

TRANSP-Based Optimization Towards Non-inductive Ramp-up

W. Wehner¹, E. Schuster¹, and F. M. Poli²

¹Lehigh University, Bethlehem, PA

²Princeton Plasma Physics Laboratory, Princeton, NJ

E-mail: wehner@lehigh.edu

NSTX-U Results Review 2016

Supported by SCGSR award.

September 21, 2016



U.S. DEPARTMENT OF
ENERGY

Office of
Science

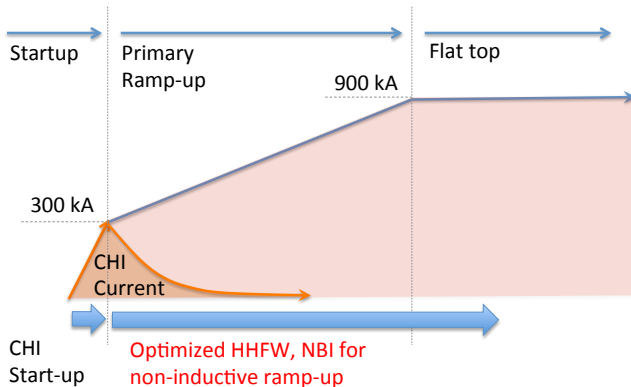


LEHIGH
UNIVERSITY.

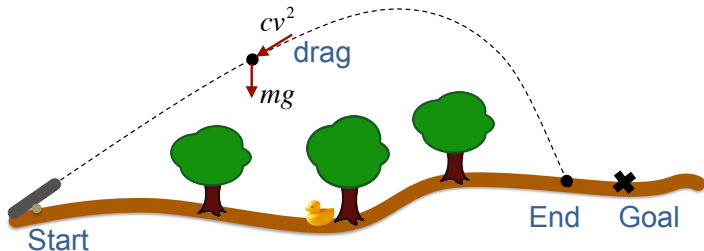
Objectives and Outline

• Main Objective

- Combine Predictive-TRANSP with numerical optimization to find a strategy for non-inductive current ramp-up.



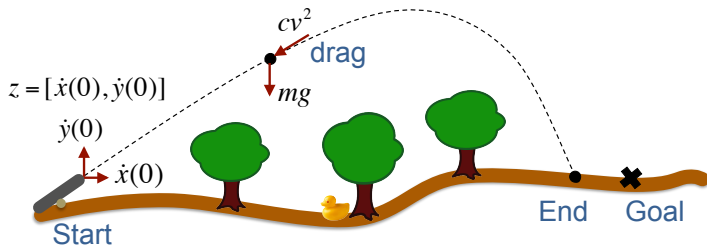
Example: Cannon Optimization



$$\begin{aligned} & \underset{\mathbf{z}}{\text{minimize}} && J(\mathbf{z}) \\ & \text{subject to} && h(\mathbf{z}) = 0 \\ & && g(\mathbf{z}) \leq 0 \end{aligned}$$

- **IDEA:** Transform control problem (cannon aiming) into optimization problem
- Pass to numerical optimization solver

Example: Cannon Optimization



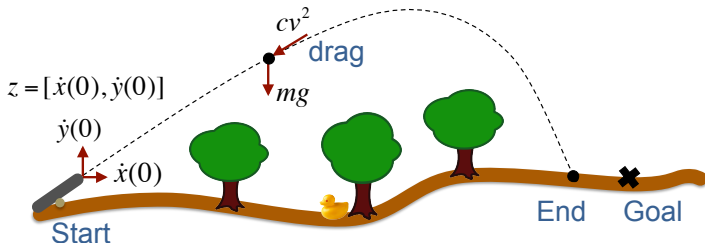
optimization variables: $\mathbf{z} = [\dot{\mathbf{x}}(0), \dot{\mathbf{y}}(0)]$

minimize $J(\mathbf{z})$

subject to $h(\mathbf{z}) = 0$

$g(\mathbf{z}) \leq 0$

Example: Cannon Optimization



optimization variables: $\mathbf{z} = [\dot{x}(0), \dot{y}(0)]$

minimize $J(\mathbf{z})$

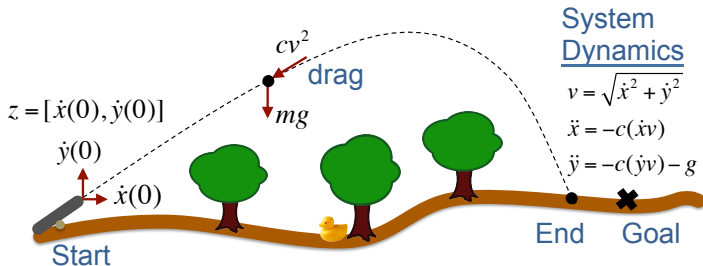
← objective: i.e. powder consumed

$$J \propto v = \sqrt{\dot{x}(0)^2 + \dot{y}(0)^2}$$

subject to $h(\mathbf{z}) = 0$

$g(\mathbf{z}) \leq 0$

Example: Cannon Optimization



optimization variables: $\mathbf{z} = [\dot{x}(0), \dot{y}(0)]$

minimize $J(\mathbf{z})$ ← optimization objective: powder consumed

$$J \propto v = \sqrt{\dot{x}(0)^2 + \dot{y}(0)^2}$$

subject to $h(\mathbf{z}) = 0$ ← equality constraints:

$$[x, y]_{\text{end}} = [x, y]_{\text{goal}}$$

$$v = \sqrt{\dot{x} + \dot{y}}, \quad \ddot{x} = -c(\dot{x}v), \quad \ddot{y} = -c(\dot{y}v) - g$$

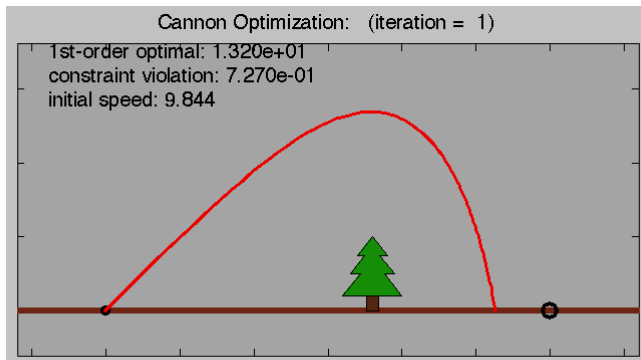
$g(\mathbf{z}) \leq 0$ ← inequality constraints:

$$y(t) \geq \text{Height Trees}$$

Cannon Targeting: Optimization-based Control

- Start with an approximate solution \mathbf{z}_0 (guess)
- Use gradient information of objective and constraints (and approximate hessian of the Lagrangian) to improve on the approximate solution

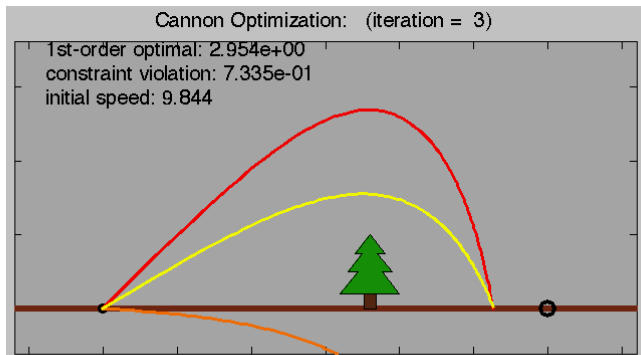
$$\mathbf{z}_{k+1} = \mathbf{z}_k + \Delta \mathbf{z}$$



Cannon Targeting: Optimization-based Control

- Start with an approximate solution \mathbf{z}_0 (guess)
- Use gradient information of objective and constraints (and approximate hessian of the Lagrangian) to improve on the approximate solution

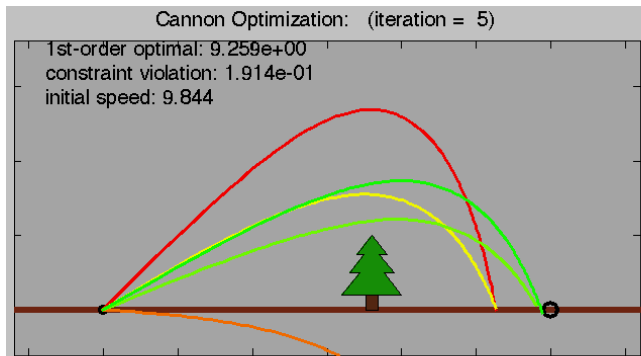
$$\mathbf{z}_{k+1} = \mathbf{z}_k + \Delta \mathbf{z}$$



Cannon Targeting: Optimization-based Control

- Start with an approximate solution \mathbf{z}_0 (guess)
- Use gradient information of objective and constraints (and approximate hessian of the Lagrangian) to improve on the approximate solution

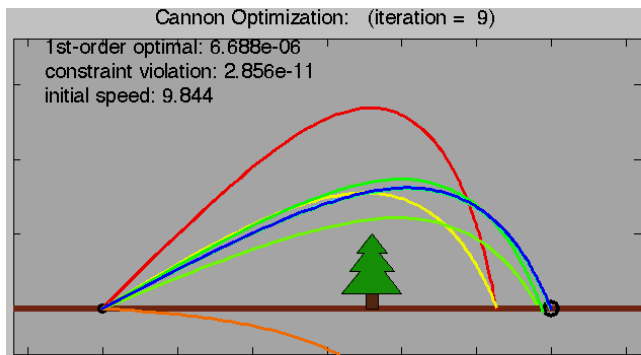
$$\mathbf{z}_{k+1} = \mathbf{z}_k + \Delta \mathbf{z}$$



Cannon Targeting: Optimization-based Control

- Start with an approximate solution \mathbf{z}_0 (guess)
- Use gradient information of objective and constraints (and approximate hessian of the Lagrangian) to improve on the approximate solution

$$\mathbf{z}_{k+1} = \mathbf{z}_k + \Delta \mathbf{z}$$



Formulation of Feedforward (FF) Control Optimization

- A feedforward (open-loop) control policy is obtained via nonlinear optimization - minimize a cost function subject to various constraints

$$\min_{u_{FF}(t)} \quad J(I_p, I_p^{NI}) \quad \left. \vphantom{\min_{u_{FF}(t)}} \right\} \begin{array}{l} \text{Cost Function,} \\ \text{Optimization Objective} \end{array}$$

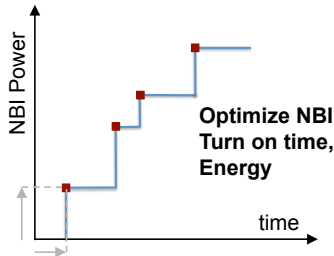
$$\text{s.t.:} \quad \dot{\psi} = f_{\psi}(\psi, u_{FF}) \quad \left. \vphantom{\dot{\psi} = f_{\psi}(\psi, u_{FF})} \right\} \begin{array}{l} \text{Model of poloidal magnetic flux evolution} \\ q \text{ profile / current profile are function of } \psi \end{array}$$

$$u_{FF}(t) \in \mathcal{U} \quad \left. \vphantom{u_{FF}(t) \in \mathcal{U}} \right\} \begin{array}{l} \text{Physical limitation on actuators:} \\ \text{Bounds / Rate Limit} \end{array}$$

$$\beta_N(t) \leq \beta_{N_{\max}} \quad \left. \vphantom{\beta_N(t) \leq \beta_{N_{\max}}} \right\} \begin{array}{l} \text{Nonlinear Constraint:} \\ \text{MHD Stability Limit} \end{array}$$

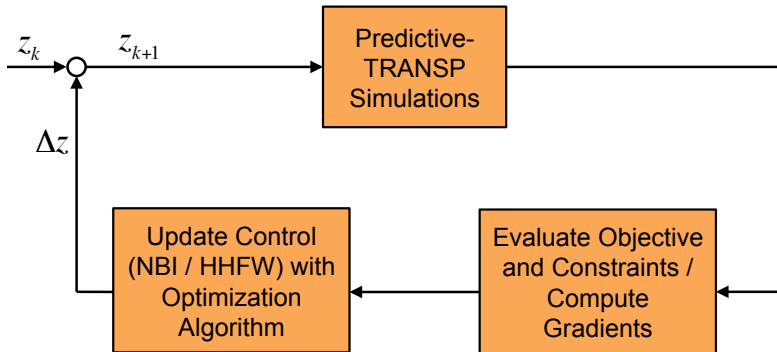
$$c(q) \leq 0 \quad \left. \vphantom{c(q) \leq 0} \right\} \begin{array}{l} \text{Constraints on shape of } (q): \\ \text{MHD Stability Limit} \end{array}$$

$$c(I_p) \leq 0 \quad \left. \vphantom{c(I_p) \leq 0} \right\} \text{Constraint on current target}$$

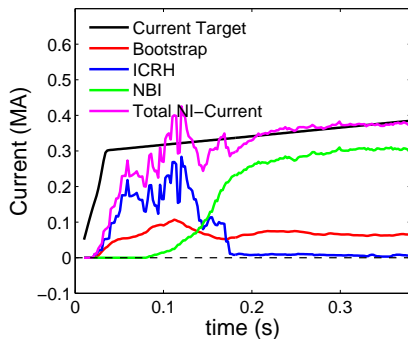
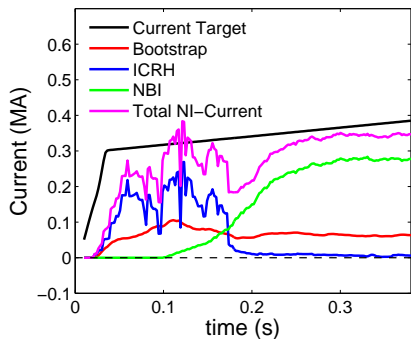


TRANSP-Based Optimization Code

- Use predictive modeling capability of the TRANSP code
- Combine with numerical optimization (OMFIT) to do automated feedforward control optimization.



TRANSP-Based Optimization For Control Design



- **Left** Figure 9 - F. M. Poli et al. Simulations of non-inductive current ramp-up and sustainment in the National Spherical Torus Experiment Upgrade. Nucl. Fusion 55 (2015) 123011 (12pp)
- **Right** Result of an optimization of the ICRH and NBI powers to meet the current target with non-inductive sources.

Other Tasks in progress

- Combine TRANSP feedback infrastructure [M. Boyer] with constrained feedback
 - Desire a feedback controller that can avoid violating stability limits

Other Tasks in progress

- Combine TRANSP feedback infrastructure [M. Boyer] with constrained feedback
 - Desire a feedback controller that can avoid violating stability limits
- Simultaneously built model-based optimization
 - Ultimately replace TRANSP-Based optimization with model-based optimization
 - Allows for analytic gradient calculations for online implementation

Other Tasks in progress

- Combine TRANSP feedback infrastructure [M. Boyer] with constrained feedback
 - Desire a feedback controller that can avoid violating stability limits
- Simultaneously built model-based optimization
 - Ultimately replace TRANSP-Based optimization with model-based optimization
 - Allows for analytic gradient calculations for online implementation

