PREDICTIVE CONTROL OF INTEGRATED POWER SYSTEMS FOR ELECTRIFIED VEHICLES

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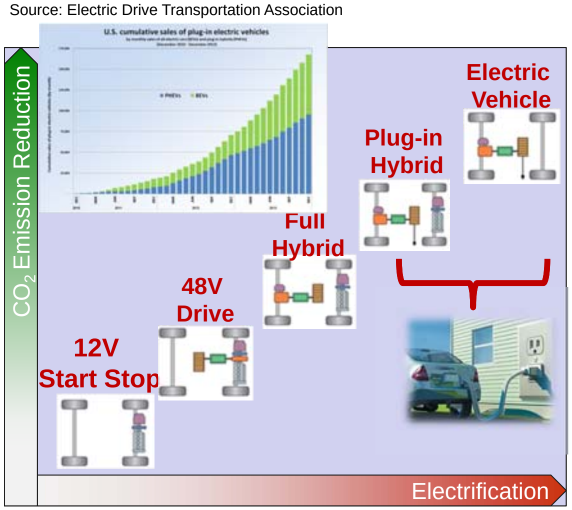
NTNU

NAME at the University of Michigan

- **Program established in 1879**
- **The major department in the U.S. having degree programs from B.S. to Ph. D with a ship focus**
- **Home of:**
  - Naval Engineering Education Center (NEEC)
  - Marine Hydrodynamic Lab.
  - Marine Renewable Energy Lab
  - Perceptual Robotics Lab
  - Real-time Adaptive Control Engineering Lab

Vehicle Electrification

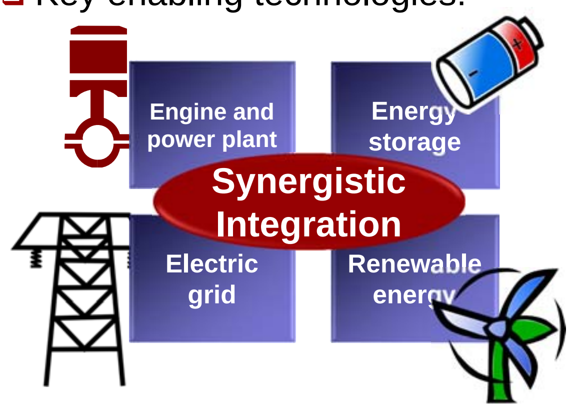
Source: Electric Drive Transportation Association



- A general trend driven by
  - Energy saving
  - Environmental protection

Vehicle Electrification

- All kinds: hybrid vehicles, all-electric ships (AES), electrified or more-electric airplanes (MEA)
- Key enabling technologies:

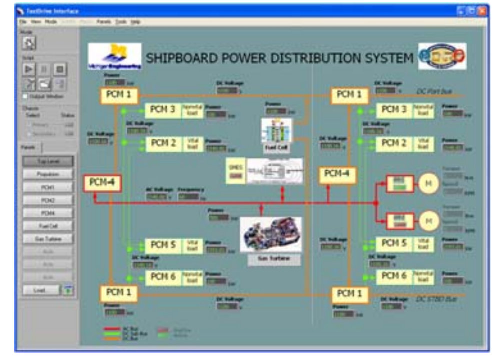


Outline

- Integrated power systems and electrified vehicles
- Optimization-based control for integrated power systems
- IPA-SQP: integrated perturbation analysis and sequential quadratic programming for real-time optimization
- Case studies of predictive control for IPS
- Conclusions

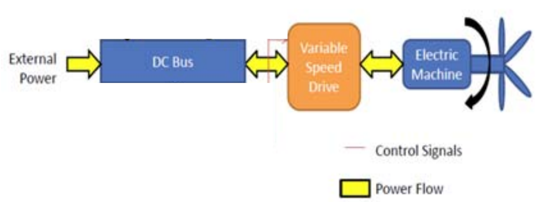
Integrated Power System

- Multiple heterogeneous power sources and power loads combined to provide energy/power solutions
  - Hybrid vehicle: engine and battery system
  - All electric ships: diesel engines, gas turbine, fuel cells



Electric Drive with Hybrid Energy Storage

- Wave excitation and propeller rotational motions cause load fluctuation on the electric drive system
- Hybrid energy storages systems with complementary characteristics can mitigate the fluctuation through energy cycling



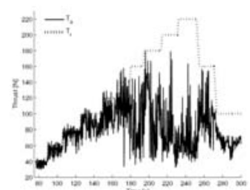
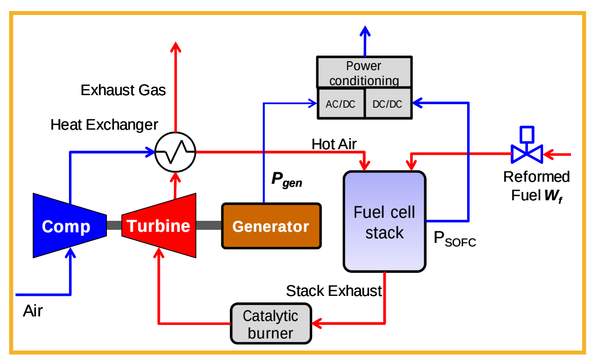


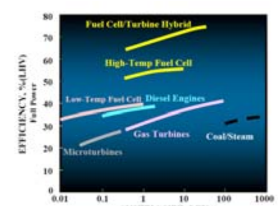
Figure 2.14: Measured thrust T_a of a ducted propeller for increasing thrust reference T_r in irregular waves. From experiments.

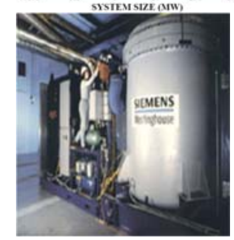
Smogeli (2006)

Combined SOFC/GT Systems

- Integrate solid oxide fuel cell and gas turbine as a new efficient power generation solution for propulsion and auxiliary power
- It achieves high efficiency through tight thermal, mechanical, and electric integration

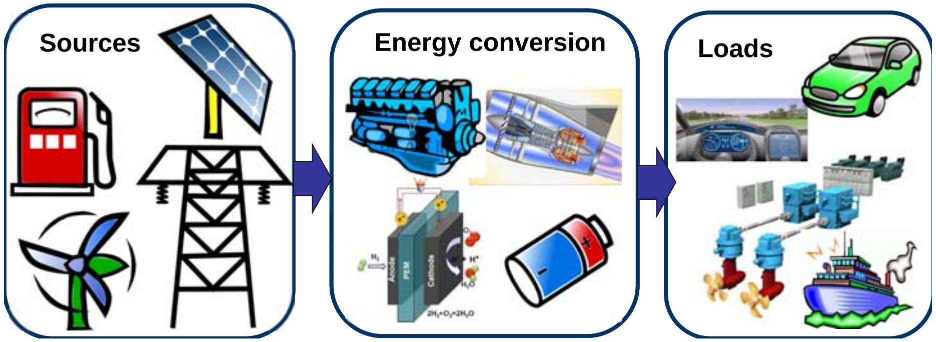






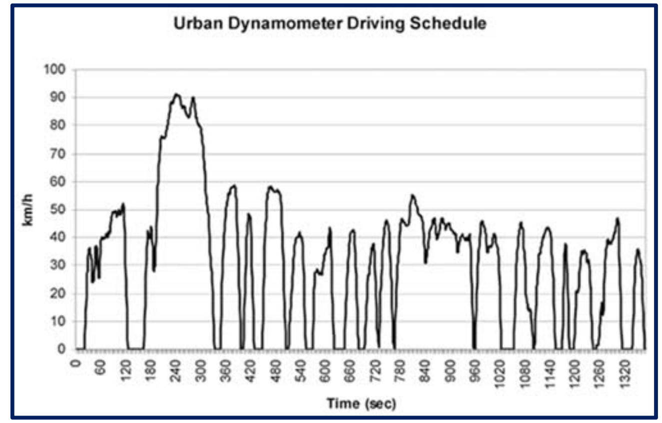
Characteristics of IPS

- Multiple and heterogeneous power/heat plants involved in energy conversion
- High efficiency and (intended for) self-sustaining
- Close thermal, chemical, mechanical and electrical couplings



IPS for Mobile Applications

- Additional requirements:
  - Dynamic load following capability
  - Fast control updates



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- **Optimization-based control for integrated power systems**
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Power Management for IPS

- Coordinate multiple, heterogeneous power plants (including energy storage devices)
- Manage transient operations
- Assure safe operation in case of component and subsystem failure
- Facilitate effective system reconfiguration
- Achieve optimal performance in terms of power quality and system operation efficiency

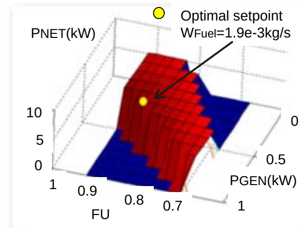
Optimization in IPS Power Management

- Optimization: A natural formalism for power management of IPS
  - Assure optimal performance during normal operation
  - Guarantee effective reconfiguration in case of failures
  - Enforce hard and soft constraints
  - Incorporate power demand profiles

➡ **Optimization-based Control**

Special Challenges

- Nonlinear and MIMO plant characteristics
- Reconfigurable underlying physical components
- Operating near boundary
- Fast dynamics
  - Power electronics: 10kHz
  - Diesel or gas turbine: ~10Hz
- Limited on-board computational resources
- Real-time operation requirements



Real-time Optimization Solvers

Dominant approaches: SQP and interior point (IP) methods

- Early termination methods By Li & Biegler, Diehl et al., Ohtsuka
  - Only one or few iterations at each sampling time
  - Deteriorated results for systems with significant nonlinearities
- Advance step controller by Zavala & Biegler
  - Complete IP type procedure
  - Predicting future state and solving optimal control problem for this future state
- Feasibility-perturbed SQP by Tenny et al.
  - All feasible intermediate iterations

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- Integrated power systems and electrified vehicles
- Predictive control for integrated power systems
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Background: IPA-SQP

Perturbation Analysis (PA)
- Derives a solution from a nominal one when some parameters are changed
- Maintains necessary conditions satisfied to first order
- Suitable in MPC context: states do not change much from step to step

Sequential Quadratic Programming (SQP)
- Popular approach to solve constrained optimization problem
- Improves the solution to make necessary conditions satisfied

IPA-SQP [Ghaemi et al. 2007;2008;2009]

- Integrated Perturbation Analysis - Sequential Quadratic Programming
- Combines the solutions derived using PA and SQP
- Predictor-corrector type scheme
  - Predictor: obtains the solution to MPC problem using neighboring optimal control theory
  - Corrector: corrects the result using SQP updates
  - Two updates merged into one: provides an efficient algorithm for nonlinear MPC implementation

Problem formulation

Minimize:

$$J = \sum_{t=k}^{k+N-1} L(x(t), u(t)) + \Phi(x(k+N))$$

Subject to

$$x(k+1) = f\big(x(k), u(k)\big); x(k) = x_0$$
$$C\big(x(k), u(k)\big) \le 0$$
$$\bar{C}\big(x(k)\big) \le 0$$

Approximation Of Optimal Solutions

Questions:

- Given a solution for the optimization with initial state x_0 (nominal solution)
- How to calculate the optimal solution for the new state $x_0 + \delta x_0$?

Neighboring extremal solution:

- Can be treated as a general nonlinear programming problem: computational demand $O(N^3)$
- For unconstrained case
  - Iterative solution available
  - Computational demand is of O(N)

Goals: develop an algorithm for constrained case with computational demand of O(N)

Neighboring Extremal Problem

Minimize:

$$\delta^2 J = \frac{1}{2}\delta x(N)^T\left(\Phi_{xx}(N) + \frac{\partial}{\partial x}\overline{C}_x^T(N)\overline{\mu}(N)\right)\delta x(N) + \frac{1}{2}\sum_{k=0}^{N-1}\begin{bmatrix}\delta x\\ \delta u\end{bmatrix}^T\begin{bmatrix}H_{xx} & H_{xu}\\ H_{ux} & H_{uu}\end{bmatrix}\begin{bmatrix}\delta x\\ \delta u\end{bmatrix}$$

Subject to

$$\delta x(k+1) = f_x(k)\delta x(k) + f_u(k)\delta u(k);\ \delta x(0) = \delta x_0$$
$$C_x^a(x(k), u(k))\delta x(k) + C_u^a(x(k), u(k))\delta u(k) = 0;$$
$$\overline{C}_x^a(x(k))\delta x(k) = 0$$

$C^a, \bar{C}^a$: active constraint sets
H: Hamiltonian function of the original optimization problem

Neighboring Extremal Solution

With proper assumptions, the NE problem has a closed-form solution:

$$\delta x(k+1) = f_x(x^0(k), u^0(k))\delta x(k) + f_u(x^0(k), u^0(k))\delta u(k)$$

$$\delta u(k) = -K^*(k)\delta x(k)\,, \qquad K^*(k) = [I\ 0]K_0 \begin{bmatrix} Z_{12}(k) \\ C_x^a(k) \end{bmatrix}$$

$$K_0(k) = \begin{bmatrix} Z_{11}(k) & C_u^{aT}(k) \\ C_u^a(k) & 0 \end{bmatrix}^{-1} \qquad \begin{aligned} Z_{11}(k) &:= H_{uu}(k) + f_u^T(k)S(k+1)f_u(k) \\ Z_{12}(k) &:= H_{ux}(k) + f_u^T(k)S(k+1)f_x(k) \\ Z_{22}(k) &:= H_{xx}(k) + f_x^T(k)S(k+1)f_x(k) \end{aligned}$$

$S(k)$ is defined through a backward-in-time iterative algorithm

Notes On NE Solution

Two key assumptions:

- Constraint activity set unchanged
  - Small perturbations
- Matrix $K_0(k)$ is invertible

$$K_0(k) = \begin{bmatrix} Z_{11}(k) & C_u^{aT}(k) \\ C_u^a(k) & 0 \end{bmatrix}^{-1}$$

  - $Z_{11}(k)$ non-singular
  - C_u^a must be of full row rank.
  - Can not handle the constraints of the type:

$$\bar{C}\big(x(k)\big) \le 0$$

Dealing with Large Perturbations

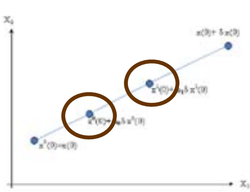
- Divide the large perturbation into smaller incremental perturbations
- However, optimality conditions may not be satisfied at each intermediate point
- Sequential quadratic programming can be used to achieve optimality at the intermediate points

$$\delta^2 \bar{J} = \frac{1}{2}\delta x(N)^T \Phi_{xx}(N)\delta x(N) + \boxed{\sum_{k=0}^{N-1} H_u^T(k)\delta u(k)} + \frac{1}{2}\sum_{k=0}^{N-1}\begin{bmatrix}\delta x \\ \delta u\end{bmatrix}^T \begin{bmatrix} H_{xx} & H_{xu} \\ H_{ux} & H_{uu}\end{bmatrix}\begin{bmatrix}\delta x \\ \delta u\end{bmatrix}$$

$$\delta x(k+1) = f_x(k)\delta x(k) + f_u(k)\delta u(k); \boxed{\delta x(0) = 0;}$$

$$C_x^a(x(k), u(k))\delta x(k) + C_u^a(x(k), u(k))\delta u(k) = 0;$$

$$\bar{C}_x^a(x(k))\delta x(k) = 0.$$



Combination of PA and SQP

$$\delta u(k) = \boxed{K_1'(k)}\delta x(k),$$

$$\delta x(k+1) = f_x(k)\delta x(k) + f_u(k)\delta u(k),$$

$$\delta x(t) = x(t) - x(t-1),$$

where

$$K_1'(k) := -[I\quad 0]K_0(k)\begin{bmatrix} Z_{21}(k)\delta x(k) + f_u(k)^{\mathrm{T}}T(k+1) + \boxed{H_u(k)} \\ \tilde{C}_x^a(k)\delta x(k)\end{bmatrix},$$

$$T(k) := f_x(k)^{\mathrm{T}}T(k+1) - \begin{bmatrix} Z_{21}(k) & \tilde{C}_x^a(k)^{\mathrm{T}}\end{bmatrix}K_0(k)\begin{bmatrix} f_u(k)^{\mathrm{T}}T(k+1) + \boxed{H_u(k)} \\ 0 \end{bmatrix}$$

Avoiding Singularity

- Matrix K_0 will be non-invertible if

$$\begin{bmatrix} Z_{11}(k) & C_u^{aT}(k) \\ C_u^a(k) & 0 \end{bmatrix}^{-1}$$

  - C does not explicitly depend on u or
  - The active constraints outnumber the controls
- Use back-propagation to avoid matrix singularity

$$\bar{C}_x^a(k)\delta x(k) = 0$$

$$\Downarrow$$

$$\bar{C}_x^a(k)(f_x(k-1)\delta x(k-1) + f_u(k-1)\delta u(k-1)) = 0$$

IPA-SQP Algorithm

- Step 1: Nominal solution $(x^0(\cdot), u^0(\cdot))$ from previous time step
- Step 2: Closed-form neighboring extremal solution $\delta u(k) = K_1(k)\delta x(k)$
- Step 3: Handling changes in the activity status of constraints
- Step 4: Update solution $x^1(\cdot) = x^0(\cdot) + \delta x(\cdot), \quad u^1(\cdot) = u^0(\cdot) + \delta u(\cdot)$
- Step 5: Optimality condition $H_u(x^1(\cdot), u^1(\cdot)) = 0$ Yes: Stop, No: Step 6
- Step 6: Use SQP to improve the solution $\left(x^1(\cdot), u^1(\cdot)\right) \rightarrow \left(x^1_{correct}(\cdot), u^1_{correct}(\cdot)\right)$

A Bench-mark Test (Non-realtime)

A ship steering problem

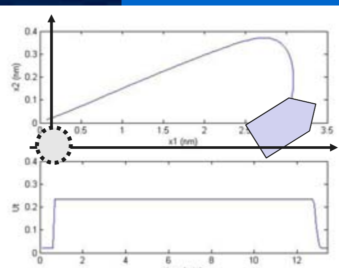
- Nonlinear model: 5 states
- Nonlinear cost and constraints:
  - state dependent constraints (obstacle avoidance)
  - Input constraints (rudder saturation)
- Long prediction horizon:
  - N=140

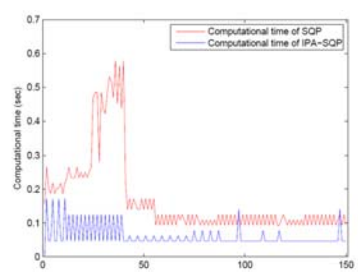
Simulation platform

- PC with Intel® CPU
- 1.83GHz

Simulation results (compare SQP vs. IPA-SQP)

- Identical trajectory
- Average computational time(measured by CPU time) reduction for IPA-SQP: 280%





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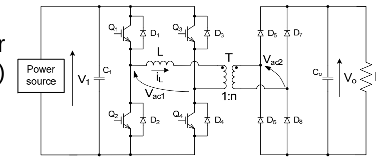
Examples

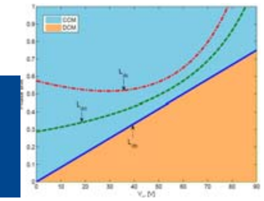
- Electronic power converter
  - Real-time optimization at 10kHz sampling rate
- Shipboard power systems
  - MPC for shipboard power application with experiment validation
- Hybrid energy storage system
  - Use MPC to exploit energy storage mechanisms of different characteristics
- Integrated solid fuel cell and gas turbine systems
  - MPC is essential in assuring safe and efficient operation of SOFC/GT

MPC of Full Bridge DC/DC Converter

- Power converter:
  - Rated at 1kW
  - Hard constraint on peak operating current
  - Fast sampling
- Algorithm specifics
  - Linear model (linearized around V_{in}=62V, V_0=80V)
  - Nonlinear constraints on peak current for the inductor (peak current limited to 75A)
  - Quadratic cost
  - Sampling time: T=150μs
  - Prediction horizon: N=8
  - Control horizon=8



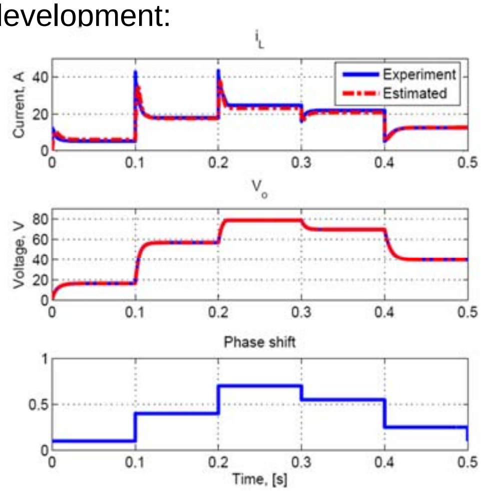
Y. Xie, et. al., "Model Predictive Control for a Full Bridge DC/DC Converter," *IEEE TCST*, 2012.
Y. Xie, et. al., "Implicit Model Predictive Control of a Full Bridge DC/DC Converter," *IEEE TPE*, 2009.



MPC of Full Bridge DC/DC Converter

Large signal dynamic model development:

$$\frac{d\bar{i}_{L1}}{dt} = \frac{\beta_1 V_1}{L_1} - \frac{4\bar{i}_{L1}\bar{V}_o}{\beta_1 T(n_1 V_1 - \bar{V}_o)},$$
$$\frac{d\bar{V}_o}{dt} = \frac{\bar{i}_{L1}}{n_1 C_{o1}} - \frac{\bar{V}_o}{RC_{o1}},$$
$$y = \bar{V}_o.$$



MPC of Full Bridge DC/DC Converter

- The plant model can be augmented with a constant disturbance model: $\tilde{x}(k+1) = A\tilde{x}(k) + B\tilde{u}(k) + B_d d(k),$

$$d(k+1) = d(k),$$
$$\tilde{y}(k) = F\tilde{x}(k).$$

- The state and disturbance estimator can be designed as:

$$\hat{\tilde{x}}(k+1) = A\hat{\tilde{x}}(k) + B\tilde{u}(k) + B_d\hat{d}(k) + H_4(-F\tilde{x}(k) + F\hat{\tilde{x}}(k)),$$
$$\hat{d}(k+1) = \hat{d}(k) + H_5(-F\tilde{x}(k) + F\hat{\tilde{x}}(k)).$$

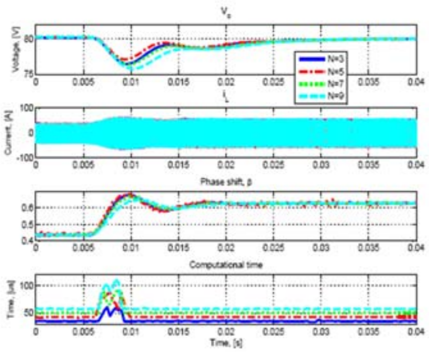
- The steady state values of the observer is

$$\begin{bmatrix} A-I & B \\ F & 0 \end{bmatrix} \begin{bmatrix} \hat{\tilde{x}}_s \\ \tilde{u}_s \end{bmatrix} = \begin{bmatrix} -B_d\hat{d}_s \\ 0 \end{bmatrix}$$

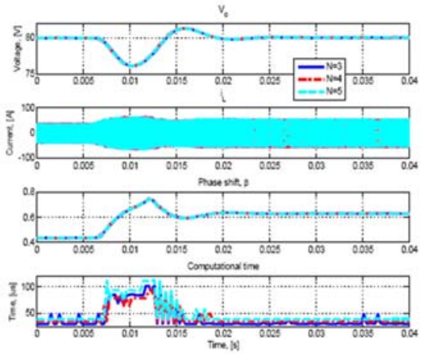
let $\Delta\tilde{x}(k) = \tilde{x}(k) - \hat{\tilde{x}}_s$ and $\Delta\tilde{u}(k) = \tilde{u}(k) - \tilde{u}_s$

MPC of Full Bridge DC/DC Converter

Performance summary of the LMPC



Performance summary of the NLMPC



	N=3	N=5	N=7	N=9
Settling time	20ms	20ms	20ms	20ms
Voltage drop	3.4V	2.9V	3.4V	4.2V
Computational time	61μs	89μs	91μs	112μs

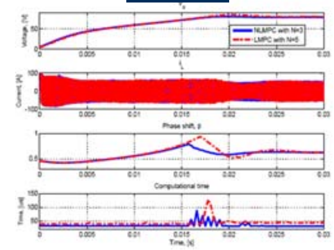
	N=3	N=4	N=5
Settling time	13ms	13ms	13ms
Voltage drop	3.9V	3.9V	3.9V
Computational time	102μs	105μs	113μs

MPC of Full Bridge DC/DC Converter

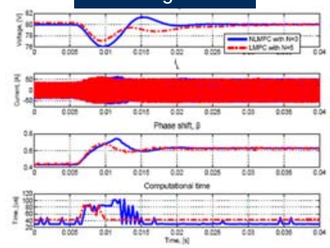
Comparison of the LMPC and NLMPC schemes under three operating conditions

- Starting
- Load regulation
- Overload

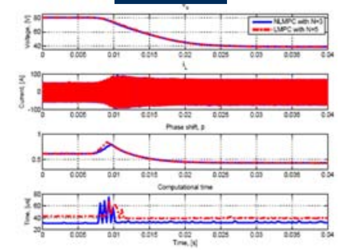
Starting



Load regulation



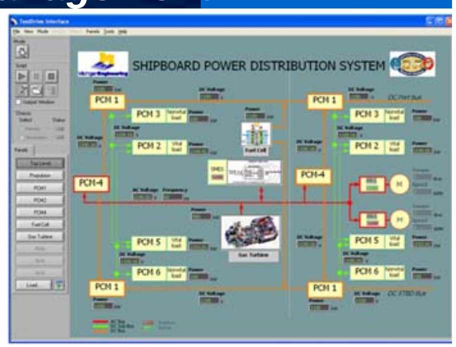
Overload



Real-time Ship Power Management

Motivation

- Shipboard integrated power systems include multiple power sources and loads
- Power management controller (PMC) coordinates power sources and loads to achieve efficient and robust operation
- Real-time implementation of MPC-based PMC is a key challenge

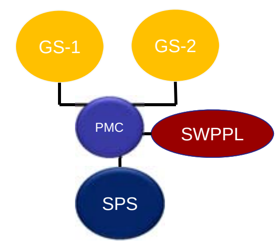


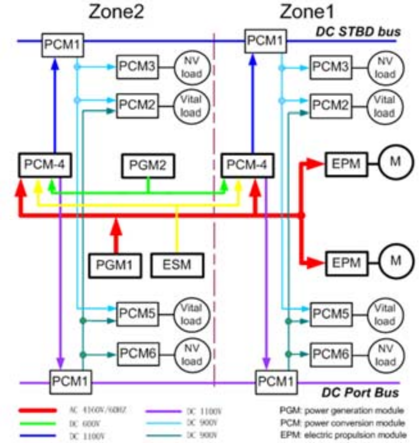
H. Park, J. Sun, et. al., "Real-time Model Predictive Control for Shipboard Power Management Using the IPA-SQP Approach," submitted to IEEE TCST, 2014.
G. Seenumani, et.al., "Real-time Power Management of Integrated Power Systems in All Electric Ships Using Time-Scale Separation," *IEEE TCST,* 2012.

Real-time Ship Power Management

Scaled shipboard power system model and test-bed

- Generation System 1 (GS-1): Gas turbine generator
- Generation System 2 (GS-2): Diesel engine
- Ship Propulsion System (SPS)
- Square Wave Pulsed Power Load





Design & Implementation

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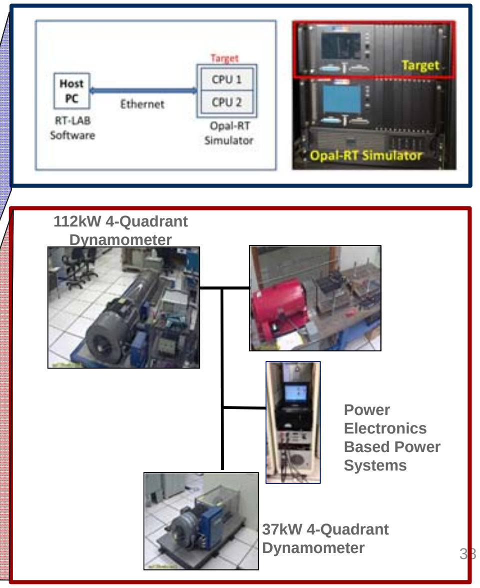
IPA-SQP based MPC algorithm development

Non real-time simulation (TPMM)

Real-time simulation (Opal-RT® simulator)

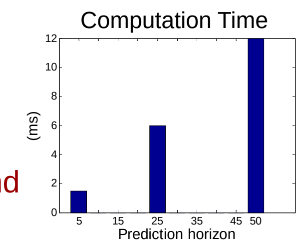
Physical test bed implementation and validation



Real-time Ship Power Management

MICHIGAN ENGINEERING

- Developed, analyzed, and tested an IPA-SQP based PMC on a test bed that simulates a ship power system
  - First real-time ship power management control results on a physical test bed with optimization-based control
- The IPA-SQP PMC was quantitatively shown to improve system performance
  - Simulation results are closely correlated to experimental results
- The IPA-SQP demonstrated robust power control
  - Dynamically coordinated sources and loads to provide power to pulse load without the knowledge of disturbances



Power/Energy Management for HESS

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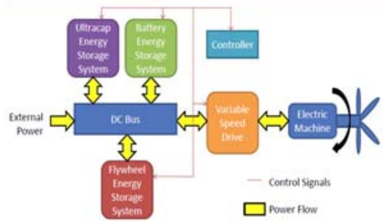
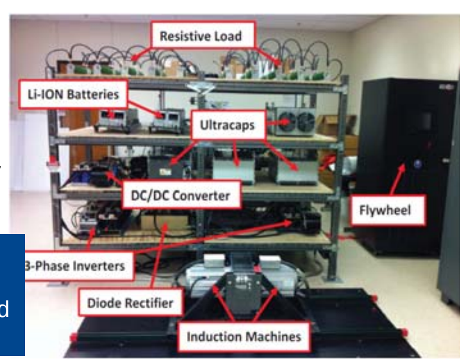
- Performance metrics:
  - Power tracking: Minimizing power tracking error
  - Energy efficiency: Minimizing losses
  - Battery protection: Avoiding high current charging/discharging
  - Power quality: Reducing voltage ripple on the bus and improving frequency regulation





Jun Hou, et.al., "Mitigating Power Fluctuations in Electrical Ship Propulsion Using Model Predictive Control with Hybrid Energy Storage System," ACC, 2014.

Combined SOFC/GT Cycle System

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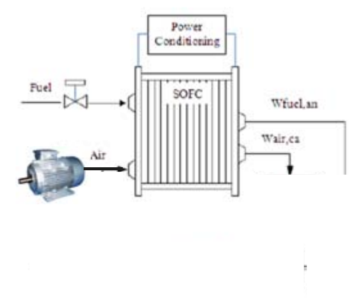
- SOFC/GT Concept and Operational Characteristics
  - Solid oxide fuel cell (SOFC)
  - Catalytic burner for energy recuperation
  - Gas turbine or micro-gas turbine (GT) as the bottoming cycle
  - Shaft-driven compressor: eliminates the need for a motor driven compressor and reduces parasitic loss
  - Shaft driven generator: energy recuperation and efficiency improvement



SOFC/GT Hybrid schematic

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Outline

- Integrated power systems and electrified vehicles
- Predictive control for integrated power systems
- IPA-SQP: integrated perturbation analysis and sequential quadratic programming for real-time optimization
- Case studies of predictive control for IPS
- **Conclusions**

Conclusions

- IPS is a critical enabling technology for vehicle electrification
- Power and energy management is the key for the reliable and efficient operation of IPS
- The special characteristics of IPS lend itself for predictive and optimization-based control
- The unique challenges (real-time, fast update) offer opportunity for research and development

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Thank you!

Questions?