# A Predictive Engine for On-Line Optimal Microgrid Control

SAND2017-8797C

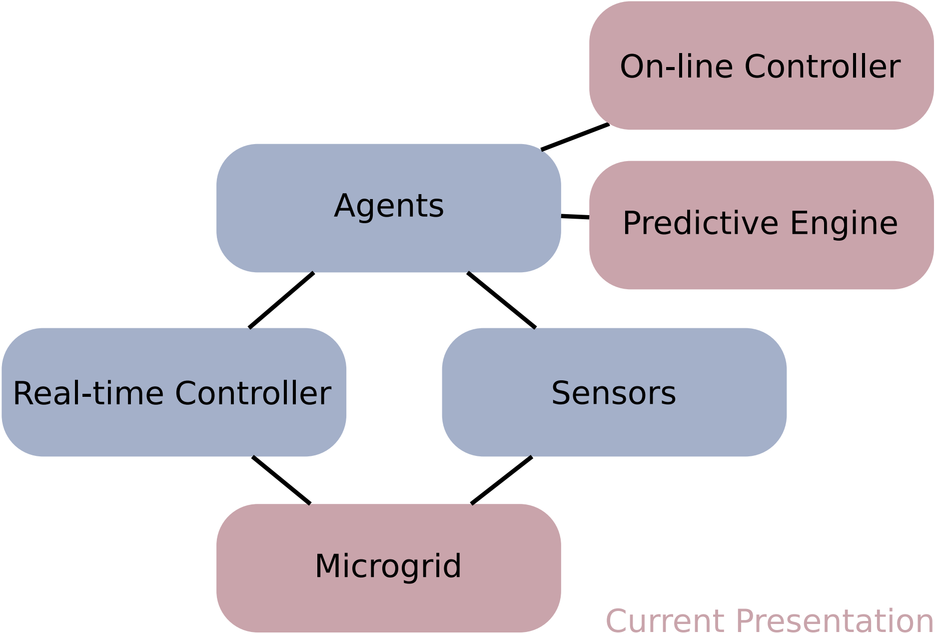
Joseph Young (OptimoJoe)
David Wilson (SNL)
Marvin Cook (SNL)

Venue: 2017 IEEE Electric Ship Technologies Symposium
Presentation Number: Microgrid PR2017-02
Version: 1.0.0
Release Date: August 17, 2017
Revision Date: August 17, 2017

www.optimojoe.com

# Overview

# Summary of Control Design



# Summary of Control Design

- Microgrid - Single or networked power grid
- Agents - Software that coordinates how the different controls operate the microgrid based on information from the sensors and its own internal algorithms
- Sensors - Any instrumentation that provide information about the microgrid
- Real-time Controller - Control that provides fast, subsecond updates
- On-line Controller - Control that provides medium to long term planning
- Predictive Engine - Algorithm that provides long term forecasting for the microgrid

# Summary of Control Design

## On-line

- Executes in a variable amount of time
- Solves for new control while the system is in operation

## Optimal Control

- Control based on an optimization formulation
- Generally, solution time only deterministic for a linear-quadratic control

## Receding Horizon Control

- Behavior of system predicted over a time period called the planning horizon
- Control based on this prediction
- Control executed for as long as the prediction remains accurate, which is called the execution horizon

This presentation details an optimal control algorithm based on an on-line optimization engine that solves for a receding-horizon control

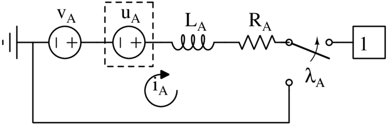
# High-level View of Optimal Control

| | |
|---|---|
| ***Minimize*** | Use of storage devices |
| | Change in boost converter duty cycles |
| | Parasitic losses |
| | Power used by storage devices |
| ***Subject to*** | Boost converter state equations (A) |
| | DC bus state equations (B) |
| | DC to DC bus state equations (C) |
| | Power and energy equations |
| | ODE discretization |
| | Bounds on voltages, currents, duty cycles, etc. |

Detail of microgrid components to come next

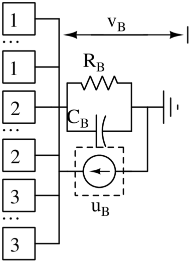
# Microgrid Components

## Boost Converter (A)



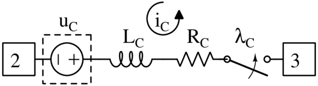

$$
\begin{aligned}
L_A \dot{i}_A = &-R_A i_A + v_A \\
&+ u_A u_{A_{switch}} \\
&- \lambda_A(\Phi_1 v_B)
\end{aligned}
$$

## DC Bus (B)




$$
\begin{aligned}
C_B \dot{v}_B = &-\frac{v_B}{R_B} + u_B u_{B_{switch}} \\
&+ \Phi_1^T(\lambda_A i_A) - \Phi_2^T i_C \\
&+ \Phi_3^T(\lambda_C i_C)
\end{aligned}
$$

## DC to DC Bus (C)




$$
\begin{aligned}
L_C \dot{i}_C = &-R_C i_C + u_C u_{C_{switch}} \\
&+ \Phi_2 v_B - \lambda_C(\Phi_3 v_B)
\end{aligned}
$$

# Overview

# Challenge of Receding-Horizon Controls

- Receding-horizon controls can effectively plan into the future
- Planning into the future requires a prediction
- Predicting the future can be difficult at best
- Receding-horizon controls handle this challenge with a shorter execution-horizon than planning
- Nonetheless, efficacy of the method depends on a good prediction
- In a microgrid, prediction generally means predicting the load demands
- If the future loads are known exactly, the following is unnecessary

# Adaptable Signals

Let $\phi : \mathbb{R} \to \mathbb{R}$ be a known signal and consider

- Time shift - $\phi(t - T)$
- Time scaling - $\phi(\alpha t)$
- Amplitude scaling - $\beta\phi(t)$

Combining each of these produces an adaptable signal

$$\beta\phi(\alpha t - T)$$

# Matching Adaptable Signals

To match $\phi$ to data $\{(t_i, y_i)\}_{i=1}^{m}$, solve

$$\min_{(T,\alpha,\beta)\in\mathbb{R}^3} \sum_{i=1}^{m} (\beta\phi(\alpha t_i - T) - y_i)^2.$$

If exact signal unknown, match against multiple signals $\{\phi_j\}_{j=1}^{n}$ by solving

$$\min_{j=1,\dots,n} \left\{ \min_{(T,\alpha,\beta)\in\mathbb{R}^3} \sum_{i=1}^{m} (\beta\phi_j(\alpha t_i - T) - y_i)^2 \right\}.$$

Essentially, match multiple signals and pick the best fit.

# Why Not Use Machine Learning?

- Machine learning certainly applicable for load prediction
- Requires large amount of data, which we may or may not have
- Potential dimensionality and mapping problems
  - Input to method is a number of samples
  - Output from method is a function at best or at least a specified number of predictions at various time intervals
  - Machine learning models must fix number of inputs, no more or less information tolerated
  - Require one machine learning model for each point in time in the output
- Optimization approach above exploits that we know the kinds of loads that will occur, but not necessarily the time delay or scaling

# Overview

Control Design

Predictive Engine

Results

Summary

# Predicting Inverse Exponential Spike in Load

Consider an inverse exponential

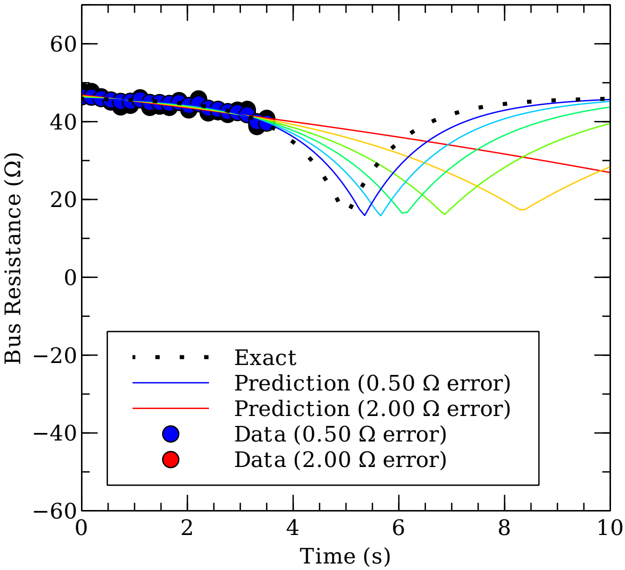
$$\phi(t) = \begin{cases} a - be^{-t} & t \geq 0 \\ a - be^{t} & t < 0 \end{cases}$$

where

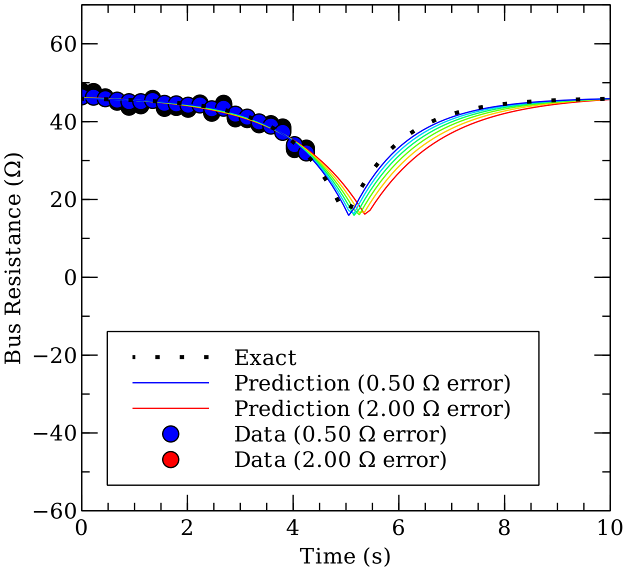
- $v = 480$ V
- $p_{\text{min}} = 5000$ W
- $p_{\text{max}} = 15000$ W
- $r_{\text{min}} = \frac{v^2}{p_{\text{min}}}$
- $r_{\text{max}} = \frac{v^2}{p_{\text{max}}}$
- $a = r_{\text{min}}$
- $b = r_{\text{min}} - r_{\text{max}}$

Want to predict this load given limited information with error

# Predicting Inverse Exponential Spike in Load



# Predicting Inverse Exponential Spike in Load



# Differentiating Between Different Loads

Consider a quadratic spike in load

$$\phi(t) = at^2 + bt + c$$

where

- $W = 5$
- $a = \frac{r_{\text{min}} - r_{\text{max}}}{W^2}$
- $b = 0\ \Omega$
- $c = r_{\text{max}}$

and an oscillatory spike in load that follows a Ricker wavelet

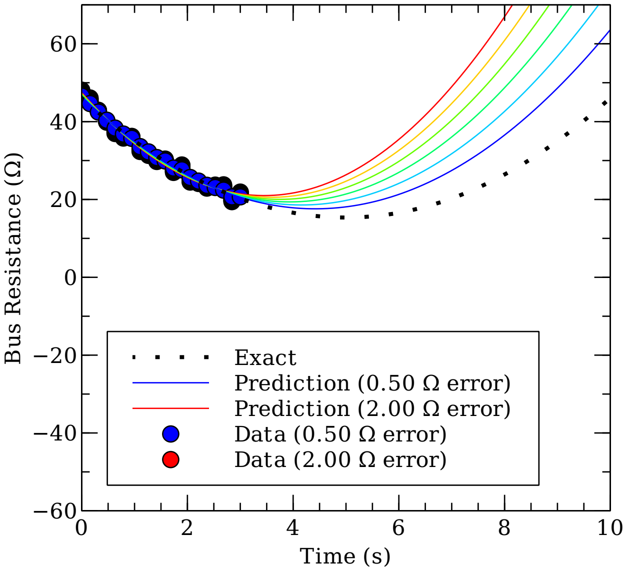
$$\phi(t) = a + b\left(1 - \frac{t^2}{\sigma^2}\right)e^{\frac{-t^2}{2\sigma^2}}$$

where

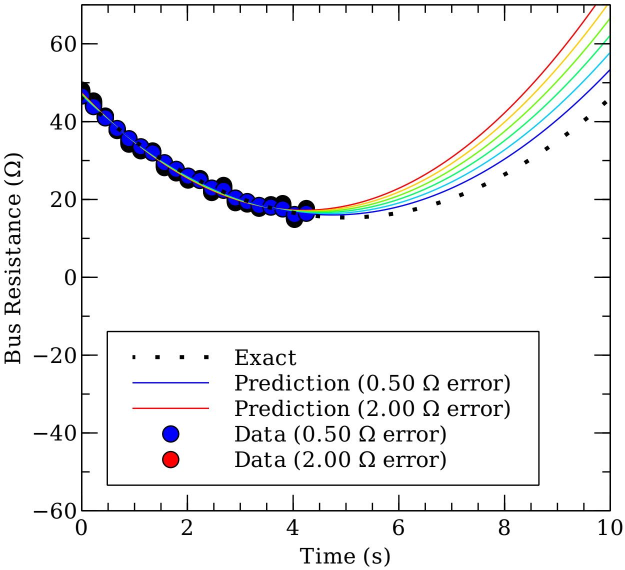
- $\sigma = 1$
- $a = r_{\text{min}}$
- $b = r_{\text{max}} - r_{\text{min}}$

Want to differentiate between three different load types and predict the correct load

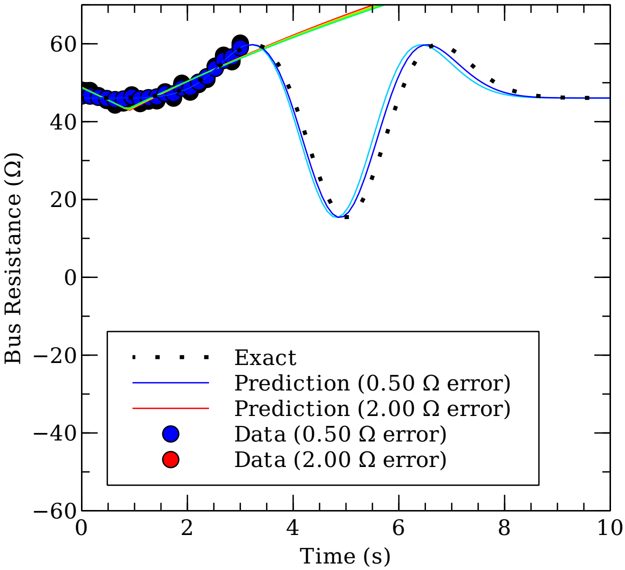
# Differentiating Between Different Loads



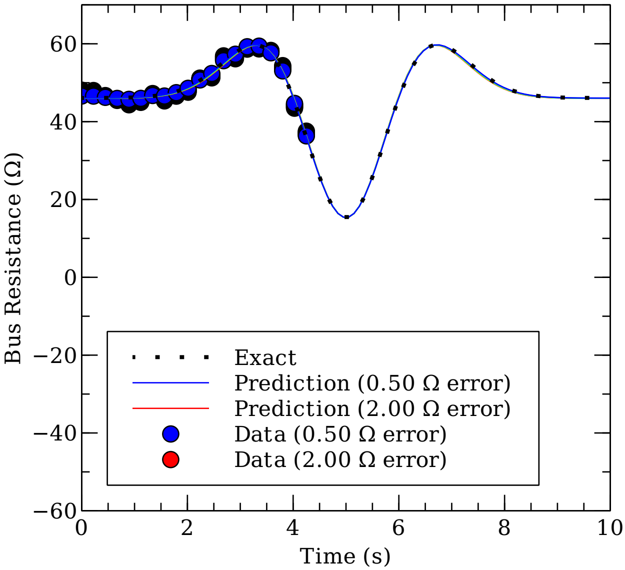
# Differentiating Between Different Loads



# Differentiating Between Different Loads

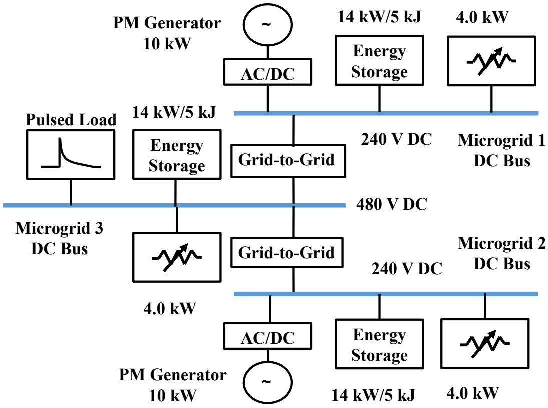


# Differentiating Between Different Loads



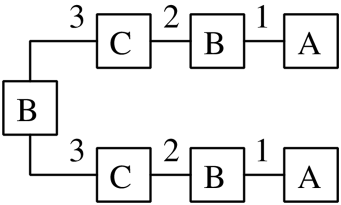
# Optimal Control for Navy Ship

Consider the Navy ship configuration



# Optimal Control for Navy Ship

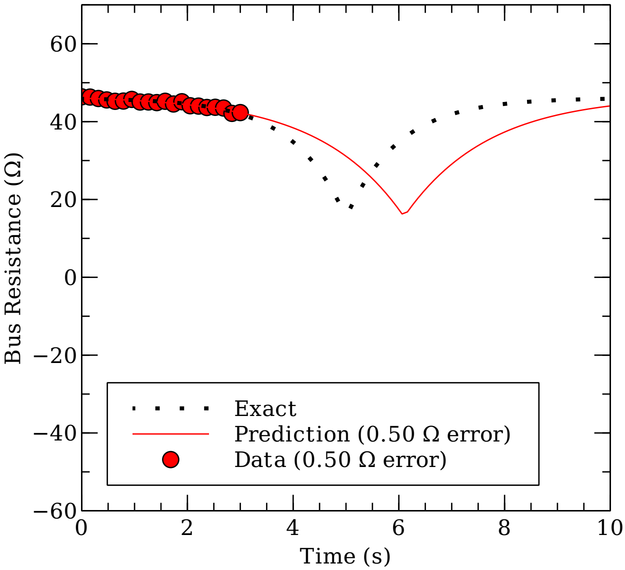
Model the Navy ship with



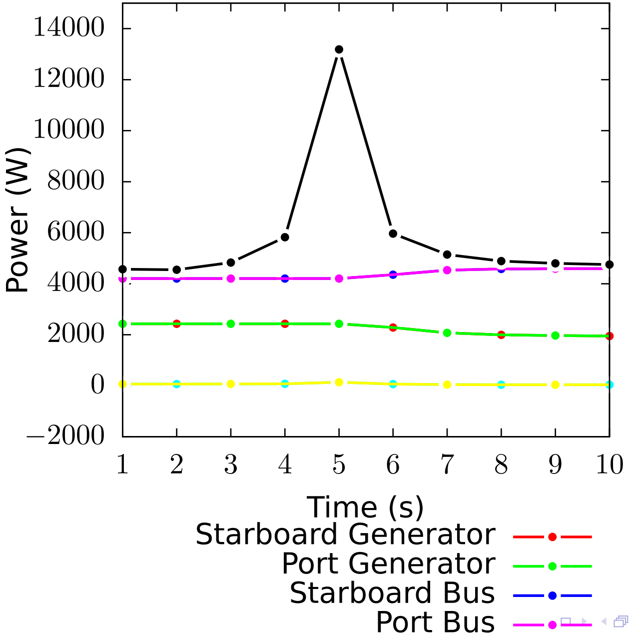

In this experiment, we

- Predict spike in load over a 3 s time horizon for a 10 s load
- Solve for an control over 10 s given both the exact load as well as prediction
- Control minimizes the use of storage devices

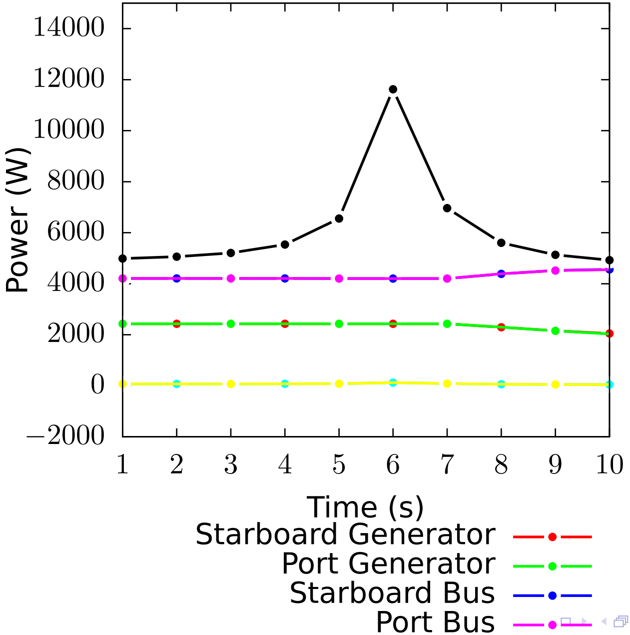
# True vs Prediction in Spike in Load



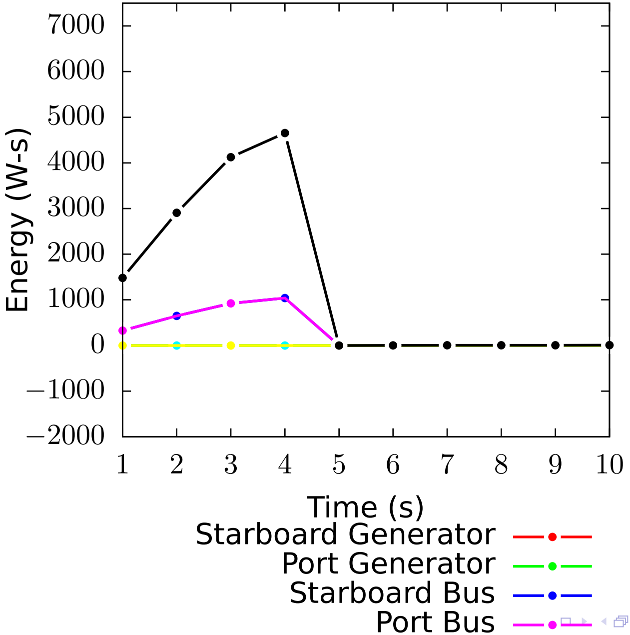
# Computed Resistive Load (True)



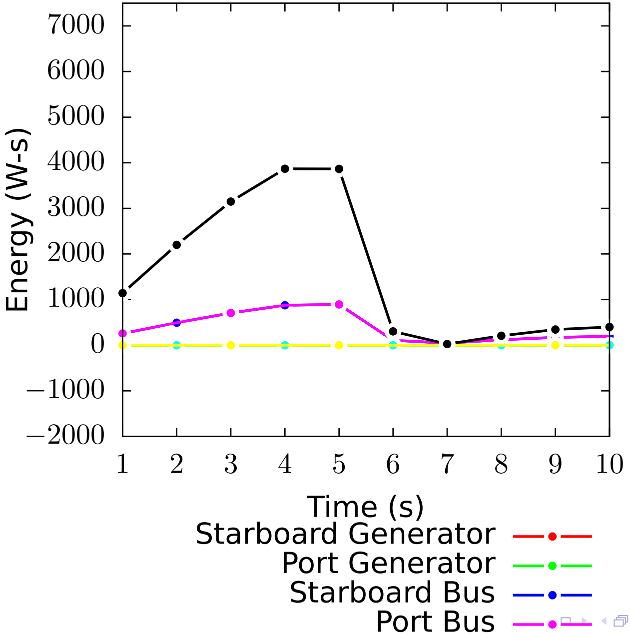
# Computed Resistive Load (Using Prediction)



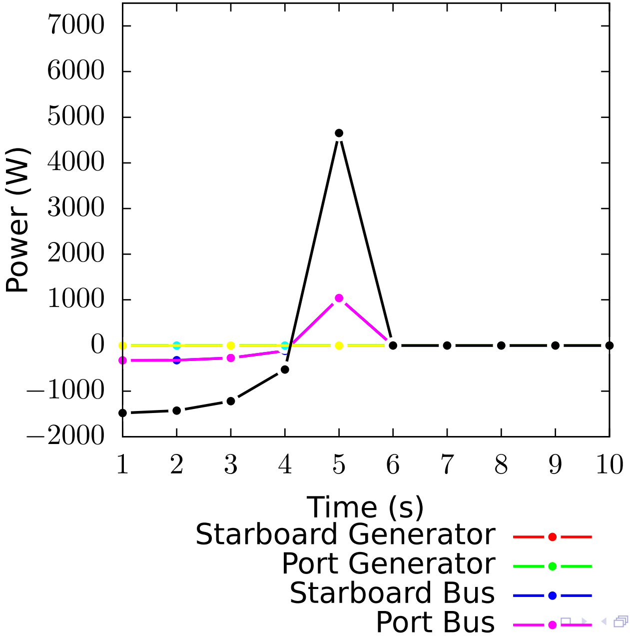
# Energy in Storage (True)



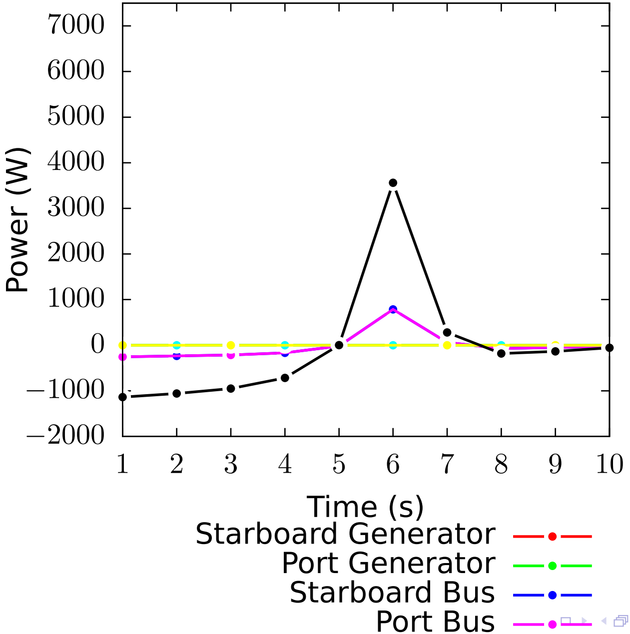
# Energy in Storage (Using Prediction)



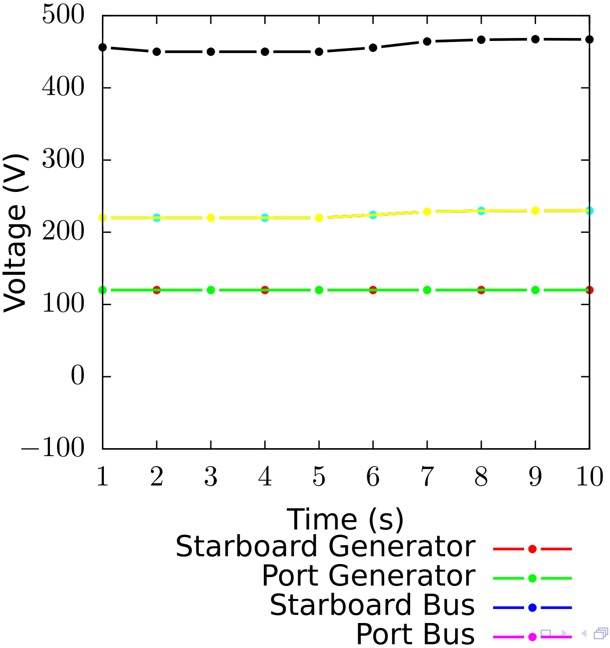
# Power from Storage (True)



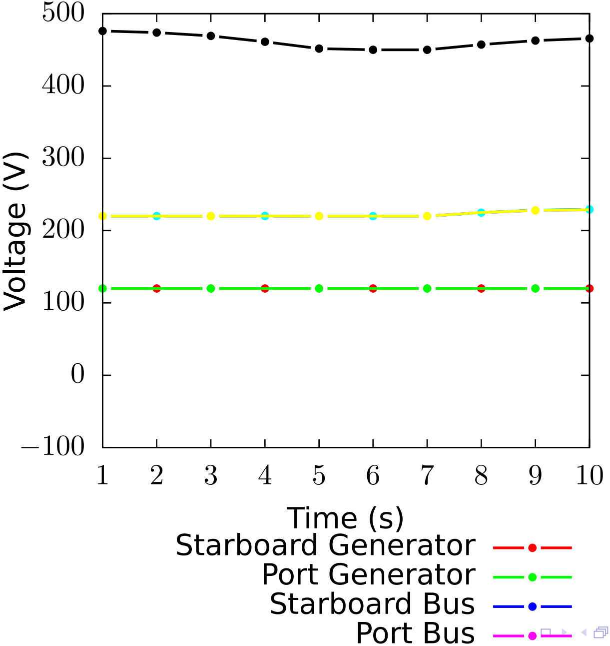
# Power from Storage (Using Prediction)



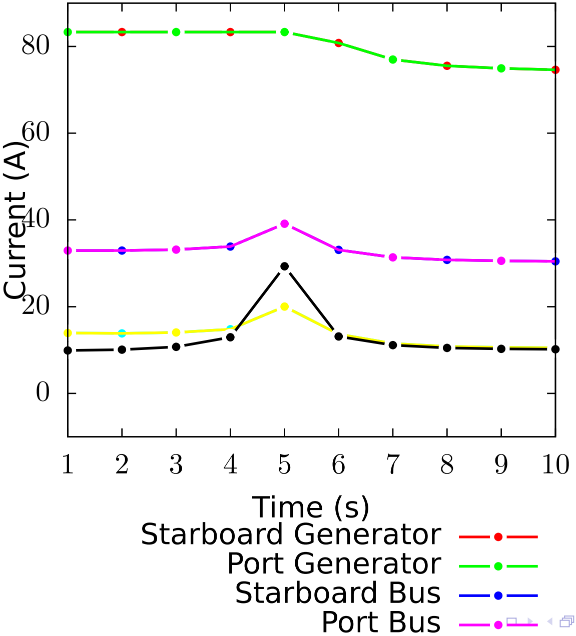
# Voltage (True)



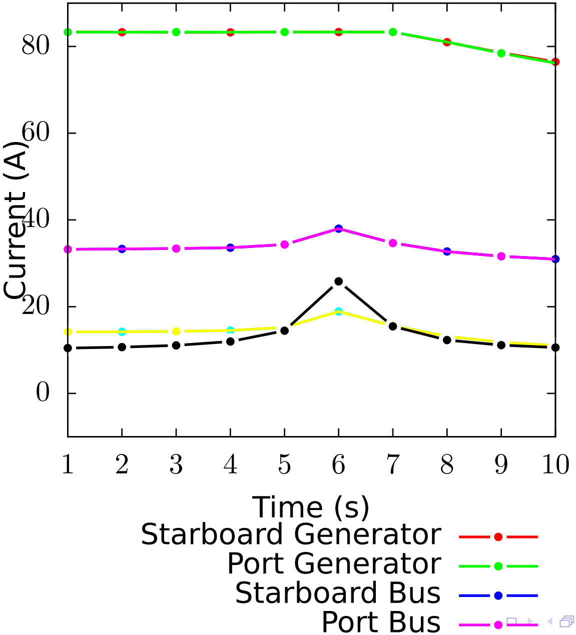
# Voltage (Using Prediction)



# Current (True)



# Current (Using Prediction)



# Overview

# Summary

## Summary of Results

- Nested control architecture consisting of
  - Agents that coordinate information between the microgrid and the various control algorithms
  - Real-time controller
  - Predictive engine
  - On-line controller
- Predictive engine works well modulo the amount of data and errors in the data
- Control inaccuracy directly correlates to error in the prediction, but operating conditions never violated

## Future Work

- Assessment of how errors and limited data affect the real-time control when integrated with the on-line control

# Acknowledgments


Authors would like to thank

- NAVSEA Naval Power Systems, Electric Ship PMS 320 program
- Sandia National Laboratories, multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525
- Sandia team members Steve Glover, Jason Neely, and Lee Rashkin

# Contact

For additional questions or interest please contact
`joe@optimojoe.com`