EFRI-COPN: Neuroscience and Neural Networks for Engineering the Future Intelligent Electric Power Grid

EFRI # 0836017

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Motivation

• It has been shown that traditional neural networks (NNs) are able to identify and optimally control nonlinear non-stationary systems.

• This has been demonstrated by the investigators on small scale power networks, represented by a few dozen state variables.

• However, practical power networks (and the future smart grid) typically consist of thousands of buses and hundreds of generators and control points with several thousands of sensors scattered throughout large geographic areas. The traditional NN architectures start to break down as it is scaled up to handle thousands of variables.
Research Objectives and Overview

• The overarching goal of this multi-disciplinary project is to infuse more neurobiology into control systems, to make them more brain-like and be able to carry out real-time control of complex systems.

• This project has two research thrusts:

  1) **neurobiology-based** & 2) **neuro-engineering-based**

  – On the neurobiology side, a novel in vitro neural system is used to explore **new learning mechanisms** that may underlie the massively parallel real-time control capabilities of the brain.

  – The neuro-engineering activity takes advantage of advances in the neurobiology thrust to develop **technologies for real-time control and decision making**, aimed at revolutionizing **nonlinear adaptive optimal control of large complex critical infrastructures** such as, but not limited to, the electric power grid.
Research Objectives and Overview

• The problem of scalability is to be addressed with new brain-inspired NN architectures that have brain-like scalable performance and are able to make adaptive optimal decisions over time.

• The project involves living in-vitro brain models, biomorphic simulations of neurocontrollers followed by hardware implementations on massively parallel computing platforms to be validated on several testbeds ranging from simulation to physical hardware.

• The hardware testbeds are of different complexity ranging from laboratory real-time simulations containing hardware as well as living neuronal networks, to a micro-grid of several hundreds of kWs, and to a part of the Mexican power grid.
Intelligent control of the power grid with new architectures and intelligent control systems is critical. The findings shall provide a better understanding of multiple-time base system identifiers, controllers and optimizers, and their interactions and scalability for large systems. The findings shall provide a better understanding of multiple-time base system identifiers, controllers and optimizers, and their interactions and scalability for large systems. Learning how the brain actually performs adaptive optimal decision making, prediction and pattern recognition among other things, and transforming this knowledge into algorithms on a chip, will constitute a breakthrough in theory and application. Neurocontrol offers nonlinear adaptive optimal control, which is particularly useful for nonlinear stochastic power networks (smart grid). Integration of renewable energy sources and plug-in vehicles into the traditional power system – Smart Grid – will reduce greenhouse gas emissions and assist human experts in control rooms. The findings shall provide a better understanding of multiple-time base system identifiers, controllers and optimizers, and their interactions and scalability for large systems. Learning how the brain actually performs adaptive optimal decision making, prediction and pattern recognition among other things, and transforming this knowledge into algorithms on a chip, will constitute a breakthrough in theory and application. Neurocontrol offers nonlinear adaptive optimal control, which is particularly useful for nonlinear stochastic power networks (smart grid). Integration of renewable energy sources and plug-in vehicles into the traditional power system – Smart Grid – will reduce greenhouse gas emissions and assist human experts in control rooms.
Project Participants (19)

- Co-PIs:
  - Steve Potter, Dept. of Biomedical Eng. (BME), Georgia Institute of Technology;
  - Ron Harley, School of Electrical and Comp. Eng., Georgia Institute of Tech. and
  - Donald Wunsch, Dept. of Electrical and Computer Eng. (ECE), Missouri S&T

- Senior Personnel:
  - Keith Corzine, Dept. of Electrical and Computer Eng., Missouri S&T

- Post-Doctoral Researcher:
  - Ahmed Saber, Dept. of Electrical and Computer Eng., Missouri S&T

- Students (13):
  - Riley Zeller-Townson, Gareth Guvanasen and Robert Ortman, BME, GTech
  - Cameron Johnson, Pinaki Mitra, Joseph Makasa, Lisa Grant, Bipul Luitel and
    Kelly Debolt, ECE, Missouri S&T
  - Dustin Howard, Jiaqi Liang, Diogenes Molina and Jing Dai, ECE, GTech.

OTHERS

- Industrial and National Labs. Collaboration
  - ABB, Spirae-Integrid, PNNL, NEETRAC, IPIC-GTech, RTDS

- International Collaborators:
  - Brazil and Mexico
From Neuroscience to Neurotechnology – Pulling it all together

Real-Time Control and Optimization of Complex Systems – Electric Power Grid

- Real Time Simulation
- Hardware Implementations
- Solar farms
- Plug-in Hybrids
- Pumped Storage
- Testbeds
- Windfarms
- Communication Delays
- Wide Area Control
- Wide Area Monitoring

Artificial Neural Networks

- Learning
- Scalability
- Speed
- Topology
- Hardware Implementations
- Convergence

Living Neural Networks

- Learning
- Sensory Mapping
- Architecture
- Motor Mapping
- Training Protocol
- Convergence

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Living Neural Network on MEA with 2-way neural interface electronics

Data input and training stimuli

MEA neural recordings

Power network signals

LNN output signals

Internet2 Link

RTPIS LAB. IN ROLLA

REAL-TIME DIGITAL SIMULATOR

HIGH PERFORMANCE COMPUTING CLUSTER

NOISE FILTERING

Generator G7 in Fig. 2

RTPIS LAB. IN ROLLA

NEUROLAB. IN ATLANTA

Stimulator

COMPUTER

LNN

Neural Translator

STIMULATION SEQUENCES

MISSOURI S&T

Internet2 Link

e_{st(1)}
WIDE AREA MONITOR AND COORDINATING CONTROLLER (WAMCC)

OBJECTIVES: COMBINED ECONOMIC AND EMISSION DISPATCH, DAMPING OF TRANSIENTS AND MINIMIZATION OF TRANSMISSION LOSSES, VOLTAGE DEVIATIONS AND CONTROL EFFORT

Data Transmission Lag

Monitoring

Control Signals

Data Transmission Lag

New England Test System

Area 1

New York Power System

Area 2

Data Transmission Lag

Area 3

Wind Farm

1000 MW

Area 4

Pumped Storage Hydro-unit

Area 5

Power System

Plug-in Hybrids

Data Transmission Lag

Control Signals

Data Transmission Lag

Plug-in Hybrids

Data Transmission Lag

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Living Neuronal Networks

- Developed hardware and software to provide a 60-electrode interface between cultured neural networks and a computer.
- The idea is to learn enough about how biological neuronal networks compute so that we can harness some of their advantages (compared to traditional computers) at processing information in real-time.
- Specifically, we are developing protocols for electrically training living networks with patterned multi-electrode stimulation.
- For this project, we are making a large advance from our previous success with in-vitro learning, by using continuous, real-time data streaming from a real-time power system simulator at RTPIS Lab. in Missouri S&T.
Spiking Neural Networks (SNNs)

\[ f_i(\lambda) = \frac{1}{T_{ref} + ISI} \]

\[ ISI = \frac{V_{\text{thresh}} - \mu_i}{\sigma_i} \int_{V_{\text{rest}} - \mu_i}^{\sigma_i} g(x) \, dx \]
SNN Based Neuroidentification

CNN Representation of 12-bus Power System
Dynamic Voltage Index

\[ DVI = \min \left\{ 1, \max_{i=1,...,\text{nbus}} \left[ \frac{V_n - v_{i,\text{min}}}{V_n - v_{i,\text{min,adm}}} \right] \right\}; \quad \text{where } V_n = 1.0, \ v_{i,\text{min,adm}} = 0.9 \]

Dish-Stirling Solar Thermal Power Generation

- Dish-Stirling solar power generation has emerged as an efficient and reliable source of renewable energy.
- As the technology moves into commercialization, models become necessary to predict system behavior under various operating conditions.
- Current literature on dish-Stirling technology is scattered, focusing on individual components within the system.
- This work establishes a background of the individual component models, and provides a method for integration of the various component models to form a comprehensive model.
- The thermal, electrical, and control systems of the dish-Stirling system are developed, along with a method for simulation.

Pumped Storage Hydro-Power Plant Models

- Improved models of pumped storage plants with different water pipe configurations.
- Modeling of the water tunnel is included. New model can simulate the hydraulic coupling of multiple units with a common water tunnel.
- Fully elastic water model is developed to compare with simplified rigid model.
- Simulations on two hydraulically coupled units under different operating conditions
- Water elasticity effects is negligible for grid fault transient dynamic studies
- Water elasticity has small effects on power system responses when studying long-term dynamics with large power excursion.

Integration of Plug-in Vehicles to the Grid

1. Models of plug-in vehicles are developed for real-time simulation

2. Parking lot models are developed – SmartParks

3. Optimal scheduling of charging and discharging times and rates for plug-in vehicles

4. Unit commitment with SmartParks

5. Grid stability with SmartParks

6. Enhancement of grid stability with coordinated intelligent controls
Plug-in Vehicles (PHEVs and EVs)

- Forecasting of Energy Demand/Source
- Dynamic Scheduling (charge/discharge rates)
### SmartPark Schedule 8/7/2008 for Profit Maximization

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Intelligent Unit Commitment with V2G - A Cost-Emission Optimization

- A gridable vehicle can be used as a small portable power plant (S3P).
- V2G can reduce dependencies on small expensive units in existing power systems, resulting in reduced operation cost and emissions.
- It can also increase reserve and reliability of existing power systems.
- As the number of gridable vehicles is much higher than units in existing power systems, unit commitment (UC) with V2G is more complex than usual UC with only thermal units.
Intelligent UC with V2G – Problem Formulation

• The objective of the UC with V2G is to minimize total operation cost and emission, where cost includes mainly fuel cost and start-up cost.

\[
\begin{align*}
\min \mathcal{T}C &= \mathcal{W}_c \times (\text{Fuel} + \text{Start-up}) + \mathcal{W}_e \times \text{Emission} \\
&= \sum_{i=1}^{N} \sum_{t=1}^{H} \left[ \mathcal{W}_c (\mathcal{F}C_i(P_i(t)) + \mathcal{S}C_i(1 - I_i(t - 1))) + \mathcal{W}_e (\psi_i \mathcal{E}C_i(P_i(t))) \right] I_i(t)
\end{align*}
\]

\[
\begin{align*}
\mathcal{F}C_i(P_i(t)) &= a_i + b_i P_i(t) + c_i P_i^2(t) \\
\mathcal{E}C_i(P_i(t)) &= \alpha_i + \beta_i P_i(t) + \gamma_i P_i^2(t)
\end{align*}
\]

\[
\mathcal{S}C_i(t) = \begin{cases} 
\text{h-cost}_i, & \text{if boiler temperature is higher than a threshold} \\
\text{c-cost}_i, & \text{if boiler temperature is lower than a threshold}
\end{cases}
\]

- charging/discharging freq.
- system power balance
- spinning reserve
- generation limits
- state of charge
- vehicle parking limits
- efficiency
- minimum up/down time
- ramp rate
- prohibited zones
- initial status
Unit Commitment with Normal Load

Conventional thermal units

Real time pricing

Power Flow from the Grid

Intelligent Energy Management Controller (IEMC)

Minimize $$ & Emissions (secondary)
Unit Commitment with Usual Load & Plug-in Vehicles

Intelligent Energy Management Controller (IEMC)

Minimize $$, Emissions (secondary) & Load Leveling (Schedule Charging)
Smart Grid Model

Intelligent Energy Management Controller (IEMC)

Power Flow to the Grid

Power Flow from the Grid

Real time pricing

Minimize $$ and Emission & Schedule

Smart Charging/Discharging

Conventional thermal units

Solar Energy Prediction Unit

Wind Energy Prediction Unit

Load Prediction Unit

Actual Wind Speed
Predicted Wind Speed

Actual Load
Predicted Load

Load (MW)

Time (minutes)

Power Flow from the Grid

Power Flow to the Grid

Real time pricing

Intelligent Energy Management Controller (IEMC)

Minimize $$ and Emission & Schedule

Smart Charging/Discharging

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## Smart Grid Model

### Graphs and Data Tables

#### Graph 1: G2V and V2G Models
- **G2V** (Grid to Vehicle): Discharging mode.
- **V2G** (Vehicle to Grid): Charging mode.

#### Data Table

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**Notes:**
- Demand* does not include the load of GVs; positive and negative values of V2G/G2V indicate discharging and charging, respectively.
- Solar farm size = 40 MW (250,731.33 m²)
- Wind farm size = 25.5 MW (17 wind turbines and 1.5 MW each)
- Total running cost = $535,172.03 (fuel cost plus start-up cost)
- Total emission = 249,566.88 ton

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Grid Stability with Plug-in Vehicles

Grid Stability with Plug-in Vehicles

Wide Area Monitoring and Control Systems

- This work focuses on the design of a wide area monitoring system (WAMS) and control system (WACS) for a multimachine power system with enhanced reliability, integrity and security.

- The proposed WAM uses current and past information from the generators to predict their future values.

- By combining features such as missing sensor fault tolerance, intrusion detection system and integrity check at the receiving end, the proposed method is more reliable and secure.

- The proposed enhanced WAMS is capable of overcoming communication delays, mitigating attacks and surviving faults.

The Challenge of Truly Getting Resilient, Robust, Reliable, Secure and Greener

What type of modeling, optimization and control capabilities are needed?
- Multi-objective
- Dynamic
- Uncertainty
- Parallel and coordinated
- Faster than real-time
Publications-to-Date

http://brain2grid.com

• Journals: 5 published/accepted

• 2 Journal papers – revise and resubmit
• 4 Journal papers – submitted
• Conference papers: 25 published and several others submitted.
Thank You!

Ganesh Kumar Venayagamoorthy, PhD, FIET, FSAIEE, SMIEEE

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