Fenichel, C. Castillo-Chavez, G. Ceddia, G. Chowell, P. Gonzalez-Parra, L. Velazquez et al. (2011)  
Adaptive human behavior in epidemiological models.  
*Proceedings of the National Academy of Sciences*, 108(15).



P. Gonzalez-Parra, L. Velazquez, M. Villalobos, and C. Castillo-Chavez (2010)  
Optimal control applied to a discrete influenza model.  
*Conference Proceedings Book of the XXXVI International Operation Research Applied to Health Services*, edited by Franco Angeli Edition



P. Gonzalez-Parra, S. Lee, L. Velazquez, and C. Castillo-Chavez (2011)  
A note on the use of optimal control on a discrete time model of influenza dynamics.  
*Math. Biosc. & Eng.* 8, 183–197.



E. Fenichel, C. Castillo-Chavez, G. Ceddia, G. Chowell, P. Gonzalez-Parra, L. Velazquez et al. (2011)  
Adaptive human behavior in epidemiological models.  
*Proceedings of the National Academy of Sciences*, 108(15).



P. Gonzalez-Parra, L. Velazquez, M. Villalobos, and C. Castillo-Chavez (2010)  
Optimal control applied to a discrete influenza model.  
*Conference Proceedings Book of the XXXVI International Operation Research Applied to Health Services*, edited by Franco Angeli Edition

Thanks to:

- SIAM Student travel award.
- Carlos Castillo Chavez and MTBI summer program.
- Program in Computational Science at the University of Texas at El Paso.
- American Association for University Women.
- Universidad Autonoma de Occidente, Cali–Colombia.

Thank you!



Thanks to:

- SIAM Student travel award.
- Carlos Castillo Chavez and MTBI summer program.
- Program in Computational Science at the University of Texas at El Paso.
- American Association for University Women.
- Universidad Autonoma de Occidente, Cali–Colombia.

Thank you!

Thanks to:

- SIAM Student travel award.
- Carlos Castillo Chavez and MTBI summer program.
- Program in Computational Science at the University of Texas at El Paso.
- American Association for University Women.
- Universidad Autonoma de Occidente, Cali–Colombia.

Thank you!

Thanks to:

- SIAM Student travel award.
- Carlos Castillo Chavez and MTBI summer program.
- Program in Computational Science at the University of Texas at El Paso.
- American Association for University Women.
- Universidad Autonoma de Occidente, Cali–Colombia.

Thank you!

Thanks to:

- SIAM Student travel award.
- Carlos Castillo Chavez and MTBI summer program.
- Program in Computational Science at the University of Texas at El Paso.
- American Association for University Women.
- Universidad Autonoma de Occidente, Cali–Colombia.

Thank you!