Vehicle Propulsion Systems
Lecture 6
Supervisory Control Algorithms

Lars Eriksson
Associate Professor (Docent)

Vehicular Systems
Linköping University

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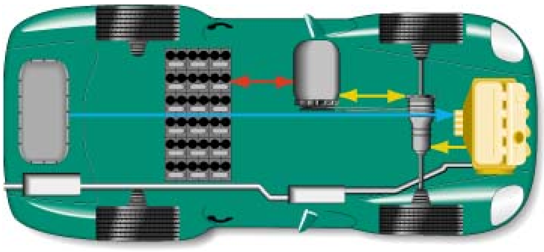
Outline

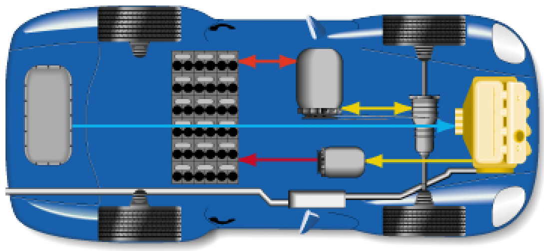
Hybrid Electrical Vehicles – Parallel

- Two parallel energy paths
- One state in QSS framework, state of charge



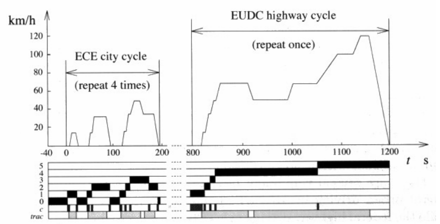
Hybrid Electrical Vehicles – Serial

- Two paths working in parallel
- Decoupled through the battery
- Two states in QSS framework, state of charge & Engine speed



Optimization, Optimal Control, Dynamic Programming

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

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

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)

$$\begin{aligned} m_v \tfrac{d}{dt} v(t) &= F_t(v(t), u(t)) \quad -(F_a(v(t)) + F_r(v(t)) + F_g(x(t))) \\ \tfrac{d}{dt} x(t) &= v(t) \\ \dot{m}_f &= f(v(t), u(t)) \end{aligned}$$

  - Starting point $x(0) = A$
  - End point $x(t_f) = B$
  - Speed limits $v(t) \leq g(x(t))$
  - Limited control action $0 \leq u(t) \leq 1$

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

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

Dynamic programming – Problem Formulation

- Optimal control problem

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

- $x(t)$, $u(t)$ 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 $u(t)$

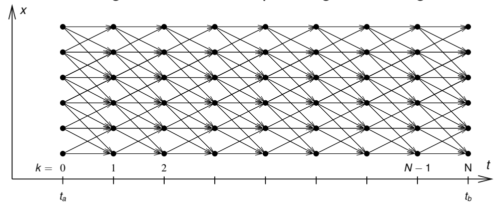
  in both amplitude and time.
- The result is a combinatorial (network) problem

Deterministic Dynamic Programming – Basic algorithm

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

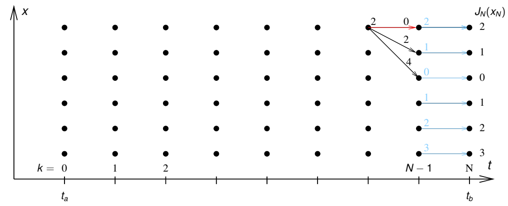
$$x_{k+1} = f_k(x_k, u_k)$$

Algorithm idea:
Start at the end and proceed backwards 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



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

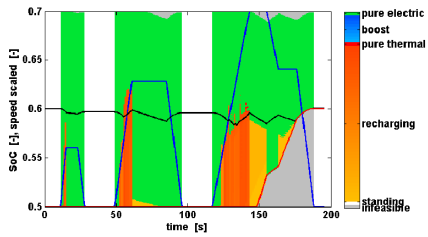
Matlab implementation – it is important to utilize matrix calculations

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

2D and 3D grid examples on whiteboard

Parallel Hybrid Example

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



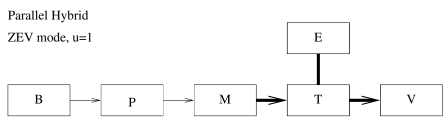
Outline

Parallel Hybrid – Modes and Power Flows

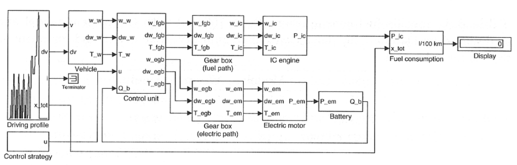
The different modes for a parallel hybrid

$$u \approx P_{batt}/P_{vehicle}$$

Battery drive mode (ZEV)



Control algorithms



- Determining the power split ratio u

$$u_j(t) = \frac{P_j(t)}{P_{m+1}(t) + P_l(t)} \qquad (4.110)$$

- Clutch engagement disengagement $B_c \in \{0, 1\}$
- Engine engagement disengagement $B_e \in \{0, 1\}$

Strategies for the Parallel Hybrid

Power split u, Clutch B_c, Engine B_e

	Mode	u	B_e	B_c
1	ICE	0	1	1
2a	ZEV	1	0	0
2b	ZEV	1	0	1
3	Power assist	[0,1]	1	1
4	Recharge	< 0	1	1
5a	Regenerative braking	1	0	0
5a	Regenerative braking	1	0	1

All practical control strategies have engine shut off when the torque at the wheels are negative or zero; standstill, coasting and braking.

Classification I – Supervisory Control Algorithms

- Non-causal controllers
  - Detailed knowledge about future driving conditions.
  - Position, speed, altitude, traffic situation.
  - Uses:
    Regulatory drive cycles, public transportation, long haul operation, GPS based route planning.
- Causal controllers
  - No knowledge about the future...
  - Use information about the current state.
  - Uses:
    "The normal controller", on-line, in vehicles without planning

Classification II – Vehicle Controllers

- Heuristic controllers
  –Causal
  –State of the art in most prototypes and mass-production
- Optimal controllers
  –Often non-causal
  –Solutions exist for simplifications
- Sub-optimal controllers
  –Often causal

On-going work to include optimal controllers in prototypes

Some Comments About the Problem

- Difficult problem
- Unsolved problem for causal controllers
- Rich body of
  engineering reports and
  research papers on the subject
  –This can clearly be seen when reading chapter 7!

Outline

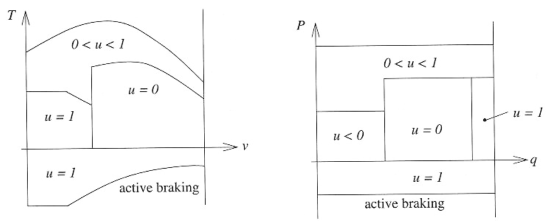
Heuristic Control Approaches

Operation usually depends on a few vehicle operation

- Rule based:
  Nested `if-then-else` clauses
  `if` $v < v_{low}$ `then` use electric motor (u=1).
  `else...`
- Fuzzy logic based
  Classification of the operating condition into fuzzy sets.
  Rules for control output in each mode.
  Defuzzyfication gives the control output.

Heuristic Control Approaches

- Parallel hybrid vehicle (electric assist)



- Determine control output as function of some selected state variables:
  vehicle speed, engine speed, state of charge, power demand, motor speed, temperature, vehicle acceleration, torque demand.

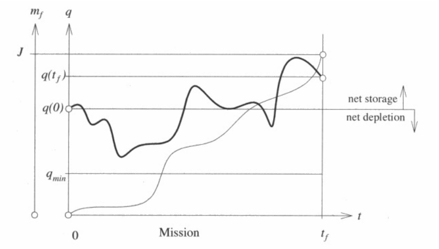
Heuristic Control Approaches – Concluding Remarks

- Easy to conceive
- Relatively easy to implement
- Result depends on the thresholds
- Proper tuning can give good fuel consumption reduction and charge sustainability
- Performance varies with cycle and driving condition
  –Not robust
- Time consuming to develop an tune for advanced hybrid configurations

Outline

Consider a driving mission

- Variables.
  Control signal – $u(t)$, System state – $x(t)$, State of charge - $q(t)$ (is a state).



Formulating the Optimal Control Problem

–What is the optimal behaviour? Defines *Performance index J*.

- Minimize the fuel consumption

$$J = \int_0^{t_f} \dot{m}_f(t, u(t))dt$$

- Balance between fuel consumption and emissions

$$J = \int_0^{t_f} \Big[\dot{m}_f(t, u(t)) + \alpha_{CO}\dot{m}_{CO}(x(t), u(t)) + \alpha_{NO}\dot{m}_{NO}(x(t), u(t)) + \alpha_{HC}\dot{m}_{HC}(x(t), u(t))\Big] dt$$

- Include driveability criterion

$$J = \int_0^{t_f} \dot{m}_f(t, u(t)) + \beta \left(\frac{d}{dt}a(t)\right)^2 dt$$

First Solution to the Problem

- Minimize the fuel consumption

$$J = \int_0^{t_f} \dot{m}_f(t, u(t))dt$$

Including constraints

- Hard or soft constraints

$$\min J(u) = \int_0^{t_f} L(t, u(t))dt$$
$$s.t.\ q(0) = q(t_f)$$

$$\min\ J(u) = \phi(q(t_f)) + \int_0^{t_f} L(t, u(t))dt$$

- How to select $\phi(q(t_f))$?

$$\phi(q(t_f)) = \alpha\,(q(t_f) - q(0))^2$$

  penalizes high deviations more than small, independent of sign

$$\phi(q(t_f)) = w\,(q(0) - q(t_f))$$

  penalizes battery usage, favoring energy storage for future use
- One more feature from the last one

Including constraints

- Including battery penalty according to

$$\phi(q(t_f)) = w\,(q(0) - q(t_f)) = -w \int_0^{t_f} \dot{q}(t)dt$$

  enables us to rewrite

$$\min\ J(u) = \int_0^{t_f} L(t, u(t)) - w\,\dot{q}(t)dt$$

Constraints That are Also Included

- State equation $\dot{x} = f(x)$ is also included – From Lecture 5
- Consider hybrid with only one state, SoC

$$\min J(u) = \phi(q(t_f), t_f) + \int_0^{t_f} L(t, u(t))dt$$
$$s.t.\ \frac{d}{dt}q = f(t, q(t), u(t))$$
$$u(t) \in U(t)$$
$$q(t) \in Q(t)$$

Outline

Analytical Solutions to Optimal Control Problems

- Core of the problem

$$\min J(u) = \phi(q(t_f), t_f) + \int_0^{t_f} L(t, u(t))dt$$
$$s.t.\ \dot{q}(t) = f(t, q(t), u(t))$$

- Hamiltonian from optimal control theory

$$H(t, q(t), u(t), \mu(t)) = L(t, u(t)) + \mu(t)\,f(t, q(t), u(t))$$

Analytical Solutions to Optimal Control Problems

- Hamiltonian

$$H(t, q(t), u(t), \mu(t)) = L(t, u(t)) + \mu(t)\, f(t, q(t), u(t))$$

- Solution (theory from Appendix B)

$$u(t) = \arg\min_{u} H(t, q(t), u(t), \mu(t))$$

with

$$\dot{\mu}(t) = -\frac{\partial}{\partial q} f(t, q(t), u(t))$$
$$\dot{q}(t) = f(t, q(t), u(t))$$

- If $\frac{\partial}{\partial q} f(t, q(t), u(t)) = 0$ the problem becomes simpler
μ becomes a constant μ_0, search for it when solving

Analytical Solutions to Optimal Control Problems

- μ_0 depends on the (soft) constraint

$$\mu_0 = \frac{\partial}{q(t_f)} \phi(q(t_f)) = /\text{special case}/ = -w$$

- Different efficiencies

$$\mu_0 = \frac{\partial}{\partial q(t_f)} \phi(q(t_f)) = \begin{cases} -w_{dis}, & q(t_f) > q(0) \\ -w_{chg}, & q(t_f) < q(0) \end{cases}$$

- Introduce equivalence factor (scaling) by studying battery and fuel power

$$s(t) = -\mu(t) \frac{H_{LHV}}{V_b\, Q_{max}}$$

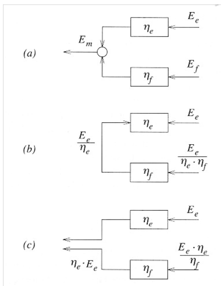
ECMS – Equivalent Consumption Minimization Strategy

Determining Equivalence Factors I

Constant engine and battery efficiencies

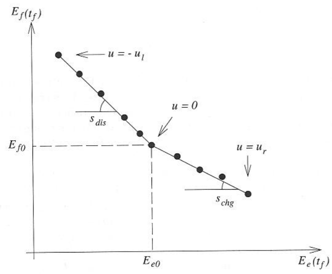
$$s_{dis} = \frac{1}{\eta_e \eta_f}$$

$$s_{chg} = \frac{\eta_e}{\eta_f}$$



Determining Equivalence Factors II

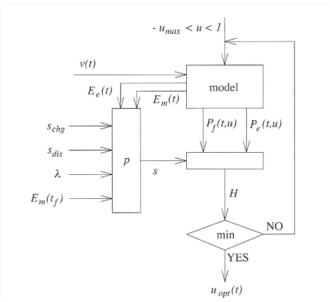
- Collecting battery and fuel energy data from test runs with constant u gives a graph



- Slopes determine s_{dis} and s_{chg}.

ECMS On-line Implementation

Flowchart



There is also a T-ECMS (telemetry-ECMS)