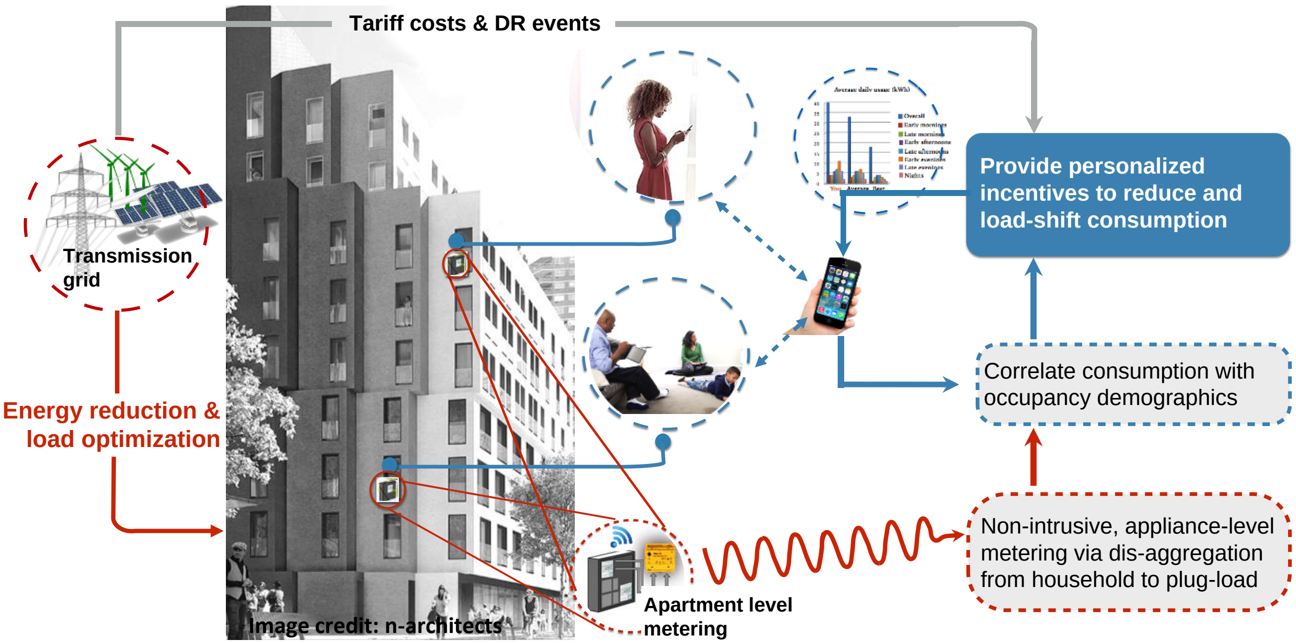
Reducing Plug-Load Electricity Footprint of Residential Buildings through Low-Cost, Non-Intrusive Sub-Metering and Personalized Feedback Technology



Columbia University (lead) and Lucid (partner), presented by Christoph Meinrenken
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Project Summary

Timeline:

Start date: 01 September 2016

Planned end date: 31 September 2019

Key Milestones:

1. Metering installed and software for load disaggregation and feedback developed (2017)
2. System integrated and end-to-end tested (2018)
3. Feedback experiments conducted, T2M stake-holders engaged, database published (2019)

Key Partners:

With budget:	Other stakeholders:
Lucid (*BuildingOS*)	Apartment tenants
	ConEdison (utility)
	Building operators
	Columbia Facilities

Budget:

To Date*:

- DOE: $696,784
- Cost Share: $189,741

Total Project :

- DOE: $1,534,397
- Cost Share: $399,682

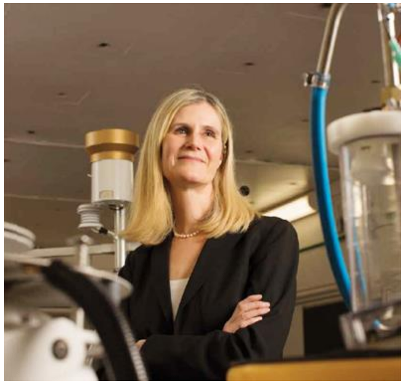
Project Outcomes:

Provide unique R&D dataset to stakeholders: Multi-family sector, apartment-level (~400 units), demographics, 10-second resolution

Enable grid-interactive efficient buildings: In addition to electricity use reduction, project's focus on load-shifting facilitates resilient grids and low GHG renewables

* As of 11 April 2018

Team



- **Prof. Patricia Culligan (PI)**
  Distributed solutions for sustainable cities
  <u>Focus in this project:</u> Metering & social science aspects of feedback
- **Prof. Kathleen McKeown (co-PI)**
  Natural Language Processing
  <u>Focus in this project:</u> Automatically generated, personalized feedback with visuals and text
- **Dr. Christoph Meinrenken (co-PI)**
  Low carbon energy systems
  <u>Focus in this project:</u> Metering hardware and load reduction/shifting -scheme vis-à-vis NY City tariffs
- **Dr. Ali Mehmani (co-PI)**
  Controls and optimization
  <u>Focus in this project:</u> Metering hardware and algorithms for load disaggregation
- **Lucid (corporate partner)**
  "BuildingOS" and tenant engagement
  <u>Focus in this project:</u> Online tenant feedback platform; market insights
- ... and 3 PhD students (please see last page for complete acknowledgments)

Challenge

Plug-load electricity consumption in the multi-family residential sector is substantial but so far remains largely unaddressed, without economic and scalable strategies for reduction

- Traditional energy audits are costly (e.g., high equipment costs from buying plug-load meters and/or labor cost from hiring home energy experts)
- Once audit ends, behavior may revert back to normal (little sustained energy savings)

Providing residents with feedback on their electricity use could be a low cost alternative, but has faced multiple obstacles, particularly in the multi-family housing sector

- Jury is still out on what type of feedback works best on what demographic
- Small apartments mean smaller variable portion of monthly electricity bills → financial upside limited, therefore need for low-cost, non-intrusive solutions particularly crucial
- Appliance-level info shown to be effective (to identify consumption hotspots and facilitate load-shifting, e.g., do laundry at night) … but application of low-cost, software-based load disaggregation so far limited to single-family homes
- No publicly available database of apartment-level electricity consumption patterns exists (e.g., when do residents use how much electricity, what for, how does it vary from family to family and by demographics?)

→ How can residential plug-load use be incorporated into smart building, grid resilience, and low GHG initiatives?

Approach in a nutshell: Automated audit of each apartment's electricity use and continued behavioral feedback*

Instead of sending an expert to someone's home and provide personalized advice ...
use a low-cost, automated data-science approach:

Step 1: Measure apt. level loads at 10-sec. (real & reactive power)

Step 2: Break down to appliance level
→ Identify consumption hotspots (e.g., fridge)

Step 3: Determine other characteristics, e.g. phantom loads from electronic devices

Image credit: n-architects

Step 4: Generate personalized feedback, e.g.:
"Your fridge consumed 50% above average for your building."
"Your electricity consumption never went below 120 Watt, causing $20 of your monthly bill."

Step 5: Use NLP to mine online expert forums for electricity saving and load shifting tips

Step 6: Augment feedback messages with behavioral tips customized to their home, e.g.:
"Did you know that cleaning the fridge grill can save substantial electricity."
"Remember to turn off lights and unplug un-used electronics."

* Overview only; please refer to Appendix (reference slides) for technical details of the 6 step process.

Impact, advantages, and differentiation

- Low-cost, scalable solution to address **electricity consumption in multi-family sector** (incl., large and small appliances, Window ACs, space heaters, electronics, lights)
- **Study first of its kind in type and size**: ~400 apartments in multi-family housing
- **New, unique dataset** available to general public (24/7 consumption profiles incl. demographic and feedback tags; real and reactive power at 10-sec time resolution) – Study of feedback effectiveness, consumption behavior, zonal coverage, etc.
- Non-intrusive appliance load metering (**NALM**): Disaggregation to appliances unlocks additional effectiveness with minimal cost to consumer or nuisance during installation
- **Personalized, targeted feedback**: Insight of effectiveness of various feedback features against multiple socio-demographic markers
- **Reduction and load-shifting** of consumption quantified in $ terms for residents, building operators, and grid stability benefits, providing crucial T2M parameters

→ **Open up multi-family residential sector as grid-interactive efficient buildings (GEBs) and for wider smart grid initiatives (renewables' penetration, real-time pricing, etc.)**

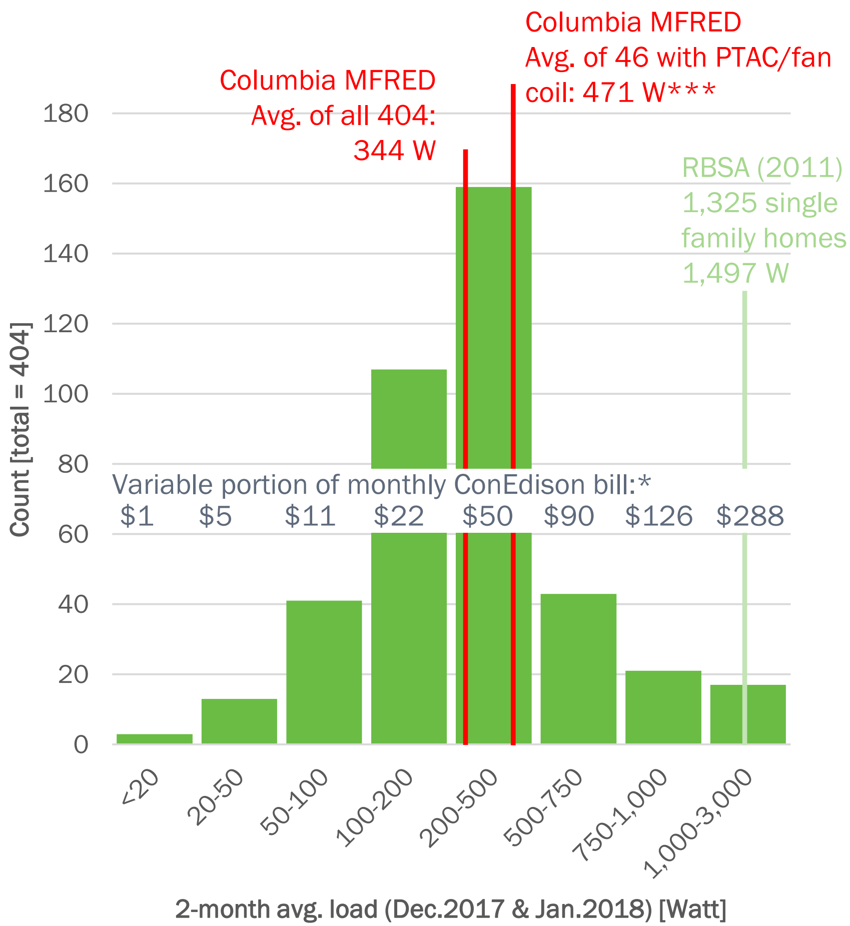
Progress overview

- We are currently in Budget Year 2 of a 3 year project (April 2018 is month 19 of 36 months)
  - **Budget Year 1**: Install metering, recruit study participants, 1st version of algorithms [COMPLETE]
  - **Budget Year 2**: Finalize algorithms, integrate system components, end-to-end tests [ON TRACK]
  - **Budget Year 3**: Run feedback experiments, analyze results, engage stakeholders

- We have made minor adjustments to the project approach in order to **mitigate key project risks**:
  (1) The long lead-time for hardware installation would have left us unable to test the basic functionality and general efficacy of the resident feedbacks generation for the entire first year of the project; we therefore used available data from another pilot building (Lenfest Hall) to test the basic system (see following slides)
  (2) The metering hardware turned out to be capable of only 10sec. time resolution (instead of the planned 1sec.). To mitigate the potential loss in accuracy for the dis-aggregation routines, we will install additional meters at plugload-level (as a further training and validation dataset)

- **(Progress details and interim results on following slides)**

Average consumption similar to single family (when corrected for square footage and for heating electricity)

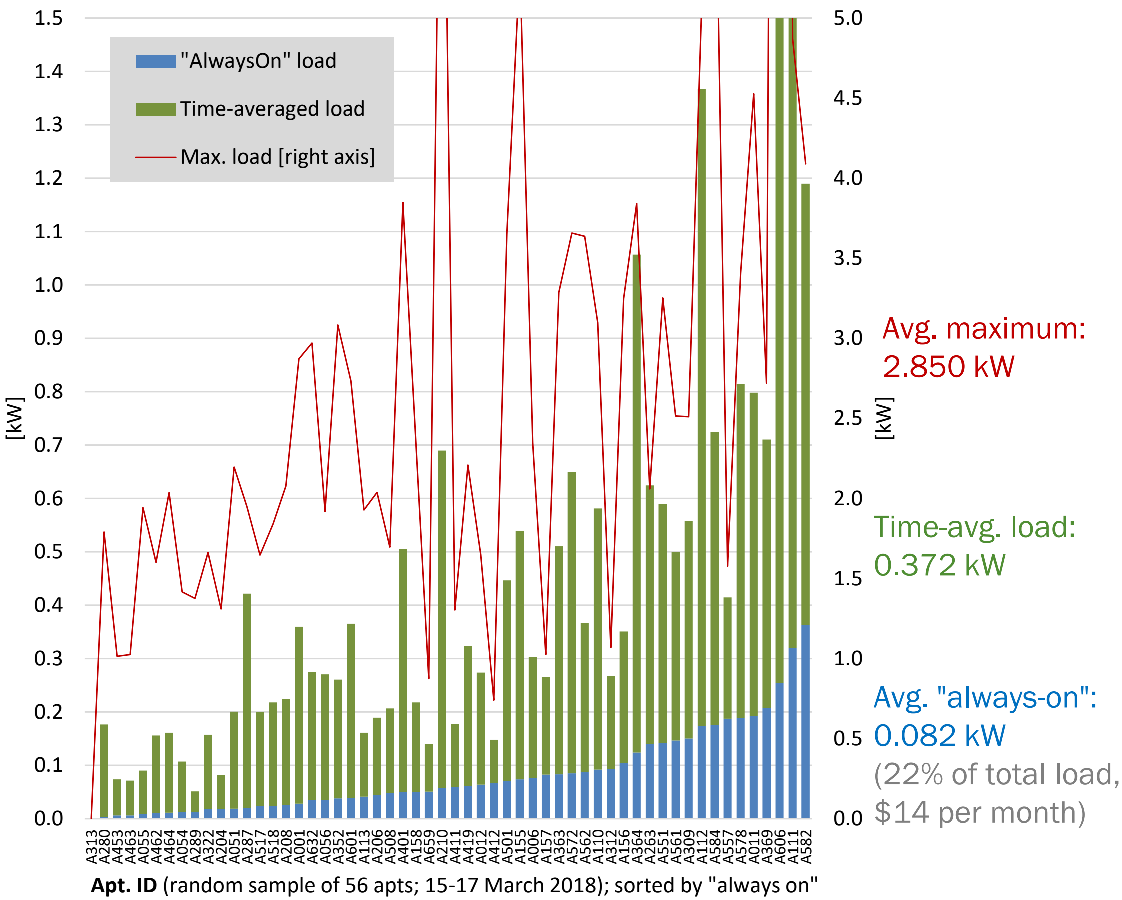


* Based on typical ~22 cents for kWh ConEd tariff (<u>not</u> time-of-use)
** Excluding 62% for heating and scaled proportionally for sqft
*** These apartments may also be larger on average

- Siemens SEM3 Micrometering has been successfully installed in 404 apartments across 14 buildings
  - Extensive testing of Siemens against utility meters has confirmed accuracy to be ±0.9% (as expected)
- Benchmarking: Nationw-wide, apartment electricity consumption strongly dependent on square-foot as well as heating mechanism
  - E.g., RBSA electricity benchmark for single family homes includes on average **62%** for heating
  - Whereas for MFRED likely very little (only 46 of 404 apts use fan coils)
- Avg. square foot:
  - MFRED: 1,260 sqft per apartment
  - RBSA: 2,006 sqft per home
- Comparing apples to apples:
  - **MFRED: 344 Watt**
  - **RBSA (scaled*): 330 Watt**
- **Conclusion: Average consumption for single family homes similar to multi-family**
  - However, further analysis needs to include geographic region and season

High time resolution of dataset allows top-down determination of "phantom loads" which appear substantial

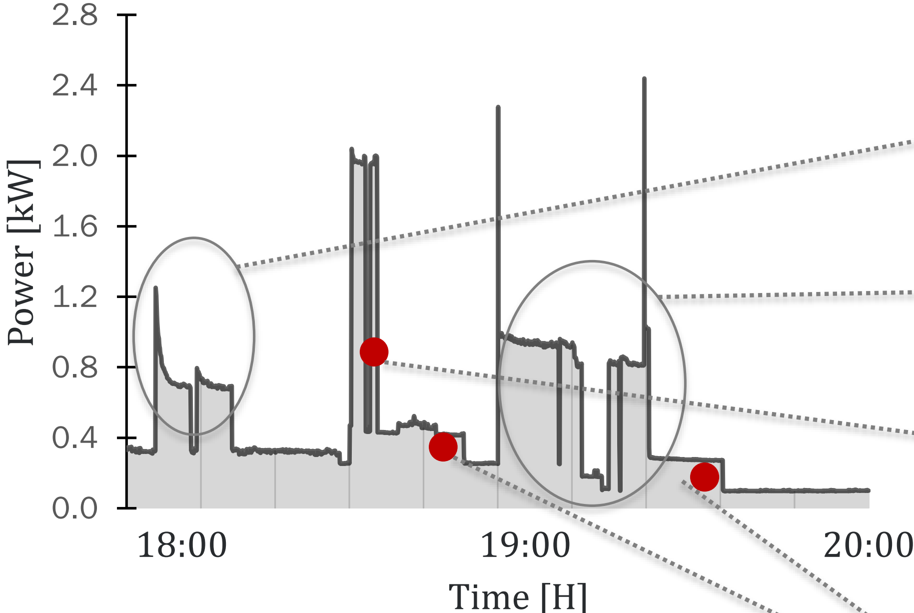
Load characteristics in sample of 56 apartments



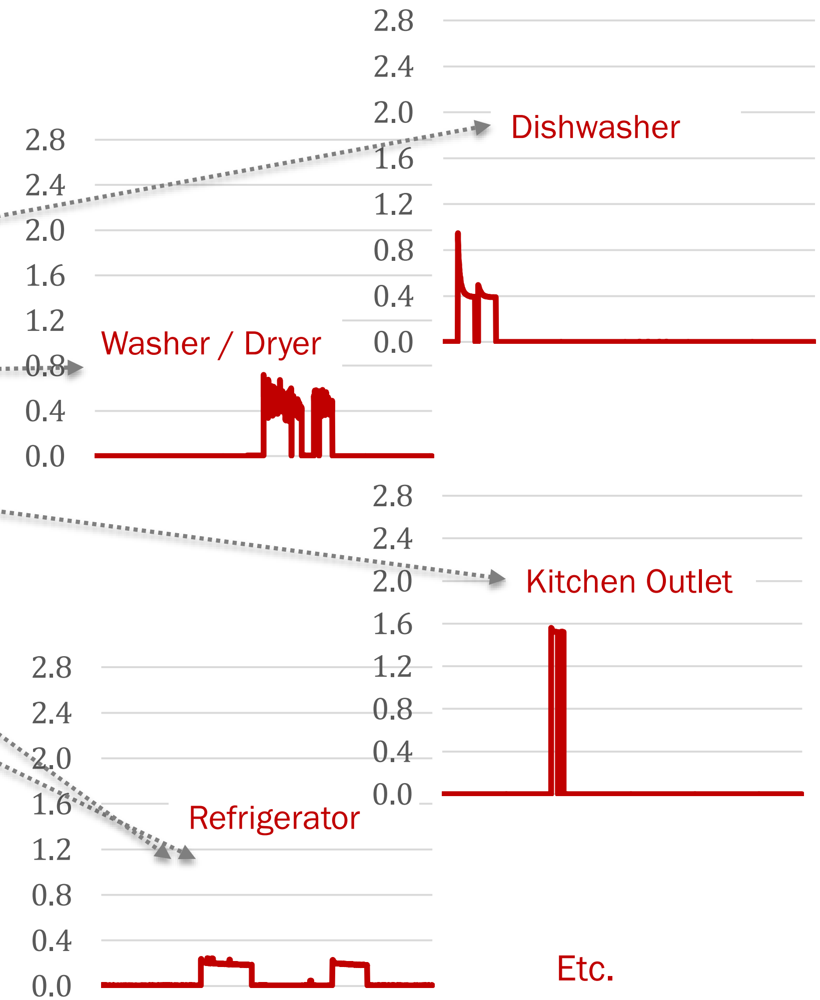
- Bottom-up benchmarks for phantom-loads vary widely:
  - IEA: 5-20% of entire load in homes and offices in Europe
  - 5 to 15 Watt per device (with some as high as ~40Watt)
  - 10-100 Watt total per home
- Our algorithm picks up, e.g.
  - Electronics' standby
  - Lights always kept on
  - Broken fridges
    → Behavioral component beyond traditional "phantom"
- Extended definition of "phantom load" is relevant for electricity saving opportunities (low hanging fruit, e.g., turn lights off)
- "Always-on" load is substantial but largely avoidable
  - ~0.005kW to 0.372kW per apt.
  - Average 0.082kW (or 22% of total load)
- → Include in feedbacks

We tested a variety of existing and novel algorithms to extract appliance level use from apt.-level use

Aggregate apartment use (metered)

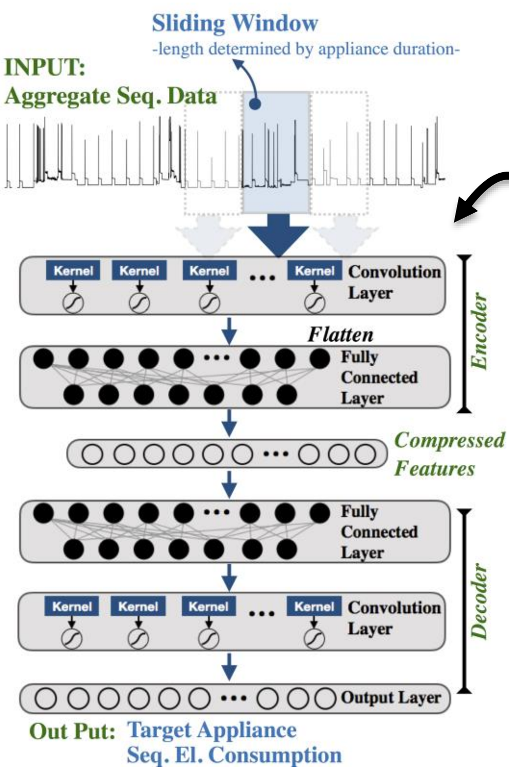


Appliance use (inferred statistically)

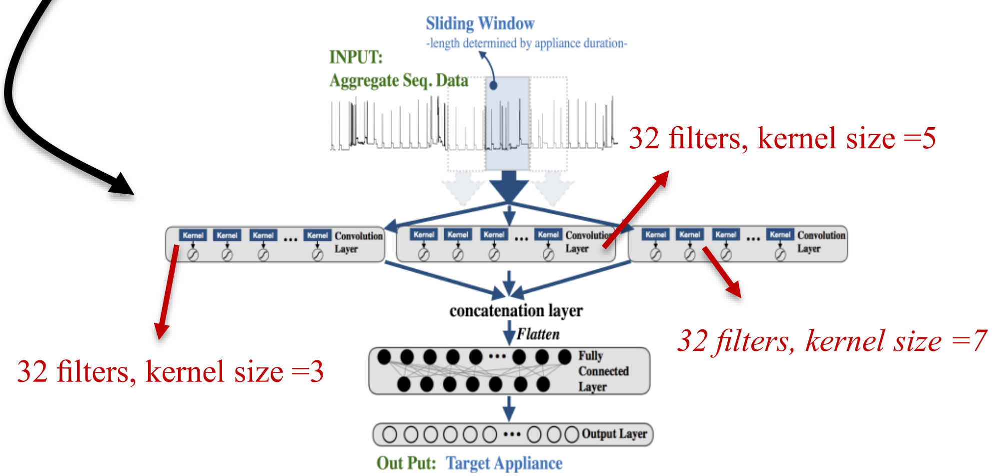


"Load disaggregation" refers to determining the appliances' individual electricity consumption from the aggregate consumption, through signal processing and machine learning strategies. This allows us to provide more detailed consumption feedback to the tenants, with the aim to increase effectiveness of load reduction and load shifting.

Based on validation against MIT's REDD dataset, ConvNETs achieves highest* disagg. accuracy (84%-96%)



Method	Error Measures	Microwave	Fridge	Dish w.	Washing m.	Overall
ConvNET	Accuracy	0.373	0.846	0.604	0.761	0.64 ± 0.20
	F score	0.239	0.803	0.561	0.697	0.57 ± 0.24
	Precision	0.149	0.731	0.440	0.644	0.49 ± 0.26
ConvNET + b-LSTM	Accuracy	0.701	0.960	0.846	0.830	0.83 ± 0.10
	F score	0.534	0.906	0.780	0.735	0.73 ± 0.15
	Precision	0.631	0.890	0.725	0.716	0.74 ± 0.10
Denoising AutoEncoder	Accuracy	0.954	0.916	0.925	0.841	0.90 ± 0.04
	F score	0.927	0.889	0.886	0.747	0.86 ± 0.08
	Precision	0.907	0.849	0.841	0.722	0.82 ± 0.07
Denoising AutoEncoder + LSTM	Accuracy	0.649	0.830	0.785	0.696	0.74 ± 0.08
	F score	0.489	0.783	0.690	0.520	0.62 ± 0.13
	Precision	0.466	0.723	0.627	0.502	0.58 ± 0.11
Parallel ConvNETs	Accuracy	0.961	0.919	0.934	0.835	0.91 ± 0.05
	F score	0.917	0.890	0.888	0.735	0.85 ± 0.08
	Precision	0.897	0.847	0.846	0.716	0.82 ± 0.07
Parallel ConvNETs + b-LSTM	Accuracy	0.738	0.789	0.741	0.80	0.76 ± 0.03
	F score	0.654	0.714	0.665	0.720	0.91 ± 0.05
	Precision	0.599	0.649	0.598	0.661	0.91 ± 0.05



Source code:
https://github.com/mehmani/MFRED-DisAgV001/blob/master/MFREDDisAgregationV3.ipynb

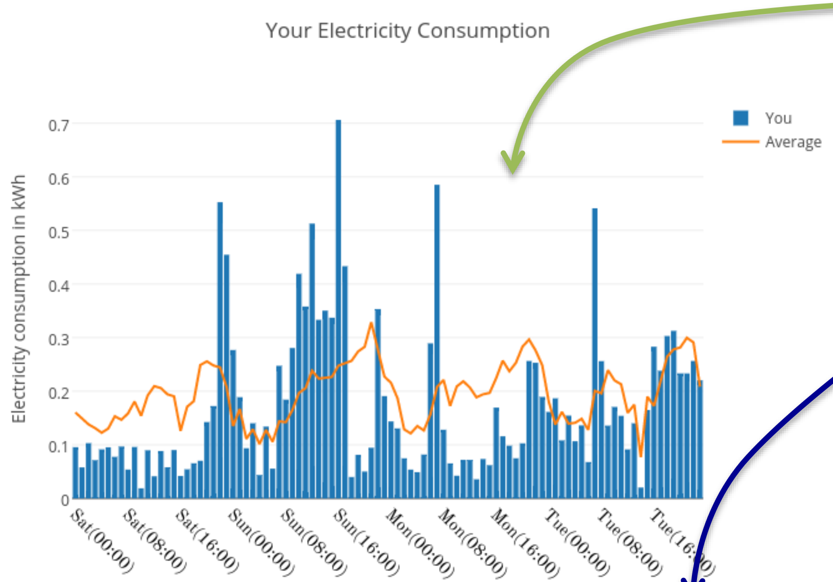
* We explored different neural network architectures using bidirectional LSTM, convolutional networks, and feed-forward deep neural networks.

The software parses each apartment's use data to generate personalized emails with selectable features

Progress slide 6 of 8: NLP-based feedback

Lenfest Energy Study

Hi All,



This feedback cycle (Wednesday-Tuesday), you used electricity equivalent to driving 20.19 miles in a 30mpg vehicle. This is 11.53% less than similar apartments in your building, with the most usage during the night-time.

Your estimated monthly power bill would be $17.15.

Hope this feedback message helps.

Approval for this study was granted by Columbia University's Institutional Review Board, under IRB Protocol Number AAAR1391(M00Y01).
Don't like these emails? Unsubscribe.

Feedback Feature Space

- Graph
- Power to Greenhouse Gas
- Power to Trees
- Power to CO2 emissions
- Power to Miles Driven
- Compare w. Previous Consumption
- Compare w. Average Consumption
- Peak usage info.
- Predicted Elec. Cost
- Compare Electricity Cost w. Pre.
- Compare Electricity Cost w. Ave.
- Positive Sentiment
- Negative Sentiment
- News Article

⋮

The feedback will be augmented with NLP-based energy savings tips targeted to each residents hotspots*

Instead of sending an expert to someone's home and devise personalized advice ...
use a low-cost, automated data-science approach:

Step 1: Measure apt. level loads at 10-sec. (real & reactive power)

Step 2: Break down to appliance level
→ Identify consumption hotspots (e.g., fridge)

Step 3: Determine other characteristics such as phantom loads from electronic devices


Image credit: n-architects

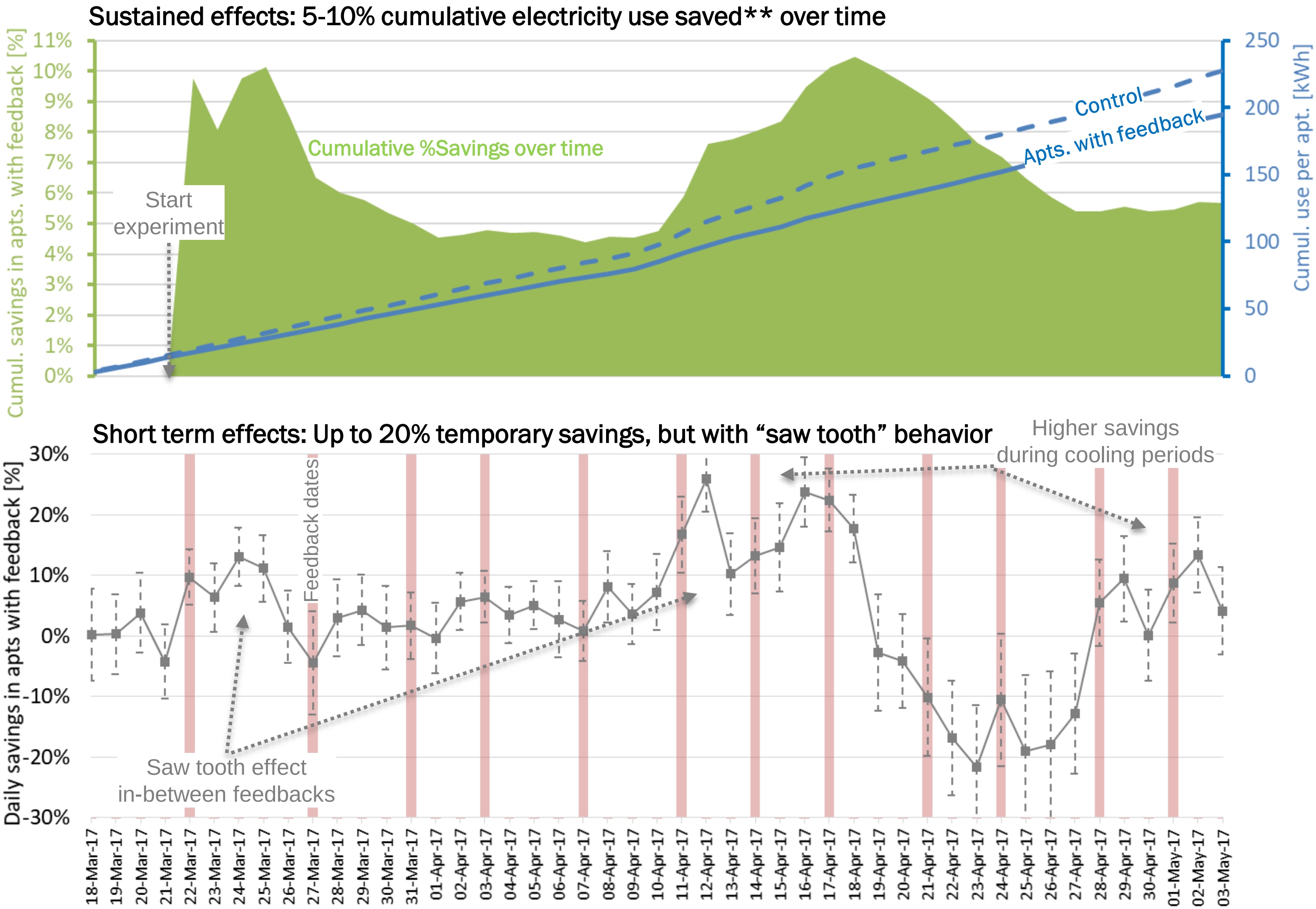
Step 4: Generate personalized feedback, e.g.:
"Your fridge consumed 50% above average for your building."

Step 5: Use NLP to mine online expert forums for electricity saving and load shifting tips

Step 6: Augment feedback messages with behavioral tips customized to their home, e.g.:
"Did you know that cleaning the fridge grill can save substantial electricity."

* Overview only; please refer to Appendix (reference slides) for technical details on step 5.

We tested early versions of our system, showing 5-10% sustained savings amidst various short term effects*



* Lenfest Hall pilot experiment (157 studios, 70 of which received feedback). ** %Savings shown are net of initial sampling bias (apts. receiving feedback had 9% lower use even before first feedback). Error bars show ±1SEM of daily saving. Note: Small apts. with student tenants → not representative of larger study.

Stakeholder Engagement

- We are currently in Budget Year 2 of a 3 year project (April 2018 is month 19 of 36 months)

Stakeholder	When	Role	Benefit to project
Columbia University Facilities	Year 1+2	Support during hardware install and building info	Access to certified electricians, communication with residents, provide apartment info such as number of rooms, square footage, etc.
Lucid	Years 1-3	Provide industry standard feedback platform for small sample	Provides basic benchmarks against to evaluate efficacy of personalized feedback, strategic partner to accelerate T2M
Residents	Years 1-3	Opt into receiving feedback; provide basic preferences (e.g. email or text messages); provide basic information about appliances	Ability to observe personal preferences of residents in feedback and study design, in order to minimize alienation of study group and maximize participation and engagement
New York building operators and managers	Workshop (year 3)	Advise on wider market landscape and feasibility of technology	Of particular interest here is the market outlook for buildings metered via 'totaling"/"submetering"* which would mean meter costs are already covered under different program
ConEdison (local utility)	Workshop (year 3)	Provide info on forthcoming time-of-day tariffs and submetering	Of particular interest here is forthcoming smart meter technology which <u>may</u> mean that disaggregation can be done via the default utility meters (i.e., no more need for other special equipment)

* Building pays a single, consolidated electricity invoice with utility, whereas individual apartment bills are determined via submeters

Remaining Project Work

- We are currently in Budget Year 2 of a 3 year project (April 2018 is month 19 of 36 months)
- The project is progressing accordingly to plan and no major deviations from the original project plan have occurred (or are expected)
- The remaining project work is as follows (for detailed tasks, milestones, and timelines, please refer to the reference slides at the end)

Remaining tasks in budget year 2 (through Sept. 2018)

- Augment feedback generation algorithms with electricity tariff calculator
- Refine cost/benefit model of technology and related T2M recommendations
- Integrate all software components into end-to-end system (from meter to emailed feedback)
- Test complete system with small sample of feedback recipients

Tasks upcoming in budget year 3 (through Sept. 2019)

- Run metering and feedback continuously for 12+ months (to capture longterm and seasonal effects)
- Analyze results by feedback features and demographics
- Stakeholder workshop: Disseminate results and acquire further feedback for T2M recommendations
- Finalize Cost/Benefit model and T2M recommendations

Thank you

Beyond the 4 co-PIs, we would like to acknowledge our entire interdisciplinary team:

- *Vijay Mody (Prof., Mechanical Engineering)*
- *Noah Rauschkolb (PhD student, Mechanical Engineering)*
- *Elsbeth Turcan (PhD student, Computer Science)*
- *Chris Hidey (PhD student, Computer Science)*
- *Sanjmeet Abrol (Masters student, Data Science)*
- *Tuhin Chakrabarty (Masters student, Data Science)*
- *Mark Kerman (Columbia University Facilities)*

Columbia University (with partner Lucid)

PI: Patricia Culligan, Robert A. W. and Christine S. Carleton Prof. of Civil Eng.

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(presenter: Christoph Meinrenken, cmeinrenken@ei.Columbia.edu)

REFERENCE SLIDES

(do not count towards 17 slide max.)

Project Budget

Project Budget:
This is a 3-year, $MM1.5 project with added 26% cost share. We are in budget period 2 of the project and our spent levels are as planned.

Variances:
Because of worse than expected time resolution of the apartment meters, we re-directed those equipment funds towards installing additional plug-load meters in a small subset of apartments (for further validation of the dis-aggregation algorithms. Federal and cost share were not changed.

Cost to Date: To date, the project spent **45%** of the total 3 year budget (federal).

Additional Funding: **None.**

Budget Overview					
FY2017 (1. Sept. 16) (as awarded)		FY 2018 (current spent*)		FY 2020 (31. Sep. '19) (total planned)	
DOE	Cost-share	DOE	Cost-share	DOE	Cost-share
$1,534,397	$398,297	$696,784	$189,741	$1,534,397	$399,682

* As of 11 April 2018

Project Plan and Schedule (past)

Columbia DoE-"Benefit" | Project schedule BP 1 (2016-17) | Tasks, milestones, and status

(Q1-Q3 milestones represent Go/No-Go points)

Task #	Task Title	Q1 (Oct, Nov, Dec)	Q2 (Jan, Feb, Mar)	Q3 (Apr, May, Jun)	Q4 (Jul, Aug, Sep)
1.0	IP-Management plan (M1-M3) Done	T 1.0 M1.0: IP management plan signed by all relevant parties and approved by DoE (M3/Q1)			
1.1	Non-intrusive metering: Identify buildings (M1-M3) Done	T 1.1 M1.1: IRB approval for >85% of targeted approximately 30 buildings identified and received (M3/Q1)			
1.2	Non-intrusive metering: Recruit participants (M1-M6) Note on status: Following IRB guidance, tenant consent required only for feedback (after metering will be installed) --> completed once metering installed	T 1.2	M1.2: Participation consent forms received and kick-off surveys for 90% of targeted apartments performed; IRB approval received (M6/Q2)		
1.3	Feedback: Basic structure and content styles (M1-M6) Done	T 1.3	M1.3: 90% of parameter choices for content style for the 1st generation feedback generation software defined (M6/Q2)		
1.4	Non-intrusive metering: Install equipment (M2-M12) Done	T 1.4		M1.4: System able to meter, wirelessly transmit, collect, and store 24/7, second-interval load data for >75% of participating apartments (M9/Q3)	M1.7: >90% of apartment meters are online [...] (M12/Q4)
1.5	Non-intrusive metering: First gen. of disaggregation (M9-M12) Done			T 1.5	M1.5: First generation of disaggregation software run on apartment–level consumption data of 20% of participating apartments (M12/Q4)
1.6	Feedback: 1st gen. of NLP-based feedback software (M4-M12) Note on status: 1st generation of software already completed (excluding appliance level) and successfully test on "Lenfest Hall" pilot building		T 1.6		M1.6: First version of NLP-based feedback generation software tested on consumption data of 20% of participating apartments (M12/Q4)
1.7	Feedback: Sign-up study participants for Lucid platform (M10-M12) Note on status: Testing of data push and dashboard setup with Lucid already under way		Ahead of schedule		T 1.7 M1.7: [...] and 90% of [Lucid] study participants are set up for feedback platform use (M12/Q4)
1.8	Cost-performance model: Initial strawman (M12) Done				T 1.8 M1.8: DoE acceptance of strawman cost-performance model (M12/Q4)
1.9	T2M roadmap: Outline (M11-M12) Done				T 1.9 M1.9: DoE acceptance of outline of T2M roadmap document (M12/Q4)

Modification: Participant recruitment only once metering installed (per IRB)

Missed one interim milestone (late delivery of equipment)

Project Plan and Schedule (current)

Columbia DoE-"Benefit" | Project schedule BP 2 (2017-18) | Tasks, milestones, and status

(Q5-Q7 milestones represent Go/No-Go points)

Task #	Task Title	Q5 (Oct–Dec)	Q6 (Jan–Mar)	Q7 (Apr–Jun)	Q8 (Jul–Sep)
2.1	Non-intrusive metering: Final software for disaggregation (M13-M15) **Completed**	T 2.1 n/a M2.1: Disaggregation is >80% accurate for Reference Energy Disaggregation (REDD) data set (M15/Q5)			
2.2	Non-intrusive metering: Software for ConEdison tariffs (M16-M18) **Completed**		T 2.2 M2.2: Software completed for >=2 tariffs. Validated ($ figures >90% accurate), where available, against bills from participants (M18/Q6)		
2.3	Feedback: Full prototype for NLP-based feedback gen. (M13-M18) **Nearly completed**	T 2.3	M2.3: Feedbacks can be generated automatically based on sub-metered use data with defined feature set (M18/Q6)		
2.4	Integration: Link metering, disagg., feedback, and email (M19-M21) **Started**			T2.4 M2.4: >90% of participants receive feedback either via Lucid platform (pilot) or via Columbia-generated emails (M21/Q7)	
2.5	Integration: End-to-end testing and debugging of prototype system (M22-M24) **Status: …**				T2.5 M2.5: Tests completed with >85% of participating apartments receiving correct messages; any required refinements implemented (M24/Q8)
2.6	Cost-performance model: Refine list of cost and revenue drivers (M24) **Status: …**				T2.6 M2.6: DoE acceptance of next iteration of cost-performance model (M24/Q8)
2.7	T2M roadmap: Refinement (M23-M24) **Status: …**				T2.7 M2.7: DoE acceptance of refined T2M roadmap document (M24/Q8)

Current status:
All tasks on track and past milestones reached

Project Plan and Schedule (future)

Columbia DoE-"Benefit" | Project schedule BP 3 (2018-19) | Tasks, milestones, and status

Task #	Task Title	Q5			Q6			Q7			Q8		
		Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
3.1	Performance metrics: Resident "total cost-of-ownership" model (M25-M27)	T 3.1		M3.1: Excel (or equivalent) model with cost/benefit data loaded for sample of 10% of participating apartments (M27/Q9)									
3.2	Performance metrics: Determine effectiveness of feedback (M25-M36) **Status: ./.**	T 3.2											M3.2: Feedback effectiveness across three perf. metrics: (i) reduced electricity use, (ii) load-shifted use, (iii) reduced bill (M33/Q11)
3.3	Stakeholder engagement workshop (M30) **Status: ./.**						T3.3 M3.3: Workshop held (M30/Q10)						
3.4	Cost-performance model: Finalize with new perf. metrics (M35-M36) **Status: …**											T3.4	M3.4: DoE acceptance of final version of cost-performance model (M36/Q12)
3.5	Dissemination: Prepare and anonymize database for public use (M34-M36) **Status: …**										T3.5		M3.5: All data anonymized and annotated with metadata, and placed on dedicated site for controlled access (M36/Q12)
3.6	T2M roadmap: Finalization (M35-M36) **Status: …**											T3.6	M3.6: DoE acceptance of final T2M roadmap document (M36/Q12)

Approach in a nutshell: Automated audit of each apartment's electricity use and continued behavioral feedback

Instead of sending an expert to someone's home and devise personalized advice …
use a low-cost, automated data-science approach:

Step 1: Measure apt. level loads at 10-sec. (real & reactive power)

Step 2: Break down to appliance level
→ Identify consumption hotspots (e.g., fridge)

Step 3: Determine other characteristics (e.g., phantom loads from electronic devices)


Image credit: n-architects

Step 6: Augment feedback messages with behavioral tips customized to their home, e.g.:
"Did you know that cleaning the fridge grill can save substantial electricity."
"Remember to turn off lights and unplug un-used electronics."

Step 5: Use NLP to mine online expert forums for electricity saving and load shifting tips

Step 4: Generate personalized feedback, e.g.:
"Your fridge consumed 50% above average for your building."
"Your electricity consumption never went below 120 Watt, causing $20 of your monthly bill."

Technical details on steps 1-6:

- Metering hardware
  - Real & reactive power @ 10sec.
  - 404 apartments
  - 14 buildings of diverse vintage
  - Diverse sizes: 1-4 bedrooms
  - Diverse demographics
- Disaggregation method
  - Trained and validated on MIT REDD and similar datasets
  - Uses Denoising Autoencoder and/or Parallel ConfNETs approaches
  - Aggregate accuracy 84-96%
- **Feedback generation**
  - About 15 features (to be reduced based on Lenfest Hall pilot results)
  - Combination of graphical and text-based feedback
  - Delivered as email to residents
- **Lenfest Hall pilot study**
  - In order to mitigate execution risks, used available apartment data (no disaggregation) to carry out pilot of end-to-end system
  - Results were used to gauge resident preferences (e.g., email instead of text message), message fatigue, and signal-to-noise of experiment

The feedback will be augmented with NLP-based energy savings tips targeted to each residents hotspots

Instead of sending an expert to someone's home and devise personalized advice ...
use a low-cost, automated data-science approach:

Step 1: Measure apt. level loads at 10-sec. (real & reactive power)

Step 2: Break down to appliance level
→ Identify consumption hotspots (e.g., fridge)

Step 3: Determine other characteristics, (e.g. phantom loads from electronic devices)

Step 6: Augment feedback messages with behavioral tips customized to their home, e.g.:
"Did you know that cleaning the fridge grill can save substantial electricity."

Step 5: Use NLP to mine online expert forums for electricity saving and load shifting tips

Step 4: Generate personalized feedback, e.g.:
"Your fridge consumed 50% above average for your building."

Technical details on step 5:

- Electricity saving tips for various appliances are available online in technical forums (e.g., *Reddit®*) and social media, often already organized by relevant categories, e.g.
  – Refrigerator
  – Coffee machine
  – Space heater
  – Windows
- **Natural Language Processing (NLP) is used to mine and summarize this information into concise tips**
  – Uses neural networks such as linear SVM and LSTM
  – Can detect relevant information spread over multiple turns of dialogue
  – Able to detect implicit or explicit causality*
  – Summarize into, e.g., "Did you know that cleaning that cleaning the fridge grill ...?"
- Before automated tips are sent to residents, team will screen tips for technical accuracy and ease of understanding
  – Avoid risk of alienating residents early in the study
  – We expect, this safe-guard will be required less and less as the system matures

* Identifying Causal Relations Using Parallel Wikipedia Articles. Christopher Hidey and Kathleen McKeown (ACL 2016)