Optimal Design of Controlled Environment Agricultural Systems Under Market Uncertainty

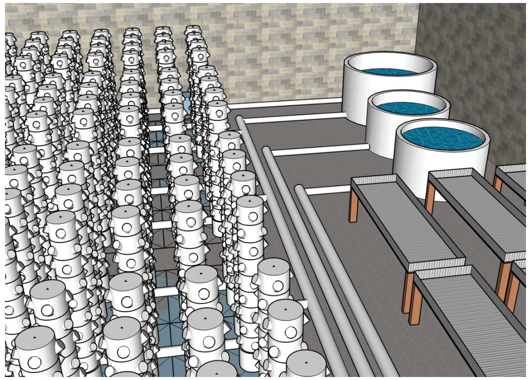
Shaylin A. Cetegen and Matthew D. Stuber*
PhD Student, Massachusetts Institute of Technology
Assistant Professor, University of Connecticut*

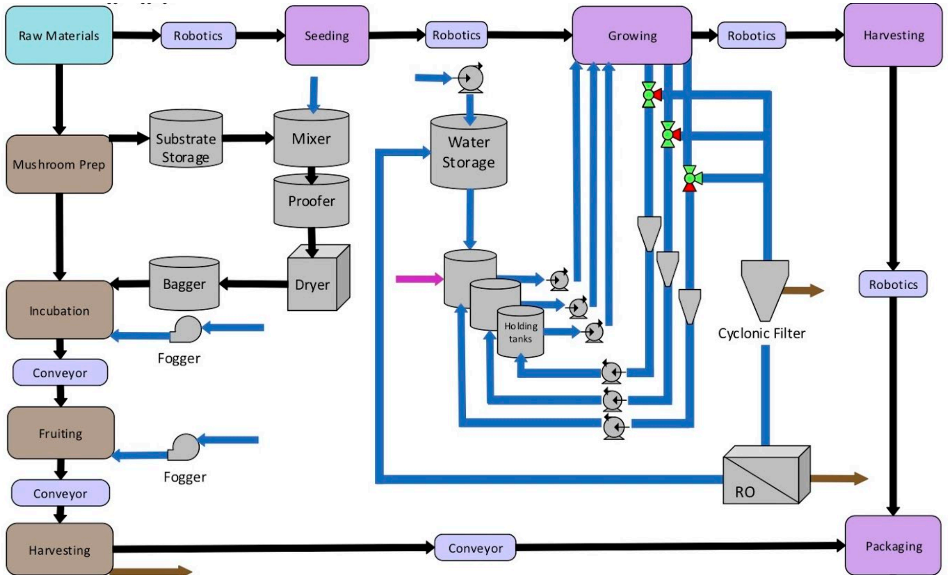
2021 AIChE ANNUAL MEETING

Process Systems and Operations Research Laboratory

Background

- Food security challenges worsening due to population growth and climate change
- Alternative approaches needed to supplement conventional food production
- Controlled environment agriculture (CEA)
  - Advantages
    - Sustainability
    - Increased food security
  - Disadvantages
    - High startup costs
    - Venture risk



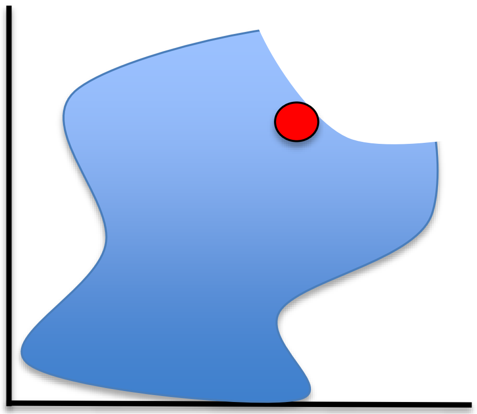


Motivation

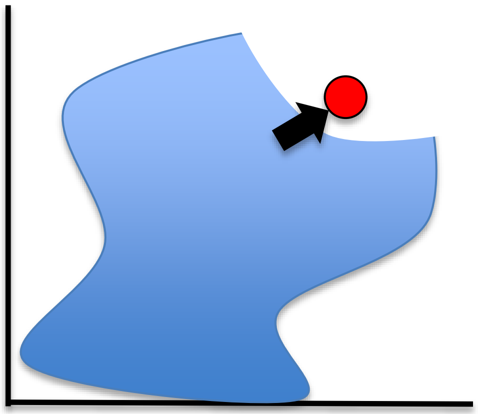
General-use CEA design and planning models to economically motivate adoption.

A realistic model must account for uncertainty.

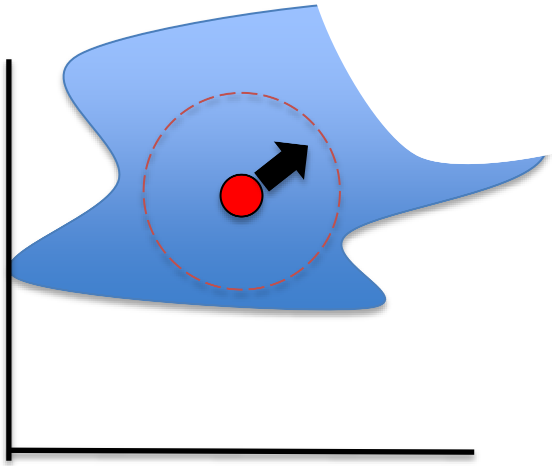
Simultaneous design and scheduling optimization.



Optimal design



Uncertainty realized



Robust-optimal design

Objective

Simultaneously optimize the design and scheduling of CEA systems for robustness to market uncertainty.

Revenue = Yield x Market Price

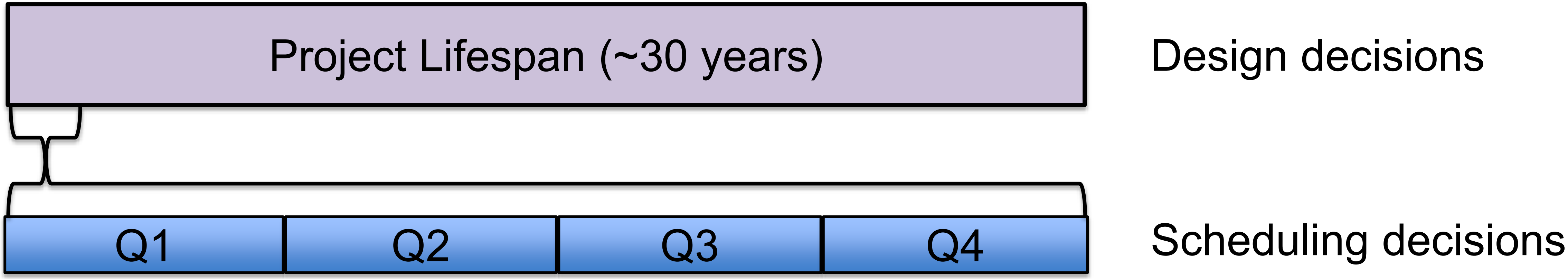
Production Mode	Uncertainty Considered
Traditional Outdoor	Yield
CEA (proposed)	Market Price

Robust Optimization

Rigorously tests the design and operating schedule under all uncertainty realizations.

Determines optimal design/operating schedule under worst-case uncertainty.

Returns a conservative design – actual performance will likely be better.



Model Features

General

- One model for economically optimal engineering design of CEA systems

Flexible

- Demand-based constraints, nutritional constraints, capital and operating cost models, location cost models

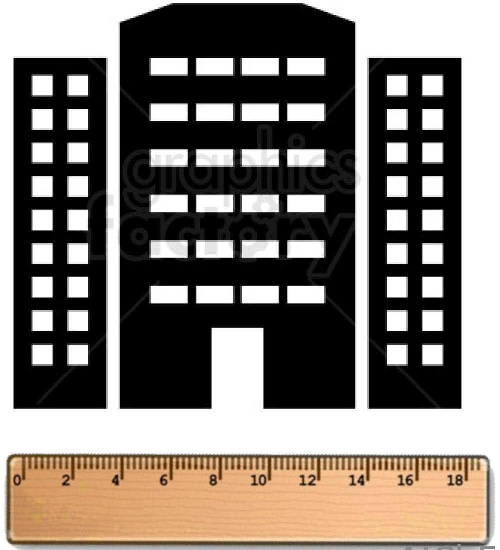
Efficient

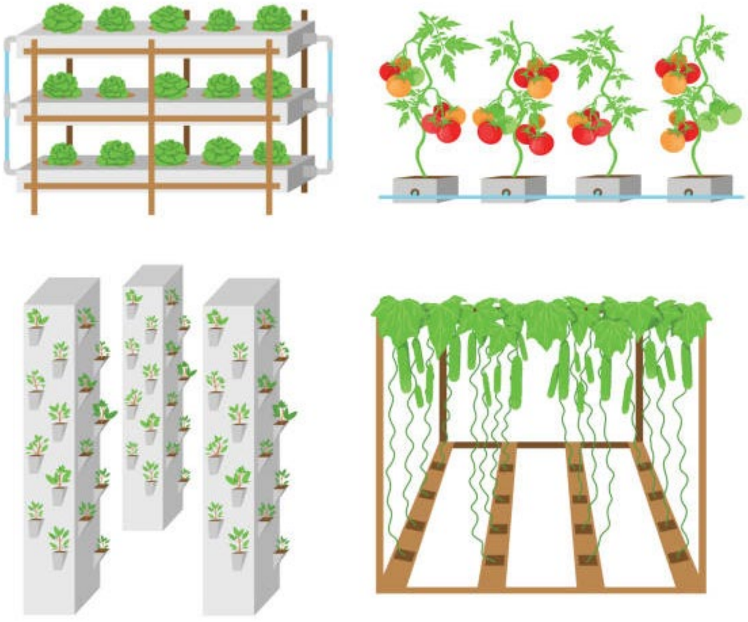
- Exploit existing solvers (IPOPT, Gurobi, EAGO) to rapidly assess economic viability of CEA systems with minimal modification required

Grower’s Model

Location

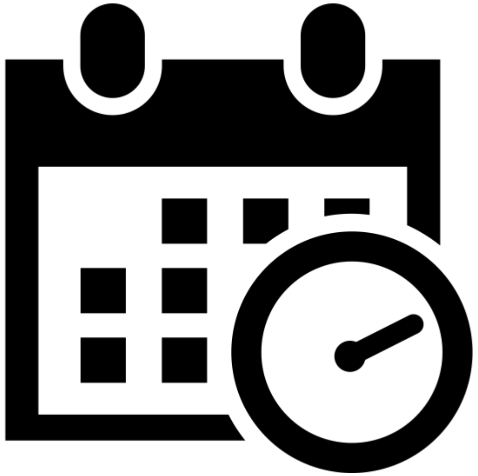
Capacity





Grow Modes

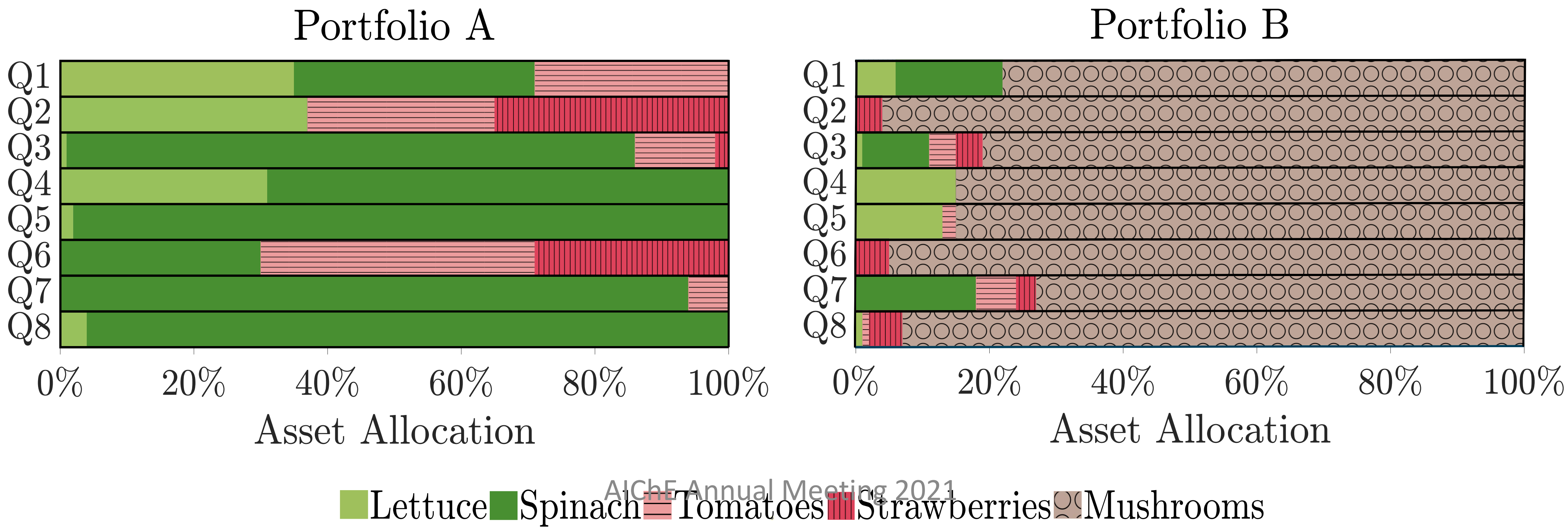
Scheduled Planting Plan



Grower’s Perspective

Simultaneous optimization of system design and operation.

- $\mathbf{d}$ Design variables: capacity, location, spatial allocation of each grow mode
- $\mathbf{X}$ Scheduling variables: crop allocations for each grow period



Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D, \mathbf{X}\in\Xi} f_{\text{NPV}}(\mathbf{d}, \mathbf{X})$$

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4} \mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \ \forall\, \mathbf{M}_j \in M_j \in \mathbb{R}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

Nonconvex objective function

- Maximize NPV over project lifespan
- Capital and operating expenses
- Annual cash-flow discounting

Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D, \mathbf{X}\in\Xi} f_{\text{NPV}}(\mathbf{d}, \mathbf{X})$$

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4} \mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \ \forall\, \mathbf{M}_j \in M_j \in \mathbb{R}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

Nonconvex objective function

Crop allocation constant sum

Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D,\mathbf{X}\in\Xi} f_{\mathrm{NPV}}(\mathbf{d},\mathbf{X})$$

Nonconvex objective function

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

Crop allocation constant sum

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

Capacity dedicated to a single grow mode

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4}\mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \forall\,\mathbf{M}_j \in M_j \in \mathbb{R}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D, \mathbf{X}\in\Xi} f_{\text{NPV}}(\mathbf{d}, \mathbf{X})$$

Nonconvex objective function

$$\text{s.t. } \mathbf{1}^{\text{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

Crop allocation constant sum

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

Capacity dedicated to a single grow mode

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4} \mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

Production limited by demand

$$\mathbf{x}_j^{\text{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \ \forall\, \mathbf{M}_j \in M_j \in \mathbb{R}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D, \mathbf{X}\in\Xi} f_{\mathrm{NPV}}(\mathbf{d}, \mathbf{X})$$

Nonconvex objective function

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

Crop allocation constant sum

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

Capacity dedicated to a single grow mode

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4}\mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

Production limited by demand

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \ \forall\,\mathbf{M}_j \in M_j \in \mathbb{IR}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

SIP constraints controlling multi-period risk exposure

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D, \mathbf{X}\in\Xi} f_{\mathrm{NPV}}(\mathbf{d}, \mathbf{X})$$

Nonconvex objective function

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

Crop allocation constant sum

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

Capacity dedicated to a single grow mode

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4} \mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

Production limited by demand

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \forall\, \mathbf{M}_j \in M_j \in \mathbb{R}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

SIP constraints controlling multi-period risk exposure

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

PSD covariance matrix

Grower's Model SIP

$$f^* = \max_{\mathbf{d}\in D,\mathbf{X}\in\Xi} f_{\mathrm{NPV}}(\mathbf{d},\mathbf{X})$$

Nonconvex objective function

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j = 1,\ j = 1,\ldots,n_p$$

Crop allocation constant sum

$$d_{z+2} = \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j = 1,\ldots,n_p,\ z = 1,\ldots,\mu$$

Capacity dedicated to a single grow mode

$$\mathbf{Qp}_{\min} \le \left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4}\mathbf{x}_{j+4(q-1)}\right) \le \mathbf{Qp}_{\max},\ q = 1,\ldots,n_y$$

Production limited by demand

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j - t_r \le 0,\ \ \forall\, \mathbf{M}_j \in M_j \in \mathbb{R}^{n_c\times n_c},\ j = 1,\ldots,n_p$$

SIP constraints controlling multi-period risk exposure

$$\mathbf{M}_j \succeq 0,\ j = 1,\ldots,n_p$$

PSD covariance matrix

Grower's Model SIP

$$f^{*}=\max_{\mathbf{d}\in D,\mathbf{X}\in\Xi} f_{\mathrm{NPV}}(\mathbf{d},\mathbf{X})$$

Nonconvex objective function

$$\text{s.t. } \mathbf{1}^{\mathrm{T}}\mathbf{x}_j=1,\ j=1,\ldots,n_p$$

Crop allocation constant sum

$$d_{z+2}=\left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\sum_{i\in\kappa_z} x_{ij}\right),\ j=1,\ldots,n_p,\ z=1,\ldots,\mu$$

Capacity dedicated to a single grow mode

$$\mathbf{Qp}_{\min}\le\left(\sum_{\zeta=1}^{\mu} d_{\zeta+2}\right)\left(\mathbf{Y}\sum_{j=1}^{4}\mathbf{x}_{j+4(q-1)}\right)\le\mathbf{Qp}_{\max},\ q=1,\ldots,n_y$$

Production limited by demand

$$\mathbf{x}_j^{\mathrm{T}}\mathbf{M}_j\mathbf{x}_j-t_r\le 0,\ \ \forall\,\mathbf{M}_j\in M_j\in\mathbb{R}^{n_c\times n_c},\ j=1,\ldots,n_p$$

SIP constraints controlling multi-period risk exposure

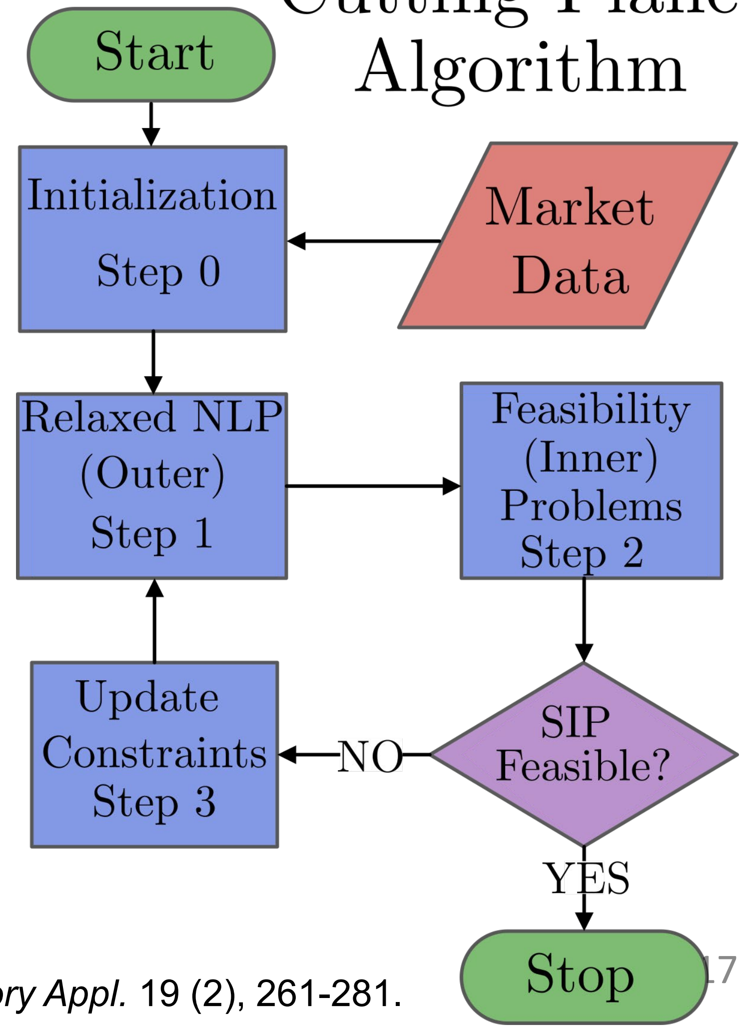
$$\mathbf{M}_j\succeq 0,\ j=1,\ldots,n_p$$

PSD covariance matrix

Solution Methodology

- The SIP must be solved to global optimality.
- Use the Blankenship & Falk cutting-plane algorithm.
- Construct SIP feasible set by iteratively solving the relaxed NLP (discretization-based procedure) and the feasibility problems.
- Use EAGO spatial B&B and JuMP for mathematical optimization in Julia

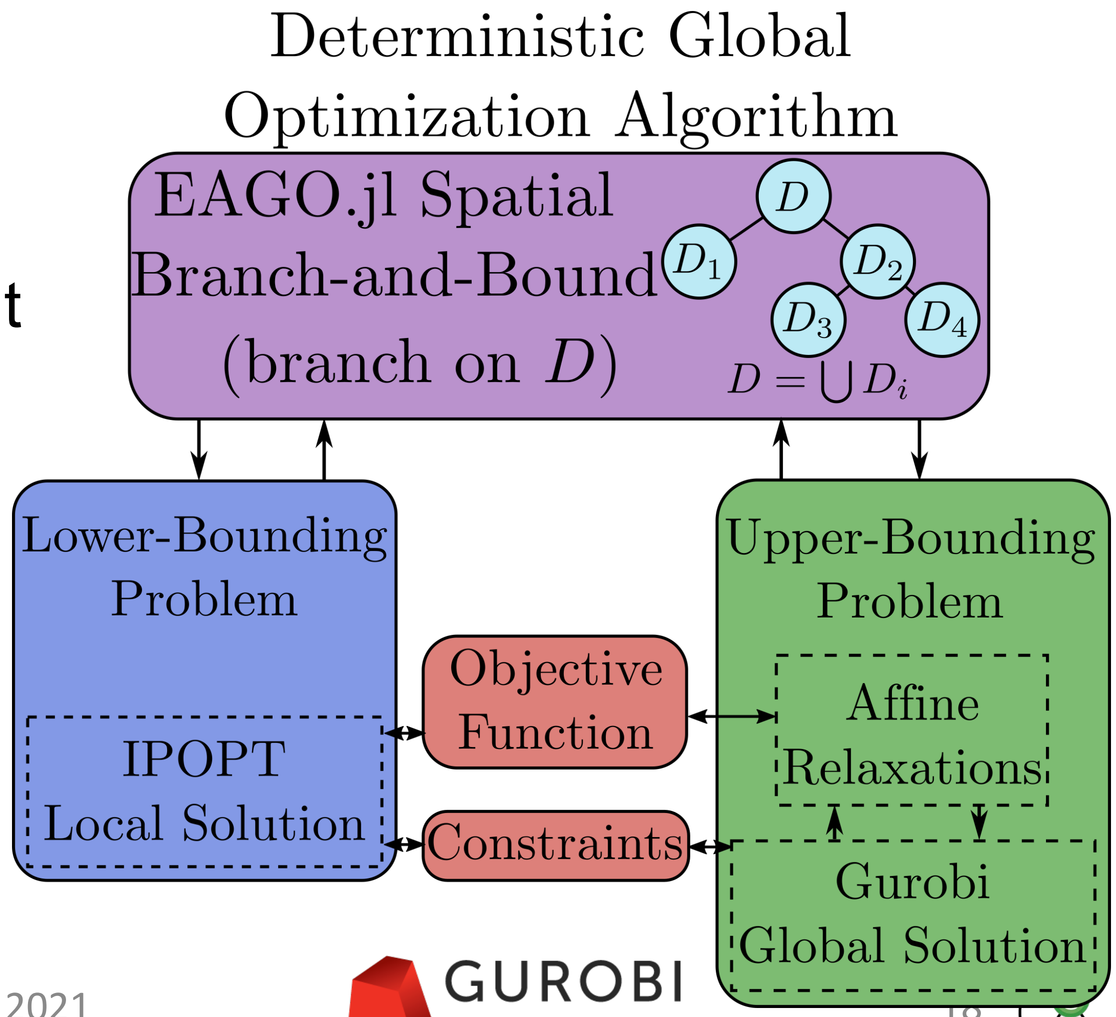
Cutting-Plane Algorithm



Blankenship, J.W., Falk, J.E., 1976. **Infinitely constrained optimization problems.** *J. Optim. Theory Appl.* 19 (2), 261-281.

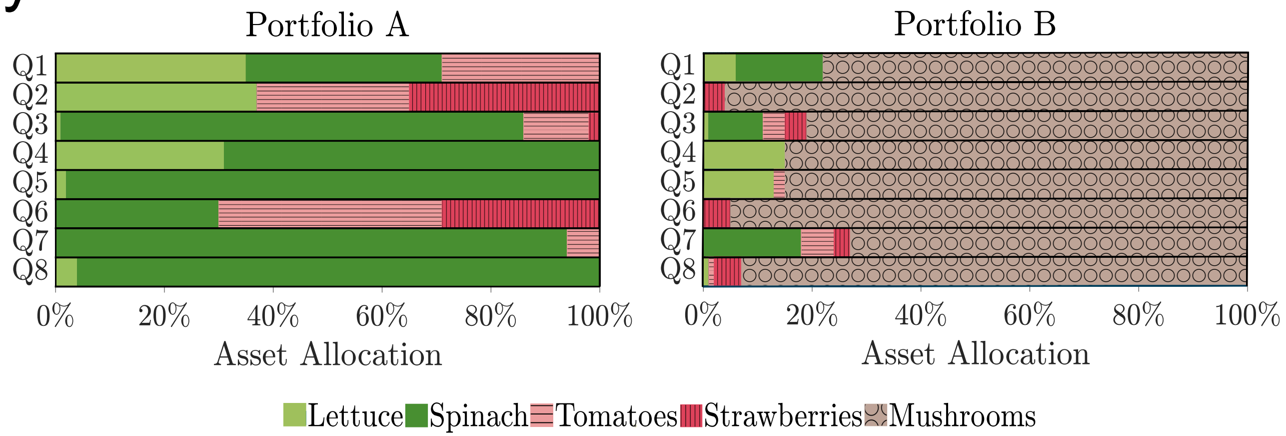
Solution Methodology

- We employ EAGO spatial B&B with custom upper- and lower-bounding problems.
- Lower-bounding problem
  - Solve NLP locally using IPOPT at current node in B&B tree
- Upper-bounding problem
  - Partially relax NLP to obtain affine and bilinear terms only, solve to global optimality using Gurobi's nonconvex solver
- Feasibility subproblems are SDPs solved reliably using SCS.



Case Study

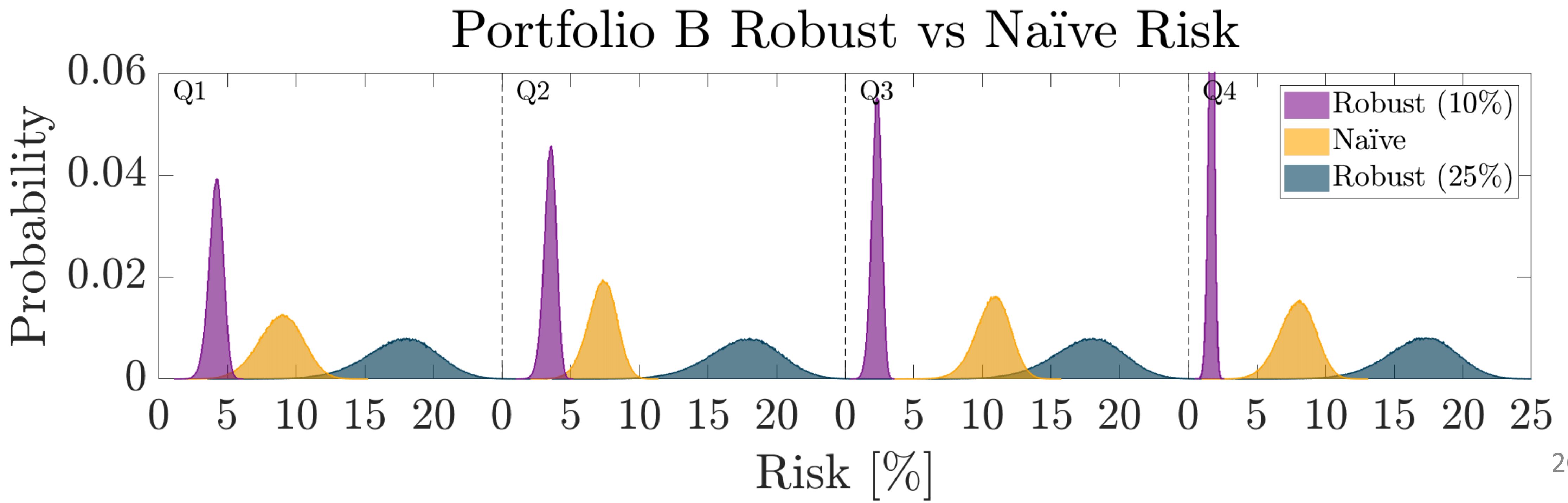
- 5 crops
  - $5^2 = 25$-dimensional uncertainty sets
- 8 growing periods
  - 8 semi-infinite constraints
- 2 growing modes



$$\text{dimensionality} = n_d + n_c n_p = \mu + 2 + n_c n_p$$

Results - Application

- Risk under Monte-Carlo simulated market returns to assess performance of robust vs naïve approach
- Robust design achieves significant risk reduction



Robust vs Naïve Allocations

NPV Reduction with Naïve Allocations vs. Robust Allocations

Tolerable Risk	**10%**	**14%**	**21.75%**	**22.5%**	**23%**	**25%**
Portfolio A	–	–	-195%	-165%	-157%	-155%
Portfolio B	-116%	-116%	-201%	-182%	-180%	-180%

- For a fixed design we observe over 100% reduction in NPV with naïve crop allocations in all simulated cases
- The economic feasibility of CEA systems is nontrivial

Summary & Conclusions

- Robust design and scheduling of CEA systems
- Economically viable robust systems designs
- Foundation for higher-complexity CEA design and planning applications

Summary & Conclusions

- Robust design and scheduling of CEA sys
- Economically viable robust systems desig
- Foundation for higher-complexity CEA des s

Computers and Chemical Engineering 149 (2021) 107285

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Optimal design of controlled environment agricultural systems under market uncertainty

Shaylin A. Cetegen[a,b], Matthew D. Stuber[a,*]

[a] Process Systems and Operations Research Laboratory, Dept. of Chemical and Biomolecular Engineering, University of Connecticut, 191 Auditorium Road, Unit 3222, Storrs, CT 06269, USA

[b] Dept. of Chemical Engineering, Massachusetts Institute of Technology, 77 Massachusetts Ave., Cambridge, MA 02139, USA

ARTICLE INFO

Article history:
Received 23 December 2020
Revised 12 February 2021
Accepted 9 March 2021
Available online 13 March 2021

Keywords:
Semi-infinite programming
Robust optimization
Global optimization
Branch-and-bound
Sustainable agriculture

ABSTRACT

We present a novel methodology for the simultaneous robust design and scheduling of controlled environment agricultural (CEA) systems under multi-period risk. This problem is formulated as a semi-infinite program with several semi-infinite constraints pertaining to mean-variance risk exposure with uncertain covariance over each period in the planning horizon. The general model enables robust optimization of CEA systems for cultivation of any crop portfolio under any number of cultivation modes, with a solution that represents an optimal design and operating schedule that is robust to worst-case uncertainty. Therefore, this methodology provides a conservative basis for engineering and investment decision-making and represents, to our knowledge, the first robust optimization approach to CEA systems. Our approach effectively increases the robustness of CEA systems to market uncertainty, improves the long-term economics of CEA systems over naïve operating strategies, and validates the economic viability of single and multi-mode CEA production of distinct crop portfolios.

1. Introduction

Conventional agribusiness operations are inherently risky as their economic feasibility depends on highly uncertain factors such as weather and food supply and demand. Unpredictable environmental changes and extreme weather events such as droughts, floods, and fires pose direct threats to crop yields, which translate to significant revenue losses for agricultural producers over time (Deschênes and Greenstone, 2007; FAO, 2018). As the duration and frequency of such events are projected to rise into the foreseeable future, their impacts will continue to endanger the global food supply (Field et al., 2012). Further, as global population growth intensifies, increasing food demand is projected to outpace the capabilities of traditional outdoor agriculture systems (Fedoroff, 2015). As long as these trends persist, the compounding effects of greater weather variability and demand-driven market volatility will continue to endanger conventional agribusiness operations. The demand for increased food production under heightened uncertainty will not only increase pressure on existing agricultural operations, but also pose a broader challenge to food security. To ensure growing demand continues to be met under increasingly volatile conditions, alternative agricultural approaches are being considered to supplement traditional outdoor growing methods.

Controlled environment agriculture (CEA) is an alternative strategy in which crops are cultivated indoors in climate-controlled environments. Decoupling crop growth from environmental conditions through CEA presents an opportunity to alleviate the stress placed on exhaustible natural resources by existing food production practices while increasing local food production and improving food access and security (Benke and Tomkins, 2017). Increased consumer demand for year-round local availability of responsibly sourced fresh produce has already motivated the establishment of CEA operations across the United States, Europe, Asia, and Australia (Despommier, 2009; Butturini and Marcelis, 2020). The adoption of this alternative growing model has risen in recent years and is expected to grow significantly with rising consumer demand and climate awareness. It is estimated that the global vertical farming market alone, a subset of the global CEA market, is projected to reach \$9.96 billion by 2025, expanding at a compound annual growth rate of more than 21% over the forecast period (Grand View Research, 2019). However, the high-risk low-reward nature of traditional agribusiness poses a challenge to the investment in and growth of this more environmentally and socially responsible alternative to traditional cultivation methods. To reap the benefits of CEA, the economic motivation for investment in this approach

* Corresponding author.
E-mail addresses: cetegen@mit.edu (S.A. Cetegen), stuber@alum.mit.edu (M.D. Stuber).

https://doi.org/10.1016/j.compchemeng.2021.107285

Acknowledgements

Members of the process systems and operations research laboratory at the University of Connecticut (https://psor.uconn.edu/)

Matthew Wilhelm

2021 AIChE ANNUAL MEETING

Process Systems and Operations Research Laboratory

UCONN
UNIVERSITY OF CONNECTICUT

Thank you for your attention!

2021 AIChE ANNUAL MEETING

Process Systems and Operations Research Laboratory