


# NSF Workshop on Control Co-Design (CCD)

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## → Outline

### 1. What You Should Know

Formulating

Solving

Modeling

### 2. Portrait of CCD Research

One Thread of Historical CCD Development

Introduction to Direct Methods for Optimal Control



①

What should control researchers know  
about design research?

## → Optimization Model-based CCD

- Many control co-design (CCD) approaches leverage model-based CCD
- Often this is further structured as *optimization model-based CCD*
  - This comes with the value, goal, or objective measure(s)
  - We also must consider what is possible — the constraints

changing: plant decisions, control decisions (1a)

(maximize or) minimize: goal (1b)

subject to: what is possible (1c)

- Let's add some more structure to the CCD problem:

changing: plant decisions  $\mathbf{x}_p$ , control decisions  $\mathbf{x}_c$  (2a)

(maximize or) minimize: goal  $J(\mathbf{x}_p, \mathbf{x}_c)$  (2b)

subject to: physical design-only constraints  $\mathbf{g}_p(\mathbf{x}_p)$  (2c)

control design-only constraints  $\mathbf{g}_c(\mathbf{x}_c)$  (2d)

coupled system constraints  $\mathbf{g}_s(\mathbf{x}_p, \mathbf{x}_c)$  (2e)

## → Design Coupling and Synergy Mechanisms

- We are here because of the **purple coupled** parts — they enable the investigation of design coupling and synergy mechanisms
- *Design coupling* — How design decisions in one domain influence the ideal design decisions in other domains
  - For example, plant decisions might impact controller gains, or control decisions modify the states that force the plant decisions to change
  - Is it strong or significant? Is it captured by the optimization model?
- *Synergy mechanism* — A specific underlying design mechanism that facilitates overall system performance improvements when two or more design elements are varied synergistically<sup>1</sup>
  - In wind energy, CCD enables the synergistic reduction in tower size with better-controlled maintenance of the optimal tip speed ratio, structural deflections, and stress<sup>2</sup>
- Certain simplified system dynamics (such as steady-state or pseudostatic models) or static analysis that neglects dynamic effects altogether don't readily support these ideas<sup>3</sup>

<sup>1</sup> Allison, Herber, and Deshmukh 2015   <sup>2</sup> Deshmukh and Allison 2015   <sup>3</sup> Allison and Herber 2014

## → What Should Our Goals Be? (Or What Have Our Goals Been?)

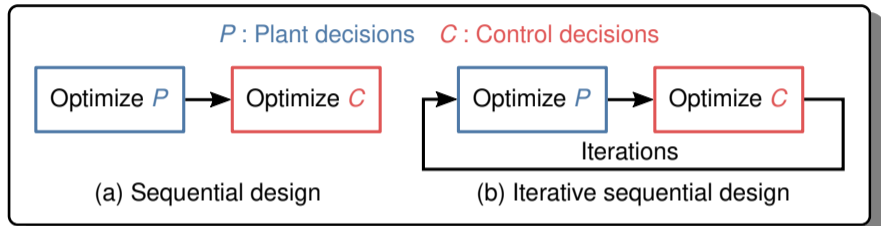
- ❓ What determines the system's value that we are driving at through a CCD perspective?
- ❓ Are we looking to understand trade-offs (multi-objective perspectives)?
  - Sometimes the result of these questions leads to separable “design”-focused goals  $J_p$  and “control”-focused goals  $J_c$
  - In other CCD application spaces, such a distinction might be unnatural or unnecessary
    - In energy systems, this might be the levelized cost of energy (LCOE)<sup>1</sup>
    - Other areas are cost-driven (minimize cost within prescribed specifications)
  - Still, limited or simplified consideration of the dynamics and controls occurs
    - For example, designing a counterbalanced robotic manipulator as a proxy for minimizing energy consumption<sup>2</sup>
  - Overall we might consider appropriately “balanced” CCD approaches
    - Ones that identify the key system-level goals without undue influence of *either* area

<sup>1</sup> Sundarraj, Lee, et al. 2021    <sup>2</sup> Allison and Herber 2014

## → Consider the Limits

- A common perspective in the design community is understanding feasible system solutions through limits
  - Inequality constraints in the optimization context
- These might be simple bounds ( $x \leq a$ ) or more complicated constraints on our independent decisions or derived quantities (e.g., outputs, states, and control signals)
  - Examples include cost, mass, geometric dimensions, deflection, stress, fatigue, packaging, temperatures, power, actuator limits, etc.
- Drivers are often failure theories, manufacturing limits, stakeholder preferences, or even engineering judgment
- ❓ A question then is what are effective CCD strategies assuming these concerns?
  - Many popular control paradigms don't directly handle such concerns
  - This has led some CCD researchers to explore methods with this specific situation in mind

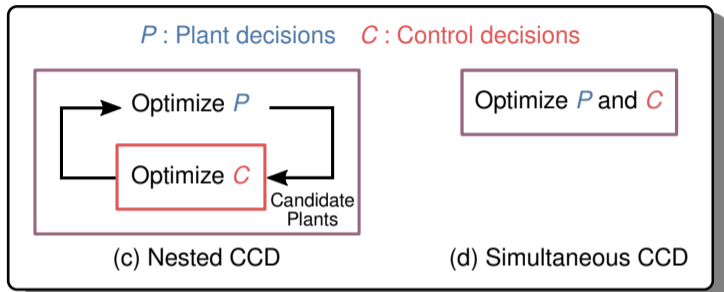
## → How Should We Solve It? — Sequential Perspective



- *Sequential design* — Determine the plant first, controller second ✘
- *Iterative sequential design* — Now we pass control design results back for plant redesign and iterate
  - What is communicated back? Might be a fixed controller and/or insights into changes related to the physical-design domain
  - This approach can suffer from slow convergence and well-posedness issues
- ❓ Can we do better?



## → How Should We Solve It? — Simultaneous and Nested CCD Strategies



- *Nested CCD* — Ask the question, if I made this physical system, what would the best controller be? This is the essence of the nested approach<sup>1</sup>
  - Embedded inner-loop optimization problem (control subproblem) within the outer loop
- *Simultaneous CCD* — Consider both at the same time in one problem
  - Could follow many paths toward the system-level optimum

<sup>1</sup> Herber and Allison 2018

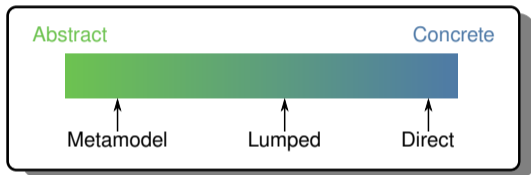
## → Simultaneous and Nested CCD Strategies — Which One?

1. **X** is faster and more scalable than **Y** — *It depends!*<sup>1</sup>
  - A poorly implemented **Y** is worse than a well implemented **X**
2. **X** is easier to implement than **Y** — *It depends!*
  - Sometimes it is easier to create one problem with simultaneous CCD
  - Sometimes it is easier to partition based on an existing control design technique for the inner-loop subproblem
3. **X** is more robust and accurate than **Y** — *It depends!*
  - Simultaneous CCD has more flexibility to explore since infeasibility is allowed while iterating/solving
  - Nested CCD can support hybrid approaches with focused exploration (often the physical design parameters) but might fail to converge if the inner loop does not always have a solution
4. **X** will result in the same solution than **Y** — *It depends!*
  - Many CCD problems do not readily support “nice” formulations
  - In certain CCD problems, concerns regarding local optima are valid

<sup>1</sup> Sundarrajan and Herber 2021

## → Modeling for Effective and Balanced CCD (1)

- Lots of ways to model and represent change to our physical systems or plants
- However, there is sometimes a disconnect between the more “controls-centric” plant modeling needs and the model concerns of physical system realization



- *Metamodel* — coefficients in a state-space model or transfer function
- *Lumped model* — physics-driven intermediate parameters
  - For example, the spring constant  $k$  in the  $a_{2,3}$  coefficient  $k/m$  of the state-space model
- *Direct model* — independent decisions, more closely connected to manufacturing
  - Instead of  $k$  from before, we might consider the spring wire diameter directly

## → Modeling for Effective and Balanced CCD (2)

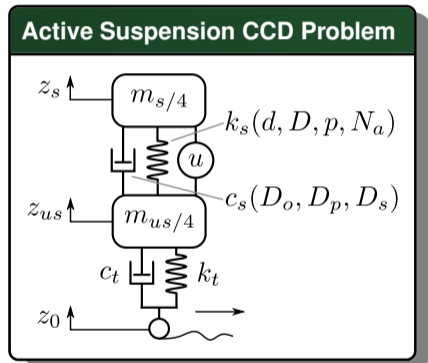
- More abstract representations might be considered plant requirements or targets, but the issue comes when there is a disconnect between this CCD result and what is physically possible, especially when plant-design constraints are ignored<sup>1</sup>
- This isn't to say there isn't value in more abstract CCD problems — we should consider the realizability of the outcome
- Linear vs. nonlinear models, low vs. high fidelity models — ensure that system performance assessment is sufficiently close to reality even if the primary (control) design methods are based on linear theory
  - Overly simplified plant models might not enable sufficient exploration and exploitation of design coupling

<sup>1</sup> Allison and Herber 2014

## → Active Suspension Case Study

The next 4 slides are from [https://www.engr.colostate.edu/%7Edrherber/files/Sundarrajan2021a\\_presentation.pdf](https://www.engr.colostate.edu/%7Edrherber/files/Sundarrajan2021a_presentation.pdf)

- **Active vehicle suspension CCD problem in this work is the one from Allison, Guo, and Han 2014**
- The system consists of two masses: sprung mass  $m_s/4$  and unsprung mass  $m_{us}/4$
- The suspension is composed of a spring  $k_s$  and damper  $c_s$ , and a force actuator  $u(t)$
- $k_t$  and  $c_t$  are the spring damper constants of the tire, and  $z_0(t)$  is the road input
- There are seven design geometric plant design variables associated with the spring and damper



## → System Dynamics and Objective

- There are four states in the system ( $z_s - z_{us}, \dot{z}_s, z_{us} - z_0, \dot{z}_{us}$ )
- The dynamics of the system are linear with respect to  $(\xi(t), u(t))$ , and nonlinear with respect to  $x_p$ :

$$\dot{\xi}(t) = \mathbf{A}(x_p)\xi(t) + \mathbf{B}u(t) + \mathbf{E}\dot{z}_0(t) \quad (6a)$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \frac{-k_t(x_p)}{m_{us/4}} & \frac{-[c_s(x_p)+c_t]}{m_{us/4}} & \frac{k_s(x_p)}{m_{us/4}} & \frac{c_s(x_p)}{m_{us/4}} \\ 0 & -1 & 0 & 1 \\ 0 & \frac{c_s(x_p)}{m_s/4} & \frac{-k_s(x_p)}{m_s/4} & \frac{-c_s(x_p)}{m_s/4} \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 \\ -1 \\ 0 \\ \frac{1}{m_s/4} \end{bmatrix}, \mathbf{E} = \begin{bmatrix} -1 \\ \frac{c_t}{m_{us/4}} \\ 0 \\ 0 \end{bmatrix} \quad (6b-c)$$

- The objective function is a combination of quadratic penalties on handling ( $z_{us} - z_0$ ), passenger comfort  $\ddot{z}_s$ , and control effort  $u$ :

$$o = \int_{t_0}^{t_f} \left[ w_1 \xi_1^2 + w_2 [\dot{\xi}_4(t, \xi, u, x_p)]^2 + w_3 u^2 \right] dt \quad (7)$$

with  $w_1 = 10^5$ ,  $w_2 = 0.5$ , and  $w_3 = 10^{-5}$  from Ref. Allison, Guo, and Han 2014

- Two design load cases  $z_0$  are simultaneously considered with a weighted sum: 1) ramp profile, 2) rough road profile

$$\min_{\xi, u, x_p} 10^{-2} o(\xi_{\text{ramp}}, u_{\text{ramp}}, x_p) + o(\xi_{\text{rough}}, u_{\text{rough}}, x_p) \quad (8)$$

## → Plant Design: Spring

- The spring physical design variables are the wire diameter  $d$ , helix diameter  $D$ , pitch  $p$ , and number of active coils  $N_a$
- The main intermediate parameter is the spring constant  $k_s(\mathbf{x}_p)$ :

$$k_s = \frac{d^4 G}{8D^3 N_a \left[ 1 + \frac{d^2}{2D^2} \right]}$$

- There are six static constraints and four dynamic constraints

## Spring Design

$$g_{o,1}(\mathbf{x}_p) = 4 - C \leq 0 \quad (10)$$

$$g_{o,2}(\mathbf{x}_p) = C - 12 \leq 0 \quad (11)$$

$$g_{o,3}(\mathbf{x}_p) = L_0 - 5.26D \leq 0 \quad (12)$$

$$g_{o,4}(\mathbf{x}_p) = L_0 - 0.40 \leq 0 \quad (13)$$

$$g_{o,5}(\mathbf{x}_p) = d + D - 0.25 \leq 0 \quad (14)$$

$$g_{o,6}(\mathbf{x}_p) = 1.2\tau(F_s) - S_{sy} \leq 0 \quad (16)$$

$$g_{i,1}(\mathbf{x}_p, \boldsymbol{\xi}) = \max_t |\xi_3(t)| - L_0 + L_s + 0.02 + \delta_g \leq 0 \quad (17)$$

$$g_{i,2}(\mathbf{x}_p, \boldsymbol{\xi}) = 0.15 + 1 - \frac{L_0 - L_s}{\delta_g + 1.1\xi_3(t)} \leq 0 \quad (18)$$

$$g_{i,3}(\mathbf{x}_p, \boldsymbol{\xi}) = \frac{1.2\tau(F_a)}{0.24S_{ut}} + \frac{\tau(F_m)}{S_{sy}} - 1 \leq 0 \quad (19)$$

$$g_{i,4}(\mathbf{x}_p, \boldsymbol{\xi}) = \frac{1.2\tau(F_a)}{241 \times 10^6} - 1 \leq 0 \quad (20)$$

## → Plant Design: Damper

- The damper physical design variables are the valve diameter  $D_o$ , working piston diameter  $D_p$ , and damper stroke  $D_s$
- The intermediate parameter is the damper constant  $c_s(\mathbf{x}_p)$ :

$$c_s = \frac{D_p^4}{8C_d C_2(D_o) D_o^2} \sqrt{\frac{\pi k_v \rho_1}{2}}$$

- There are three static and dynamic constraints

### Damper Design

$$g_{o,7}(\mathbf{x}_p) = d - D + D_p + 0.022 \leq 0 \quad (22)$$

$$g_{o,8}(\mathbf{x}_p) = 2D_s - 0.394 \leq 0 \quad (23)$$

$$g_{o,9}(\mathbf{x}_p) = L_0 - L_s - D_s \leq 0 \quad (24)$$

$$g_{i,5}(\mathbf{x}_p, \boldsymbol{\xi}) = \frac{4c_s(D_o) \max_t |\dot{\xi}_3(t)|}{\pi D_p^2} - 4.75 \times 10^6 \leq 0 \quad (25)$$

$$g_{i,6}(\mathbf{x}_p, \boldsymbol{\xi}) = \max_t |\dot{\xi}_3(t)| - 5 \leq 0 \quad (26)$$

$$g_{i,7}(\mathbf{x}_p, \boldsymbol{\xi}) = \frac{4\pi D_o^2 c_s(D_o) \max_t |\dot{\xi}_3(t)|}{4k_v \pi D_p^2} - 0.03 \leq 0 \quad (27)$$



②

Portrait of CCD research through now:  
physical-system design perspective

## → Introduction

- With concerns of ...
  - Bidirectional coupling
  - General objective functions
  - Time-domain specifications
  - Inclusion of various limits
  - Comprehensive plant design representations, including independent design variables and nonlinear dynamics
  - Understanding system performance limits and optimal dynamic and control behaviors

... a certain direction of CCD research arose

## → One Thread of Historical CCD Development (1)

### Early Integrated Design Methods

- 1980's–1990's: Control Structure Interaction (CSI) optimizing the structure and controller to minimize unwanted structural vibration modes<sup>1</sup>
- 1980's–present: Multidisciplinary Design Optimization (MDO) but developed around fundamentally static system models<sup>2</sup>

### Initial CCD Research

### *A Breakthrough: Direct Optimal Control in CCD*

### CCD Method Maturation and Impact

### Going Forward

<sup>1</sup> Crawley and Luis 1987; Manning 1991; S. S. Rao and Sunar 1994 1997; Martins and Lambe 2013; Allison and Herber 2014

<sup>2</sup> Sobieszczanski-Sobieski and Haftka

## → One Thread of Historical CCD Development (2)

### Early Integrated Design Methods

### Initial CCD Research

- Late 1990's/early 2000's: CCD theory and method development<sup>1</sup>
- Advances based on certain assumptions such as unidirectional design coupling and LQR/G control
- Cannot account for plant design in a comprehensive manner<sup>2</sup> (e.g., state-dependent failure modes)

### *A Breakthrough:* Direct Optimal Control in CCD

### CCD Method Maturation and Impact

### Going Forward

<sup>1</sup> Fathy et al. 2001; Reyer et al. 2001    <sup>2</sup> Allison and Herber 2014; Allison, Guo, and Han 2014; Herber and Allison 2018

## → One Thread of Historical CCD Development (3)

### Early Integrated Design Methods

### Initial CCD Research

### *A Breakthrough: Direct Optimal Control in CCD*

- 2011: First publication of CCD with direct transcription (DT) enabling comprehensive plant design while being generally efficient and scalable<sup>1</sup>
- 2017: Revised CCD theory for bi-directional problems<sup>2</sup>

### CCD Method Maturation and Impact

### Going Forward

<sup>1</sup> Allison, Guo, and Han 2014    <sup>2</sup> Herber and Allison 2018

## → One Thread of Historical CCD Development (4)

### Early Integrated Design Methods

### Initial CCD Research

### *A Breakthrough: Direct Optimal Control in CCD*

### CCD Method Maturation and Impact

- Expanded applications, growing impact (new programs – NSF and ARPA-E)
- 2019: Labeled an engineering game changer<sup>1</sup>
- Deeper understanding of these methods and better implementations with solution time 100x less than initial efforts<sup>2</sup>
- Expansion beyond basic deterministic CCD with open-loop optimal control (e.g., distributed CCD, stochastic CCD, robust MPC, etc.)

### Going Forward

<sup>1</sup> Garcia-Sanz 2019   <sup>2</sup> Sundarraj and Herber 2021

## → One Thread of Historical CCD Development (5)

**Early Integrated Design Methods**

**Initial CCD Research**

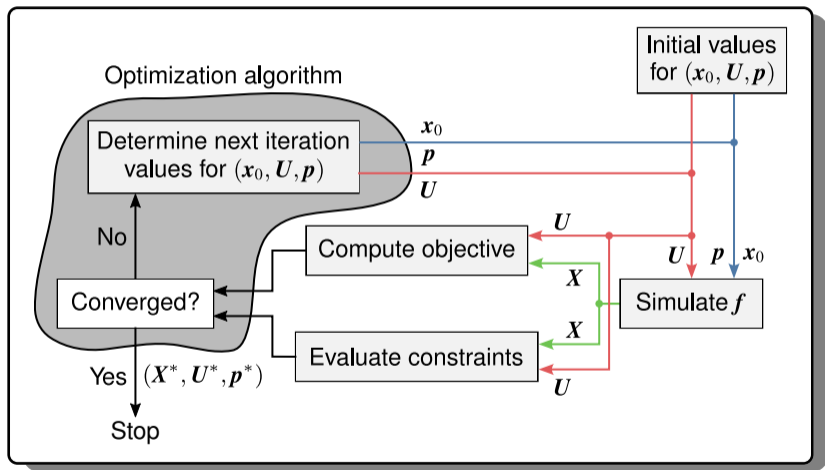
***A Breakthrough: Direct Optimal Control in CCD***

**CCD Method Maturation and Impact**

**Going Forward**

- Incorporating detailed physical models (perhaps possible with surrogate modeling and machine learning)
- Account for uncertainty in the presence of design coupling
- Bridging the gap between the open-loop control insights and closed-loop control solutions
- Getting into the lab, physical experiments, and on actual products, especially when supporting higher-TRL development efforts

## → Simulation-based Method Block Diagram

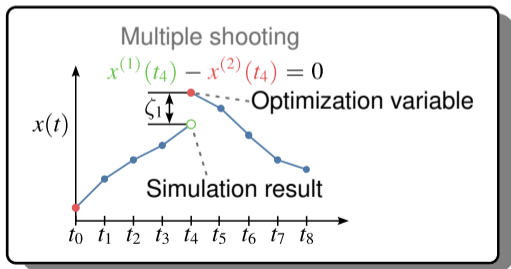
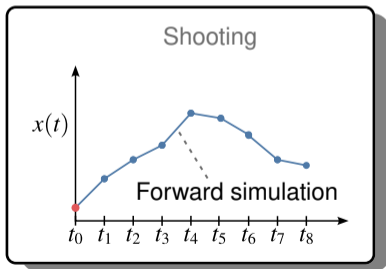




## → Multiple Shooting or Break Up the Long Simulation

- In the multiple shooting approach<sup>1</sup>, we partition the time horizon into smaller time segments, and separate simulations are performed on each segment
- This results in a multiphase problem that requires continuity constraints, i.e., continuous states at each time segment:

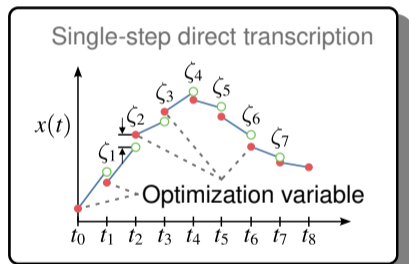
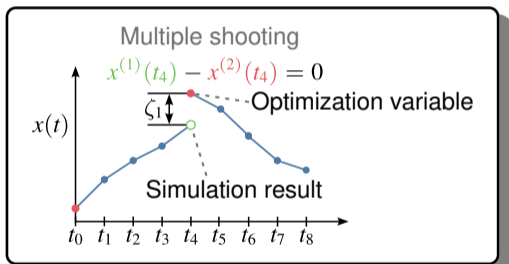
$$\underbrace{x^{(1)}(t_1)}_{\text{simulation result}} = \underbrace{x^{(2)}(t_1)}_{\text{optimization variable}} \quad (3)$$



<sup>1</sup> Section 3.4 in *Practical Methods for Optimal Control and Estimation Using Nonlinear Programming*

## → Multiple Shooting vs. Direct Transcription

- ❓ What if we reduce the simulation (shooting) horizon to only two points?
  - This idea is the essence of a single-step direct transcription (DT) (or time-marching or integral DT) method<sup>1</sup>



<sup>1</sup> See Chapters 2 & 3 in *Practical Methods for Optimal Control and Estimation Using Nonlinear Programming*, Chapters 8 & 10 in *Nonlinear Programming*, and Betts 1998; A. V. Rao 2010; Kelly 2017

## → Direct Transcription Comments

- Although it may be counterintuitive to create such a large problem with many more variables and constraints, it is in fact often better than the alternatives
  - For example, finite-horizon LQR is solved with matrix multiplications and an inverse
- There are many tools available to help construct and solve DT problems with a variety of different numerical methods (and some do support the inclusion of plant design variables)
  - You don't have to (and probably shouldn't) do this on our own
- DT is closely related to model predictive control (MPC); individual MPC problems are DT-like problems
  - An MPC strategy solves open-loop problems sequentially with feedback from what the system actually did under previous control actions
- Similar to linear-quadratic problems from classical control theory, linear-quadratic dynamic optimization problems can be efficiently solved as quadratic programs (QPs)
  - Used in some studies with LQDO-amenable CCD problems using the nested CCD strategy

## → References

- J. T. Allison, T. Guo, and Z. Han (2014). “Co-Design of an Active Suspension Using Simultaneous Dynamic Optimization”. *Journal of Mechanical Design* 136.8. DOI: 10.1115/1.4027335
- J. T. Allison and D. R. Herber (2014). “Multidisciplinary design optimization of dynamic engineering systems”. *AIAA Journal* 52.4. DOI: 10.2514/1.j052182
- J. T. Allison, D. R. Herber, and A. P. Deshmukh (2015). “Integrated design of dynamic sustainable energy systems”. *International Conference on Engineering Design*
- J. T. Betts (1998). “Survey of numerical methods for trajectory optimization”. *Journal of Guidance, Control, and Dynamics* 21.2. DOI: 10.2514/2.4231
- — (2010). *Practical Methods for Optimal Control and Estimation Using Nonlinear Programming*. Society for Industrial and Applied Mathematics. DOI: 10.1137/1.9780898718577
- L. T. Biegler (2010). *Nonlinear Programming*. Concepts, Algorithms, and Applications to Chemical Processes. Society for Industrial and Applied Mathematics. DOI: 10.1137/1.9780898719383
- E. F. Crawley and J. de Luis (1987). “Use of piezoelectric actuators as elements of intelligent structures”. *AIAA Journal* 25.10. DOI: 10.2514/3.9792
- A. P. Deshmukh and J. T. Allison (2015). “Multidisciplinary dynamic optimization of horizontal axis wind turbine design”. *Structural and Multidisciplinary Optimization* 53.1. DOI: 10.1007/s00158-015-1308-y
- H. K. Fathy et al. (2001). “On the coupling between the plant and controller optimization problems”. *American Control Conference*. DOI: 10.1109/acc.2001.946008

## → References (Continued)

- M. Garcia-Sanz (2019). "Control co-design: an engineering game changer". *Advanced Control for Applications: Engineering and Industrial Systems* 1.1. DOI: 10.1002/adc2.18
- D. R. Herber and J. T. Allison (2018). "Nested and simultaneous solution strategies for general combined plant and control design problems". *Journal of Mechanical Design* 141.1. DOI: 10.1115/1.4040705
- M. Kelly (2017). "An introduction to trajectory optimization: how to do your own direct collocation". *SIAM Review* 59.4. DOI: 10.1137/16m1062569
- R. Manning (1991). "Optimum design of intelligent truss structures". *Structures, Structural Dynamics, and Materials Conference*. DOI: 10.2514/6.1991-1158
- J. R. R. A. Martins and A. B. Lambe (2013). "Multidisciplinary Design Optimization: A Survey of Architectures". *AIAA Journal* 51.9. DOI: 10.2514/1.j051895
- A. V. Rao (2010). "A survey of numerical methods for optimal control". *Advances in the Astronautical Sciences* 135.1
- S. S. Rao and M. Sunar (1994). "Piezoelectricity and Its Use in Disturbance Sensing and Control of Flexible Structures: A Survey". *Applied Mechanics Reviews* 47.4. DOI: 10.1115/1.3111074
- J. A. Reyer et al. (2001). "Comparison of Combined Embodiment Design and Control Optimization Strategies Using Optimality Conditions". *ASME Design Engineering Technical Conference*. DETC2001/DAC-21119

## → References (Continued)

- J. Sobieszczanski-Sobieski and R. T. Haftka (1997). “Multidisciplinary aerospace design optimization: survey of recent developments”. *Structural Optimization* 14.1. DOI: 10.1007/bf01197554
- A. K. Sundarrajan and D. R. Herber (2021). “Towards a fair comparison between the nested and simultaneous control co-design methods using an active suspension case study”. *American Control Conference*. DOI: 10.23919/acc50511.2021.9482687
- A. K. Sundarrajan, Y. H. Lee, et al. (2021). “Open-loop control co-design of floating offshore wind turbines using linear parameter-varying models”. *International Design Engineering Technical Conferences*. DOI: 10.1115/detc2021-67573

Thanks!