INDiC: **I**mproved **N**on-Intrusive load monitoring using load **D**ivision and **C**alibration

Nipun Batra

Haimonti Dutta

Amarjeet Singh

CCLS

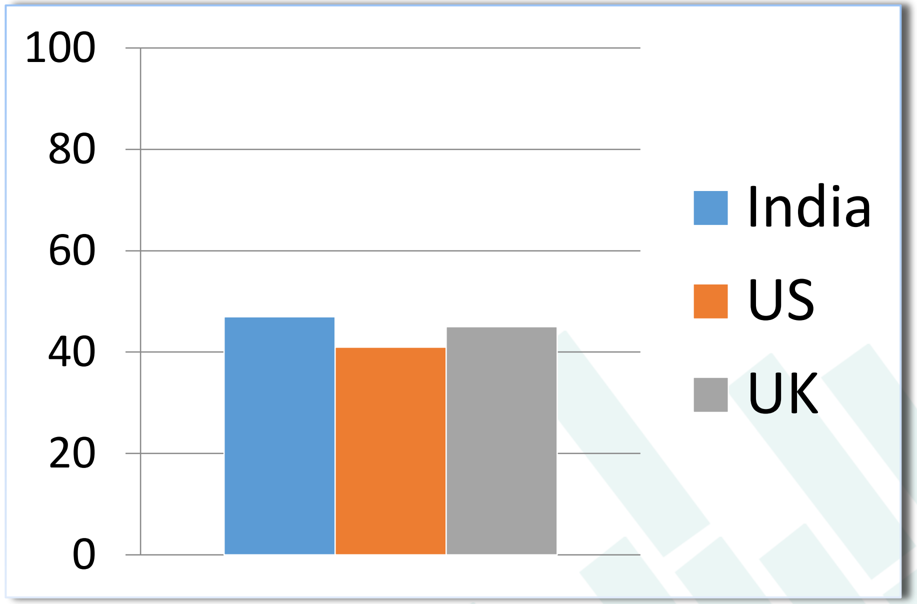
INDRAPRASTHA INSTITUTE *of* INFORMATION TECHNOLOGY **DELHI**

11/20/2013

Motivation

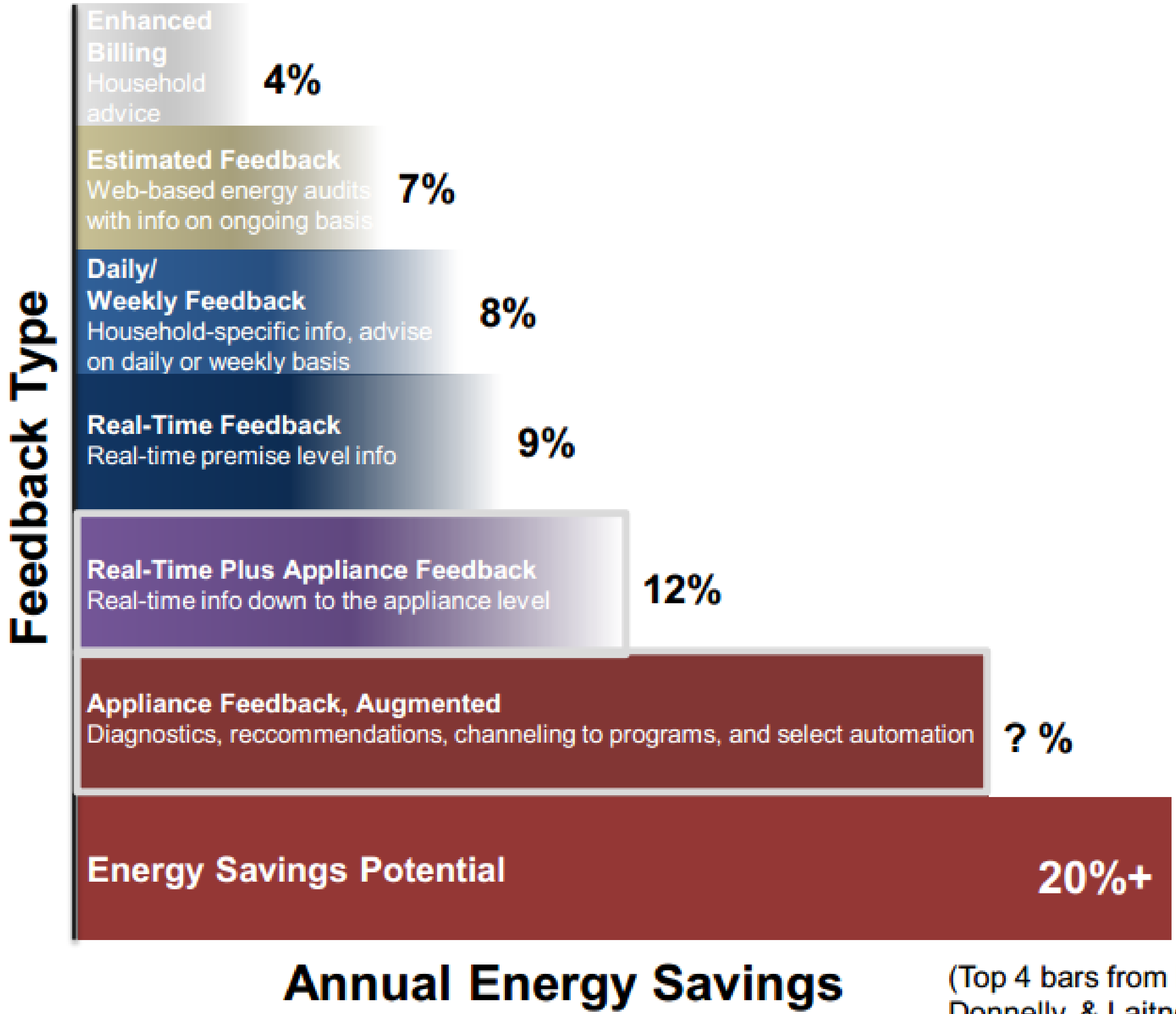
- Buildings contribute significantly to overall energy (electricity, gas, etc.) usage
- New buildings constructed at rapid rate

Contribution of buildings to overall energy consumption (2011)



Efficacy of appliance specific feedback

Providing appliance specific feedback to end users can save upto 15% energy.



(Top 4 bars from Ehrhardt-Martinez, Donnelly, & Laitner, 2010)

Systems for providing appliance specific feedback

Appliance monitors

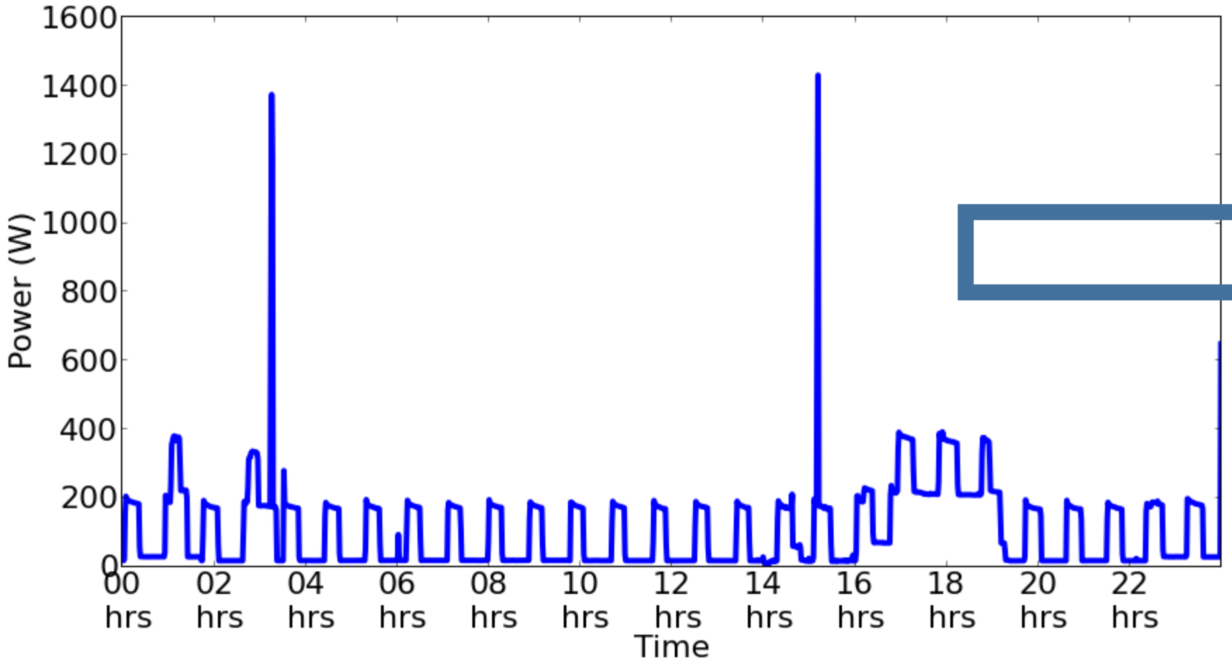
- Provide appliance specific information
- Scale poorly
- Cost increases with each appliance
- Intrusive

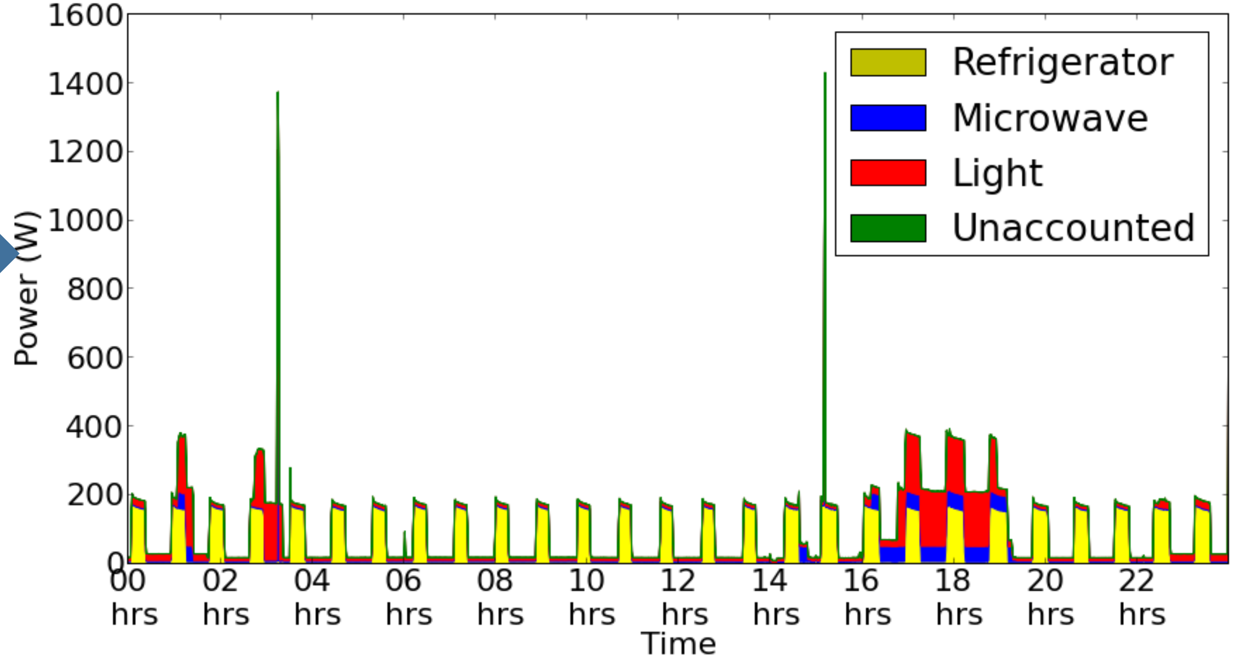
Smart meter

- Give whole home power information
- Information must somehow be broken into different appliances
- Non intrusive
- Cost effective

Non Intrusive Load Monitoring (NILM)

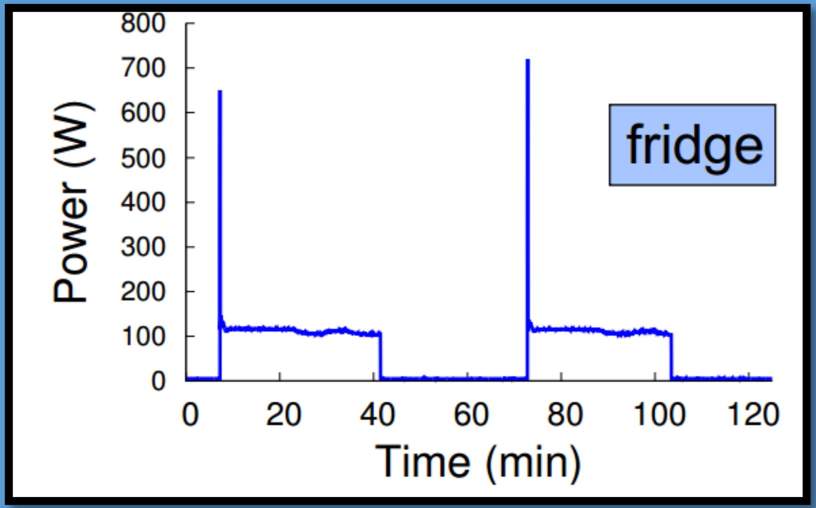
Breaking down aggregate power observed at meter into different appliances

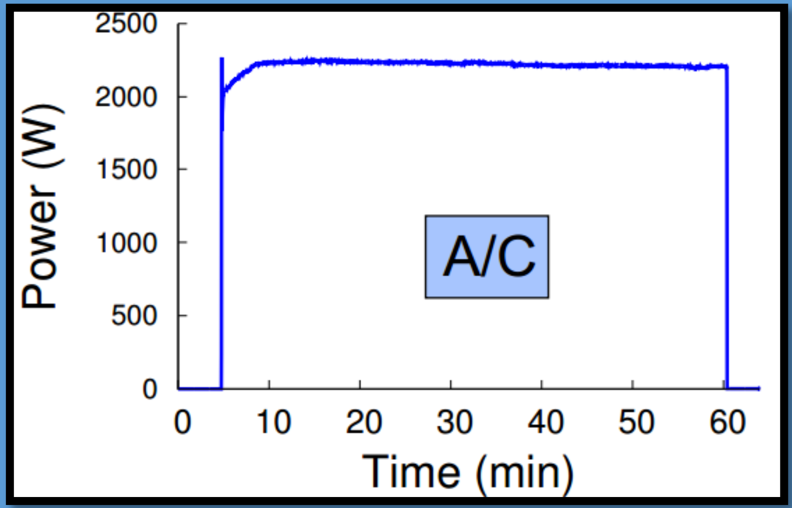


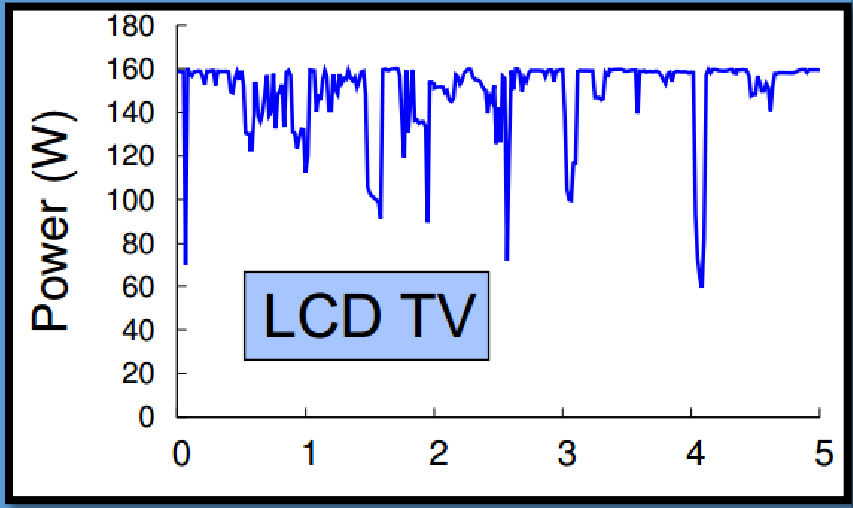


Why NILM works?

- Each appliance has a unique signature
- This is based on the appliance circuitry





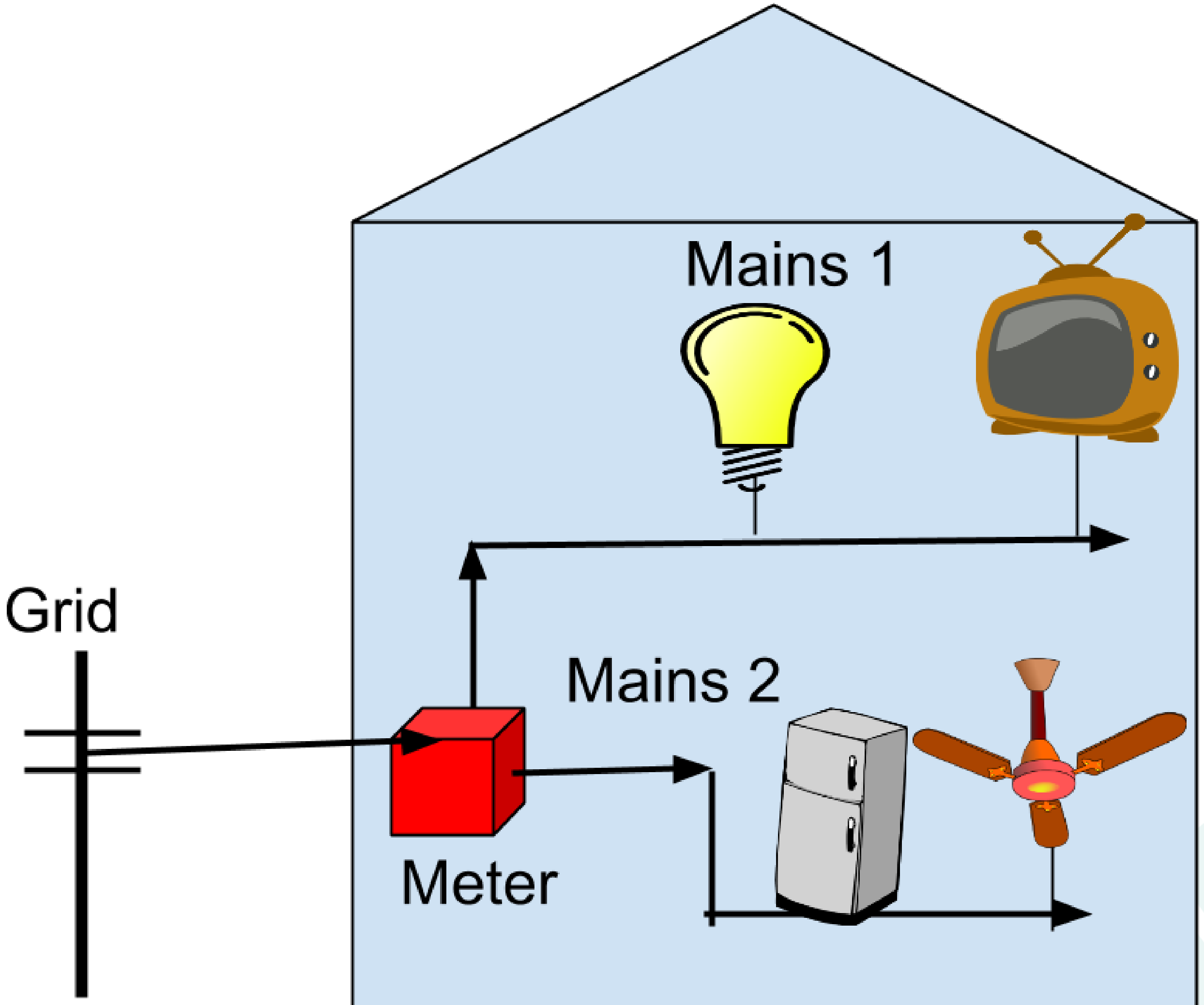


Borrowed from Empirical Characterization and Modeling of Electrical Loads in Smart Homes, Barker et. al

Key Idea I-Load division

Different loads are assigned to different mains

Smart meter capable of measuring individual mains

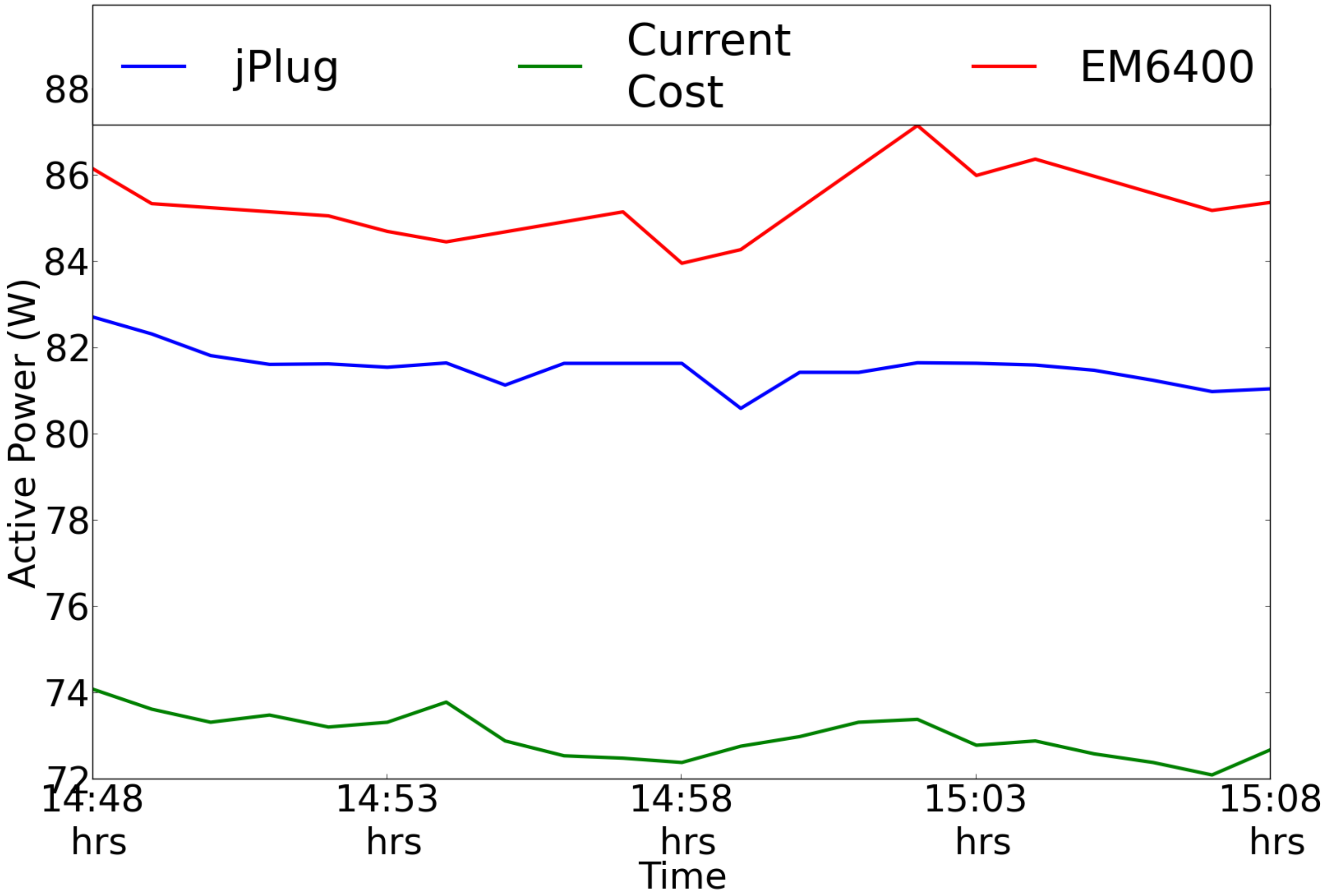


Key Idea I-Load Division

- Instead of doing NILM on Mains 1+ Mains 2, as done before, perform NILM on both separately
- Intuition:
  - Separating out independent components
  - Less noise (as noise is distributed too!)
  - More scalable

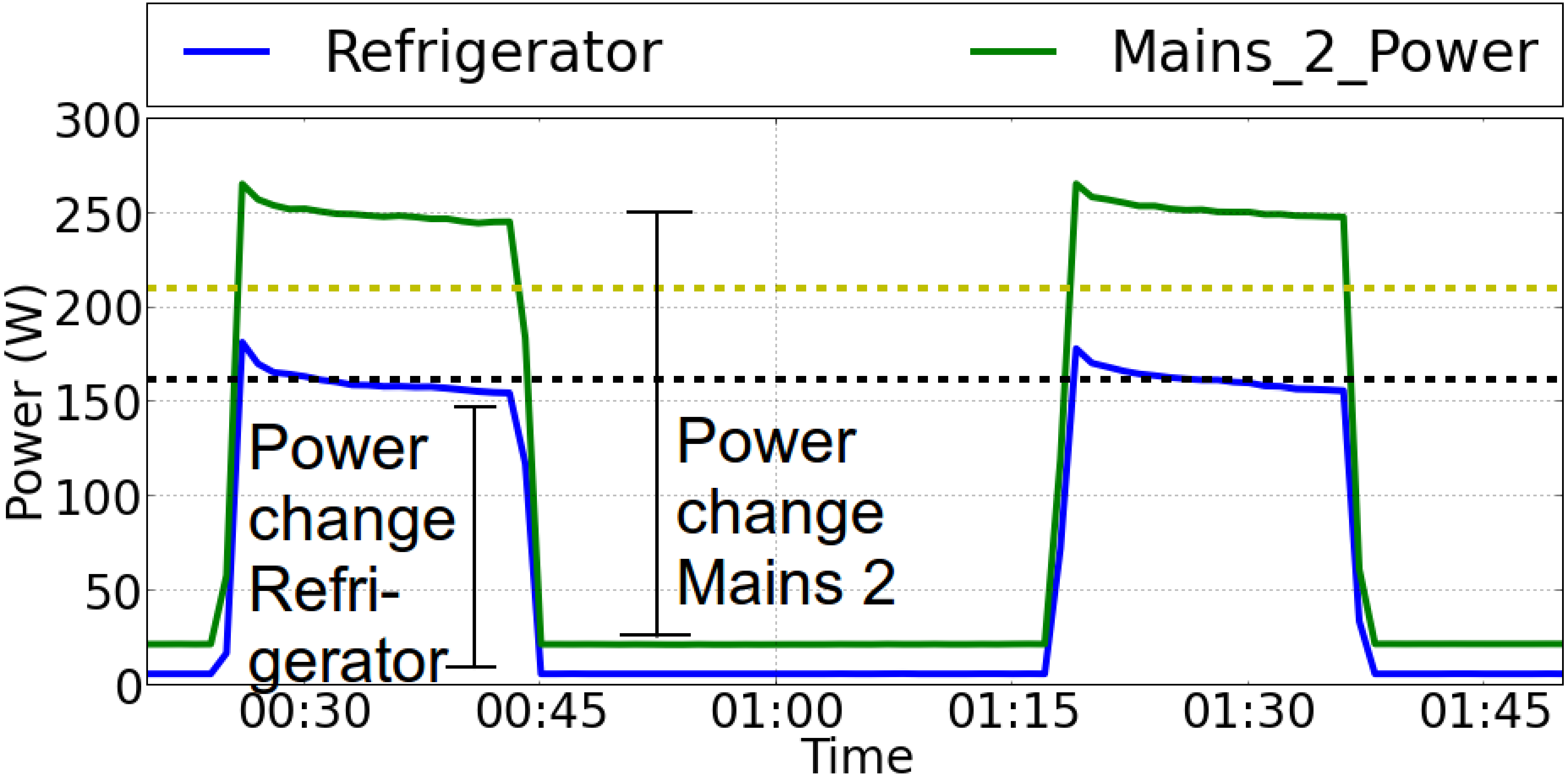
Key Idea II- Calibration

Different appliance monitors may measure different power for the same appliance



Key Idea II- Calibration

Power change measured by appliance monitor is significantly lesser than the measurement done at mains



INDiC

Raw data

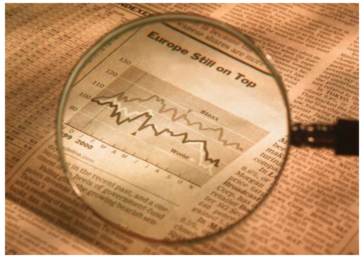
Load division

Mains 1 data

Calibrate

Processed Mains 1 data

Apply NILM



Mains 2 data

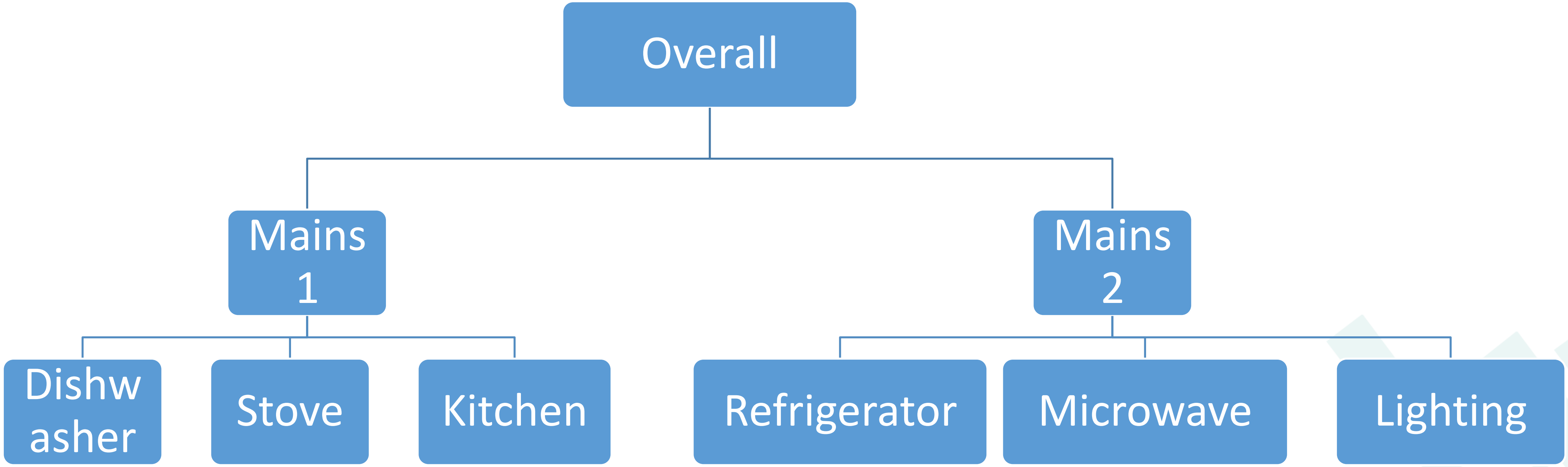
Calibrate

Processed Mains 2 data

Apply NILM

Experiments-I Load Division

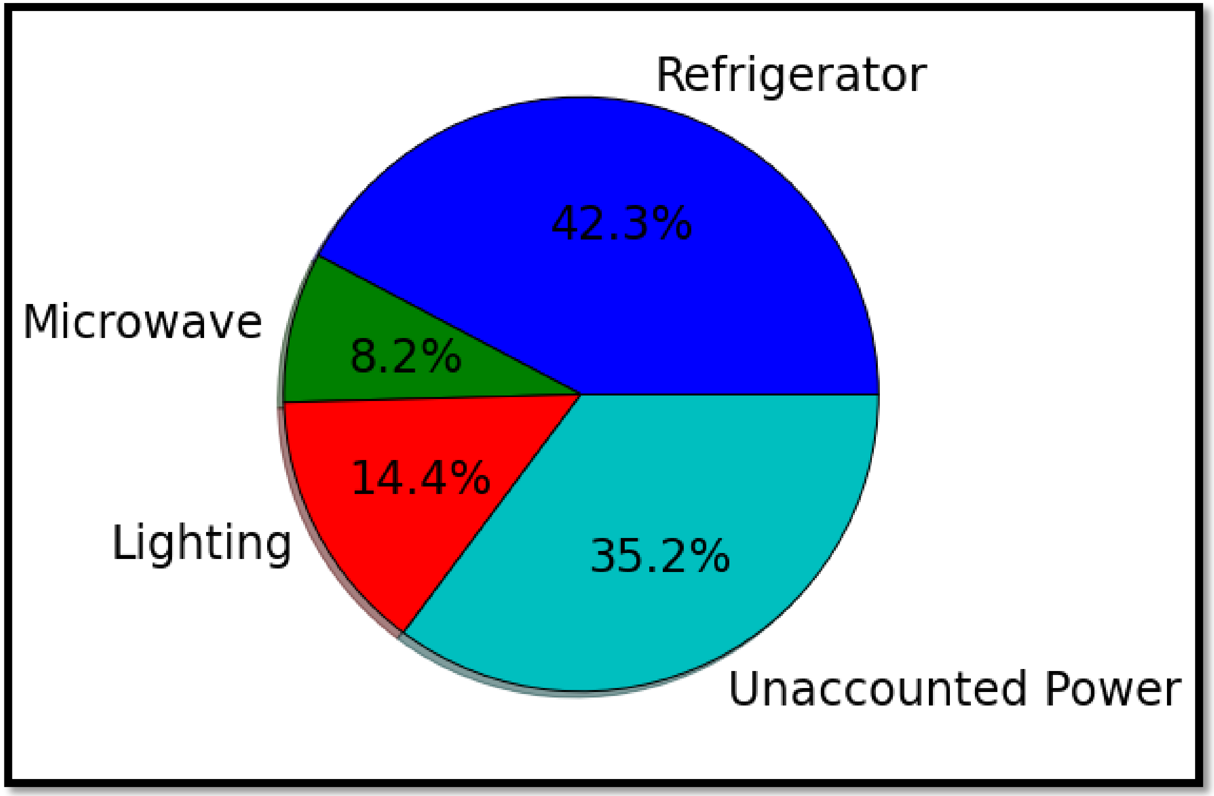
- REDD dataset from MIT
- Problem complexity almost halved!



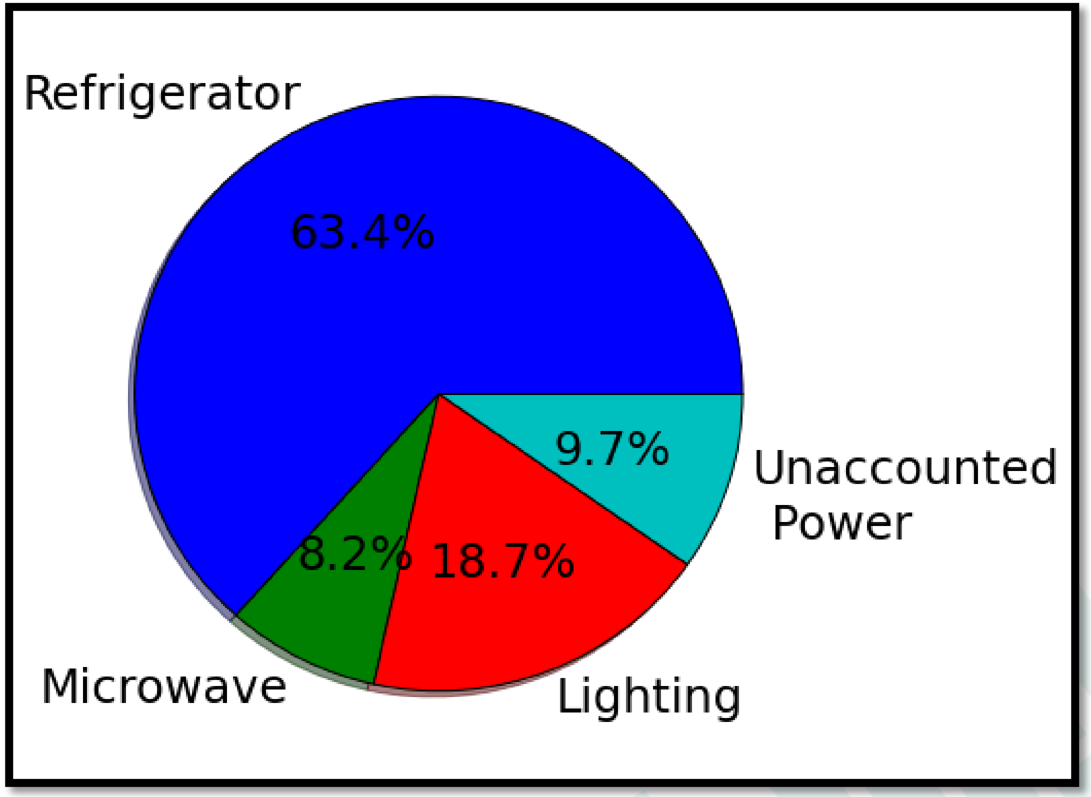
Experiment II Calibration

- Unaccounted power or noise reduces after calibration
- Should improve accuracy

Before calibration



After calibration



Combinatorial Optimization (CO) based NILM

- Take all possible combinations of appliances in different states and match to total power
- Exponential in number of appliances
- Load division gives exponential improvements!!

Toy example illustrating CO

Fan	AC	Total Power (W)
OFF	OFF	0
OFF	ON	1000
ON	OFF	200
ON	ON	1200

Evaluation Metrics

- Mean Normalized Error (MNE)
  - Normalized error in energy assigned to an appliance
  - Given by
    $\sum_t \; |Predicted\ Power_t - Actual\ Power_t| / \sum_t \; |Actual\ Power_t|$
- RMS Error (RE (Watts))
  - RMS error in power assigned to an appliance

Results

- Refrigerator's accuracy improves significantly

[i,j] entry: Number of instances in i^{th} state predicted in j^{th} state

Refrigerator Confusion Matrix

Without INDiC

	State 1	State 2	State 3
State 1	4740	288	41
State 2	1775	2860	176
State 3	112	63	25

With INDiC

	State 1	State 2	State 3
State 1	4541	430	98
State 2	221	4434	156
State 3	5	44	151

Results -II

Both MNE and RE reduce significantly after applying INDiC

Appliance	Without INDIC		With INDiC	
	MNE (%)	RE (W)	MNE (%)	RE (W)
Refrigerator	52	91	25	67
Dishwasher	662	131	73	52
Lighting	176	64	63	43

Acknowledgments

- TCS Research and Development for supporting Nipun Batra through PhD fellowship
- NSF-DEITy for project fund