







# Distributed Control Design for Balancing the Grid Using Flexible Loads

NREL Autonomous Energy Grids Workshop



#### Sean Meyn



Department of Electrical and Computer Engineering — University of Florida

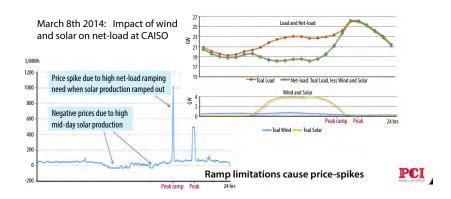
Based on joint research with Dr. Y. Chen, J. Mathias, P. Barooah, UF & A. Bušić, Inria

Thanks to to our sponsors: Google, NSF, DOE, ARPA-E



# Distributed Control Design for Balancing the Grid Outline

- Challenges
- 2 Virtual Energy Storage
- Oemand Dispatch
- Questions and Conclusions
- References



# **Challenges**

Large sunk cost

- Large sunk cost
- 2 Engineering uncertainty

- Large sunk cost
- 2 Engineering uncertainty
- Olicy uncertainty

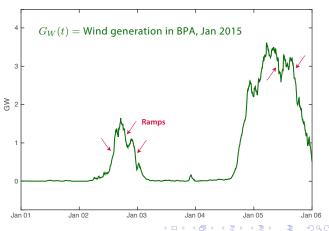
- Large sunk cost
- 2 Engineering uncertainty
- Olicy uncertainty
- Volatility

Start at the bottom...

What's so scary about volatility?

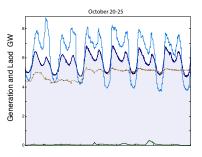


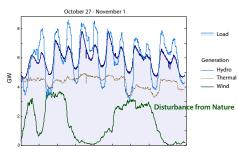
Volatility



What's so scary about volatility?

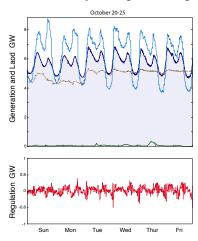
#### ■ Volatility ⇒ greater regulation needs

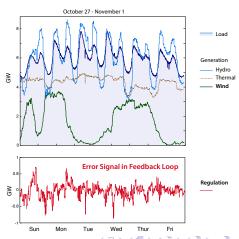




What's so scary about volatility?

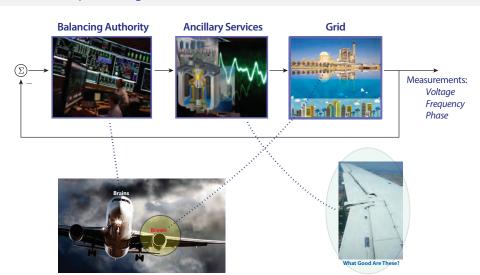
#### ■ Volatility ⇒ greater regulation needs





# Comparison: Flight control

How do we operate the grid in a storm?



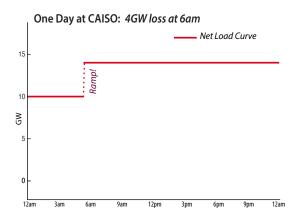
### Frequency Decomposition

#### Taming the Duck



# Frequency Decomposition

#### **Smoothing Contingencies**



# Demand Response the Answer?

CPUC Decision 14-03-026 March 27, 2014

#### BEFORE THE PUBLIC UTILITIES COMMISSION OF THE STATE OF CALIFORNIA

... to Enhance the Role of Demand Response in Meeting the State's Resource Planning Needs and Operational Requirements.

Bidding demand response into the CAISO energy markets has been an objective of the Commission since the initiation of R.07-01-041 in 2007.<sup>81</sup> The Commission has moved forward with directing the utilities to revise their tariffs to allow retail customers to bid demand response into the CAISO energy markets<sup>82</sup> and authorized the utilities to bid demand response into the market.<sup>83</sup> To our dismay, very little demand response capacity has been integrated into the CAISO's markets to date.<sup>84</sup> But how much demand response should be bid into the CAISO market? What are our goals for either side of bifurcation and, how do we get there from here?

# Demand Response the Answer?

CPUC Decision 14-03-026 March 27, 2014

#### BEFORE THE PUBLIC UTILITIES COMMISSION OF THE STATE OF CALIFORNIA

... to Enhance the Role of Demand Response in Meeting the State's Resource Planning Needs and Operational Requirements.

Bidding demand response into the CAISO energy markets has been an objective of the Commission since the initiation of R.07-01-041 in 2007.<sup>81</sup> The Commission has moved forward with directing the utilities to revise their tariffs to allow retail customers to bid demand response into the CAISO energy markets<sup>82</sup> and authorized the utilities to bid demand response into the market.<sup>83</sup> To our dismay, very little demand response capacity has been integrated into the CAISO's markets to date.<sup>84</sup> But how much demand response should be bid into the CAISO market? What are our goals for either side of bifurcation and, how do we get there from here?

Need to rethink role of demand-side resources

# Demand Response the Answer?

#### Audrey Zibelman's bold plan to transform New York's electricity market



TOPICS V

FEATURES

What's most critical to Zibelman is the creation of liquidity and transparency in the marketplace, as well as erasing barriers to entry. "Regardless of whether it's one distributed platform provider or multiple utilities," she said, "I want—from the customer-facing and market-facing approach—for everything to be very consistent."

#### Unpacking the value of demand

One of the most radical ideas in the REV is that New York is having demand —as opposed to generation—be the state's primary energy resource.

"Rather than demand being the last resource you manage in the system, it's the first resource," Zibelman said. "Demand can respond much more quickly than any other resource."

Like many other regions in the country, New York has slowing overall demand for electricity, but a growing gap between peaks and non-peaks, which diminishes the overall efficiency of the electricity system.

Need to rethink role of demand-side resources





# Virtual Energy Storage

# Capacity of Virtual Energy Storage

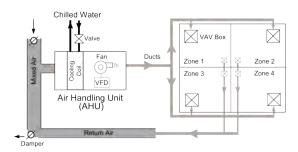


HVAC flexibility to provide additional ancillary service

- Buildings consume 70% of electricity in the US
- Buildings have large thermal capacity

HVAC flexibility to provide additional ancillary service

- Buildings consume 70% of electricity in the US
- Buildings have large thermal capacity
- Modern buildings have fast-responding equipment:
   VFDs (variable frequency drive)

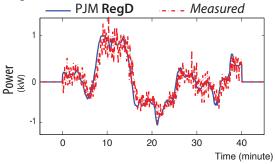


Tracking RegD at Pugh Hall

In one sentence: Ramp up and down power consumption, just 10%, to track regulation signal.

Tracking RegD at Pugh Hall

Ramp up and down power consumption, just 10%, to In one sentence: track regulation signal.

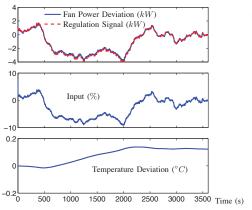


ignore the measurement noise

How demand response from commercial buildings will provide the regulation ..., Allerton, 2012

# Pugh Hall @ UF

#### How much?

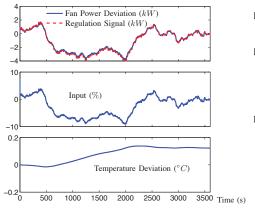


- ▷ One AHU fan with 25 kW motor:
  - > 3 kW of regulation reserve
- Pugh Hall (40k sq ft, 3 AHUs): > 10 kW

Indoor air quality is not affected

# Pugh Hall @ UF

#### How much?



- ▷ One AHU fan with 25 kW motor:
  - > 3 kW of regulation reserve
- Pugh Hall (40k sq ft, 3 AHUs): > 10 kW

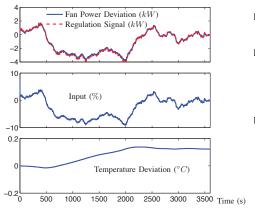
Indoor air quality is not affected

▷ 100 buildings:

> 1 MW

# Pugh Hall @ UF

#### How much?



- ▷ One AHU fan with 25 kW motor:
  - > 3 kW of regulation reserve
- ▶ Pugh Hall (40k sq ft, 3 AHUs):

> 10 kW

Indoor air quality is not affected

▶ 100 buildings:

> 1 MW

just using 10% of the fans

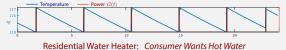
100,000 residential water heaters



Question: What is the capacity in terms of

- Virtual energy storage (MWh)
- Virtual power (MW)

100,000 residential water heaters



Question: What is the capacity in terms of

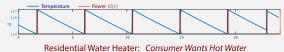
- Virtual energy storage (MWh)
- Virtual power (MW)

#### **Power Capacity**

Average power consumption:  $P_{\text{avg}} = 8 \text{ MW}$  (without usage)

Peak power:  $P_{\rm peak}=200~{\rm MW}$ 

100,000 residential water heaters



Question: What is the capacity in terms of

- Virtual energy storage (MWh)
- Virtual power (MW)

#### **Power Capacity**

Average power consumption:  $P_{\text{avg}} = 8 \text{ MW}$  (without usage)

Peak power:  $P_{\text{peak}} = 200 \text{ MW}$ 

**Answer:**  $P_+ = P_{\text{avg}}$  and  $P_- = P_{\text{peak}} - P_{\text{avg}}$ 

100,000 residential water heaters



Question: What is the capacity in terms of

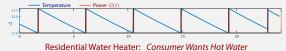
- Virtual energy storage (MWh)
- Virtual power (MW)

#### **Energy Capacity**

Suppose system is *fully charged* at time t = 0.

T= time to discharge: All units off for  $0 \le t \le T$ 

100,000 residential water heaters



Question: What is the capacity in terms of

- Virtual energy storage (MWh)
- Virtual power (MW)

#### **Energy Capacity**

Suppose system is *fully charged* at time t = 0.

T= time to *discharge*: All units off for  $0 \le t \le T$ 

Answer:  $E = T \times P_{\text{avg}}$ 

100,000 residential water heaters



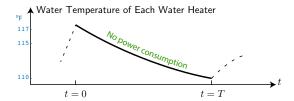
Question: What is the capacity in terms of

#### **Energy Capacity**

Suppose system is *fully charged* at time t = 0.

T= time to discharge: All units off for  $0 \le t \le T$ 

Answer:  $E = T \times P_{\text{avg}}$ 



 $\sim$  agrees with H. Hao et. al., Aggregate flexibility of thermostatically controlled loads, 2015

100,000 residential water heaters

### **Capacity**

$$P_+ = P_{\mathsf{avg}}$$

$$P_- = P_{\mathsf{peak}} - P_{\mathsf{avg}}$$

$$E = T \times P_{\mathrm{avg}}$$

100,000 residential water heaters

### **Capacity**

$$P_+ = P_{\mathsf{avg}}$$

$$P_- = P_{\mathsf{peak}} - P_{\mathsf{avg}}$$

$$E = T \times P_{\mathsf{avg}}$$

For a single high-end unit:

$$E_1 = 6 \text{ hrs} \times 100 \text{ Watts}$$

 $\approx$  10 MW, 60 MWh battery system

100,000 residential water heaters

### Capacity

$$P_+ = P_{\mathsf{avg}}$$

$$P_{-} = P_{\mathsf{peak}} - P_{\mathsf{avg}}$$

$$E = T \times P_{\mathsf{avg}}$$

For a single high-end unit:  $E_1 = 6$  hrs  $\times$  100 Watts

pprox 10 MW, 60 MWh battery system



How do we compare?

100,000 residential water heaters

### **Capacity**

$$P_{+} = P_{\mathsf{avg}}$$

$$P_- = P_{\mathsf{peak}} - P_{\mathsf{avg}}$$

$$E = T \times P_{\mathsf{avg}}$$

For a single high-end unit:  $E_1 = 6$  hrs  $\times$  100 Watts

 $\approx 10 \text{ MW, } 60 \text{ MWh}$  battery system

### How do we compare?



 $\approx$  30 MW, 120 MWh battery system

100,000 residential water heaters

### **Capacity**

$$P_+ = P_{\mathsf{avg}}$$

$$P_{-} = P_{\mathsf{peak}} - P_{\mathsf{avg}}$$

$$E = T \times P_{\mathsf{avg}}$$

For a single high-end unit:  $E_1 = 6 \text{ hrs} \times 100 \text{ Watts}$ 

pprox 10 MW, 60 MWh battery system

### $\approx$ 30 MW, 120 MWh battery system



The Escondido system consists of 24 containers hiding nearly 20,000 modules that hold 20 batteries each ... 10% round-trip energy loss, cooling required, ...  $P_+ \neq P_- \neq 30$  MW ...

100,000 residential water heaters

### Capacity

$$P_+ = P_{\mathsf{avg}}$$

$$P_{-} = P_{\mathsf{peak}} - P_{\mathsf{avg}}$$

$$E = T \times P_{\mathsf{avg}}$$

For a single high-end unit:  $E_1 = 6 \text{ hrs} \times 100 \text{ Watts}$ 

 $\approx$  10 MW, 60 MWh battery system

### $\approx$ 30 MW, 120 MWh battery system

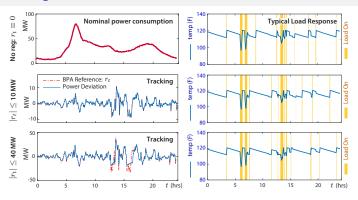


The Escondido system consists of 24 containers hiding nearly 20,000 modules that hold 20 batteries each ... 10% round-trip energy loss, cooling required, ...  $P_{+} \neq P_{-} \neq 30 \text{ MW} \dots$ 

The population of California is 40 million, and the electricity doesn't just go into the hot tubs

## Tracking with 100,000 Water Heaters

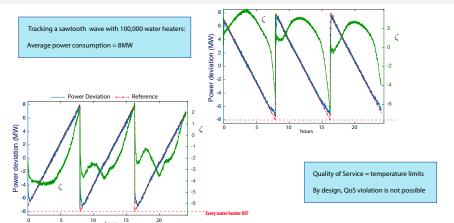
#### Power Limits - Regulation



Tracking results with 100,000 water heaters, and the behavior of a single water heater in three cases, distinguished by the reference signal [1].

## Tracking with 100,000 Water Heaters

Energy Limits - Ramps and Contingencies



Distributed Control Design for Balancing the Grid Using Flexible Loads, Springer 2018

## DER Flexibility Assessment & Valuation

Ongoing GMLC project - PNNL/ORNL/UF

Virtual Battery-Based Characterization and Control of Flexible Building Loads Using VOLTTRON

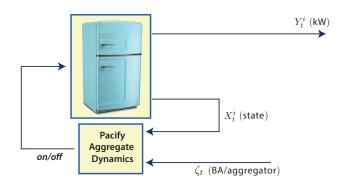


Total

\$/year

189,696

55,746



## **Demand Dispatch Design**

Demand Dispatch the Answer?

### Players:

Grid operator = Balancing Authority, or BA Consumers (residential in this lecture)

A partial list of the needs of the grid operator, and each consumer:

Demand Dispatch the Answer?

A partial list of the needs of the grid operator, and each consumer:

• High quality AS? (Ancillary Service)

#### Demand Dispatch the Answer?

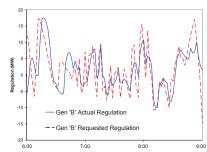
A partial list of the needs of the grid operator, and each consumer:

• High quality AS? (Ancillary Service)

Fig. 10. Coal-fired generators do not follow regulation signals precisely....

Some do better than others





Regulation service from generators is not perfect

Frequency Regulation Basics and Trends — Brendan J. Kirby, December 2004

Demand Dispatch the Answer?

A partial list of the needs of the grid operator, and each consumer:

- High quality AS?
- Reliable?

Will AS be available each day? It may vary with time, but capacity must be predictable.

Demand Dispatch the Answer?

A partial list of the needs of the grid operator, and each consumer:

- High quality AS?
- Reliable?
- Cost effective?

Demand Dispatch the Answer?

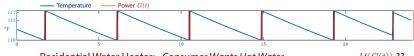
A partial list of the needs of the grid operator, and each consumer:

- High quality AS?
- Reliable?
- Cost effective?
- Is the incentive to the consumer reliable?

Demand Dispatch the Answer?

A partial list of the needs of the grid operator, and each consumer:

- High quality AS?
- Reliable?
- Cost effective?
- Is the incentive to the consumer reliable?
- Customer QoS constraints satisfied?
   Fresh fish, comfy house, clean pool, hot water, cool data centers, happy farmers, ...



Residential Water Heater: Consumer Wants Hot Water

 $\mathcal{U}(G(t))$  ??

Demand Dispatch the Answer?

A partial list of the needs of the grid operator, and each consumer:

- High quality AS?
- Reliable?
- Cost effective?
- Is the incentive to the consumer reliable?
- Customer QoS constraints satisfied?

Demand dispatch can do all of this (by design)

#### Related Prior Research

### Schweppe's FAPER Concept

#### Frequency adaptive, power-energy rescheduler

US 4317049 A

#### **ABSTRACT**

A frequency adaptive, power-energy re-scheduler (FAPER) that includes a frequency transducer that notes frequency or frequency deviations of an electrical system and logic means which controls and re-schedules power flow to a load until in part on the basis of the deviations in frequency from a nominal frequency and in part on the needs to the load unit as expressed by an external sensor signal obtained from the physical system affected by the load unit. Publication number Publication type Application number Publication date Filing date Priority date ① Inventors

US4317049 A Grant US 06/076,019 Feb 23, 1982 Sep 17, 1979 Sep 17, 1979

Sep 17, 1979
Fred C. Schweppe

Original Assignee Export Citation Massachusetts Institute Of Technology BiBTeX, EndNote, RefMan

Patent Citations (4), Referenced by (69), Classifications (10)

External Links: USPTO, USPTO Assignment, Espapenet

#### Related Prior Research

- Schweppe's FAPER Concept
- Mathematical foundations: Malhamé et. al. in 80s [Mean-Field Model]

#### Related Prior Research

- Schweppe's FAPER Concept
- Mathematical foundations: Malhamé et. al. in 80s [Mean-Field Model]
- Randomized control:
   Callaway, Hiskens, Mathieu, Kizilkale, Malhamé, Strbac, Almassalkhi, Hines
   Often system inversion to obtain linear MFM

#### Related Prior Research

• Industry now recognizes the value of randomization for distributed control

#### Related Prior Research

### Industry now recognizes the value of randomization for distributed control

#### Electrical load disconnect device with electronic control US 8328110 B2

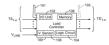
#### ABSTRACT

Electrical load spreading arrangements reduce peak power demand. An enclosure houses an electronic circuit board, which receives at a first input terminal a first themostat control signal from a thermostat intended to control a first air conditioning unit and at a second input terminal a second thermostat control signal from a thermostat intended to control a second AC unit. A controller on the circuit board is programmed with instructions stored in a memory coupled to the controller causing the controller to monitor the first and second input terminals to determine the timing and duration of the thermostat control signals passed to the output terminals for advantage or deviating or deactivation the

Publication number US8328110 B2 Publication type Grant Application number US 12/499.347 Publication date 11 Dec 2012 Filing date 8 Jul 2009 Priority date 8 Jul 2009 Fee status Paid Also published as US20110006123 Inventors Jeffrey O. Sharp Original Assignee Schneider Electric USA, Inc. Export Citation BiBTeX, EndNote, RefMan Patent Citations (5), Classifications (8), Legal Events (3) External Links; USPTO, USPTO Assignment, Espacenet

AC units such that overlapping operation of the AC units is reduced particularly during peak demand periods. A similar arrangement may be applied to a broader class of HVAC equipment, including water heaters, for example.

#### IMAGES (5)







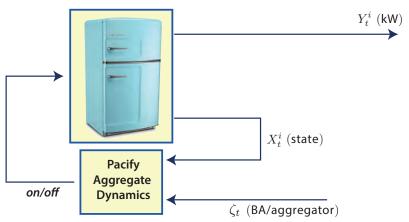






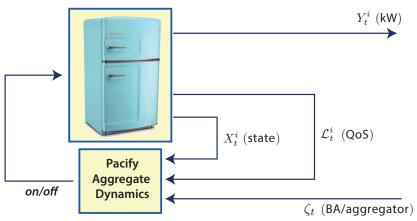
Intelligence at the Load distinguishes our work from others

### Step 1: Load-level Feedback Loops



Intelligence at the Load distinguishes our work from others

### Step 1: Load-level Feedback Loops



Intelligence at the Load

distinguishes our work from others

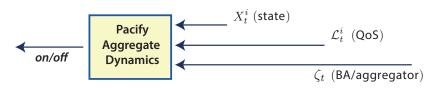
### Step 1: Load-level Feedback Loops

**Basic Ingredients:** 

1. Randomized decision rule design.

Maps  $(X, \zeta)$  to a probability of on/off

2. Secondary control monitors QoS, on slower time-scale



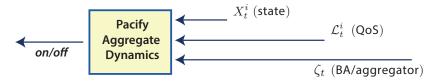
Intelligence at the Load

distinguishes our work from others

### Step 1: Load-level Feedback Loops

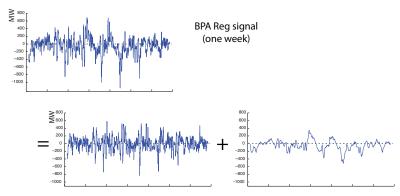
#### **Basic Ingredients:**

- 1. Randomized decision rule design.
  - Maps  $(X, \zeta)$  to a probability of on/off
- 2. Secondary control monitors QoS,
  - on slower time-scale
- 3. Newest innovation: additional filtering of  $\zeta$  to invert mean-field dynamics in a specific frequency range



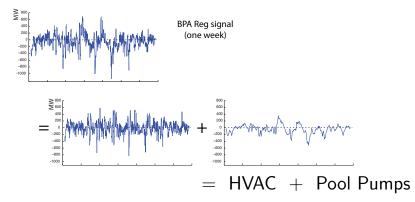
Intelligence at the Load

### Step 2: Condition Grid Reference Signal



Intelligence at the Load

### Step 2: Condition Grid Reference Signal

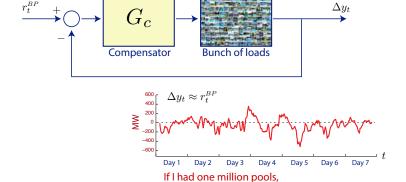


Assume BA has measurements of aggregate power consumption

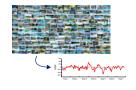
Step 3: Actuator Feedback Loop Easily controllable by design

### Assume BA has measurements of aggregate power consumption

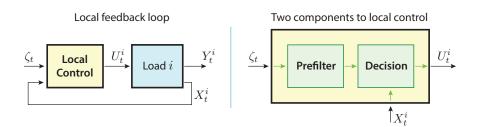
### Step 3: Actuator Feedback Loop Easily controllable by design



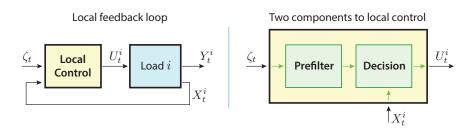
my problems would be solved! -TB, 2015



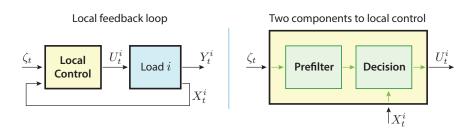




Each load monitors its state and a regulation signal from the grid.



- Each load monitors its state and a regulation signal from the grid.
- Prefilter and decision rules designed to respect needs of load and grid



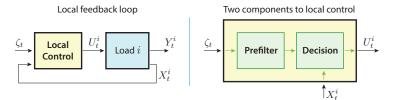
- Each load monitors its state and a regulation signal from the grid.
- Prefilter and decision rules designed to respect needs of load and grid
- Randomized policies required for finite-state loads

### MDP model

### MDP model

The state for a load is modeled as a controlled Markov chain. Controlled transition matrix:

$$P_{\zeta}(x, x') = P\{X_{t+1} = x' \mid X_t = x, \ \zeta_t = \zeta\}$$

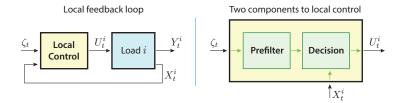


#### MDP model

#### MDP model

The state for a load is modeled as a controlled Markov chain. Controlled transition matrix:

$$P_{\zeta}(x, x') = P\{X_{t+1} = x' \mid X_t = x, \zeta_t = \zeta\}$$



#### Questions:

• How to design  $P_{\zeta}$ ? • How to analyze aggregate of similar loads?

# How to analyze aggregate?

Mean field model, R. Malhame et. al. 1984 -

#### State process:

$$\mu_t(x) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\{X_t^i = x\}, \quad x \in \mathsf{X}$$

Evolution: 
$$\mu_{t+1} = \mu_t P_{\zeta_t}$$

# How to analyze aggregate?

Mean field model, R. Malhame et. al. 1984 -

#### State process:

$$\mu_t(x) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\{X_t^i = x\}, \quad x \in \mathsf{X}$$

Evolution:  $\mu_{t+1} = \mu_t P_{\zeta_t}$ 

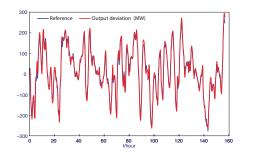
Output (mean power): 
$$y_t = \sum_x \mu_t(x) \mathcal{U}(x)$$

Nonlinear state space model

Linearization useful for control design

# How to analyze aggregate?

Mean field model, R. Malhame et. al. 1984 -



### State process:

$$\mu_t(x) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\{X_t^i = x\}, \quad x \in \mathsf{X}$$

Evolution:  $\mu_{t+1} = \mu_t P_{\zeta_t}$ 

Output (mean power): 
$$y_t = \sum_x \mu_t(x) \mathcal{U}(x)$$

Nonlinear state space model

Linearization useful for control design

Goals: Desirable properties for the mean field model, with strict bounds on QoS to consumer

Approaches: Start with a nominal model, with Markov transition law  $P_0$ .

Goals: Desirable properties for the mean field model, with strict bounds on QoS to consumer

Approaches: Start with a nominal model, with Markov transition law  $P_0$ .

- Myopic Design:  $P_{\zeta}(x,x') = \exp(\zeta \mathcal{U}(x') \Lambda_{\zeta}(x)) P_0(x,x')$ . Encourages movement to x' if
  - $\zeta > 0$
  - Power consumption  $\mathcal{U}(x') > 0$ .

Goals: Desirable properties for the mean field model, with strict bounds on QoS to consumer

Approaches: Start with a nominal model, with Markov transition law  $P_0$ .

- Myopic Design:  $P_{\zeta}(x,x') = \exp(\zeta \mathcal{U}(x') \Lambda_{\zeta}(x)) P_0(x,x')$ .
- Optimization:  $\check{P}_{\zeta} = \underset{P,\pi}{\operatorname{arg\,max}} \big\{ \zeta \pi(\mathcal{U}) \mathcal{K}(P \| P_0) : \pi P = \pi \big\}$

# How to design $P_{\mathcal{C}}$ ?

Goals: Desirable properties for the mean field model, with strict bounds on QoS to consumer

Approaches: Start with a nominal model, with Markov transition law  $P_0$ .

- Myopic Design:  $P_{\zeta}(x, x') = \exp(\zeta \mathcal{U}(x') \Lambda_{\zeta}(x)) P_0(x, x')$ .
- Optimization:  $\check{P}_{\zeta} = \arg\max\{\zeta\pi(\mathcal{U}) \mathcal{K}(P||P_0) : \pi P = \pi\}$ We have shown that the linearized MFM is passive if  $P_0$  is reversible.

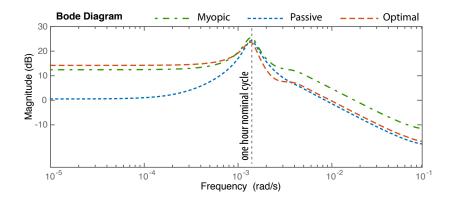
Goals: Desirable properties for the mean field model, with strict bounds on QoS to consumer

Approaches: Start with a nominal model, with Markov transition law  $P_0$ .

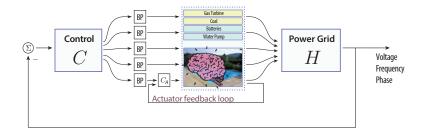
- Myopic Design:  $P_{\zeta}(x,x') = \exp(\zeta \mathcal{U}(x') \Lambda_{\zeta}(x)) P_0(x,x')$ .
- Optimization:  $\check{P}_{\zeta} = \underset{P,\pi}{\arg\max} \big\{ \zeta \pi(\mathcal{U}) \mathcal{K}(P \| P_0) : \pi P = \pi \big\}$ We have shown that the linearized MFM is passive if  $P_0$  is reversible.
- An alternative to the optimization approach: Passivity by design

# Nonlinear state space model: $\mu_{t+1} = \mu_t P_{\zeta_t}$ , $y_t = \langle \mu_t, u \rangle$

Linearization useful for control design



Three designs for a refrigerator: transfer function  $\zeta_t \to y_t$ 



# **Questions and Conclusions**

# Question of Time Scales

Question: Can a smart fridge provide synthetic droop?

# Question of Time Scales

Question: Can a smart fridge provide synthetic droop?

• There is hope: They did a good job in the past!

# Question of Time Scales

#### Question: Can a smart fridge provide synthetic droop?

- There is hope: They did a good job in the past!
- Other local services may also be feasible and valuable

# Electrical load disconnect device with electronic control

US 8328110 B2

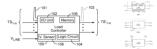
#### **ABSTRACT**

Electrical load spreading arrangements reduce peak power demand. An enclosure houses an electronic circuit board, which receives at a first input terminal a first thermostat control signal from a thermostat intended to control a first air conditioning unit and at a second input terminal a second thermostat control signal from a thermostat intended to control a second AC unit. A controller on the circuit board is programmed with instructions stored in a memory coupled to the controller causing the controller to monitor the first and second input terminals to determine the timing and duration of the thermostat control sinals assayed to the output terminals for activating or deactivation the

US8328110 R2 Publication number Publication type Grant Application number US 12/499 347 Publication date 11 Dec 2012 Filing date 8 Jul 2009 Priority date 8 Jul 2009 Fee status Paid Also published as US20110006123 Inventors Jeffrey O. Sharp Original Assignee Schneider Electric USA, Inc. **Export Citation** BiBTeX EndNote RefMan Patent Citations (5), Classifications (8), Legal Events (3) External Links: USPTO, USPTO Assignment, Espacenet

AC units such that overlapping operation of the AC units is reduced particularly during peak demand periods. A similar arrangement may be applied to a broader class of HVAC equipment, including water heaters, for example.

#### IMAGES (5)











# Question: What is the State of Charge

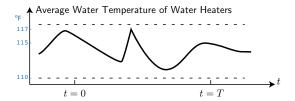
- Estimating the state for the MFM is not realistic in general [16]
- Estimating the baseline is a philosophical question

# Question: What is the State of Charge

- Estimating the state for the MFM is not realistic in general [16]
- Estimating the baseline is a philosophical question
- How do we define and estimate the State of Charge?

# Question: What is the State of Charge

- Estimating the state for the MFM is not realistic in general [16]
- Estimating the baseline is a philosophical question
- How do we define and estimate the State of Charge?

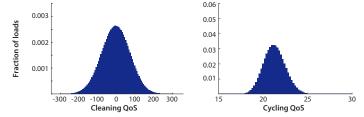


Function of average water temperature

The Mean Field Model is based on the Law of Large Numbers

The Mean Field Model is based on the Law of Large Numbers

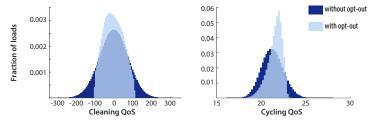
There is an associated Central Limit Theory



QoS over one week for a population of swimming pools

The Mean Field Model is based on the Law of Large Numbers

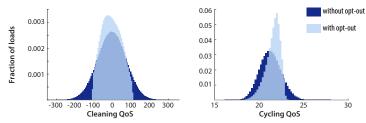
There is an associated Central Limit Theory



QoS over one week for a population of swimming pools

The Mean Field Model is based on the Law of Large Numbers

There is an associated Central Limit Theory



QoS over one week for a population of swimming pools

#### More generally:

- What is the cost to consumers? Any additional cycling or energy cost?
- A better science for enforcing QoS/cost constraints

### Question: Value of Performance

Do we need such accurate tracking?

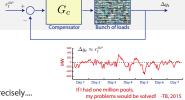
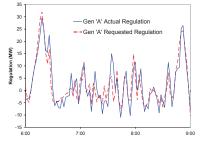
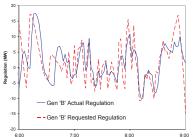


Fig. 10. Coal-fired generators do not follow regulation signals precisely.... Some do better than others



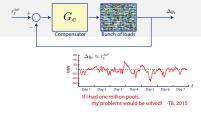


#### Regulation service from generators is not perfect

Frequency Regulation Basics and Trends — Brendan J. Kirby, December 2004

# Question: Value of Performance

Do we need such accurate tracking?



The grid today is reliable\*, despite the poor services offered by generators Questions remain:

- What is the cost of poor tracking?
- How do we deal with dynamics/uncertainty in capacity of virtual storage from loads?

### Question: Control Architecture

Smart Fridge / Dumb Grid?

Local intelligence at each load  $\implies$  ensemble looks like a giant battery.

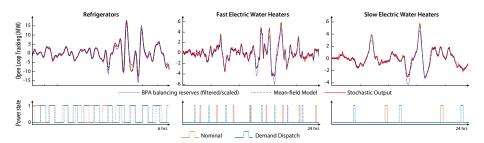


### Question: Control Architecture

Smart Fridge / Dumb Grid?

Local intelligence at each load  $\implies$  ensemble looks like a giant battery.

Open-loop tracking with 40,000 heterogeneous TCLs:

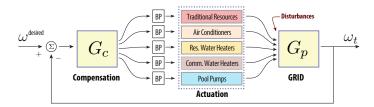


# Question: Control Architecture

Smart Fridge / Dumb Grid?

Local intelligence at each load  $\implies$  ensemble looks like a giant battery.

• Does one-way communication suffice?



Rationality  $\Longrightarrow$  risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.



Rationality ⇒ risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.

Trouble with current thinking:

 Long-term risk. The marginal-cost framework does not provide adequate incentives for investment – this was recognized by EDF many decades ago.

Rationality  $\Longrightarrow$  risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.

- Long-term risk. The marginal-cost framework does not provide adequate incentives for investment – this was recognized by EDF many decades ago.
  - This was also recognized by Schweppe in the 80s [2].

Rationality  $\Longrightarrow$  risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.

- Long-term risk. The marginal-cost framework does not provide adequate incentives for investment – this was recognized by EDF many decades ago.
  - This was also recognized by Schweppe in the 80s [2].
- Short term risk faced by grid operator:
  - Will services be available when needed?
  - Quality sufficient?

Rationality  $\Longrightarrow$  risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.

- Long-term risk. The marginal-cost framework does not provide adequate incentives for investment – this was recognized by EDF many decades ago.
  - This was also recognized by Schweppe in the 80s [2].
- Short term risk faced by grid operator:
  - Will services be available when needed?
  - Quality sufficient?
- What do consumers want?

Rationality  $\Longrightarrow$  risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.

- Long-term risk. The marginal-cost framework does not provide adequate incentives for investment – this was recognized by EDF many decades ago.
  - This was also recognized by Schweppe in the 80s [2].
- Short term risk faced by grid operator:
  - Will services be available when needed?
  - Quality sufficient?
- What do consumers want? Risk comes in many flavors:
  - Is my power available?

Rationality  $\implies$  risk-aware

Since Schweppe, there has been a passion for competitive equilibrium analysis, with power treated as the commodity of interest.

- Long-term risk. The marginal-cost framework does not provide adequate incentives for investment – this was recognized by EDF many decades ago.
  - This was also recognized by Schweppe in the 80s [2].
- Short term risk faced by grid operator:
  - Will services be available when needed?
  - Quality sufficient?
- What do consumers want? Risk comes in many flavors:
  - Is my power available?
  - Is my bill predictable?

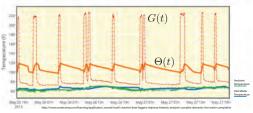
What do consumers want?

A rational agent last week in San Francisco wants a shower ...

What do consumers want?

### A rational agent last week in San Francisco wants a **shower** ...





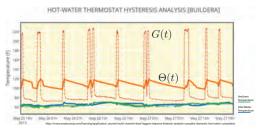
Typical water heater trajectories

 $\Theta(t)$ : Temperature

G(t): Power consumption

What do consumers want?

#### A rational agent last week in San Francisco wants a shower ...



Typical water heater trajectories

 $\Theta(t)$ : Temperature

G(t): Power consumption

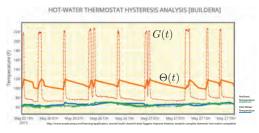
Not-so rational agent:

$$\max_{G} \int_{0}^{T} \Bigl( \mathcal{U}(G(t)) - p(t)G(t) \Bigr) \, dt$$

- Big question: Science for long-term contracts that ensures
  - Long-term incentives
  - Appropriate risk allocation on every time-scale

What do consumers want?

#### A rational agent last week in San Francisco wants a **shower** ...



Typical water heater trajectories

 $\Theta(t)$ : Temperature

G(t): Power consumption

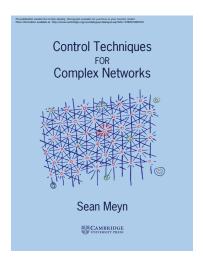
Not-so rational agent:

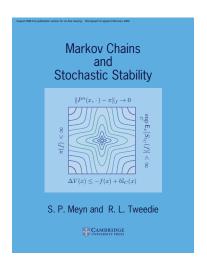
$$\max_{G} \int_{0}^{T} \left( \mathcal{U}(G(t)) - p(t)G(t) \right) dt$$

- Big question: Science for long-term contracts that ensures
  - Long-term incentives
  - Appropriate risk allocation on every time-scale
  - Requires cost/value calculations for virtual energy storage



Thank You





### References

### Selected References I

- [1] Y. Chen, U. Hashmi, J. Mathias, A. Bušić, and S. Meyn. Distributed Control Design for Balancing the Grid Using Flexible Loads. In *IMA volume on the control of energy markets and grids* (to appear). Springer, 2017. [See bibliography there for other references]
- [2] R. Moye and S. Meyn. Redesign of U.S. electricity capacity markets. In IMA volume on the control of energy markets and grids. Springer, 2017.
- [3] Y. Chen. Markovian demand dispatch design for virtual energy storage to support renewable energy integration. PhD thesis, University of Florida, Gainesville, FL, USA, 2016.
- [4] H. Hao, B. M. Sanandaji, K. Poolla, and T. L. Vincent. Aggregate flexibility of thermostatically controlled loads. *IEEE Trans. on Power Systems*, 30(1):189–198, Jan 2015.
- [5] M. Chertkov and V. Y. Chernyak. Ensemble control of cycling energy loads: Markov Decision Approach. In IMA volume on the control of energy markets and grids. Springer, 2017.
- [6] D. Callaway and I. Hiskens. Achieving controllability of electric loads. Proceedings of the IEEE, 99(1):184 –199, January 2011.
- [7] S. H. Tindemans, V. Trovato, and G. Strbac. Decentralized control of thermostatic loads for flexible demand response. *IEEE Trans. Contr. Sys. Techn.*, 23(5):1685–1700, 2015.

### Selected References II

- [8] M. Almassalkhi, J. Frolik, and P. Hines. Packetized energy management: asynchronous and anonymous coordination of thermostatically controlled loads. In *American Control Conference*, pages 1431–1437, 2017.
- [9] H. Hao, T. Middelkoop, P. Barooah, and S. Meyn. How demand response from commercial buildings will provide the regulation needs of the grid. In 50th Allerton Conference on Communication, Control, and Computing, pages 1908–1913, 2012.
- [10] H. Hao, Y. Lin, A. Kowli, P. Barooah, and S. Meyn. Ancillary service to the grid through control of fans in commercial building HVAC systems. *IEEE Trans. on Smart Grid*, 5(4):2066–2074, July 2014.
- [11] A. Bušić and S. Meyn. Ordinary Differential Equation Methods For Markov Decision Processes and Application to Kullback-Leibler Control Cost. *Under revision*, SIAM J. Control and Opt., 2016.
- [12] J. Mathias, A. Bušić, and S. Meyn. Demand dispatch with heterogeneous intelligent loads. In Proc. 50th Annual Hawaii International Conference on System Sciences, Jan 2017.
- [13] A. Bušić and S. Meyn. Distributed randomized control for demand dispatch. In IEEE Conference on Decision and Control, pages 6964–6971, Dec 2016.

### Selected References III

- [14] S. Meyn, P. Barooah, A. Bušić, Y. Chen, and J. Ehren. Ancillary service to the grid using intelligent deferrable loads. IEEE Trans. Automat. Control, 60(11):2847–2862, Nov 2015.
- [15] Y. Chen, A. Bušić, and S. Meyn. Estimation and control of quality of service in demand dispatch. IEEE Trans. on Smart Grid, 2017 (prelim. version IEEE CDC, 2015)
- [16] Y. Chen, A. Bušić, and S. Meyn. State estimation for the individual and the population in mean field control with application to demand dispatch. *IEEE Transactions on Automatic Control*, 62(3):1138–1149, March 2017.
- [17] P. Barooah, A. Bušić, and S. Meyn. Spectral decomposition of demand-side flexibility for reliable ancillary services in a smart grid. In Proc. 48th Annual Hawaii International Conference on System Sciences (HICSS), pages 2700–2709, Kauai, Hawaii, 2015.
- [18] Y. Chen, A. Bušić, and S. Meyn. Individual risk in mean-field control models for decentralized control, with application to automated demand response. In *Proc. of the* 53rd IEEE Conference on Decision and Control, pages 6425–6432, Dec. 2014 (Journal version to appear, Annals of Applied Prob).
- [19] J. Mathias, R. Kaddah, A. Bušić, and S. Meyn. Smart fridge / dumb grid? demand dispatch for the power grid of 2020. In Proc. 49th Annual Hawaii International Conference on System Sciences (HICSS), and ArXiv e-prints:1509.01531 (2015).