

Laboratory and Field Evaluations of Grid-Interactive Water Heaters

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Outline

- Smart Neighborhood
 - Using model predictive control for home-level optimization of heat pump water heaters

- Virtual Battery
 - Estimating demand limiting capability of standard electric water heaters



Smart Neighborhood - Hoover Alabama Site

Distributed Energy Resources Community Microgrid



Reynolds Landing Neighborhood



Smart Neighborhood - Architecture

Cloud-Based Operation

- Integrate with vendor API
- Virtual machine for home-level agents
- Virtual machine for aggregator
- Virtual machine for learning agents



Smart Neighborhood - Water Heater Model

Single-Node Model

- Mixed integer linear programming
- Fast solution
- Computationally light
- Guaranteed global optimum



Source And Contract And Research and Integration Center

Smart Neighborhood - Objective Function





Smart Neighborhood - Example Set of Data



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Smart Neighborhood - Example Set of Data



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Smart Neighborhood - Example Set of Data



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Smart Neighborhood – Conclusions and Future Work

- Challenging to work with equipment APIs (sensing overrides, achieving desired response with API inputs)
- Initial results aimed at load shaping are very encouraging

- Improve cycling behavior of MPC implementation
- Implement learning algorithm for hot water use
- Evaluate benefits to customer, utility, and society



Virtual Battery

- Objectives
 - Can building loads be used like batteries to provide demand-side power balancing?
 - Quantify typical power flexibility of building loads
 - Residential and Commercial HVAC
 - Residential Water Heaters
 - Commercial Refrigeration
 - How can the loads be controlled?



Virtual Battery – Load Leveling/Peak Limiting

- Evaluate the load leveling/peak limiting potential of electric resistance water heaters
 - 2-node model
 - Use measured hot water usage from Smart Neighborhood
 - Evaluate two control algorithms
 - Priority-Based Control
 - Model Predictive Control

Virtual Battery – Aggregate Hot Water Use



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Virtual Battery – Priority-Based Control



Note: Only lower element is controlled with PBC

Virtual Battery – Priority-Based Control

 40%-50% peak power reduction with negligible effect on upper tank temperatures



~600 W per WH peak power reduction potential



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Virtual Battery – Model Predictive Control



Power Exceeding Power Limit Target Minimum Temperature

Maximum Temperature Deviation from Set Point



Forecast period = 4 h Forecast interval = 2 h

Virtual Battery – Model Predictive Control

- 50+% load reduction with better temperature control than PBC
- Higher energy use

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 No cycling penalty in objective function, results in too many cycles



OAK RIDGE BUILDING TECHNOLOGIES ~700 W per WH peak power reduction





Virtual Battery – PBC + HPWH

 30% peak power reduction with negligible effect on upper tank temperature



~115 W per WH peak power reduction potential

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23:00 02:00 05:00 08:00 11:00 14:00 17:00 20:00 23:00

Virtual Battery – Water Heating

- Relatively diverse/asynchronous operation of water heaters allows for large flexibility and potential to use simple control strategies
- For aggregate control of water heaters, simple control strategies like priority-based control are likely sufficient
- This was just one example, load following or shaping is also feasible

