

Agent-Based Modeling for Smart Grid: Application to Consumer Reaction to Demand Response

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Outline

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- Smart Grid
 - Background on current energy grid
 - What is Smart Grid?
 - Demand Response
- Agent-Based Modeling
 - Defining the Environment
 - Defining the Agents
- Analyzing the Results
 - No DR Scheme
 - DR Scheme
- Conclusions/Impacts
- Acknowledgments and Questions

Smart Grid Case Study

- “‘Municipalization’—the legal process whereby the city would form its own utility company—has been on the table since 2004. When Xcel countered with the offer of an ambitious city-wide smart grid in 2008, Boulder accepted. But Xcel and its partners didn’t do a cost-benefit analysis prior to starting the project, and the portion of the costs consumers would pay rose from a projected \$15.3 million to (at last count) \$44.8 million...[municipalization] passed” [1]
- Lessons Learned:
 - Strong need to fully understand Smart Grid – especially costs
 - Reputation of the utility is at stake

Background

- Current energy grid is over 100-years old – significant improvements are needed to accommodate future needs in our increasingly digitized society [2]
- Current shortcomings manifest as:
 - Inability to accurately and quickly locate faults
 - Sizable losses during distribution
 - Blackouts
 - Cascading effects resulting from incorporation of renewable sources of electricity production
- The Smart Grid seeks to incorporate various technologies and programs in order to mitigate these issues
- One of the Enabling Technologies: two-way communications between power generator/distributor and power consumer

Smart Grid

Goals

- Enable informed participation by customers
- Accommodate all generation and storage options
- Enable new products, services, and markets
- Provide power quality for a range of needs
- Optimize asset utilization and efficient optimization
- Operate resiliently under disturbances, attacks, and natural disasters



U.S. Department of Energy, *Smart Grid Systems Report*, July 2009

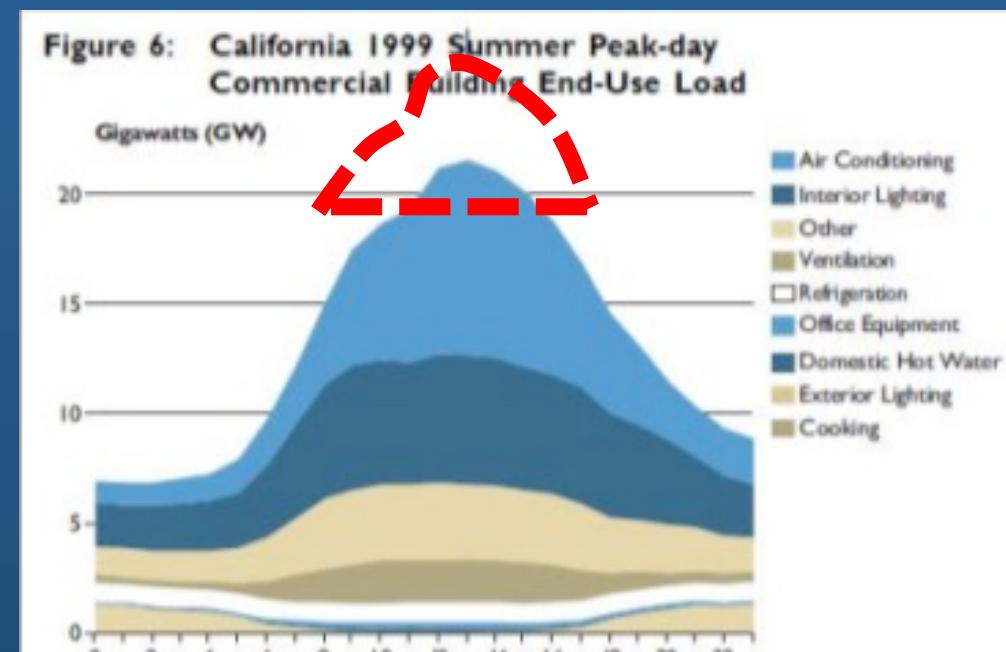
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Demand Response (DR)

- Peaks drive extra expenses (and waste)
 - Capital for increased generation capacity
 - Purchase of premium price electricity externally

Hourly Commercial Electricity Loads, divided by activity

- DR goal:
reduce peaks

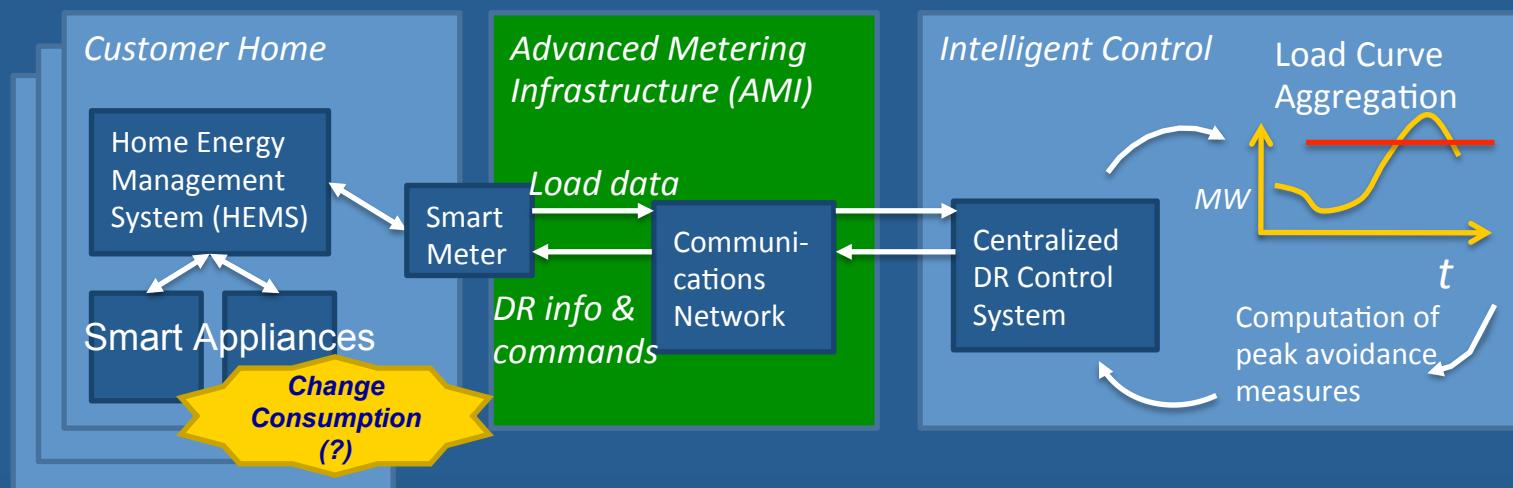


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Benefits of DR

- “[The redistribution of loads] reduces the potential chances of forced outages or full-scale blackouts” [3]
- Results of a pilot conducted by Xcel including DR: “[Grid]-centric Smart Grid initiatives have produced a 90% reduction in reactive power outages and voltage complaints and up to 5% reduction in power demands” [4]

Generic DR Scheme



- Types of DR programs
 - Price-based (tiered or dynamic)
 - Direct load control (DLC)
 - Automatically modify electricity consumption through control of “smart” appliances
 - Challenge: low impact on consumer

Evaluating DR Schemes

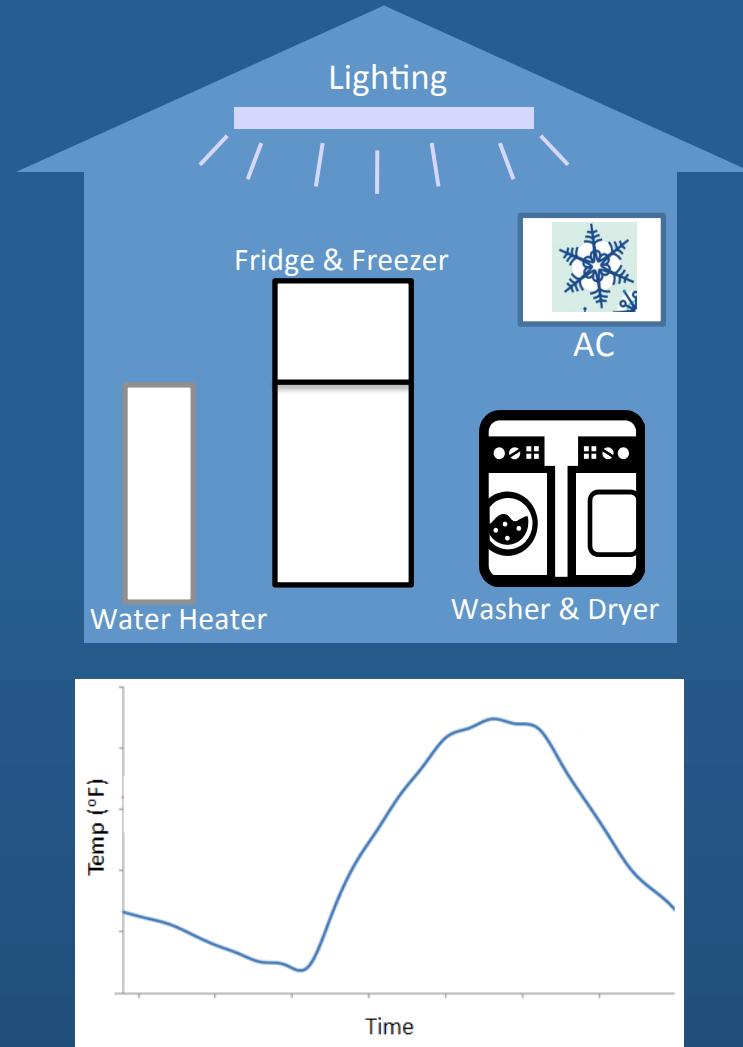
- Currently, DR is assessed by conducting pilot studies, that are:
 - Expensive
 - Risk the reputation of the power generator/distributor
- Today, there are approximately 100 pilot studies examining Smart Grid (including DR) being conducted throughout the world [4]
- Some results showed that the pilot programs hurt the reputation of the utility
- In 2010, the World Economic Forum highlighted the need for consumer segmentation and consumer behavior analysis [4]

Agent-Based Modeling and Simulation

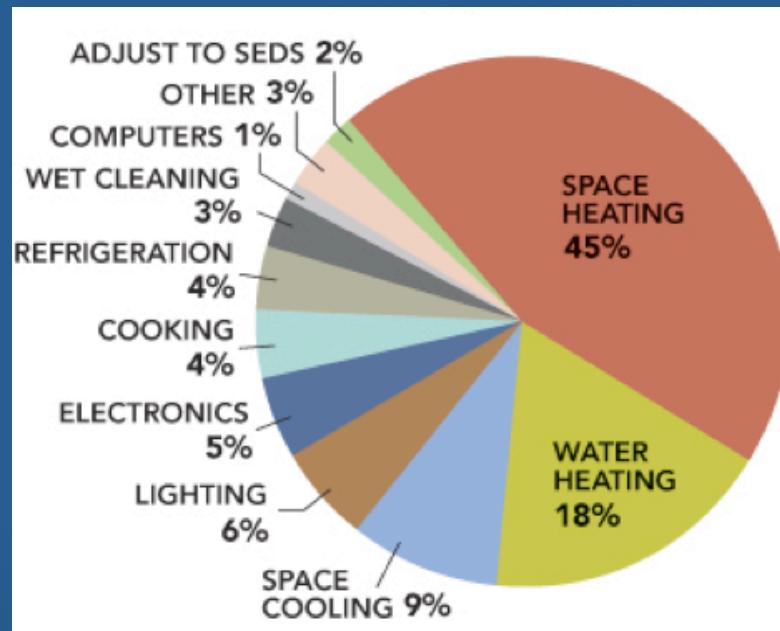
- Central idea: global behavior of a complex system derives from low-level interactions among its constituent elements
- Various definition of agents can be found [6,7], but most include the terms *adaptive* and *autonomous*
- Agents can have varying levels of fidelity depending on the problem being explored
- Can build a virtual world to examine the effects of DR

Defining the Environment

- Environment is broken into two categories:
 - Internal: includes layout of house and appliances within, temperature changes result from external temperature and internal sources of heat production (e.g., residents, appliances)
 - External: everything outside of the house – the only factor that is currently accounted for in the model is the external temperature
- Houses are modeled as one large room with appliances placed randomly throughout



Defining the Environment: Appliances



Source: US Department of Energy

Attribute \ Appliance	Baseload	Water Heaters	Lights	Refrigerator	Freezers	Washers	Dryers	Space Heating & Cooling
Under complete control from the agent			X					X
Autonomous from agent control	X	X				X	X	
Partly influenced by agents' actions				X	X			

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Defining the Environment: Assumptions

- Electricity consumption is modeled with several different loads
 - Water heater
 - HVAC
 - Washer & Dryer
 - Refrigerator & Freezer
 - Lights
 - Baseload
- Currently, agent behavior only includes changing the thermostat setting and turn the lights on and off, other appliances are based off of a probability schedule
- House is not connected to the ground (i.e. all heat transfer occurs with the same thermal coefficient)

Defining the Agents

Attribute	Notes
Size of house	Non-symmetric triangular distributions were used when the user defines the value
Thermal coefficient of heat transfer	
Daily schedules of different categories of agents	
Agent's threshold of discomfort	
Average number of appliances per household	Internal logic assigns the correct number to various agents
Percentage of residents leaving household during day	
Percentage of agents in each category for daily schedule	Broken into 3 categories: early-bird, normal, night-owl

- Fanger's Equation
 - Determines the thermal comfort of a group by taking into account: ambient temperature, humidity, clothing, metabolic activity, etc.
 - Used to determine the comfort level of the agents

Value of PMV	-3	-2	-1	0	1	2	3
Definition	Cold	Cool	Slightly cool	Comfortable	Slightly warm	Warm	Hot

Quantifying Annoyance

- Two types of annoyance:
 1. Frustration: When an agent wants to use an appliance, but cannot because of DR
 2. Discomfort: When an agent is uncomfortable because the temperature is too hot or too cold

$$\text{Annoyance} = \alpha \text{ Frustration} + \beta \text{ Discomfort}$$

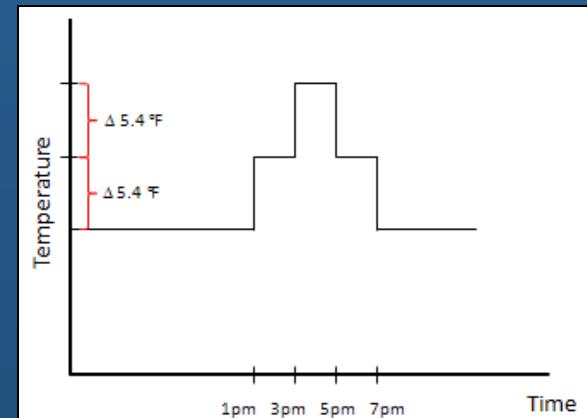
- For this model, we only consider the Discomfort type of annoyance (i.e., $\alpha = 0$)

Running the Model

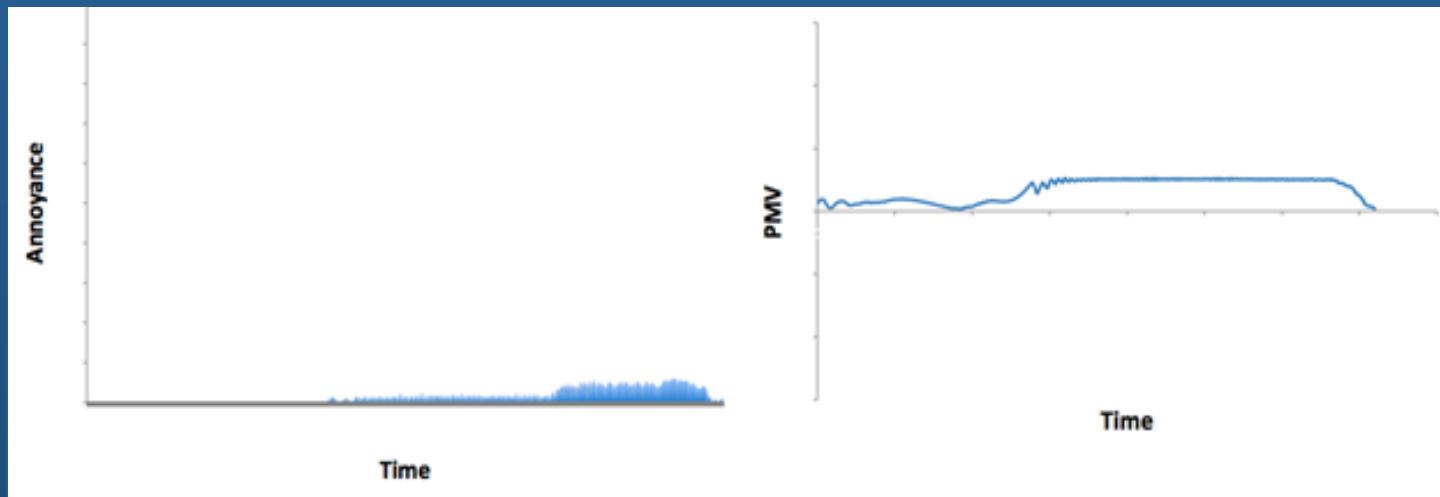
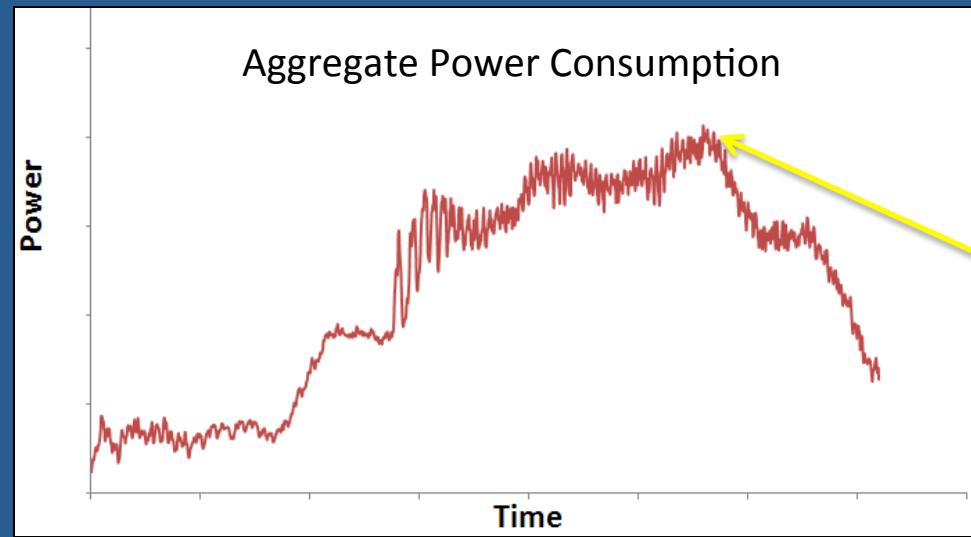
- Will use 200 households in a 24-hour simulation in order to see the effect of a DR scheme

Agent ID	House Size (ft ²)	Insulation Factor	# of Residents	Wake Up Time	# of Res. Leaving	Leave Time	Arrive Home Time	Bed Time	PMV Threshold
1	1644	0.3	3	6:19am	0	-	-	10:22pm	1.34
58	2321	0.3	2	7:14am	2	8:26 am	6:30pm	10:50pm	1.42

- Two cases identified:
 - Standard Run (No DR)
 - Used as a baseline
 - Agents can still experience Discomfort
 - DR event
 - Based on two-level, pre-defined DR scheme

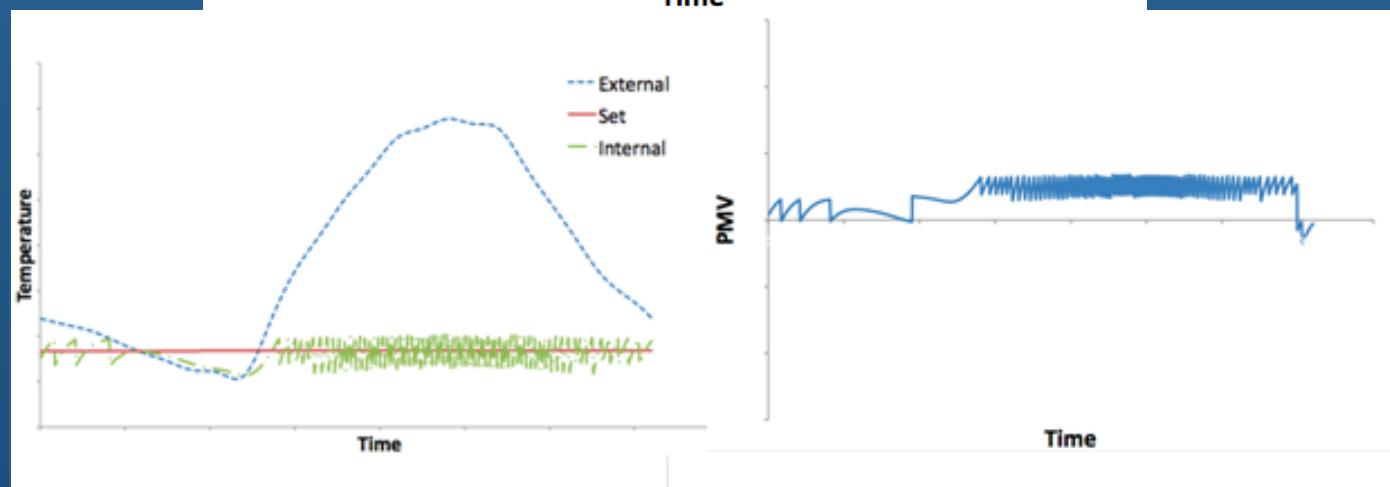
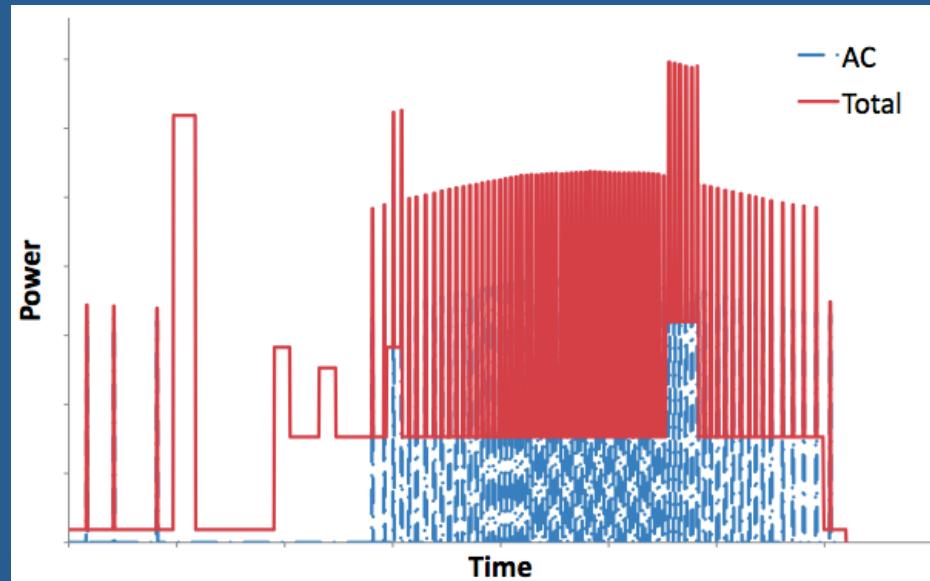


No DR Event



No DR Event: Individual Behavior

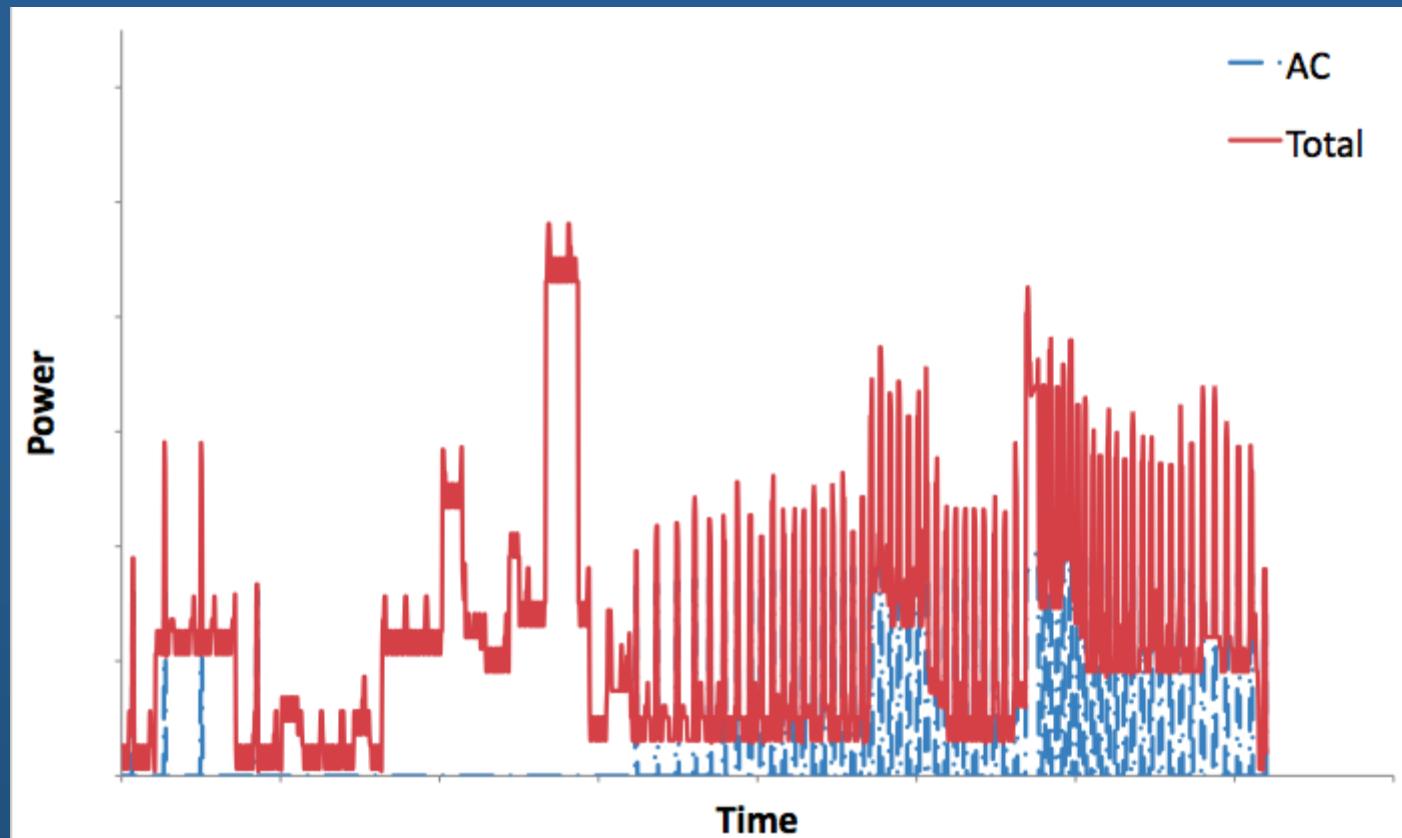
Agent 1:



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No DR Event: Individual Behavior

Agent 58:



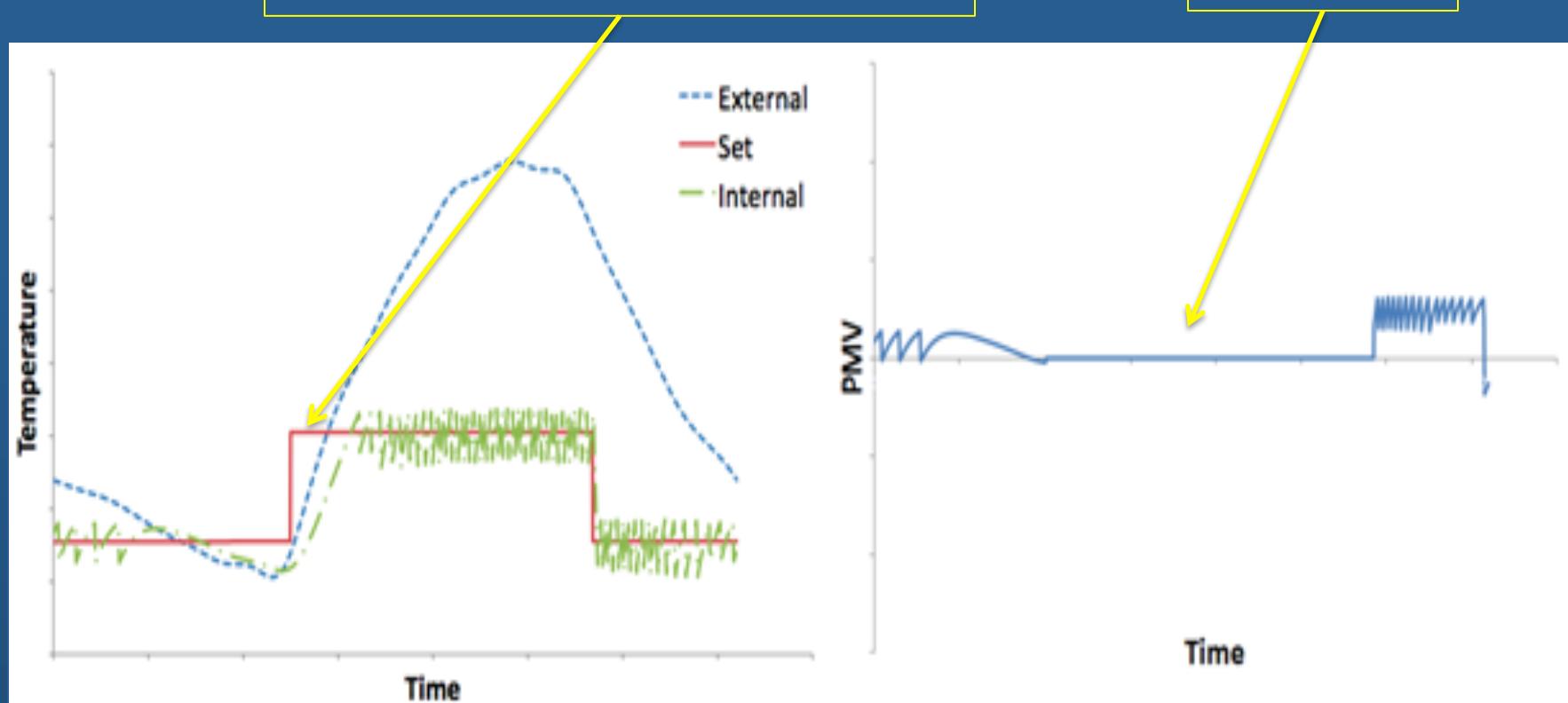
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No DR Event: Individual Behavior

Agent 58:

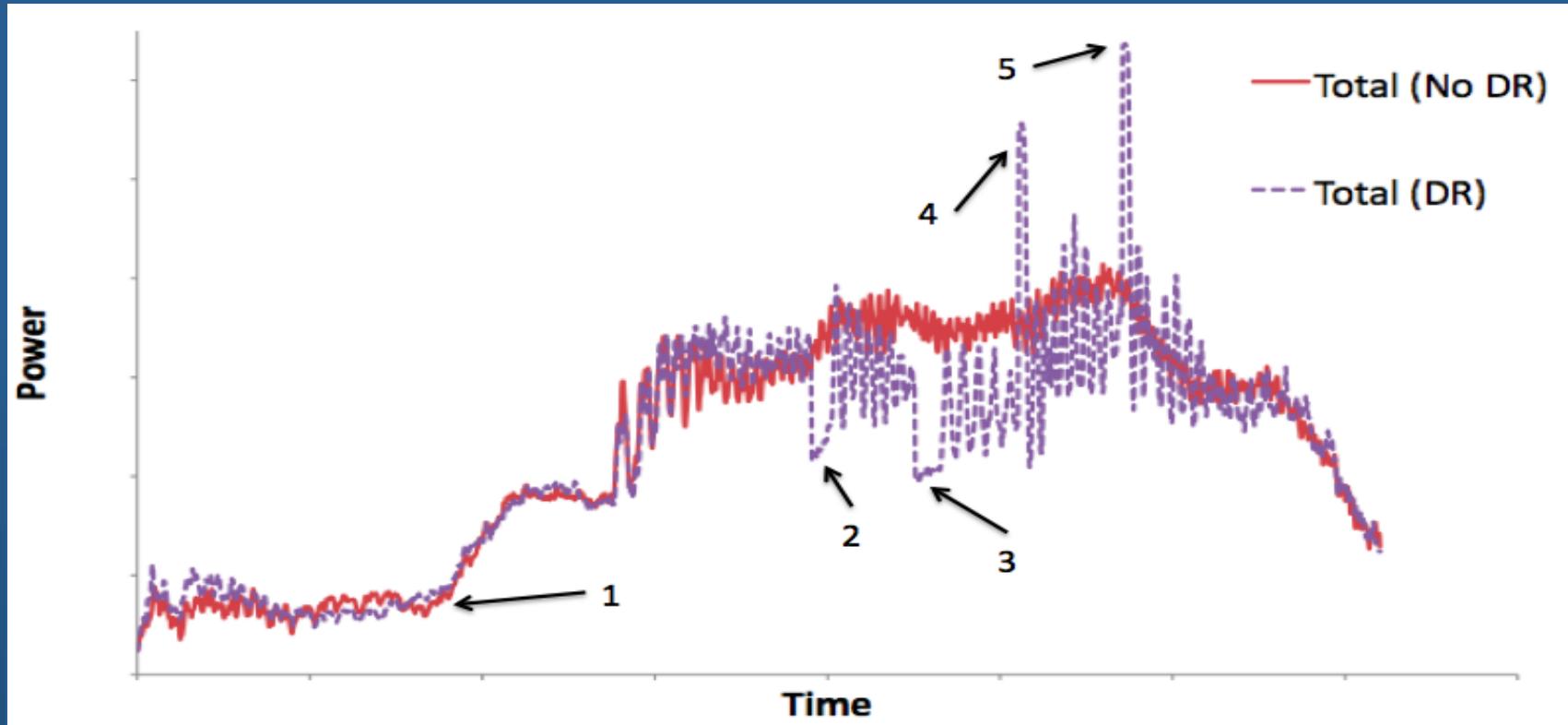
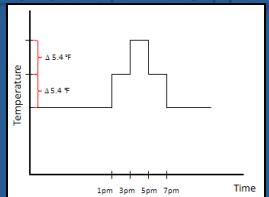
No residents at home during this time so they increase the set temperature on the thermostat

No residents at home so PMV equals zero

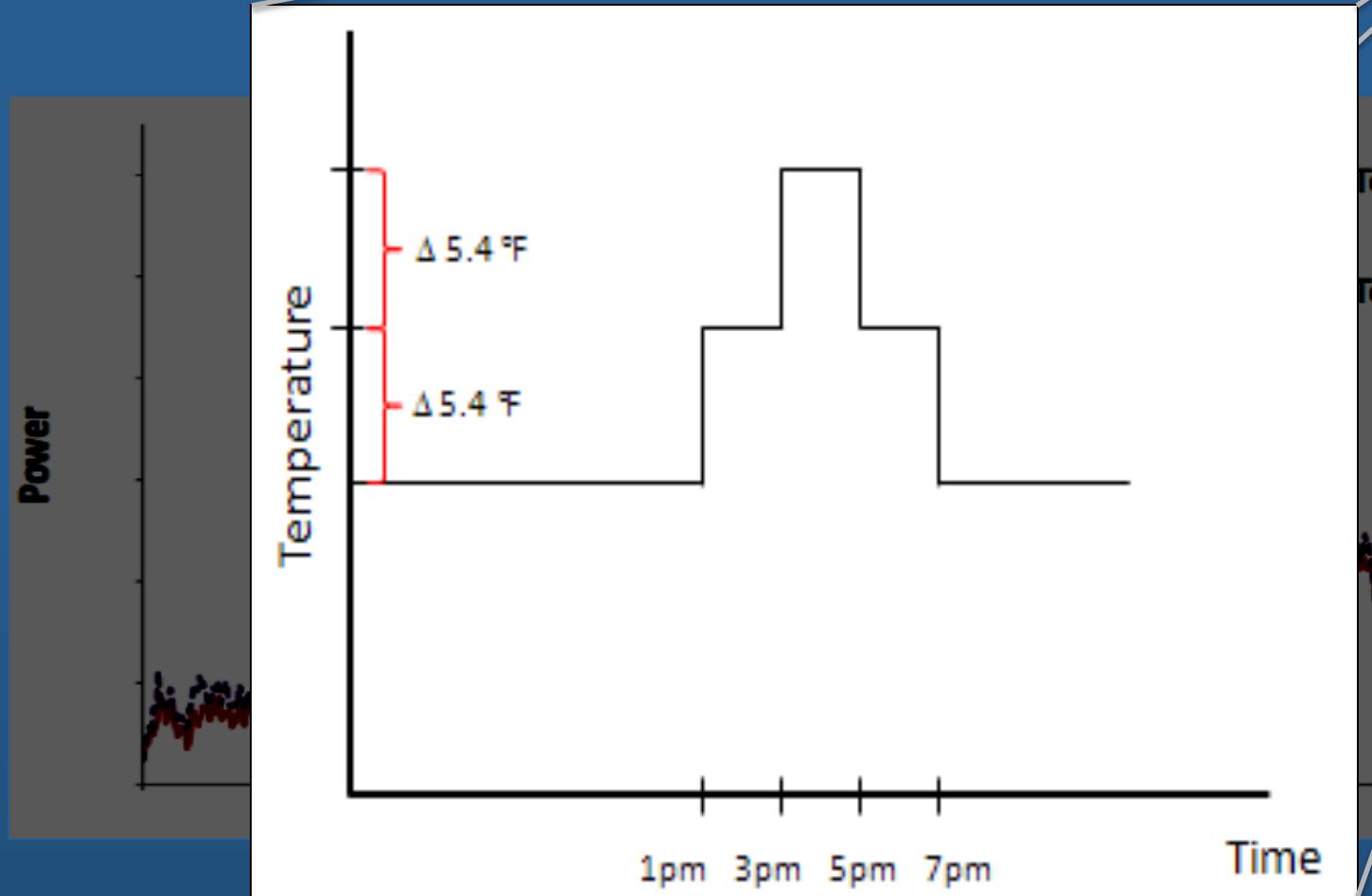
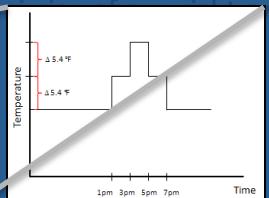


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DR Event

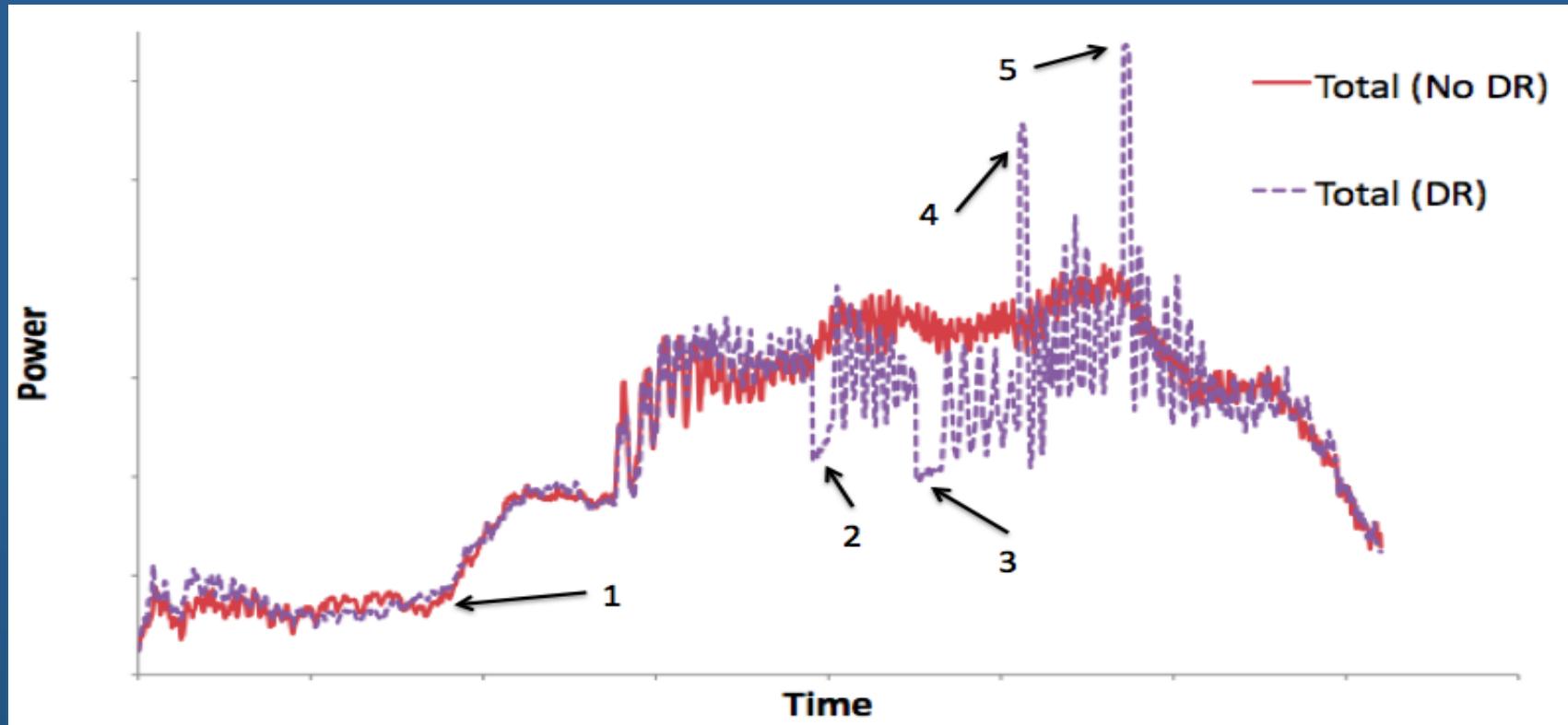
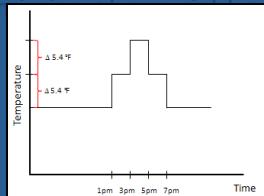


DR Event



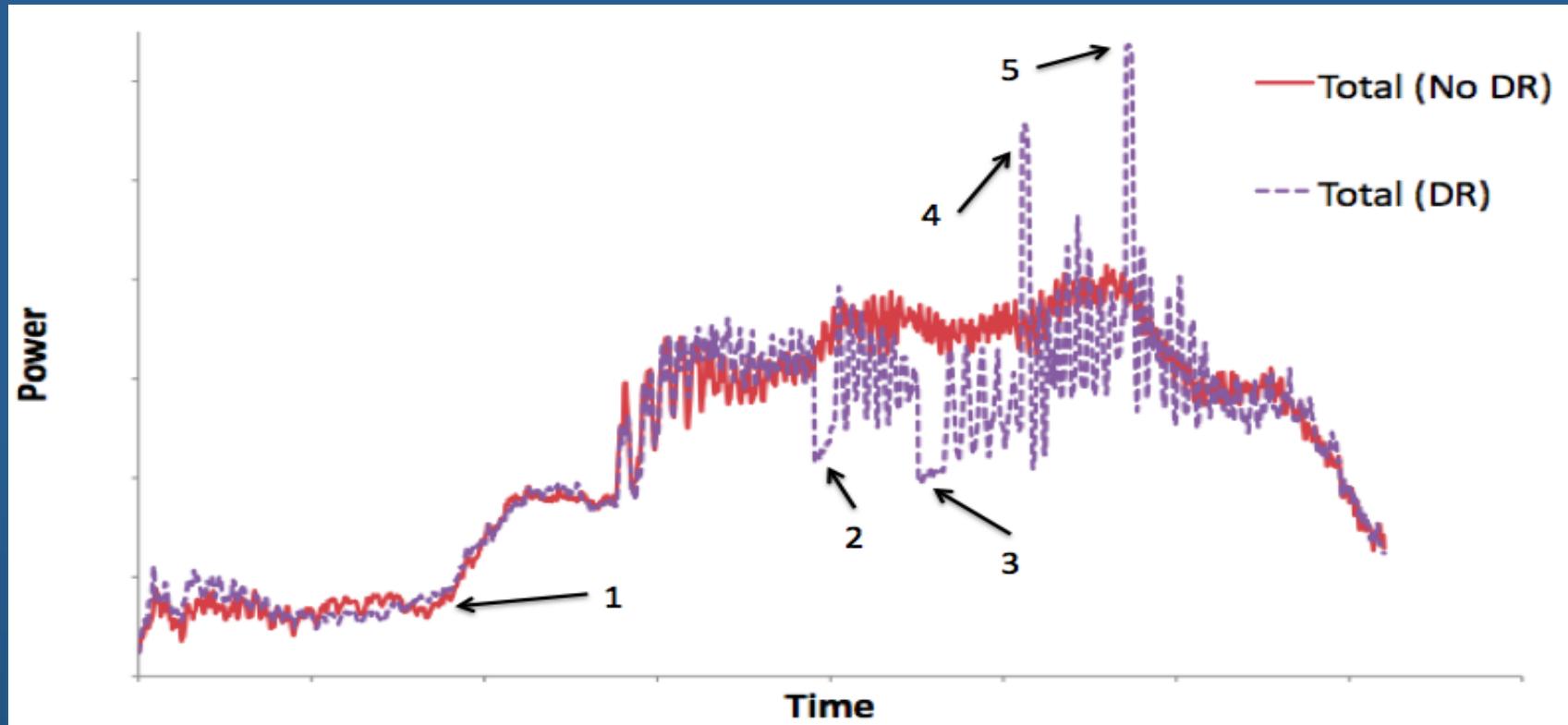
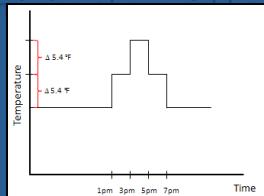
Total (No DR)
Total (DR)

DR Event



Point 1 - shows a slight variation in power, but this is purely due to the probabilistic treatment used to set some attributes in the model.

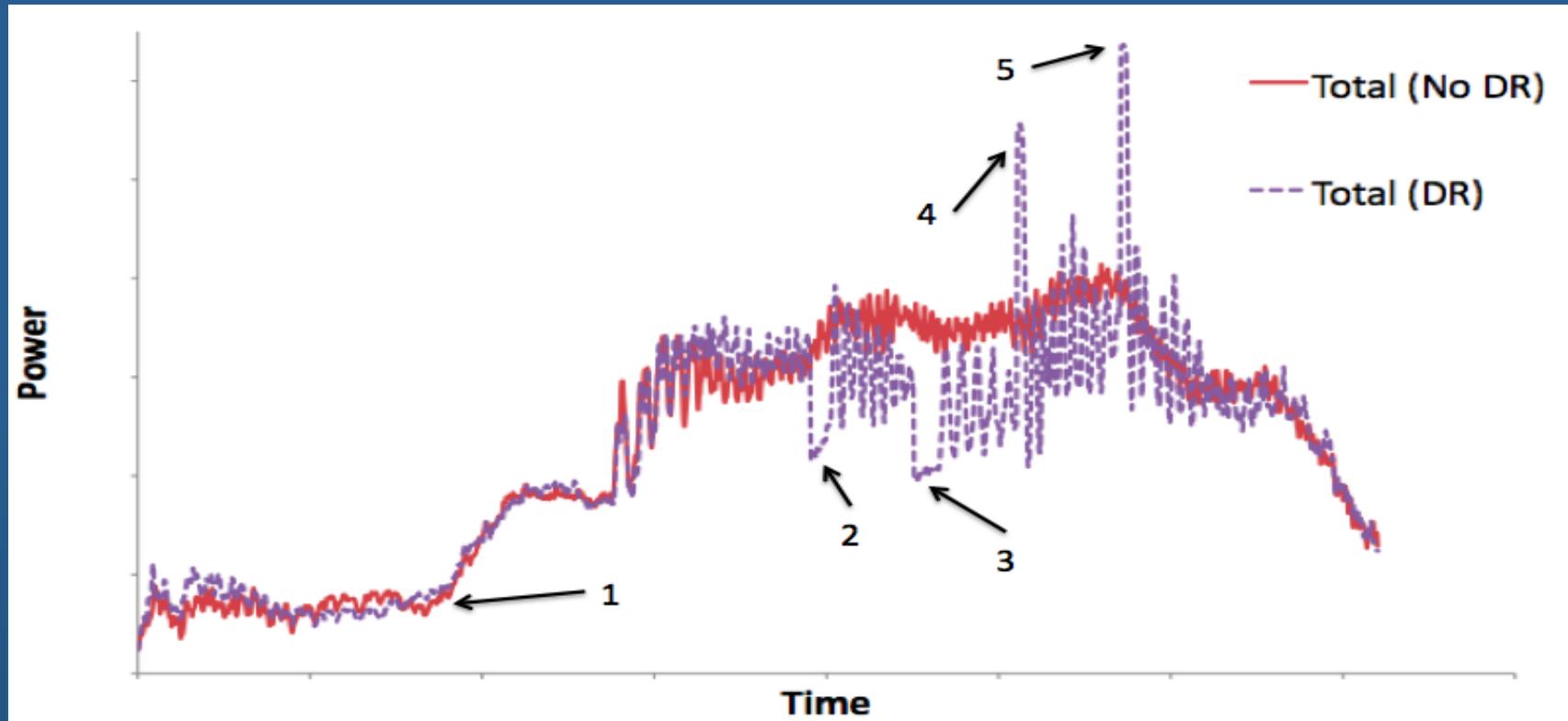
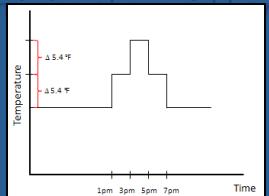
DR Event



Point 2 - shows the first dip in total power that comes from the DR event.

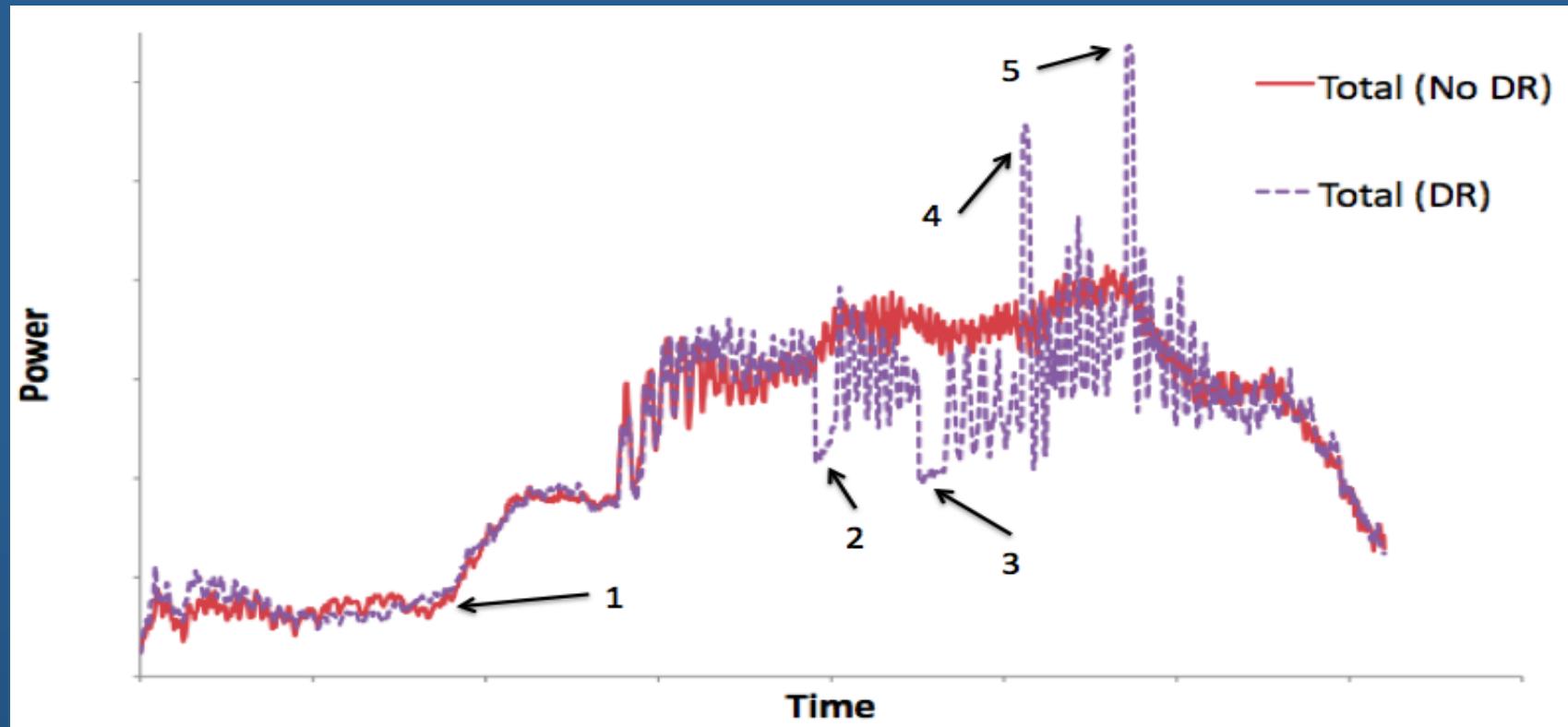
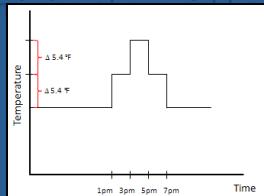
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DR Event



Point 3 - shows a second dip in total power that arises from the stepped nature of the DR event implemented.

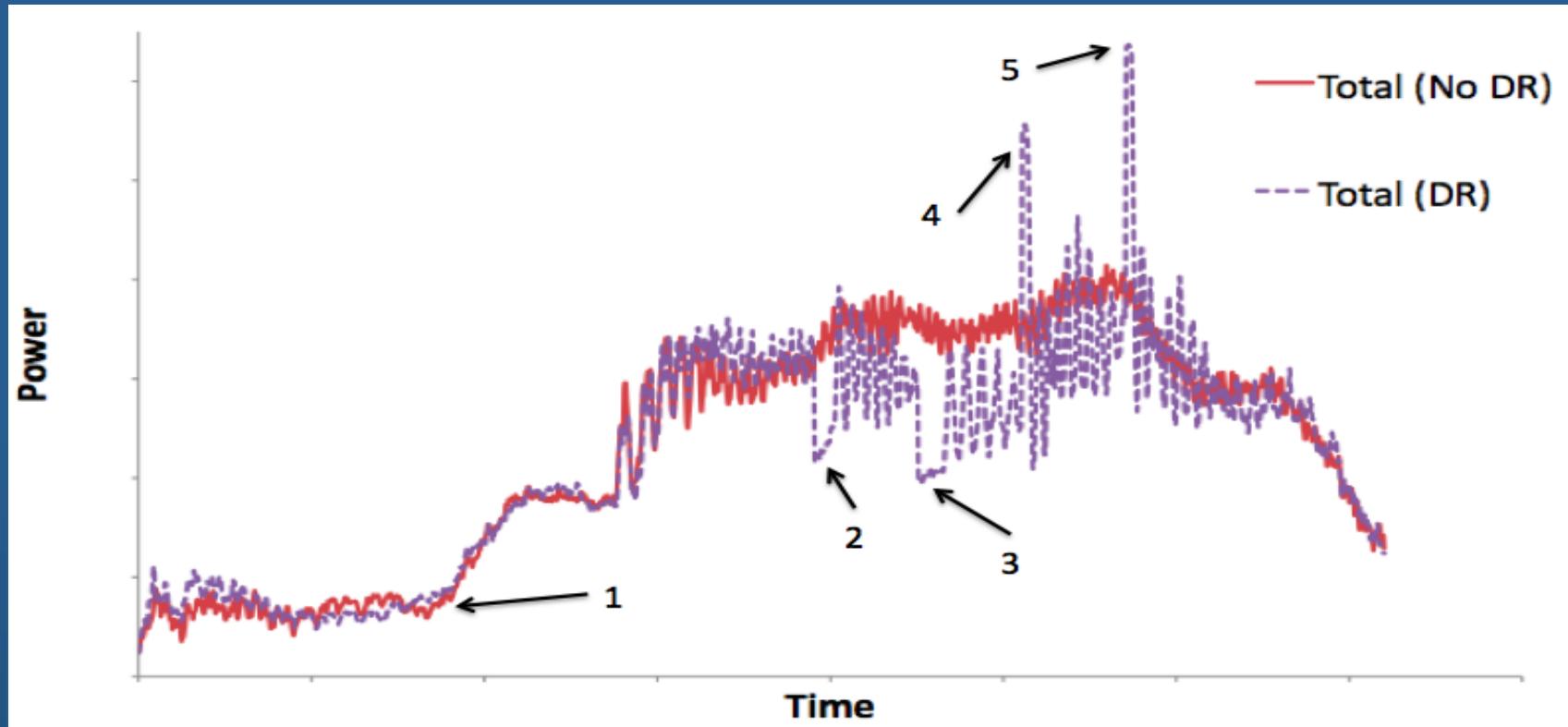
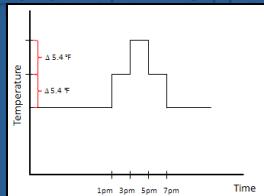
DR Event



Point 4 - highlights the first rebound effect, which occurs when the all the agents simultaneously turn on their air-conditioning because the DR event is over.

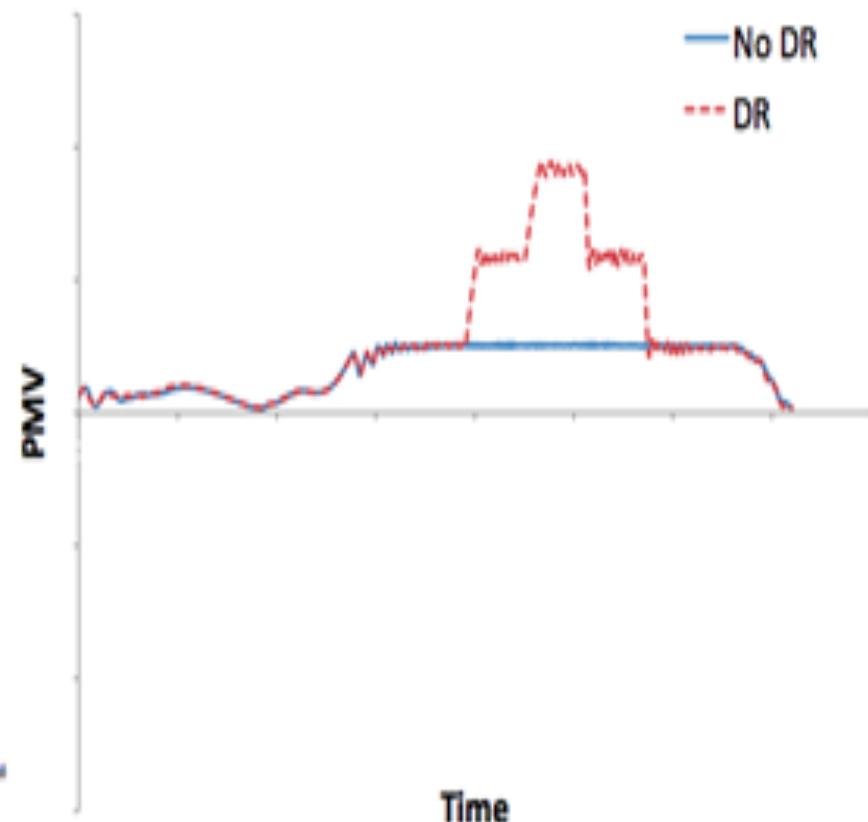
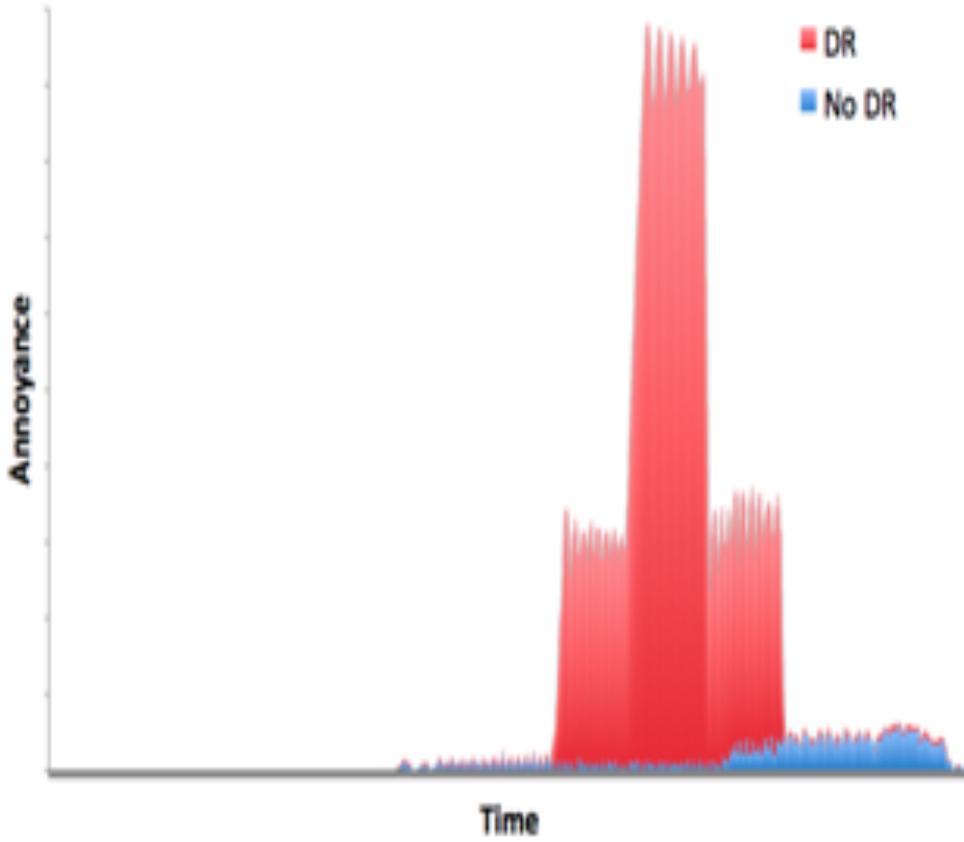
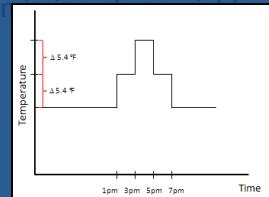
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DR Event

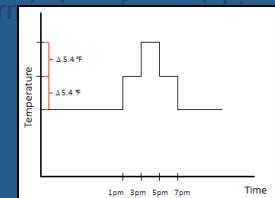


Point 5 - illustrates a larger rebound effect than Point 4 because at this point agents are given back complete control of their thermostat setting. The rebound effect is so evident in this model because no mitigating steps have been taken.

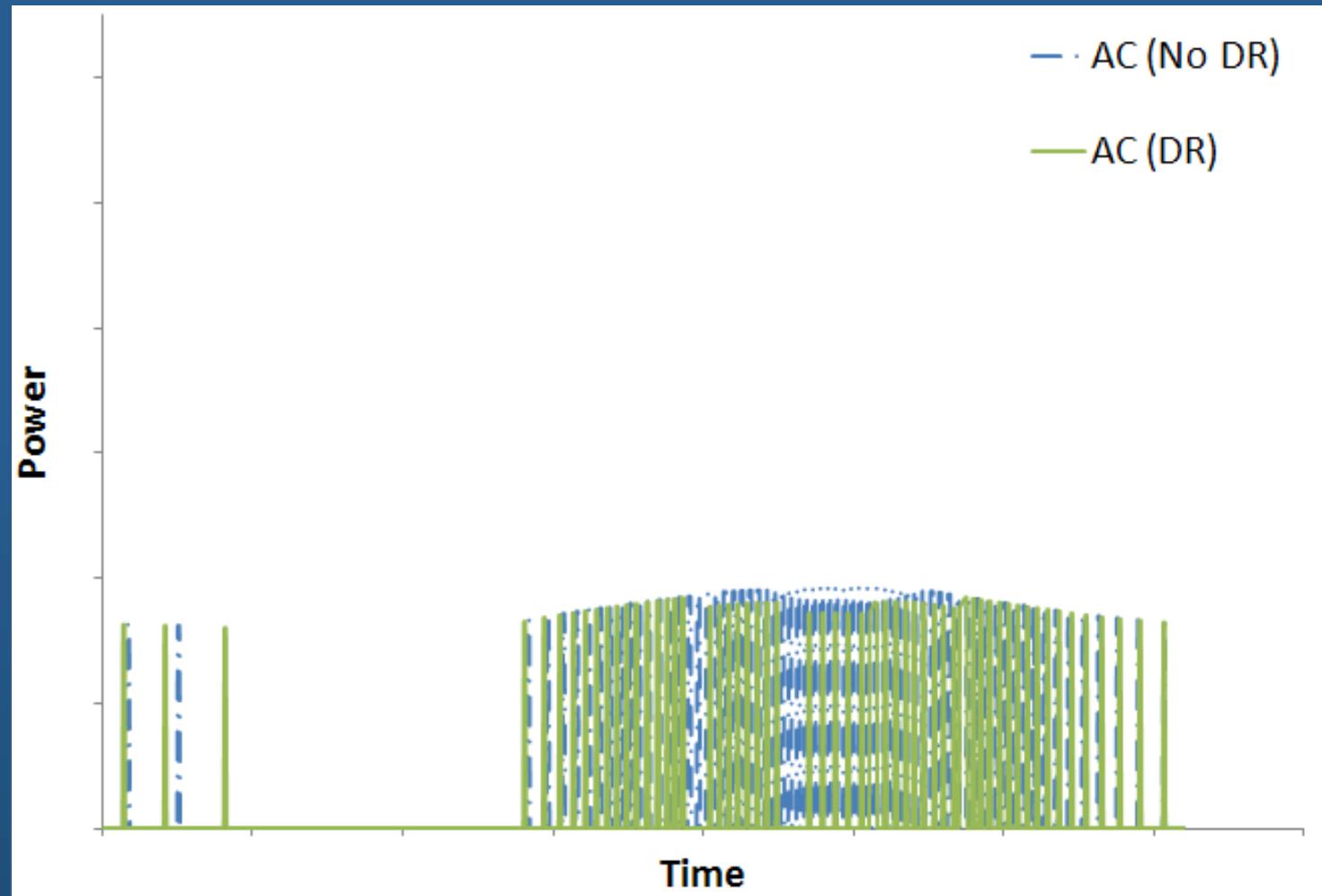
DR Event: Annoyance



DR Event: Individual Behavior

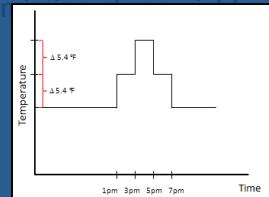


Agent 1

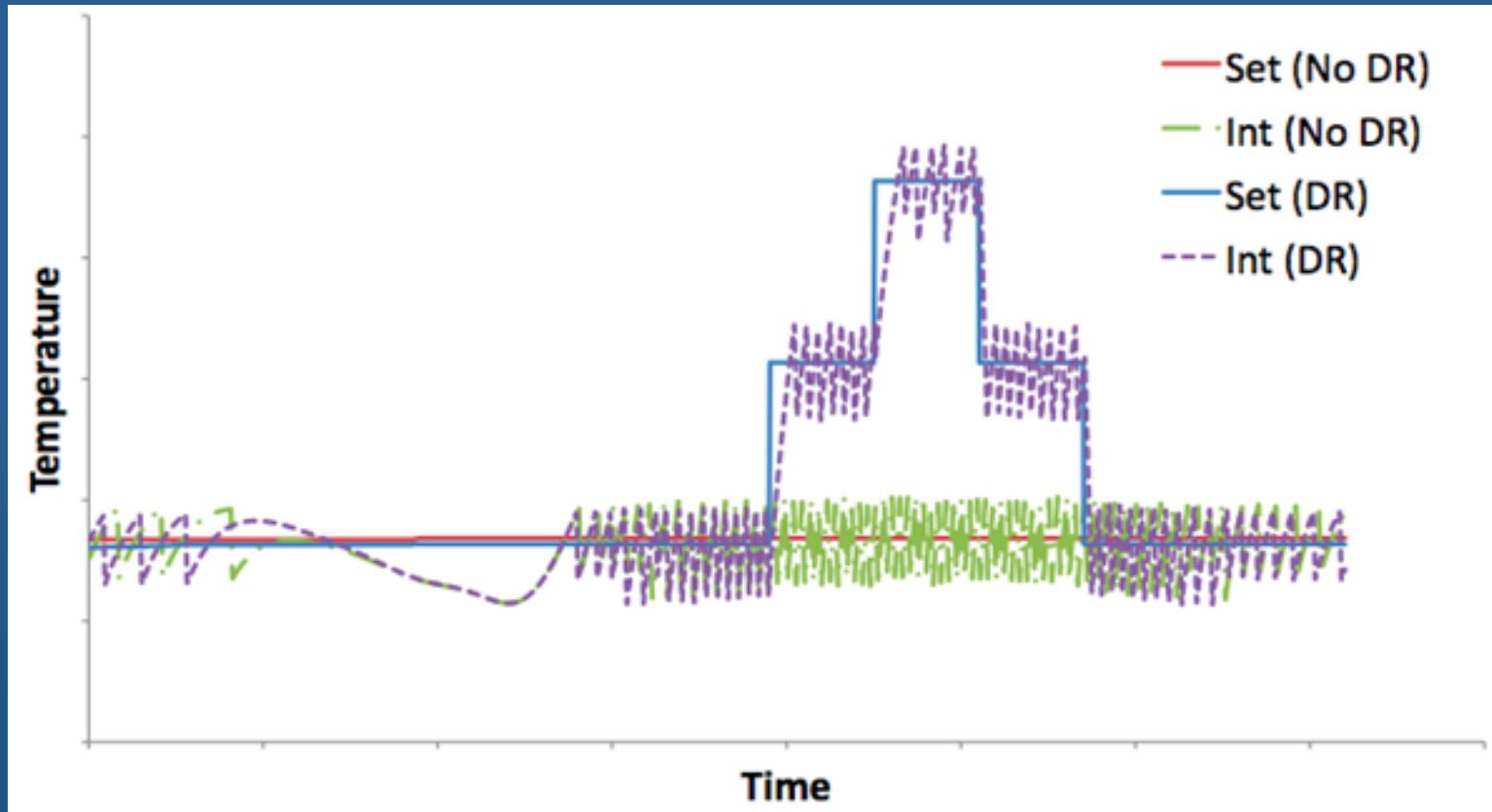


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DR Event: Individual Behavior



Agent 1



Agent 58 not shown because their usage does not change since they are gone throughout the day

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Conclusions

- This methodology can allow for examining many different DR schemes in order to gauge consumer reaction
- After simulating these DR schemes, the power generator/distributor can then determine which DR schemes seem the most promising
- By conducting pilot studies with this smaller number of DR schemes, the power generator/distributor has minimized their risk (in terms of money & reputation)

Conclusions

- Since ABM/S allows to examine the effects in a bottom-up approach, the code can be modified to include other DR schemes (e.g., pricing-based)
- This methodology is also extendable to include other areas of the Smart Grid and their (potential) impact on DR
 - Distributed storage
 - Distributed generation
 - Etc.

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Questions?

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