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A Predictive Engine for On-Line Optimal Microgrid Control

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1 Introduction

This research presents a predictive engine that integrates into an on-line optimal control planner for electrical microgrids. This controller models the behavior of the underlying system over a specified time horizon and then solves for a control over this period. In an electrical microgrid, such predictions are challenging to obtain in the presence of errors in the sensor information. As microgrids become more complex and cyber threats more common, it becomes likely that some kind of instrumentation error will occur. In order to overcome these difficulties, details are provided about a predictive engine robust to errors.

2 Optimal Control Engine

Kirchhoff's circuit laws are used to model the microgrid based on the formulation by Wilson et al. [1]. In this model, power generation is represented as either a current or voltage source and the power/energy storage device is represented similarly. Next, the circuit equations are solved while optimizing a user specified metric such as minimizing the use of the storage devices or minimizing the change in the boost converter duty cycles. For example,

Minimize	Use of 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.

where the components A, B, and C are described with the following circuits

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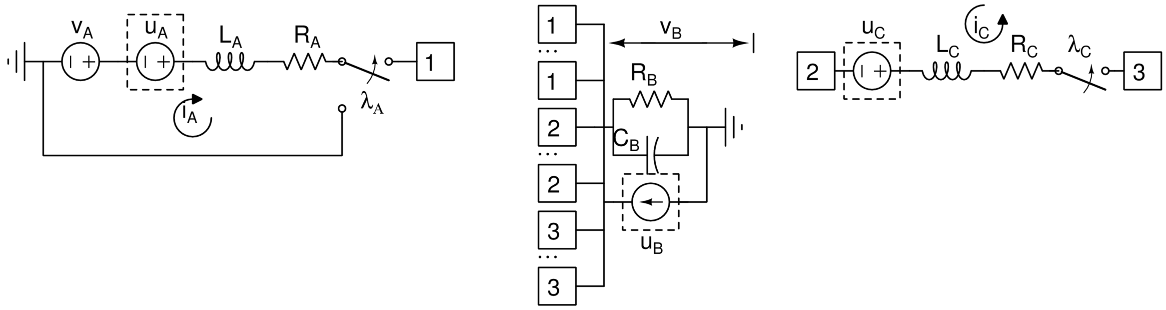
Boost converter (A) DC bus (B) Connector between DC buses (C)



Since the optimal control problem above is highly nonlinear, a hard guarantee on how long it takes the optimizer to solve the formulation can not be provided. That said, one can still use such a formulation in an on-line control. An *on-line control* repeatedly solves the control problem on a system in operation over a specified time horizon. The key behind an on-line controller is that although the state of the system depends on a collection of unknown inputs, if the behavior of the system can be predicted well enough, a useful control can be obtained.

3 Predictive Engine

In order to build a predictive engine, it is assumed that one knows the overall shape of the signal to predict, but not how it's scaled or whether it's time delayed. To that end, let $\phi : \mathbb{R} \to \mathbb{R}$ be the known signal and consider three modifications of the function

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

Combining each of these produces an adaptable signal of the form

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

It can be observed that the adaptable signal allows one to adjust and match the actual signal in three different ways, but it does not allow adaptation to an arbitrary signal. That's the penalty one must pay for predicting the future.

In order to match the adaptable signal to data, $\{(t_i, y_i)\}_{i=1}^m$, the following optimization problem is solved

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

4 Results

In order to better understand how well the predictive engine compensates for errors, consider a resistive load on a microgrid. Given a 480 V bus, a spike in power is generated with a base of 5 kW and a max of 15 kW by generating an inverse exponential representing resistance since $p = v^2/R$. To that end, let

$$\phi = \begin{cases} a - b\mathrm{e}^{-t} & t \geq 0 \\ a - b\mathrm{e}^{t} & t < 0 \end{cases}$$

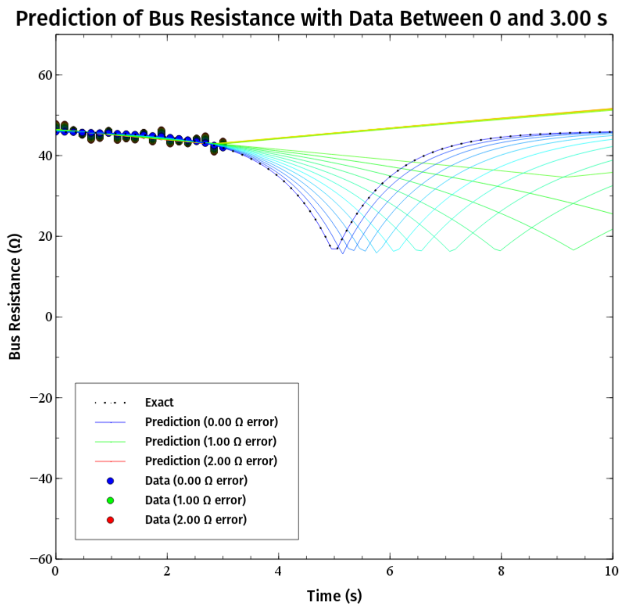
where

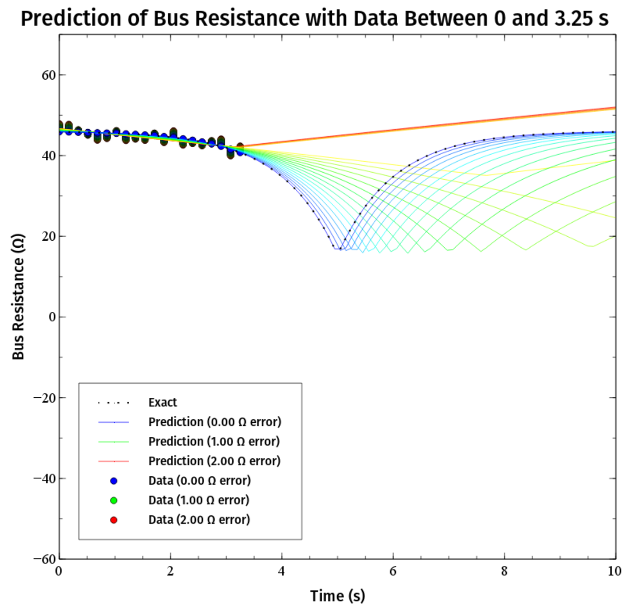
- $v = 480$ V
- $p_{\text{min}} = 5000$ W
- $p_{\text{max}} = 15000$ W
- $r_{\text{min}} = \frac{v^2}{p_{\text{min}}}$
- $r_{\text{max}} = \frac{v^2}{p_{\text{max}}}$

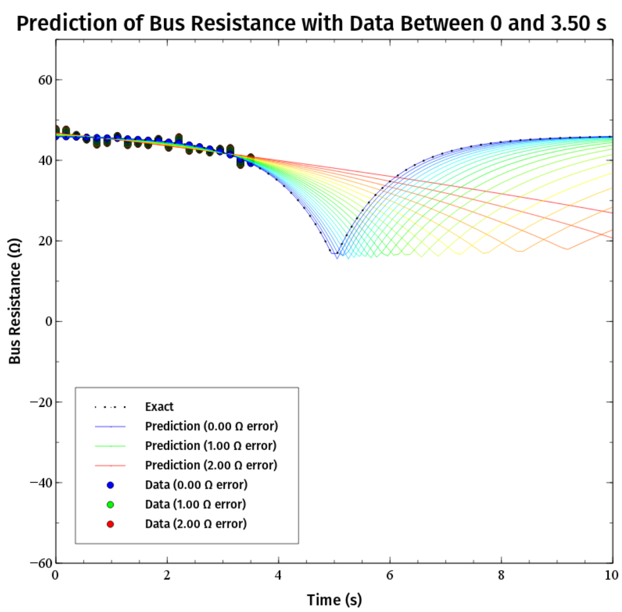
- $a = r_{\text{min}}$
- $b = r_{\text{min}} - r_{\text{max}}$

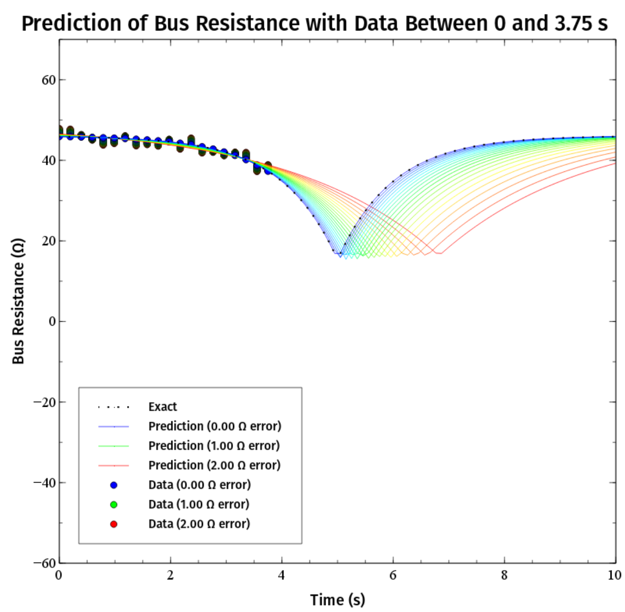
The spike is shifted forward by 5 s. In order to model faulty or corrupted sensors, generated data is created with uniformly distributed random errors that vary between 0 and $\pm 2\ \Omega$ over a time interval that varies from 3 to 4.25 s. In all situations, 20 samples are collected. In order to match the curve to the data, Optizelle [2] is used and employs an inexact trust-region Newton algorithm. In all situations, the algorithm converged quickly and to a locally optimal solution.

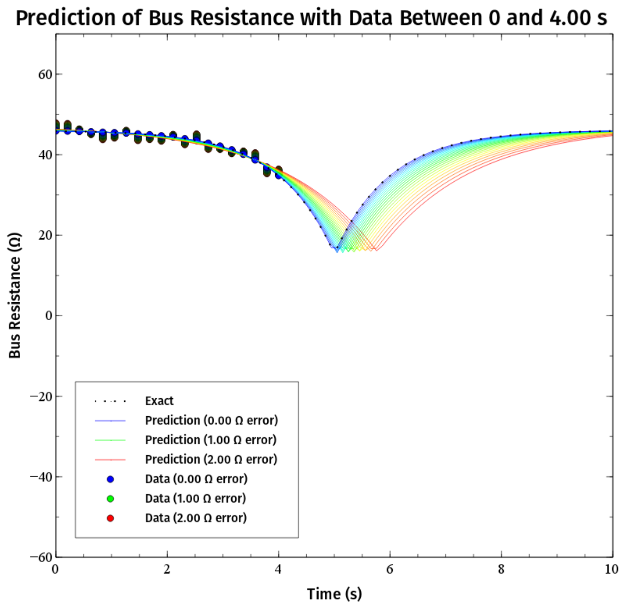
It can be observed that the predictions become more accurate as data is collected over a broader time period. Certainly, data collection over a smaller period can be tolerated, but it necessitates less error.

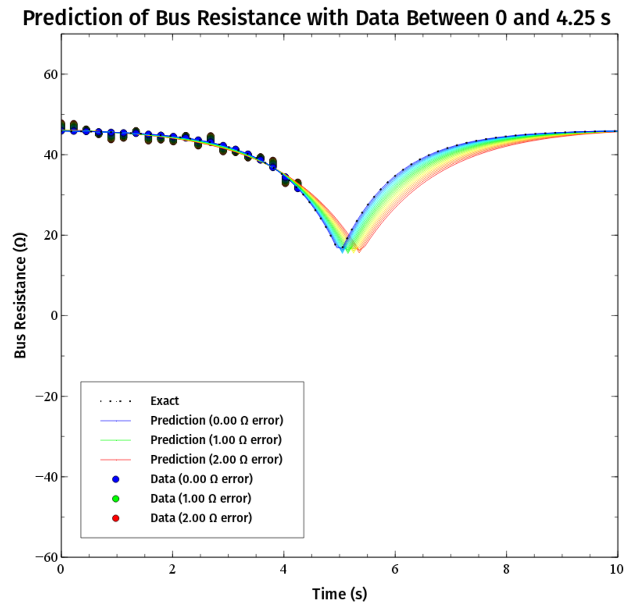












5 Conclusions

This research presented details of the design and performance of a predictive engine integrated into an on-line optimal control planner for electrical microgrids. This discussion describes how an on-line optimal control planner implements a receding-horizon control that relies on a predictive engine to predict the behavior of a system. Next, it was shown how to produce a predictive engine for the the kinds of loads seen in a microgrid. In the computational example, it was observed that one could accurately predict a spike in load given a limited amount of information with error.

In an extended presentation, the performance of the predictive engine across many different kinds of spikes in load will be characterized. In addition, the predictive engine will be integrated directly into the on-line optimal control planner and its affect on the performance will be demonstrated.

References

[1] D. G. Wilson, J. C. Neely, M. A. Cook, S. F. Glover, J. Young, and R. D. Robinett. Hamiltonian control design for dc microgrids with stochastic sources and loads with applications. In *2014 International Symposium on Power Electronics, Electrical Drives, Automation and Motion*, pages 1264–1271, June 2014.

[2] Joseph Young. Optizelle – an open source software library designed to solve general purpose nonlinear optimization problems. www.optimojoe.com, 2013–2017.