Focus Area : Energy/Power Management Systems

Grid integration, micro grids, power on demand, high efficiency conversion, high density power electronics, power converter for harsh environments, sensor networks for power systems, control and optimization of power circuits/electronics fault management and security in power systems.

Core faculty: Juan Rivas-Davila, Stephen Boyd, Sanjay Lall, Ram Rajagopal, David Tse Affiliated faculty:Dimitry Gorinevsky, Marco Pavone, Daniel C. O'Neill

Smart Grid: Stochastic Optimization for Smart Grid

Big Data analytics, non-parametric model, quantile regression, ADMM optimization

Dimitry Gorinevsky and Stephen Boyd

Smart Grid: Data-driven Risk Analytics for Energy and Climate

Long tail models. Optimal Bayesian estimation. Value at Risk. Big Data analytics. Year-to-year trend of 100 year event risk. Peak power load for utility. Extreme weather events in changing climate.

Dimitry Gorinevsky, with Stephen Chu (Physics)

Smart Grid: VISDOM: Data Analytics Platform for Smart Grid

Web platform and open source software for

- **Consumer response modeling and prediction**
- **Example 2 Load scheduling and forecasting**
- Rate and real-time pricing design
- **Targeting storage, solar, DR and other technologies**
- **Fault isolation and service restoration**

Contact: Chin Woo Tan [\(tancw@stanford.edu\)](mailto:tancw@stanford.edu) PI: Ram Rajagopal

Smart Grid: Line Sensor for Distribution Networks Very low cost, high accuracy power sensing for

- Self-powered, voltage and current sensor using a novel active measurement technique.
- Applications: outage and topology detection, voltage control, PMU.

Smart Grid: Energy-efficient robotic transportation networks

Objective: to generate models and methods for the *system-level* control of robotic transportation networks wherein shared, self-driving, and electric vehicles provide mobility and connect to the smart grid for recharging (Figure 1).

Current work:

- Queueing-theoretical models of robotic transportation networks (RTN).
- Dynamic routing algorithms for RTN.
- Optimization of battery recharging.
- Demo involving autonomous NAVIA shuttles (Figure 2). Collaboration with SLAC and US Army ARIBO program.

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Contact: Marco Pavone

Smart Grid: Work based on power Data

•**Demand Response (DR)**

Energy provider

Energy consumers reduce electricity use at time of market high price.

–**DR policy requires a prediction of consumer energy consumption patterns.** –**There exists a wide variety of load shapes;** Data can contain a million of load shapes.

- •**Approach**: Cluster load shapes into K classes, using Dynamic Time Warping (DTW).
- **Model of Consumer:** Daily activities generates power consumption patterns. Timing varies within bound.
	- **Example** : S1 and S2 are Ben's load shapes. He showers an hour late on day2 so the corresponding power usage shifts to the right. We want to group S1 and S2 together.

Previous work: Clustering load shapes based on L2 dissimilarity penalizes mismatch across the horizon. Sanjay Lall, Nicky Teeraratkul

Our approach: Clustering load shapes based DTW dissimilarity produces optimal alignment between two series, allowing them to match. Stanford ENGINEERING

- **Implementation :** Calculate DTW distance between load shape vectors using dynamic program with a set of allowed search path, then use DTW distance matrix in divisive hierarchical clustering.
- **Result**: Compared to using L2, clustering using DTW,
	- We get half a number of clusters.
	- Each cluster is more compact.
	- Household is represented by a fewer clusters -> **Easier to continue the prediction problem for DR.**

With a fixed number of clusters, DTW achieves smaller WC, which indicates more compactness.

Data Centers: Distributed Control of Microgrids Designing algorithms and hardware for plug and play control of microgrids:

- **Stable control of networks of inverters and DC/DC** converters.
- Constant power load modeling.
- Distributed asynchronous AC and DC OPF solving.
- Low-cost embedded controller supporting storage, solar, fuel cells for power optimization and local voltage control in Data Centers, Buildings, Campus.

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Power Electronics: Aircore magnetics

- Air-core components not subject to saturation or Curie temperature limitations
- Toroidal are an improvements over solenoids as the magnetic field is constrained to the torus
	- Lower stray fields → Lower EMI issues
- PCB toroids have better copper coverage and lower loss and very repeatable
- Better air-core passives are possible with new fabrication techniques

Prof. Juan Rivas, Wei Liang, Luke RaymondStanford ENGINEERING

Power Electronics: 3D Printed Passive Components

(a) 3D CAD model

(b) 3D printed plastic mold

(c) cast silver model

Fig.: Steps in the fabrication of a 3D inductor. (a) shows the OpenJSCAD model, (b) shows a translucent plastic model and (c) shows a sterling silver inductor. The 3D inductor has 10nH inductance and its dimensions are OD=18mm, ID=6mm, N=4. Also notice the rounded cross section.

- 3D Printing can overcome limitations of PCBs and wirewound indutors
- Overhangs, curved surfaces possible
- Design flexibility to optimize cross section
	- Higher quality factor
	- FEM tools allow 3D printing all passives in power converters

Power Electronics: 3D Printed Passive Components

 (a) CAD (b) Cast (c) FEM Fig.: toroid inductor with a round cross section. OD=29mm, ID=11mm, N=20.

Prof. Juan Rivas, Wei Liang, Brian Holman

Power Electronics: Performance evaluation of diodes under high voltage and high slew rat Thermocouple 70.5 deg C

 3.5

• SiC diodes at 10's of MHz and high dv/dt present losses that can limit applcation at high volgates

• Understanding and accurate modeling may lead to higher power density supplies for x-rays, satellites

Prof. Juan Rivas, Luke Raymond, Wei Liang

Estimated Diode loss at various output voltages, $I_{\text{OIT}}=100 \text{mA}$ (600V SiC Diodes)

