## Vehicle Propulsion Systems Lecture 6

Deterministic Dynamic Programming and Some Examples

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# Energy consumption for cycles



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# Hybrid Electrical Vehicles – Parallel

### Two parallel energy paths



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# Model implemented in QSS

# Conventional powertrain



Efficient computations are important –For example if we want to do optimization and sensitivity studies.

# Outline

### Repetition

"Traditional" Optimization Problem motivation Different Classes of Proble

Optimal Control Problem Motivati

Deterministic Dynamic Program

Problem setup and basic solution idea Cost Calculation – Two Implementation Alternatives The Provided Tools

### Case Studies

Energy Management of a Parallel Hybrid

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# Hybrid Electrical Vehicles - Serial

- Two paths working in parallel
- Decoupled through the battery



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# Component modeling

- Model energy (power) transfer and losses
- Using maps  $\eta = f(T, \omega)$



Electric motor map

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 Using parameterized (scalable) models –Willans approach

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### Problem motivation

What gear ratios give the lowest fuel consumption for a given drivingcycle?

### -Problem presented in appendix 8.1



### Problem characteristics

- ► Countable number of free variables,  $i_{g,j}, j \in [1, 5]$
- A "computable" cost,  $m_f(\cdots)$
- A "computable" set of constraints, model and cycle
- The formulated problem

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 $\min_{i_{g,j}, j \in [1,5]}$  $m_f(i_{g,1}, i_{g,2}, i_{g,3}, i_{g,4}, i_{g,5})$ model and cycle is fulfilled s.t.

### **Optimization – Non-Linear Programming**

Non-linear problem

$$\begin{array}{rcl} \min_{x} & f(x) \\ \text{s.t.} & g(x) &= 0 \\ & x &> 0 \end{array}$$

- For convex problems -Much analyzed: existence, uniqueness, sensitivity -Many algorithms
- For non-convex problems -Some special problems have solutions -Local optimum is not necessarily a global optimum

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### Some comments on problem solver

- Find the "right" problem formulation
- Use the right solver for the problem

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### **Optimal Control – Problem Motivation**

Car with gas pedal u(t) as control input: How to drive from A to B on a given time with minimum fuel consumption?

- Infinite dimensional decision variable u(t).
- Cost function  $\int_0^{t_f} \dot{m}_f(t) dt$
- Constraints:

Model of the car (the vehicle motion equation)

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- Starting point x(0) = AEnd point  $x(t_t) = B$ Speed limits  $v(t) \le g(x(t))$ Limited control action  $0 \le u(t) \le 1$
- In general difficult (impossible) problem to solve analytically.

# **Optimization – Linear Programming**

- Linear problem
  - min  $c^T x$ s.t. Ax х
- Convex problem
- Much analyzed: existence, uniqueness, sensitivity

b =

> 0

- Many algorithms: Simplex the most famous
- About the word Programming
  - -The solution to a problem was called a program

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# Mixed Integer and Combinatorial Optimziation

Problem

min f(x, y)0 s.t. g(x, y)=  $\geq$ 0 х  $Z^+$ F ν

- Inherently non-convex y Generally hard problems to solve.
- Much analyzed -Existence, uniqueness, sensitivity -Many types of problems
  - -Many different algorithms

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## Outline

### **Optimal Control Problem Motivation**

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## General problem formulation

Performance index

$$J(u) = \phi(x(t_b), t_b) + \int_{t_a}^{t_b} L(x(t), u(t), t) dt$$

System model (constraints)

$$\frac{d}{dt}x = f(x(t), u(t), t), x(t_a) = x_a$$

State and control constraints

 $u(t) \in U(t)$  $x(t) \in X(t)$ 

### **Optimal Control – Historical Perspective**

- Old subject
- Rich theory
  - Old theory from calculus of variations
  - Much theory and many methods were developed during 50's-70's
  - Theory and methods are still being actively developed
- Dynamic programming, Richard Bellman, 50's.
- A modern success story:
- -Model predictive control (MPC)
- Now a new interest for collocation methods:
   A few during 1990's
   Much interest 2000–

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# Dynamic programming – Problem Formulation

Optimal control problem

$$\min J(u) = \phi(x(t_b), t_b) + \int_{t_a}^{t_b} L(x(t), u(t), t) dt$$
s.t.  $\frac{d}{dt} x = f(x(t), u(t), t)$ 
 $x(t_a) = x_a$ 
 $u(t) \in U(t)$ 
 $x(t) \in X(t)$ 

- ▶ x(t), u(t) functions on  $t \in [t_a, t_b]$
- Search an approximation to the solution by discretizing
  - the state space x(t)
    and maybe the control signal u(t)
  - in both amplitude and time.
- The result is a combinatorial (network) problem

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## Deterministic Dynamic Programming – Basic algorithm

$$J(x_0) = g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k)$$
$$x_{k+1} = f_k(x_k, u_k)$$

Algorithm idea:

Start at the end and proceed backward in time to evaluate the optimal cost-to-go and the corresponding control signal.



# Deterministic Dynamic Programming – Basic Algorithm

Graphical illustration of the solution procedure



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# Dynamic Programming (DP) - Problem Formulation

- Find the optimal control sequence  $\pi^0(x_0) = \{u_0, u_1, \dots, u_{N-1}\}$  minimizing:
  - $J(x_0) = g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k, w_k)$
- subject to:

$$\begin{aligned} x_{k+1} &= f_k(x_k, u_k, w_k) \\ x_0 &= x(t=0) \\ x_k &\in X_k \\ u_k &\in U_k \end{aligned}$$

Disturbance w<sub>k</sub>

Stochastic vs deterministic DP

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### Deterministic Dynamic Programming - Basic algorithm

$$J(x_0) = g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k)$$
$$x_{k+1} = f_k(x_k, u_k)$$

Algorithm:

- 1. Set k = N, and assign final cost  $J_N(x_N) = g_N(x_N)$
- 2. Set *k* = *k* − 1
- 3. For all points in the state-space grid, find the optimal cost to go

$$J_k(x_k) = \min_{u_k \in U_k(x_k)} g_k(x_k, u_k) + J_{k+1}(f_k(x_k, u_k))$$

- 4. If k = 0 then return solution
- 5. Go to step 2

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# Arc Cost Calculations

There are two ways for calculating the arc costs

- Calculate the exact control signal and cost for each arc. –Quasi-static approach
- Make a grid over the control signal and interpolate the cost for each arc.
  - -Forward calculation approach

Matlab implementation - it is important to utilize matrix calculations

- Calculate the whole bundle of arcs in one step
- Add boundary and constraint checks

# Pros and Cons with Dynamic Programming

### Pros

- Globally optimal, for all initial conditions
- Can handle nonlinearities and constraints
- Time complexity grows linearly with horizon
- Use output and solution as reference for comparison

### Cons

- Non causal
- Time complexity grows "exponentially" with number of states
- Only open loop scheme

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# The Provided Tools for Hand-in Assignment 2

Task:

Investigate optimal control of one parallel and one series hybrid configuration in different driving profiles.

- Some Matlab-functions provided
  - Skeleton file for defining the problems
  - 2 DDP solvers, 1-dim and 2-dim.
  - 2 skeleton files for calculating the arc costs for parallel and serial hybrids

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### Parallel Hybrid Example

- Fuel-optimal torque split factor  $u(SOC, t) = \frac{T_{e-motor}}{T_{enotor}}$
- ECE cycle
- ▶ Constraints  $SOC(t = t_f) \ge 0.6$ ,  $SOC \in [0.5, 0.7]$



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# **Calculation Example**

- Problem 200s with discretization  $\Delta t = 1$ s.
- Control signal discretized with 10 points.
- Statespace discretized with 1000 points.
- One evaluation of the model takes 1µs
- Solution time:
  - Brute force:
    - Evaluate all possible combinations of control sequences. Number of evaluations,  $10^{200}$  gives  $\approx 3 \cdot 10^{186}$  years.
  - Dynamic programming: Number of evaluations: 200 · 10 · 1000 gives 2 s.

This example comes from ETH slides

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  - Different Classes of Problems
- Optimal Control

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Case Studies Energy Management of a Parallel Hybrid

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# Parallel Hybrid Example

- Fuel-optimal torque split factor  $u(SOC, t) = \frac{T_{e-motor}}{T_{enotor}}$
- NEDC cycle
- ▶ Constraints  $SOC(t = t_f) = 0.6$ ,  $SOC \in [0.5, 0.7]$

