### Vehicle Propulsion Systems Lecture 5

Deterministic Dynamic Programming and Some Examples

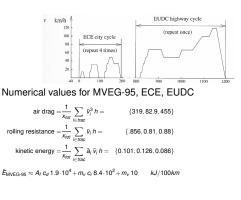
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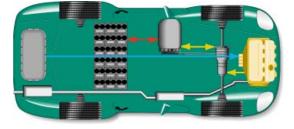
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### Energy consumption for cycles



### Hybrid Electrical Vehicles - Parallel

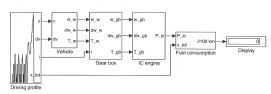
### Two parallel energy paths



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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

Cost Calculation – Two Implementation Alternatives

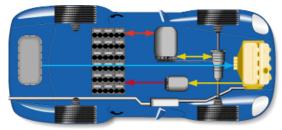
Energy Management of a Parallel Hybrid

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### Hybrid Electrical Vehicles - Serial

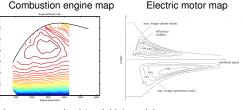
- Two paths working in parallel
- Decoupled through the battery



Component modeling

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

### Electric motor map



 Using parameterized (scalable) models -Willans approach

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## Outline

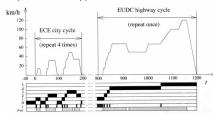
### "Traditional" Optimization Problem motivation **Different Classes of Problems**

Cost Calculation - Two Implementation Alternatives

### **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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 $\begin{array}{c} \min_{\substack{i_{g,j}, \ j \in [1,5] \\ \text{s.t.}}} & m_f(i_{g,1}, i_{g,2}, i_{g,3}, i_{g,4}, i_{g,5}) \\ \text{s.t.} & \text{model and cycle is fulfilled} \end{array}$ 

### **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)

$$\begin{array}{lll} m_{v} \frac{d}{dt} v(t) &= F_{t}(v(t), u(t)) & -(F_{a}(v(t)) + F_{r}(v(t)) + F_{g}(x(t))) \\ \frac{d}{dt} x(t) &= v(t) \\ \dot{m}_{f} &= f(v(t), u(t)) \end{array}$$

- ► Starting point x(0) = A
- End point x(t<sub>f</sub>) = B
   Speed limits v(t) < q(x(t))</li>

Limited control action 
$$0 \le u(t) \le 1$$

Difficult (impossible) problem to solve analytically

- Linear problem
  - $\begin{array}{c} \min_{x} c^{T} x \\ \text{s.t.} & Ax \\ x \end{array}$
- 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
- $\begin{array}{rcl} \min_{x} & f(x,y) \\ \text{s.t.} & g(x,y) &= & 0 \\ & x & \geq & 0 \\ & y & \in & Z^{+} \end{array}$
- 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

### Repetition

Traditional" Optimization Problem motivation Different Classes of Problems

### Optimal Control Problem Motivation

Deterministic Dynamic Programming Problem setup and basic solution idea Cost Calculation – Two Implementation Alternative The Provided Tools

#### Case Studies

Energy Management of a Parallel Hybrid

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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

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

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### **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)

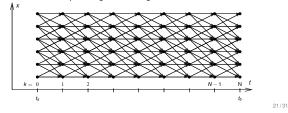
in both amplitude and time.

The result is a combinatorial (network) problem

DDP – Basic Algorithm

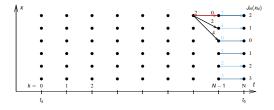
$$J(x_0) = g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k)$$
$$x_{k+1} = f_k(x_k, u_k)$$

Bellman's Theory and Algorithm: -Start at the end and proceed backward in time -Determine the optimal cost-to-go -Store the corresponding control signal



# Deterministic Dynamic Programming – Basic Algorithm

Graphical illustration of the solution procedure



### Outline

#### Repetition

"Traditional" Optimization Problem motivation Different Classes of Proble

Optimal Control

# Deterministic Dynamic Programming

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

#### Case Studie

Energy Management of a Parallel Hybrid

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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 wk

Stochastic vs Deterministic DP

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### DDP - 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

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### The Provided Tools for Hand-in Assignment 2

Task:

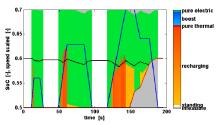
Investigate optimal control of one parallel and one series hybrid configuration in different driving profiles.

- 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.

(Example contributed by ETH)

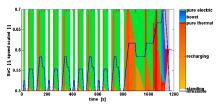
### Outline

**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  $SOC(t = t_f) = 0.6$ ,  $SOC \in [0.5, 0.7]$



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