Tracking Control in The Wasserstein Space

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Many Applications for Autonomous Swarms



Emergency Response



Logistics



Entertainment



Transportation



Defense



Data Collection

Motivation

The Problem in Focus:

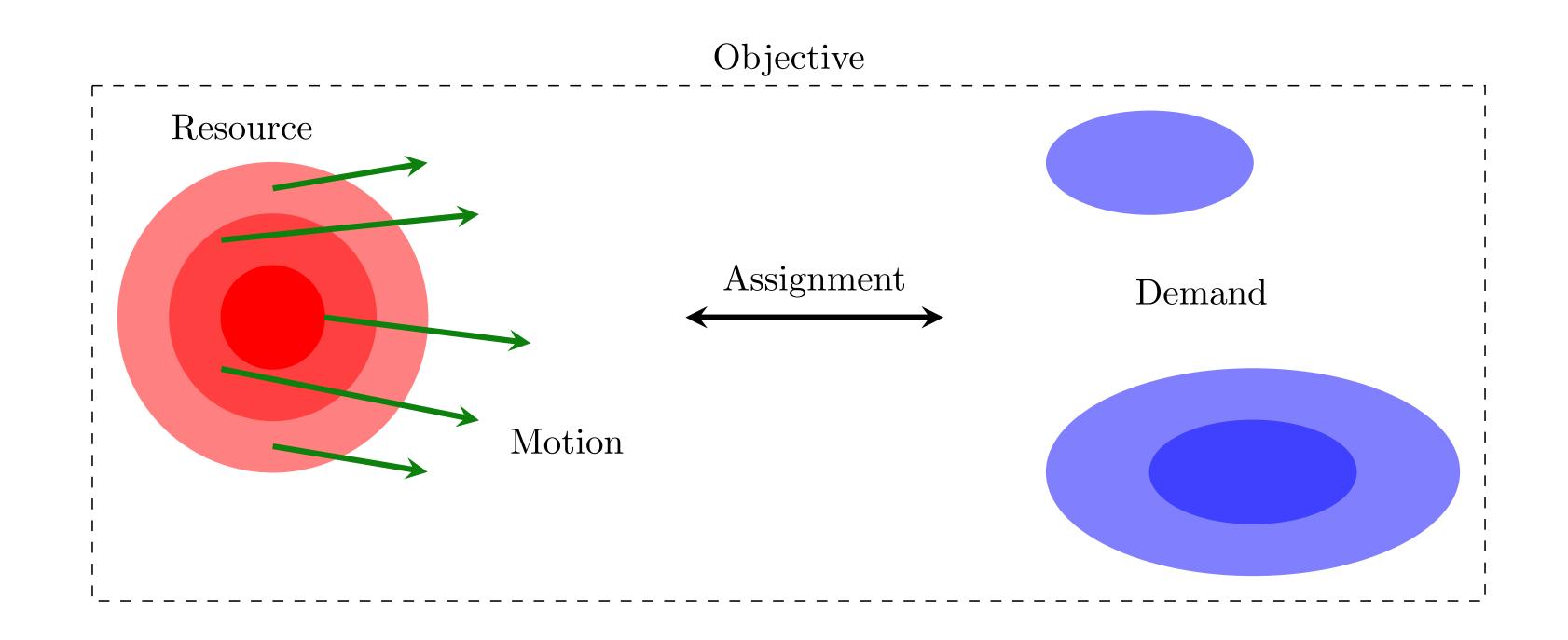
- Large swarms robust/efficient, but hard to model/control
- Want to develop theoretical foundations for design heuristics

Aim to Answer Questions:

- How should large swarms move and communicate?
- Which control architectures can achieve which behaviors?
- What are the attainable performance limits of these architectures?

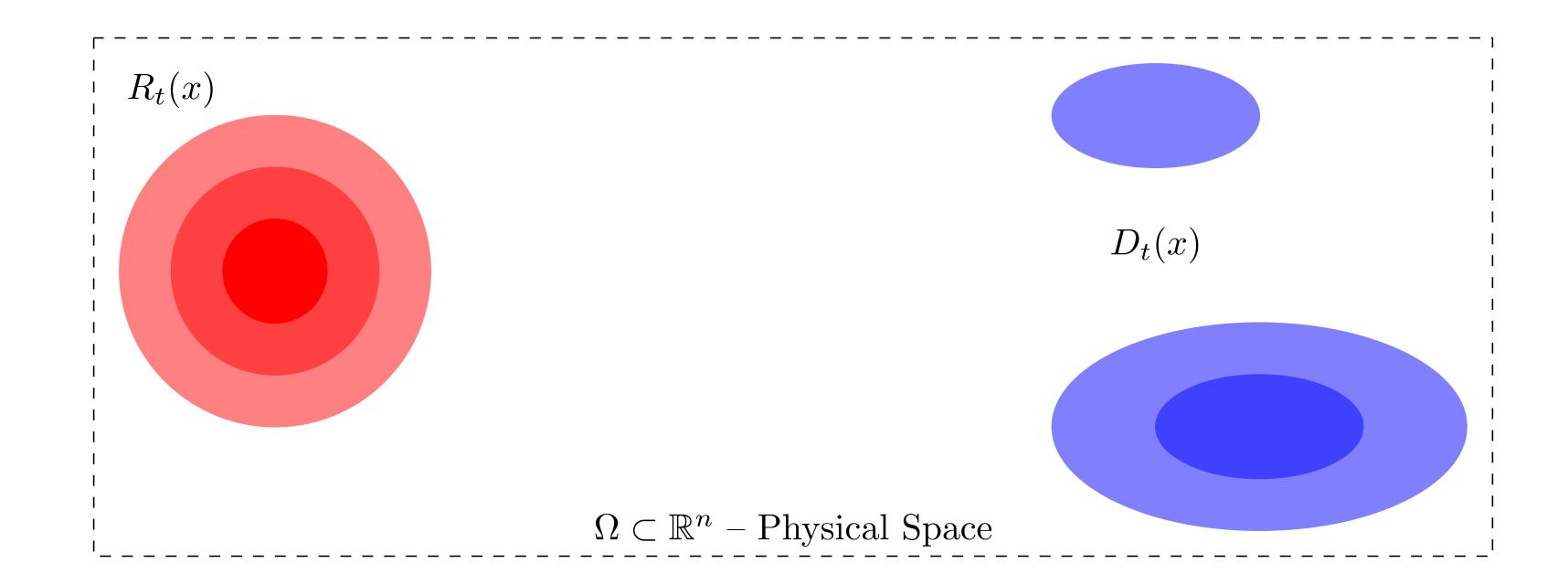
Approach

- This work: what sorts of motion patterns are optimal?
- Looking at motion planning and control for tracking
- Using continuum models, optimal transport, optimal control



Problem Formulation: Resource/Demand Densities

- Resource = controlled mobile agents (provides services)
- Demand = known entity (requires services)



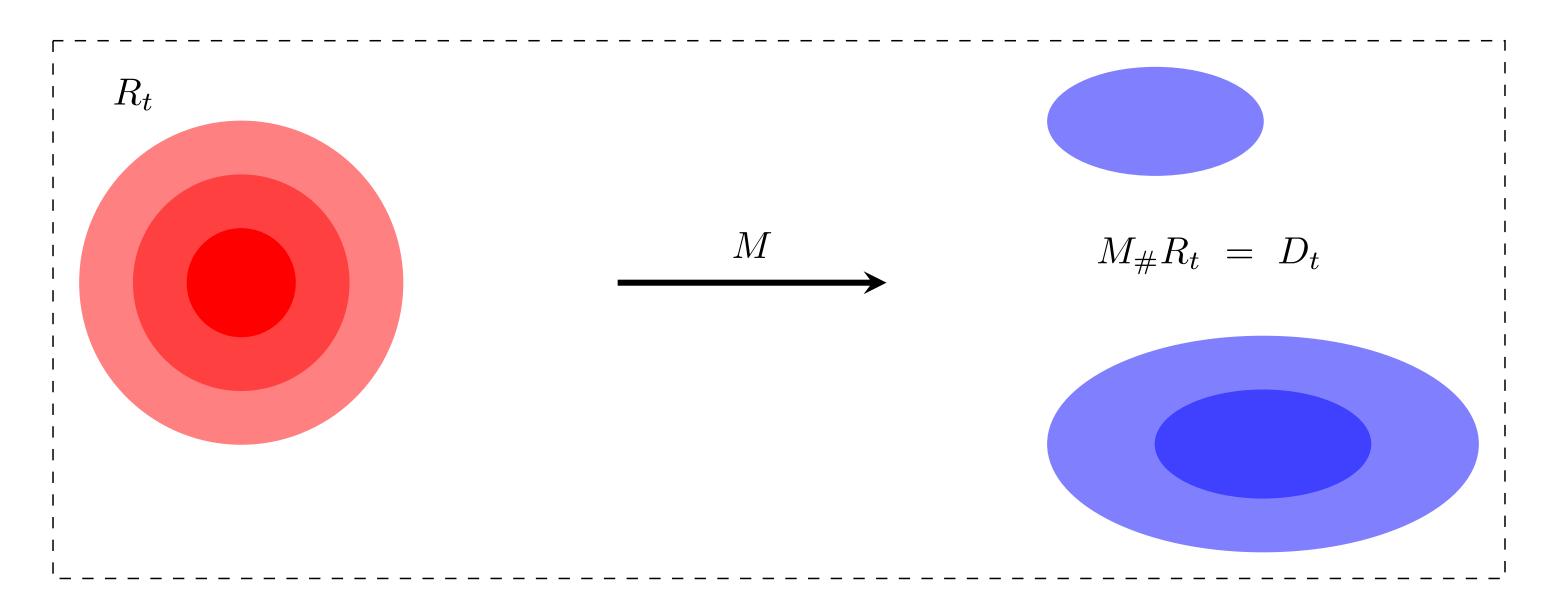
Problem Formulation: Assignment

Monge Problem (Optimal Transport):

$$\inf \int_{\Omega} ||M(x) - x||_2^2 R_t(x) dx \qquad \text{s.t.} \qquad M_\# R_t = D_t$$

$$M_{\#}R_t = D_t$$

- # denotes measure pushforward
- Minimizer $\bar{M}_{R_t o D_t}$ is optimal assignment map
- Minimum $W_2^2(R_t, D_t)$ is Wasserstein distance

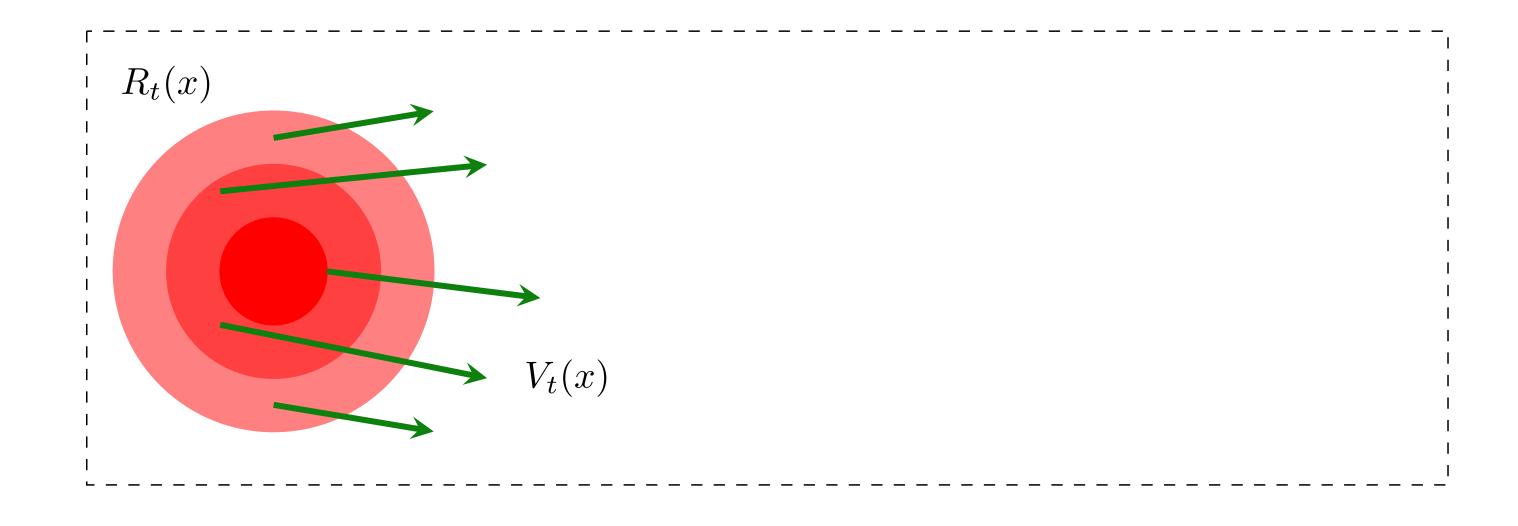


Problem Formulation: Dynamic Model

- Tracking → want resources close to demand
- ullet Control resource through **velocity field** V

Dynamics (Continuity Equation):

$$\partial_t R_t(x) = -\nabla \cdot (R_t(x) V_t(x))$$



Motion Cost:

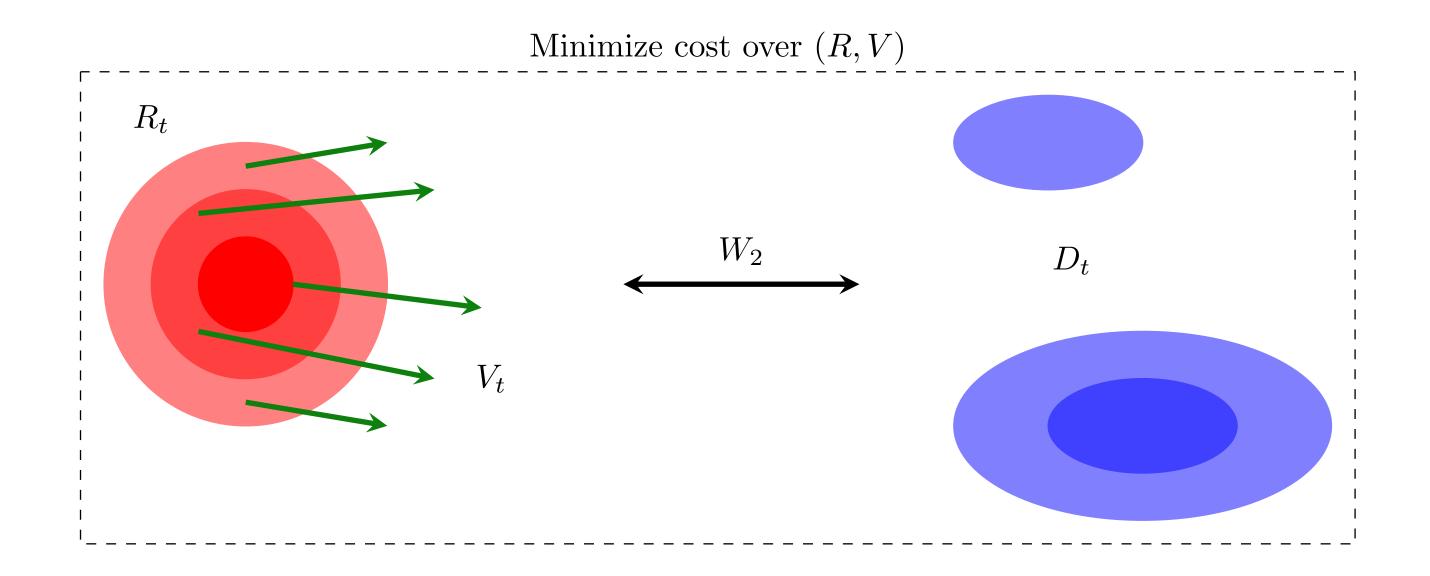
$$||V_t||_{L^2(R_t)}^2 := \int_{\Omega} ||V_t(x)||_2^2 R_t(x) dx$$

Formal Problem Statement

Given an initial resource distribution ${\it R}_0$ and demand trajectory ${\it D}$ over [0,T], solve

$$\inf_{R,V} \int_{0}^{T} \underbrace{W_{2}^{2}(R_{t},D_{t})}_{\text{Assignment Cost}} + \alpha \|V_{t}\|_{L^{2}(R_{t})}^{2} dt \qquad \text{s.t.} \qquad \underbrace{\partial_{t}R_{t} = -\nabla \cdot (R_{t}V_{t})}_{\text{Dynamic Constraint}}$$

- Intuitively, "R should track D efficiently"
- Trade-off parameter α controls relative importance of costs
- D constant in time → regulation problem



Structural Features of Solution

Necessary Conditions for Optimality:

Optimal velocity field is irrotational!

$$\partial_t R_t = -\nabla \cdot (R_t \nabla \Lambda_t)$$

$$\partial_t \Lambda_t = -\frac{1}{2} ||\nabla \Lambda_t||_2^2 + \frac{1}{2c} \phi(R_t, D_t)$$

$$R_0 = R_0$$
 Nonlinear two-point boundary value PDE

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- ullet Optimal solutions are **noncausal:** need to know D ahead of time
- Computationally expensive
- How to approach this?

Approach and Main Results

Main tools: Otto calculus, calculus of variations, optimal control

	Regulation	Tracking
1-D	Solutions fully characterized (NecSys '22)	Solutions fully characterized (TCNS '25, in review)
n-D	Solutions fully characterized (CDC '23)	Ongoing work (CDC '24,)

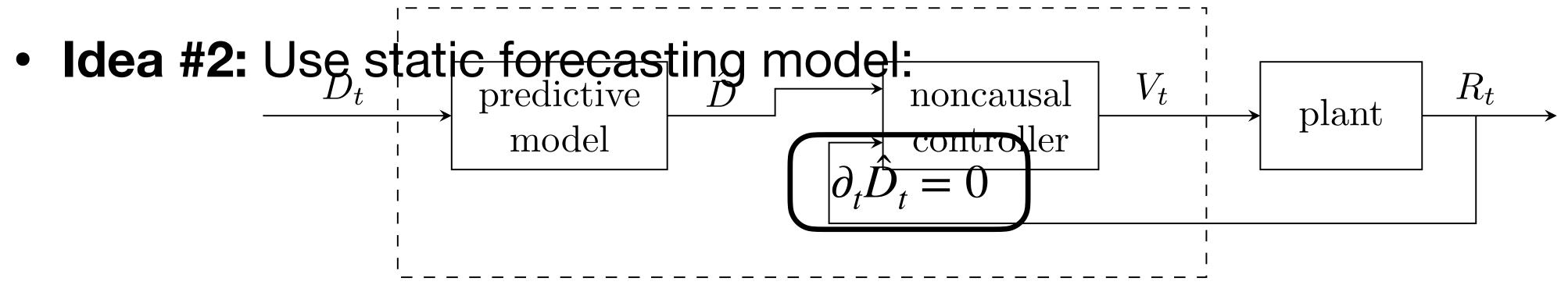


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Solutions decouple by linearized OT, causal

Suboptimal Tracking With Model-Predictive Control

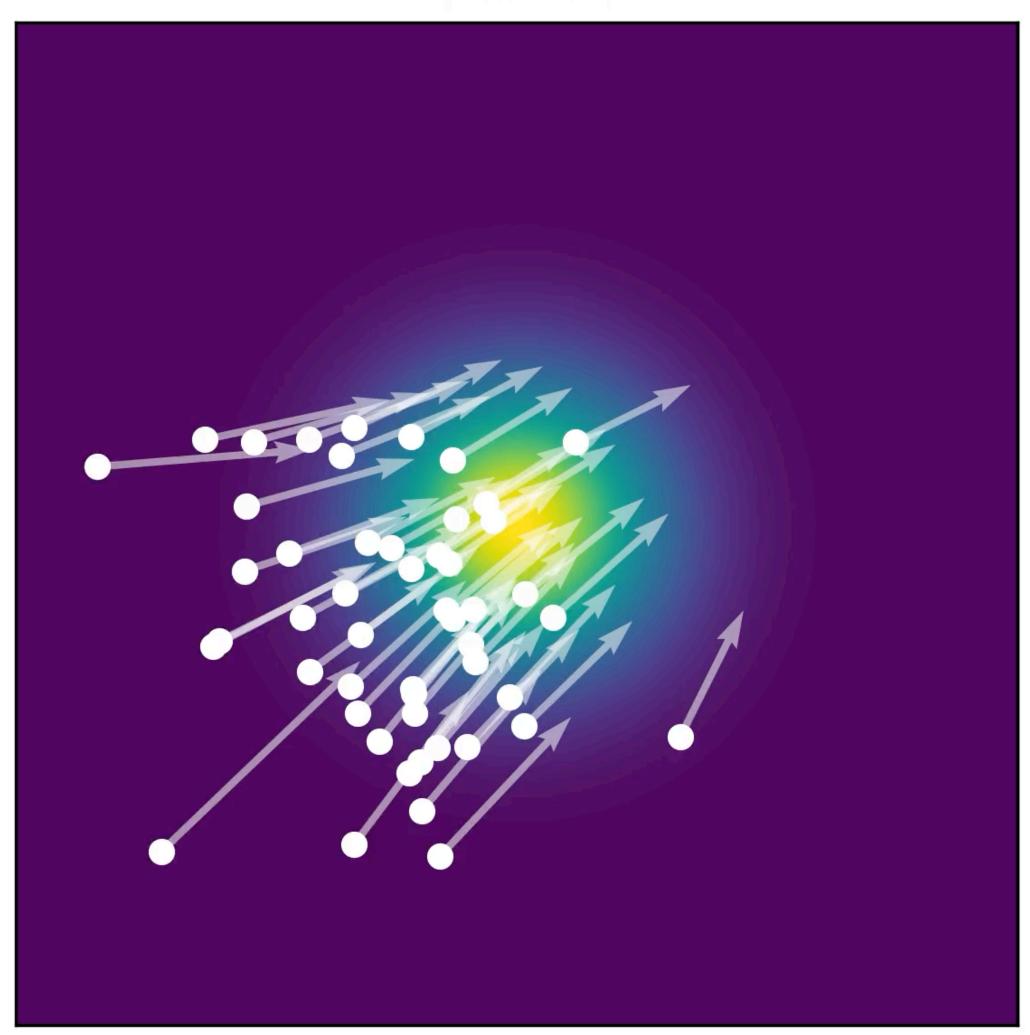
- Problem #1: Need to address noncausality
- Idea #1: use model to forecast demand trajectory, use forecasted trajectory in necessary conditions in receding horizon scheme
- Problem #2: Don't have model for demand



• (Also solves Problem #3: computational cost)

Model-Predictive Control Simulations

t = 0.000



Conclusion

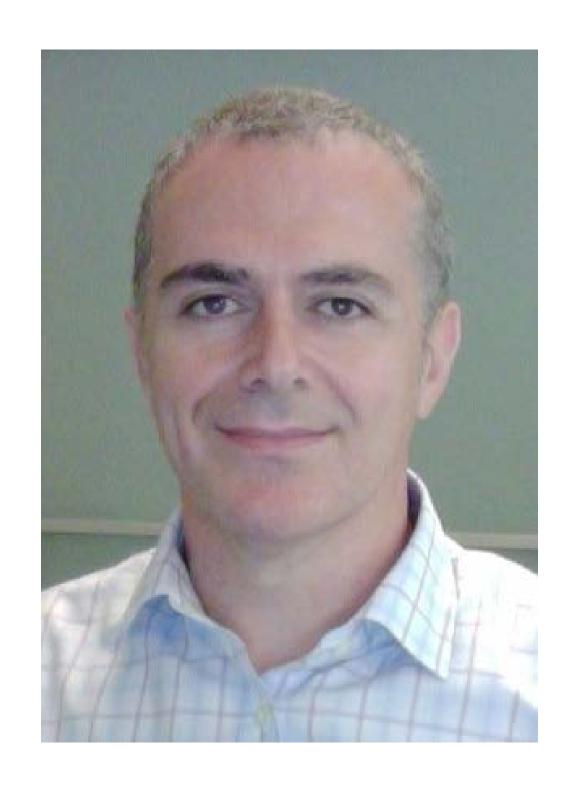
Takeaways:

- Simplified models can provide insight and design heuristics
- Leveraging geometric structure can be powerful

Future Work:

- Solving necessary conditions
- More sophisticated demand models
- Investigating resulting controllers

Thanks to My Collaborators



Bassam Bamieh



Stacy Patterson



Jared Jonas

Thanks for Watching! Questions?

Personal Website



Google Scholar

