Building Smarter Energy Systems and the path towards a sustainable future

Omid Ardakanian
University of British Columbia

University of Toronto
27 March 2017
Global Warming is Unequivocal

Data source: NASA/GISS
Credit: NASA Scientific Visualization Studio
Global Warming is Unequivocal

Data source: NASA/GISS
Credit: NASA Scientific Visualization Studio
Global Warming is Unequivocal

“The 10 warmest years in the 132-year record all have occurred since 2000, with the exception of 1998.”

Data source: NASA/GISS
Credit: NASA Scientific Visualization Studio
Global Efforts to Combat Climate Change

But even then, energy sector $\text{CO}_2$ emissions are not on track for a 2°C scenario.

Source: IEA World Energy Outlook 2016
Global Efforts to Combat Climate Change

But even then, energy sector CO₂ emissions are not on track for a 2°C scenario

To achieve 2°C target, the energy sector must be carbon-neutral by 2100

Source: IEA World Energy Outlook 2016
Urgent Action Needed to Reduce Carbon Emissions
Urgent Action Needed to Reduce Carbon Emissions

14%  18%  39%

IEA World Energy Outlook 2016
Urgent Action Needed to Reduce Carbon Emissions

How to integrate low-carbon and renewable energy resources into the energy portfolio?

How to increase efficiency, utilization, and economic viability of energy systems?
Urgent Action Needed to Reduce Carbon Emissions

How to integrate low-carbon and renewable energy resources into the energy portfolio?

How to increase efficiency, utilization, and economic viability of energy systems?

Monitor, Model, Manage!
Unprecedented Opportunities
Unprecedented Opportunities

- Aging infrastructure
Unprecedented Opportunities

• Aging infrastructure

• New economic and social needs
Unprecedented Opportunities

- Aging infrastructure
- New economic and social needs
- Declining costs of low-carbon and renewable technologies


Cost deflation has affected diverse technologies across the energy spectrum
Unprecedented Opportunities

- Aging infrastructure
- New economic and social needs
- Declining costs of low-carbon and renewable technologies
- Pervasive sensing and control
Research on Sustainable Computing
### Research on Sustainable Computing

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# Research on Sustainable Computing

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| Buildings              | **Sub-Metering** |
|                        | *GreenNets’11* |

| Power Grids            | **Phasor Measurement Units** |
|                        | *ongoing* |

| Power Grids            | **Distribution Component Sizing** |
|                        | *eEnergy’12* |
|                        | *GreenMetrics’12* |

| Power Grids            | **PV and Storage Integration** |
|                        | *SpringerBrief’16* |

| Power Grids            | **System Identification** |
|                        | *PES GM’17* |

| Power Grids            | **Event Detection & Classification** |
|                        | *ISGT’17* |
Energy Data Collection and Analysis
Energy Data Collection and Analysis

every 10 sec
temperature
humidity
air flow
acoustic
light
Energy Data Collection and Analysis

2010

WeatherDuck

every 10 sec
temperature
humidity
air flow
acoustic
light
Energy Data Collection and Analysis

- **2010**
  - **WeatherDuck**
  - every 10 sec
  - temperature
  - humidity
  - air flow
  - acoustic
  - light

- **2011**
  - **CurrentCost Envi**
  - every 6 sec
  - per phase current
Energy Data Collection and Analysis

- **2010**: WeatherDuck
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- **2014**: Smart Meters
  - hourly
  - electricity consumption
Energy Data Collection and Analysis

2010
WeatherDuck
- every 10 sec temperature
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2011
CurrentCost Envi
- every 6 sec per phase current

2014
Smart Meters
- hourly electricity consumption

2015
PMUs
- 120Hz voltage and current phasors

- 2015 PMUs
- 2014 Smart Meters
- 2011 CurrentCost Envi
- 2010 WeatherDuck

other notes
Energy Data Collection and Analysis

2010
WeatherDuck
- every 10 sec
- temperature
- humidity
- air flow
- acoustic
- light

2011
CurrentCost Envi
- every 6 sec per phase current

2014
Smart Meters
- hourly electricity consumption

2015
PMUs
- 120Hz voltage and current phasors

2016
HVAC Sensors
- every 10-15 min
- supply air flow
- temperature, …
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SpringerBrief’16 |

Penetration of Electric Vehicles is Expected to Increase in Future

150 million electric cars on the road by 2040
Opportunistic EV Charging Leads to Grid Congestion

1 EV charger ~ 5-10 households
Opportunistic EV Charging Leads to Grid Congestion

1 EV charger ~ 5-10 households

1) Overloads transformers
2) Increases peak demand
Opportunistic EV Charging Leads to Grid Congestion

Schedule charging of EVs

1) Overloads transformers
2) Increases peak demand

1 EV charger ~ 5-10 households
Opportunistic EV Charging Leads to Grid Congestion

Spatial/temporal uncertainties

1 EV charger ~ 5-10 households

Schedule charging of EVs

1) Overloads transformers
2) Increases peak demand
Possible Approaches to Coordinate EV Charging
Possible Approaches to Coordinate EV Charging

- **Scheduling**: solve an optimal power flow (OPF) problem to determine the charge powers
  - a non-convex optimization problem solved hours ahead
  - precise model of the distribution network (unavailable)
  - EV arrival and departure times (unknown)
Possible Approaches to Coordinate EV Charging

- **Scheduling:** solve an optimal power flow (OPF) problem to determine the charge powers
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- **Distributed feedback control:** let the system solve power flow equations
  - measure steady-state response using sensors installed at hotspots
  - signal congestion using an overlay network connecting sensors to EV chargers
Possible Approaches to Coordinate EV Charging

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• **Distributed feedback control:** let the system solve power flow equations
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  - signal congestion using an overlay network connecting sensors to EV chargers

It is a TCP-like congestion control algorithm!
Pervasive Sensing and Control in Radial Distribution Systems
Pervasive Sensing and Control in Radial Distribution Systems

every line or transformer has a rated capacity and a setpoint

smart EV chargers
Pervasive Sensing and Control in Radial Distribution Systems

every line or transformer has a rated capacity and a setpoint

Subtransmission substation

Phasor Measurement Units (PMUs)

smart EV chargers
Pervasive Sensing and Control in Radial Distribution Systems

every line or transformer has a rated capacity and a setpoint
TCP-Inspired Control

sum of controlled and uncontrolled loads

measured equipment loading =

demands of EV chargers +

controlled load

uncontrolled load

capacity

time

line/transformer loading
Fair Allocation of Available Capacity

Network Utility Maximization Problem:

$$\max \sum_{\substack{rate_x \\ x \in C}} \log(rate_x)$$

subject to

$$0 \leq rate_x \leq \maxrate_x \quad \forall x \in C$$

$$\sum_{\substack{rate_x \mid x \in C(l) \}} + \text{homeload}_l \leq \text{setpoint}_l \quad \forall l \in L$$

proportional fairness

charge power

chargers in subtree $l$

[Kelly98], [Low99], [Yaïche00]
Fair Allocation of Available Capacity

Network Utility Maximization Problem:

$$\max_{x \in C} \sum_{x \in C} \log(rate_x)$$

subject to

$$0 \leq rate_x \leq \maxrate_x \quad \forall x \in C$$

$$\sum_{x \in C(l)} rate_x + \text{home}load_l \leq \text{setpoint}_l \quad \forall l \in L$$

Control rules are obtained by solving this optimization problem

proportional fairness

[Kelly98], [Low99], [Yaïche00]
Dual Decomposition for Distributed Control

Iteration K, Phase 1

Master Problem
(solved at the substation)

Subproblem 1
(solved at EV charger 1)

Subproblem n
(solved at EV charger n)

prices

... prices

1. PMUs update congestion prices and send them to downstream EV chargers

\[ \text{price}_l \leftarrow \max\{\text{price}_l - \text{stepsize} \times (\text{setpoint}_l - \text{load}_l), 0\} \]
Dual Decomposition for Distributed Control

Iteration K, Phase 2

Master Problem (solved at the substation)

EV load

rate_1

rate_n

Subproblem 1 (solved at EV charger 1)

Subproblem n (solved at EV charger n)

Phase 2: New rates are obtained from solving subproblems using new congestion prices

\[
rate_s \leftarrow \min \left\{ \frac{1}{\text{path price}_s}, \text{maxrate}_s \right\}
\]
Dual Decomposition for Distributed Control

Iteration K, Phase 2

We can accommodate 10 times more EVs than the uncontrolled charging scenario!

Phase 2: New rates are obtained from solving subproblems using new congestion prices

\[
rate_s \leftarrow \min \left\{ \frac{1}{path\ price_s}, maxrate_s \right\}
\]

(solved at EV charger 1) (solved at EV charger n)
Open-Source Simulation Software

- Modular design, suitable for defining large-scale simulation scenarios
- Interfaces with optimization software and power flow solvers
- Includes plotting and reporting services

Download code from GitHub
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Reducing Energy Consumption of Commercial Buildings
Reducing Energy Consumption of Commercial Buildings

HVAC accounts for 40-60% of energy use in commercial buildings
Reducing Energy Consumption of Commercial Buildings

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14% reduction in carbon emissions
Reducing Energy Consumption of Commercial Buildings

HVAC accounts for 40-60% of energy use in commercial buildings.

14% reduction in carbon emissions

Software Defined Buildings

Berkeley
UNIVERSITY OF CALIFORNIA
HVAC in Moderate Climates
HVAC in Moderate Climates

AHU

Zone
HVAC in Moderate Climates

AHU

Supplies air at 14°C

Zone
HVAC in Moderate Climates

AHU

Supplies air at 14°C

VAV with Reheat

Zone
HVAC in Moderate Climates

AHU

Supplies air at 14°C

VAV with Reheat

Reheats supply air to a setpoint, e.g. 23°C

Zone
HVAC in Moderate Climates

- AHU supplies air at 14°C.
- VAV with Reheat reheats supply air to a setpoint, e.g. 23°C.
- Zone

No occupancy sensor!
HVAC in Moderate Climates

BMS
- Archives data
- Controls indoor climate

AHU
Supplies air at 14°C

VAV with Reheat
Reheats supply air to a setpoint, e.g. 23°C

Temp sensor

Damper position sensor
Reheat discharge Sensor

No occupancy sensor!

Zone
HVAC in Moderate Climates

BMS
- Archives data
- Controls indoor climate

AHU
- Supplies air at 14°C

VAV with Reheat
- Reheats supply air to a setpoint, e.g. 23°C
- Damper position sensor
- Reheat discharge sensor

Temp sensor

No occupancy sensor!

Zone

VAV Control Logic

BuildSys'16
HVAC Systems are Inefficient
HVAC Systems are Inefficient

• HVAC systems run on a static schedule based on building manager’s intuition.
  – Does not take occupancy into account
  – Wastes energy in conditioning empty or partially-occupied spaces
HVAC Systems are Inefficient

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- To optimize HVAC energy consumption, zones should be conditioned only when occupied
HVAC Systems are Inefficient

- HVAC systems run on a static schedule based on building manager’s intuition.
  - Does not take occupancy into account
  - Wastes energy in conditioning empty or partially-occupied spaces
- To optimize HVAC energy consumption, zones should be conditioned only when occupied

Occupancy sensors are not available! Retrofitting is costly and intrusive.
Exploiting Existing HVAC Sensors
Exploiting Existing HVAC Sensors

Amount of reheating in a room
Exploiting Existing HVAC Sensors

Amount of reheat in a room

Ground truth occupancy
Exploiting Existing HVAC Sensors

Reheat goes down when zone is occupied

Amount of reheat in a room

Ground truth occupancy
Exploiting Existing HVAC Sensors

Reheat goes down when zone is occupied

Amount of reheat in a room

Ground truth occupancy

BuildSys ’16
Overall Analysis Pipeline

- Occupancy indicative signal
- Distillation
- Step Change Detection
- Decomposition & Filtering
- Frequency bands
Overall Analysis Pipeline
Overall Analysis Pipeline

occupancy indicative signal

- Distillation
- Step Change Detection
- Apparent Occupancy Computation
- Clustering

- Decomposition & Filtering
- Energy Savings Calculation
- Defining Schedules

frequency bands

normal zones

anomalous zones

aggressiveness
Testbed
Testbed

Three large UC Berkeley campus buildings
– 117, 109 and 270 zones respectively
– Buildings had different BMS systems
– 3-6 months of data analyzed
Validation

Collected limited ground truth data:
- Manually logged occupancy hours of 7 shared and private offices in our testbed
- Extracted occupancy hours from video recordings (a security camera installed in a lab)
Validation

Collected limited ground truth data:
- Manually logged occupancy hours of 7 shared and private offices in our testbed
- Extracted occupancy hours from video recordings (a security camera installed in a lab)
Schedules and Tradeoffs

Ease of implementation
- harder
- easier

Reheat Energy Savings (pct.)

Comfort Violation (pct.)
Schedules and Tradeoffs

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Reheat Energy Savings (pct.)

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per building
static/naive

26
Schedules and Tradeoffs

Ease of implementation
- harder
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Reheat Energy Savings (pct.)

Comfort Violation (pct.)

per building
- static/naive

static/learned

26
Schedules and Tradeoffs

- Reheat Energy Savings (pct.)
- Comfort Violation (pct.)

Ease of implementation:
- Harder
- Easier

- Static/naive (per building)
- Adaptive/per-day
- Adaptive/weekday-weekend
- Adaptive/weekly
- Static/learned

26 per building
Schedules and Tradeoffs

Ease of implementation
- harder
- easier

Reheat Energy Savings (pct.)
- static/naive
- adaptive/weekday-weekend
- adaptive/weekly
- adaptive/per-day
- static/learned
- customized per zone

Comfort Violation (pct.)
- per building

BuildSys’16
Schedules and Tradeoffs

Reheat Energy Savings (pct.)
Comfort Violation (pct.)
Ease of implementation
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- easier

- static/naive
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- adaptive/weekly
- adaptive/learned
- adaptive/per-day
- customized per zone

sweet spot
> 40% energy savings on reheat and
~ 2% comfort violation
Saving on Reheat Energy

Occupancy & Relative Energy Consumption on Weekdays

- No Schedule
- Per Day Schedule-Aggressiveness:10
- Weekly Schedule-Aggressiveness:10
- Per Day Schedule-Aggressiveness:20
- Weekly Schedule-Aggressiveness:20

Normalized Energy Consumption due to Reheat

Occupied Zones (pct.)

Building occupancy profile
Saving on Reheat Energy

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Normalized Energy Consumption due to Reheat

Occupied Zones (pct.)

Actual occupancy

- Building occupancy profile
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Normalized Energy Consumption due to Reheat

Occupied Zones (pct.)

Actual occupancy

Current reheat schedule
Saving on Reheat Energy

Reheat profiles under our smarter schedules

Actual occupancy

Current reheat schedule

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BuildSys’16
Saving on Reheat Energy

Possible reheat energy savings

Reheat profiles under our smarter schedules

Occupy & Relative Energy Consumption on Weekdays

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- Weekly Schedule-Aggressiveness:20

- Building occupancy profile

Nomalized Energy Consumption due to Reheat

Occupied Zones (pct.)
Saving on Reheat Energy

Possible reheat energy savings

This approach can be readily applied to any commercial building with a BMS that archives data.
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Power Grid Modernization

39% reduction in carbon emissions
Power Grid Modernization

39% reduction in carbon emissions

pervasive control

pervasive monitoring
Power Grid Modernization

39% reduction in carbon emissions

pervasive control
Enabling Large-Scale Integration of Active End-Nodes

- electric cars
- solar cells and inverters
- micro wind turbines
- batteries
Enabling Large-Scale Integration of Active End-Nodes

- electric cars
- solar cells and inverters
- micro wind turbines
- batteries

Avoid distribution network problems
- over- and under-voltage
- overloads
- reverse power flows
Enabling Large-Scale Integration of Active End-Nodes

- electric cars
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Avoid distribution network problems
- over- and under-voltage
- overloads
- reverse power flows

Decentralized control
- substation controller
- balancing zone controllers
- end-nodes
Detecting Rare Events in Massive Amounts of Data in Real-Time
Detecting Rare Events in Massive Amounts of Data in Real-Time

image: power standards lab
Detecting Rare Events in Massive Amounts of Data in Real-Time

Data set available at plot.upmu.org

image: power standards lab
Detecting Rare Events in Massive Amounts of Data in Real-Time

Data set available at plot.upmu.org
The Range of Relevant Time Increments in Power System Planning and Operation Spans 15 Orders of Magnitude!

[vonMeier14]
Data Storage and Analysis Infrastructure
Data Storage and Analysis Infrastructure

Statistical summaries of data can be efficiently retrieved at different temporal resolutions.
Data Storage and Analysis Infrastructure

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Beyond Predictive Analytics

Model Validation
- Inferring the admittance matrix from time-synchronized measurements: $I = YV$
- Sparse recovery techniques

Event Detection and Classification
- Data-driven approach
- Candidate events labelled by domain experts
- A library of various events

Equipment Health Monitoring
- Predictive maintenance
- Informed recommendations

high-precision, high-sample-rate data from many locations
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This analytics framework is currently used by several power system operators in California

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System Identification
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- Inferring network topology from voltage and current phasor measurements

Ohm Law

\[ I_{bus} = Y_{bus} V_{bus} \]

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\( N \): number of nodes
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- Inferring **network topology** from voltage and current phasor measurements
  - only a small number of nodes are monitored

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\[
\hat{Y}_{bus} = \arg\min_{Y \in \mathbb{C}^{N \times N}} \| (V_{bus}^K \otimes 1^N) \text{vec}(Y) - \text{vec}(I_{bus}^K) \|_2 \\
\text{s.t.: } Y \in \mathbb{S}^N, \quad \| \text{vec}(Y) \|_0 \leq \delta
\]
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• Online detection and localization of events
Future Work

smarter, greener, more adaptive and resilient against climate change and natural disasters
Smart Buildings
Continuous commissioning of buildings is overly **costly** and does **not scale**
Smart Buildings

“Substantial efficiency savings left untapped!”
Smart Buildings

**Solution:** deploy analytics applications without a priori building-specific knowledge across many buildings comprising already deployed sensor networks

“Substantial efficiency savings left untapped!”
Adaptive Fault-Tolerant Buildings
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- Automated point mapping
Adaptive Fault-Tolerant Buildings

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  - requires a concrete ontology for sensors, control points, subsystems and relationships among them
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  - addressing privacy concerns (differential privacy, downsampling, …)
Smart Cities
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A city is a complex system comprised of a large number of distributed physical resources delivering a wide range of services to citizens.
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Sensors and real-time analytics are employed in a smart city to solve problems in various urban sectors.
Smart Cities
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• Optimal control of coupled infrastructures (gas, water, electricity, ...) and active end-nodes
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  - convex relaxations (SDP or SOCP)
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• Turning historical data into actionable information for urban planners
Building Prototype Energy Systems

Campus as a living laboratory!
Building Prototype Energy Systems

Deploy

• Controlled plug loads
• Sub-metering devices
• PV cells and inverters
• Batteries
• Electric cars/bikes

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Implement and evaluate
- Demand response
- Building-to-grid applications
  - Turning buildings into already deployed, low-cost storage options for the grid
- Indoor climate control
- Smart lighting
- Fault detection and diagnosis
- System identification

Campus as a living laboratory!
S. Keshav, Catherine Rosenberg, Lukasz Golab, Negar Koochakzadeh, Rayman Singh (Waterloo), David Culler, Sascha von Meier, Randy Katz, Claire Tomlin, Ye Yuan, Michael Andersen, Roel Dobbe (Berkeley), Steven Low (Caltech), Vincent Wong (UBC), Emma Stewart, Daniel Arnold, Ciaran Roberts, Anna Liao (LBNL), Alex McEachern (PSL), Arka Bhattacharya (Google), Bob Singh, Ravi Seethapathy (HydroOne)