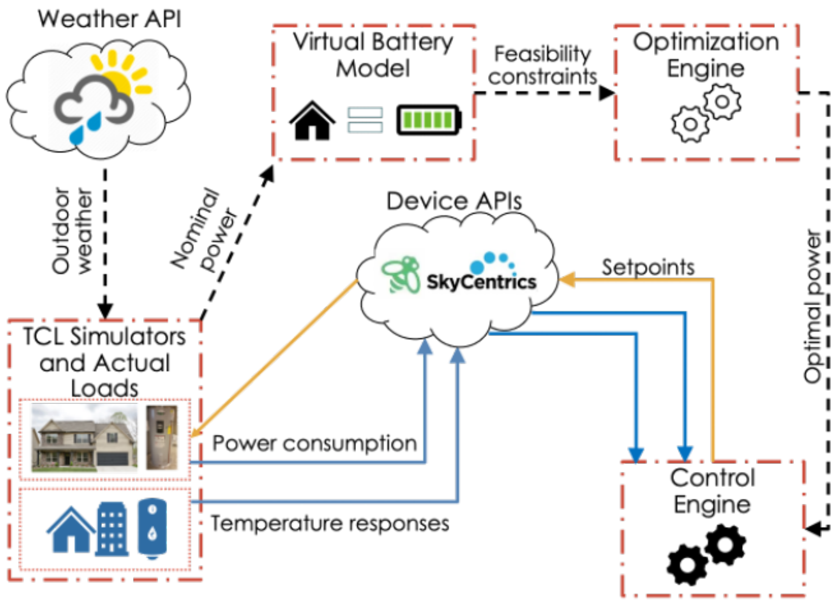
Hierarchical Model-Free Transactive Control of Building Loads to Support Grid Services



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Project Summary

Timeline:

Start date: 10/01/2018

Planned end date: 03/31/2022

Key Milestones

1. Large-scale (10,000 loads) tested and validated the hierarchical control strategy in simulation; 09/30/20
2. Field validated MFC to verify at least 80% reduction in computational requirements for grid-integrated efficient building (GEB) control as compared to MPC; 06/30/21

Budget:

Total Project $ to Date:

- DOE: $2,100,000
- Cost Share: $0

Total Project $:

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- Cost Share: $0

Key Partners:

Southern Company (SoCo)
University of Tennessee (UTK)

Project Outcome:

- Computationally efficient control retrofits to residential and small commercial buildings that enable ancillary services to the grid
- Open-source software and hardware specification document of the control platform to enable load integration and deployment
- Field-demonstration of the control technology and documentation of lessons learned

Team

Oak Ridge National Laboratory

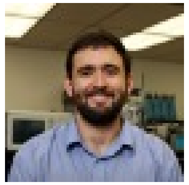
- Integration of the model-free control (MFC) strategy with the energy market
- Large-scale simulation-based testing of the hierarchical model-free transactive control mechanism
- Field testing of the hierarchical model-free transactive control mechanism at the ORNL Yarnell Station research house and the Southern Company smart neighborhood facility

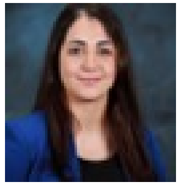

Dr. Mohammed Olama


Dr. Kadir Amasyali


Dr. Yang Chen


Dr. Byungkwon Park


Mr. Christopher Winstead


Ms. Helia Zandi


Mr. Jeffrey Munk


Dr. Teja Kuruganti

The University of Tennessee Knoxville

- Theoretical development of the MFC strategy


Dr. Seddik Djouadi


Ms. Bhagyashri Telsang


Mr. Tumin Wu

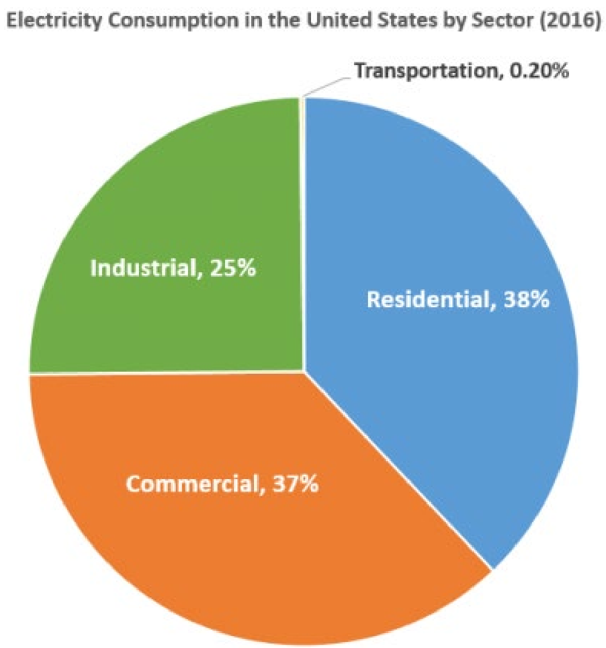
Southern Company

- Providing access and technical support for field testing and validation of the proposed control strategy at the smart neighborhood facility


Dr. Justin Hill

Challenge

- Traditionally, demand side management programs target industrial and large commercial buildings
- Residential buildings offer a potentially substantial (4.4 quads of electricity annually, ~ 38% of the total US electricity consumption) but underutilized source of ancillary grid services
- Some of the technical challenges include
  - Residential loads are small and disperse requiring aggregation of many buildings (scalability)
  - Unpredictable usage, making model identification difficult (modeling)
  - Satisfying occupant comfort constraints (customer satisfaction)
  - Implementing GEB mechanisms on computationally constrained environments (computational complexity)



https://www.epa.gov/energy/

Technical Approach

Control Development (FY19)

- Develop dynamic models for the different building loads—such as HVAC systems, water heaters, water pumps, and lighting
- Develop the hierarchical model-free and game-theoretic control approach

Scalable Solution (FY20)

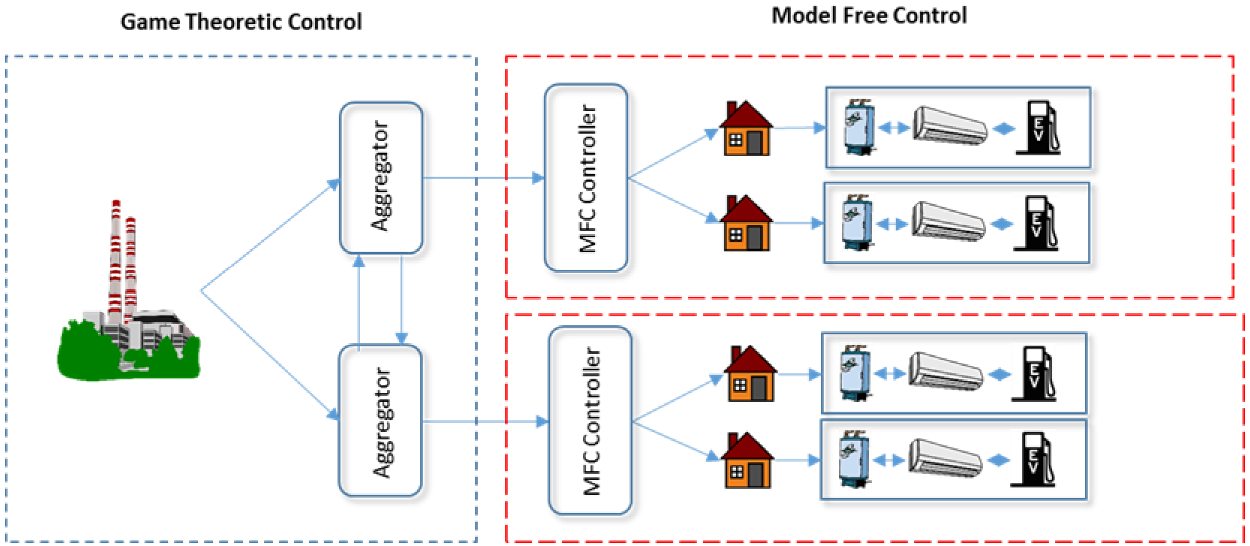
- Develop the system architecture
- Perform system-level simulations and analysis of various configurations of components (<100 loads)
- Develop a scalable solution for application over a large number of buildings (~10,000 loads)

Field Testing (FY21)

- Hardware testing of the control approaches at the ORNL Yarnell Station research house
- Hardware testing of the control approaches at the Southern Company smart neighborhood

Two-layer Control Scheme

- Control exists in two hierarchies
- Aggregators negotiate upstream with a utility (and in competition with each other) in a Game Theoretic control
- The aggregator controls downstream equipment with Model Free Control
- Game Theoretic control in the upper-layer is utilized to generate a tracking signal for use in the MFC lower-layer



Hierarchical Control

Upper Control Hierarchy

Day-ahead Market

Stackelberg Game

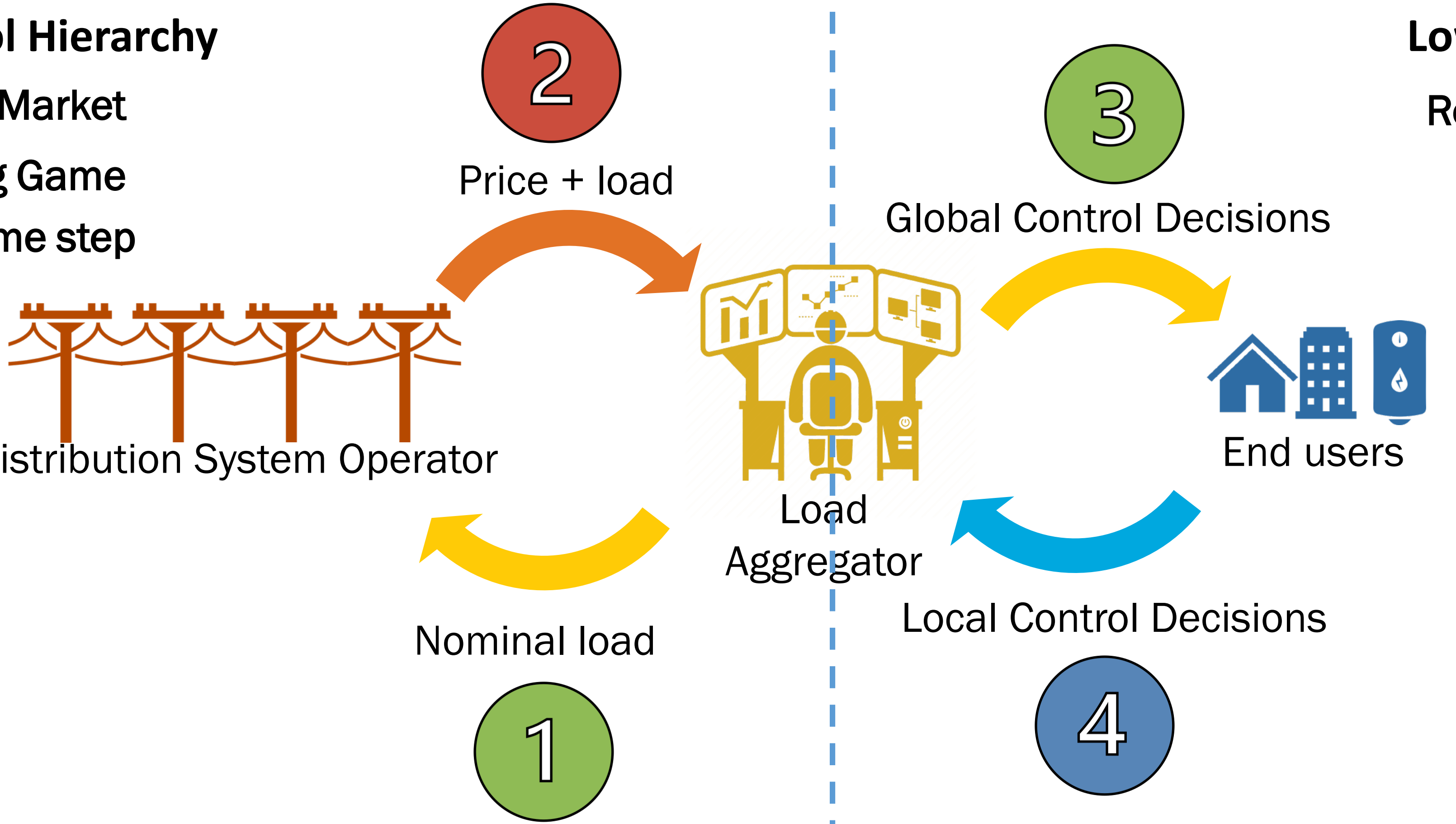
One-hour time step

Lower Control Hierarchy

Real-time Load Dispatch

Model-free Control

10-minute time step



GT Objectives:

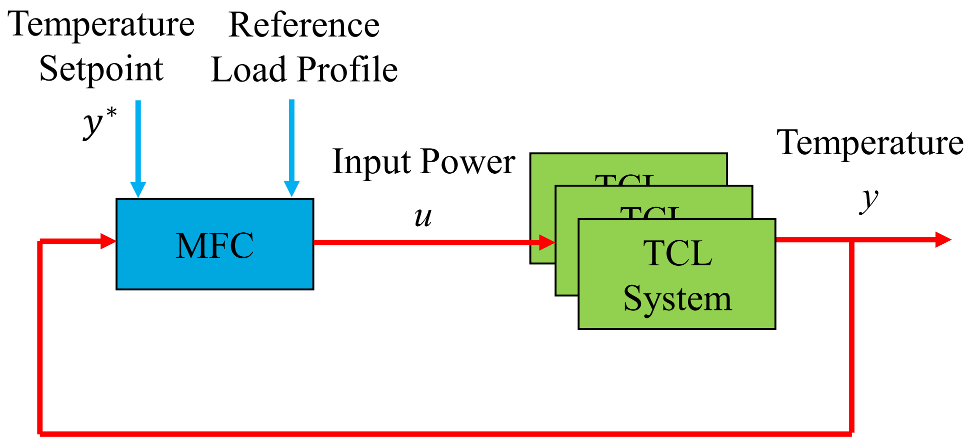
- Minimize peak demand / load shifting (DSO)
- Maximize DSO profit (DSO)
- Minimize electricity bills (LAs)
- Maintain end users' satisfaction (LAs)

MFC Objectives:

- The total TCLs consumption tracks the optimal reference power profile
- Maintain TCLs' temperatures within comfort bands

Model Free Control: Overview

- MFC, a relatively new form of control introduced in 2009 by Fleiss and Join[1], is based on "an elementary continuously updated local model via the unique knowledge of the input-output behavior"
- Deal with unknown linear and nonlinear system models and/or disturbances
- Computationally efficient
- The control gain K_p is explicitly computed at every time step
- The tracking error asymptotically converges to 0 for $K_p > 0$. This indicates that the MFC strategy is asymptotically stable[2]



$$\dot{y} = F + \alpha\, u$$

$$\hat{F} = \frac{-6}{L^3}\int_{t-L}^{t} [(L-2\sigma)y(\sigma) + \alpha\sigma(L-\sigma)u(\sigma)]d\sigma$$

$$u = -\frac{\hat{F} - \dot{y}^* + K_p(y - y^*)}{\alpha}$$

$$\dot{e} + K_p e = 0,\ e = y - y^*$$

$$e(t) = e(t_0)\exp\left(-K_p(t - t_0)\right)$$

$$K_p = \frac{\log e(t_0) - \log e(t)}{t - t_0}$$

[1]M. Fliess and C. Join, "Model-free control and intelligent PID controllers: Towards a possible trivialization of nonlinear control?," *IFAC Proc. Volumes,* vol. 42, no. 10, pp. 1531-1550, 2009.
[2]B. Telsang, M. Olama, S. Djouadi, J. Dong, and T. Kuruganti, "Stability analysis of model-free control under constrained inputs for control of building HVAC systems," in Proc. of the American Control Conference (ACC'19), Philadelphia, PA, July 2019.

One Leader N-follower Stackelberg Game

Upper level: determines the **price**

$$\max_{p_t, l_{n,t}} \sum_{n,t} p_t . l_{n,t} - \sum_{n,t} C_t . l_{n,t} + \sum_{n,t} S(l_{n,t}, D_{n,t}) - \theta . T . m$$

Revenue — Elec. Cost — Customer Satisfaction — Peak Demand

$C_t \leq p_t$ (boundary for prices)

$m \geq \sum_n l_{n,t}, \forall t$ (peak load calculation)

Lower level: determines the load

$$\max_{l_{n,t}} \sum_t S(l_{n,t}, D_{n,t}) - \sum_t p_t . l_{n,t}$$

Customer Satisfaction — Elect. Bill

Parameters	Definition
T, N	Total hours, total aggregators
$D_{n,t}$	Nominal demand of LA n
C_t	Incremental marginal cost of electricity
$\alpha_{n,t}$	Users' sensitivity to comfort
θ	Penalty weight on peak load
Variables	**Definition**
p_t	Unit sale price of electricity
$l_{n,t}$	Actual load for LA n in response to price
m	Peak load

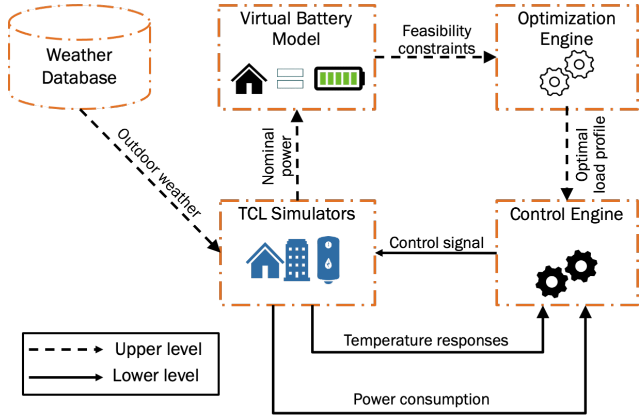
$b_{n,t} = b_{n,t-1} + dr_{n,t-1} - P_{0_{n,t-1}}$ (Battery-equivalent model for LA n)

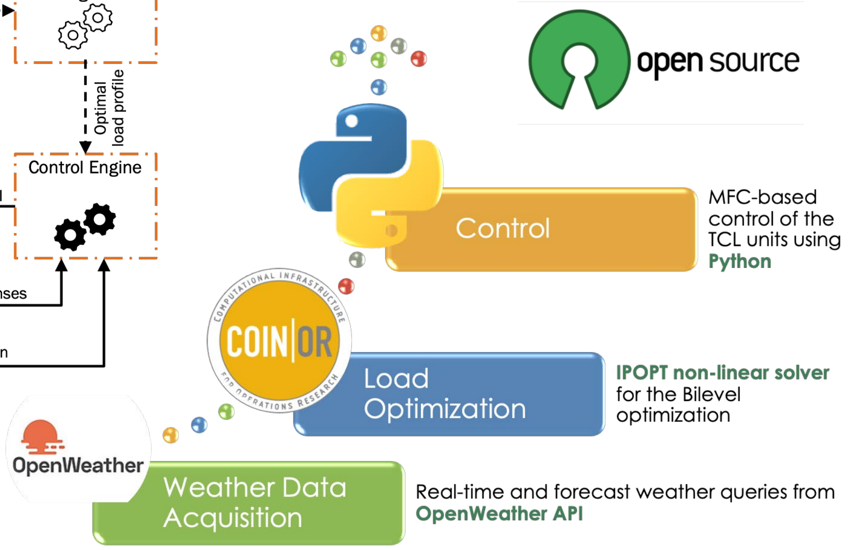
$\underline{B}_{n,t} \leq b_{n,t} \leq \bar{B}_{n,t}$ (Bound of virtual battery SOC for LA n)

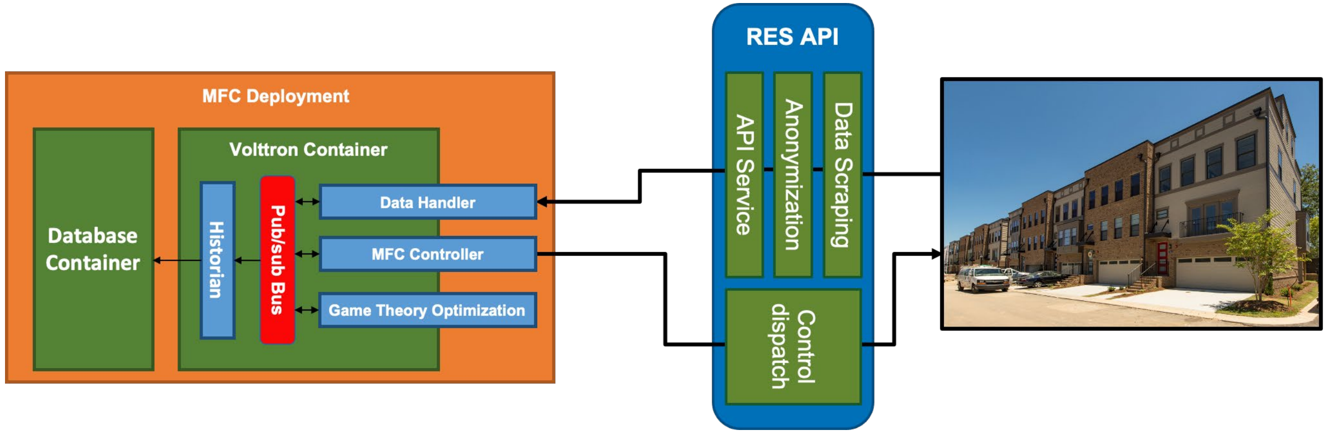
$S(l_{n,t}, D_{n,t}) = \sum_t D_{n,t} \cdot \left(\frac{l_{n,t}}{D_{n,t}}\right)^{\alpha_{n,t}}$ (Customer satisfaction for LA n)

Implementation Control Schema

- **Cloud** implementation with associated data-gathering and control modules
- **Containerization** eases deployment concerns across different possible environments
- MFC controller and associated functions ran on **Volttron** framework as agents
- Database and historian allows for post test data analysis and visualization



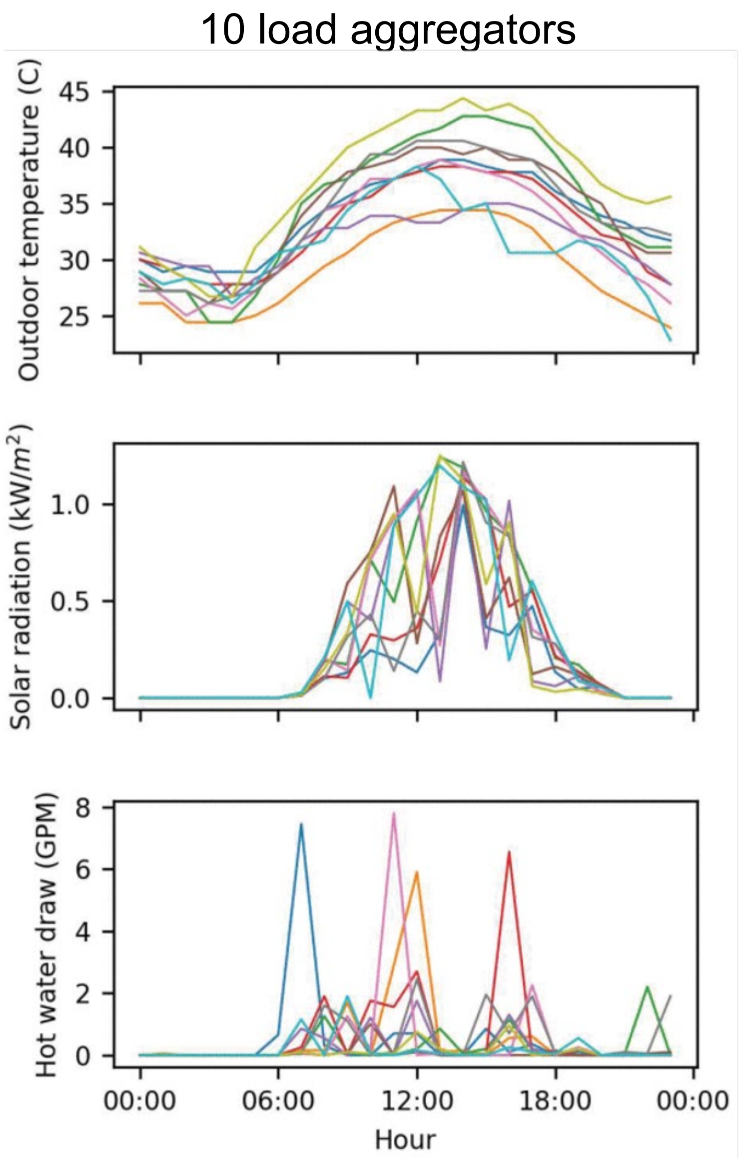




Large-scale Simulation-based Case Study

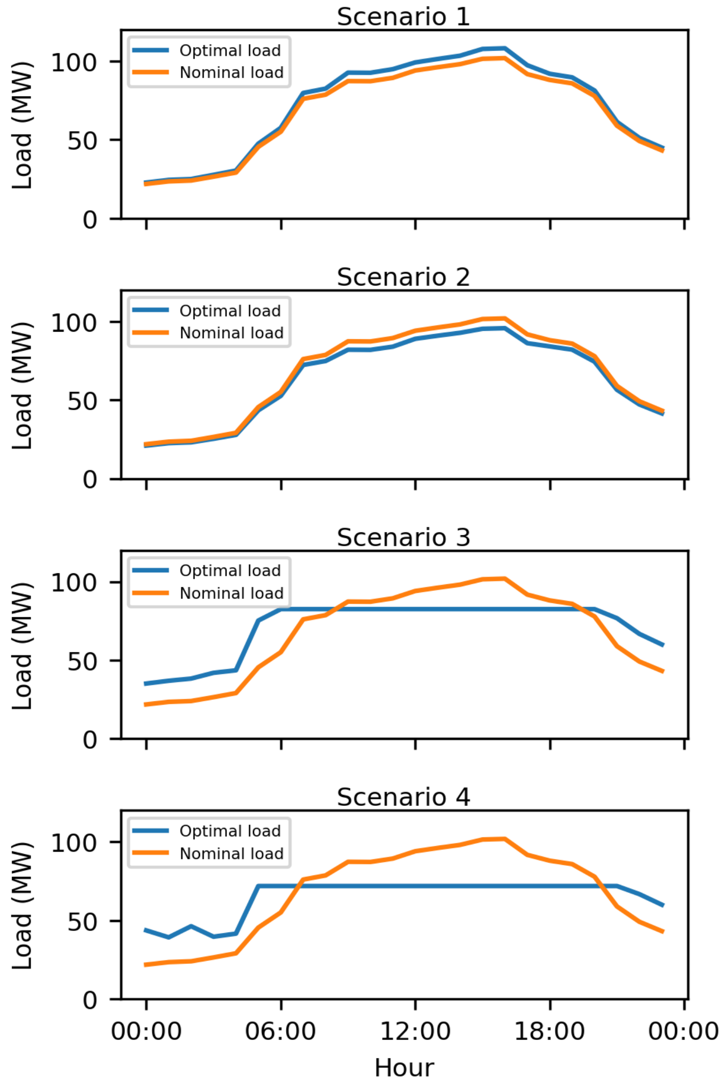
- Ten load aggregators, each has 1,000 TCLs. Totally 10,000 heterogenous TCLs, including residential/commercial HVAC and WH units
- External temperature, solar radiation, hot water usage are used to generate nominal power profiles
- Four scenarios

1. Flat pricing
   Peak load reduction weight (θ) = 10
2. Flat pricing
   Peak load reduction weight (θ) = 20
3. Time-of-use pricing
   Peak load reduction weight (θ) = 10
4. Time-of-use pricing
   Peak load reduction weight (θ) = 20



Results

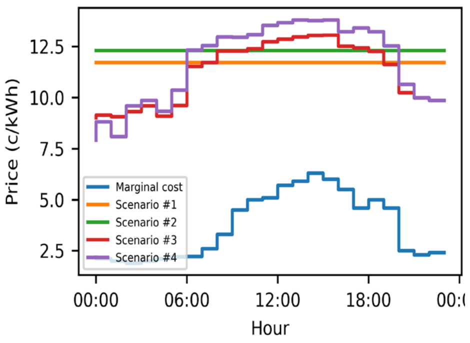
Peak Load Reduction



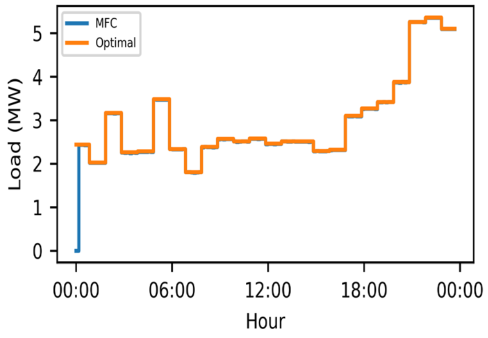
Four Scenarios

1. Flat pricing
   Peak load reduction weight (θ) = 10
2. Flat pricing
   Peak load reduction weight (θ) = 20
3. Time-of-use pricing
   Peak load reduction weight (θ) = 10
4. Time-of-use pricing
   Peak load reduction weight (θ) = 20

Optimal price signals

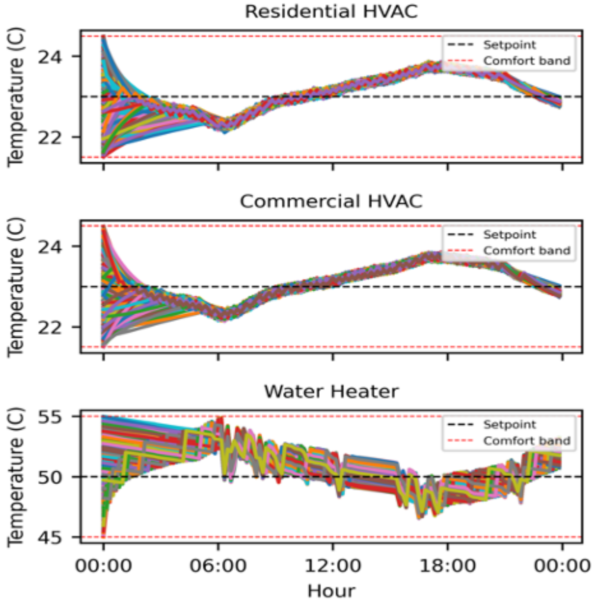


Power Tracking



Results of the Stackelberg game

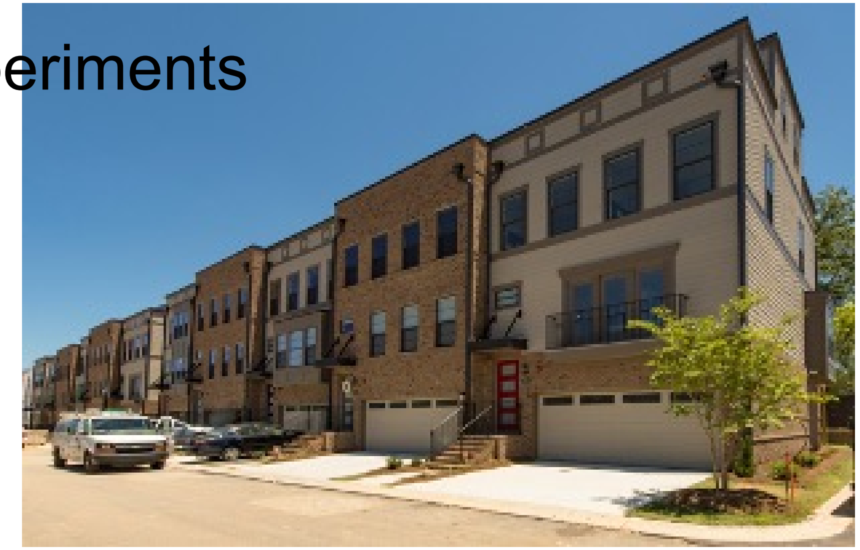
Objective	Scenario 1	Scenario 2	Scenario 3	Scenario 4
DSO Profit	\$128,371	\$125,033	**\$129,625**	\$126,087
DSO Satisfaction	369,423	225,935	**404,451**	292,971
Peak Load	108.20 MW	95.69 MW	82.51 MW	**71.92 MW**
LA 1 Cost	\$20,785	\$19,686	\$20,428	**\$19,336**
LA 1 Satisfaction	41,336	39,242	41,188	39,164



- TOU achieves more profit and peak reduction
- Tradeoff between peak load and profit
- Temperature within comfort bound
- Perfect power tracking

Field Testing: Case Studies with Actual Loads

Four weeks of experiments

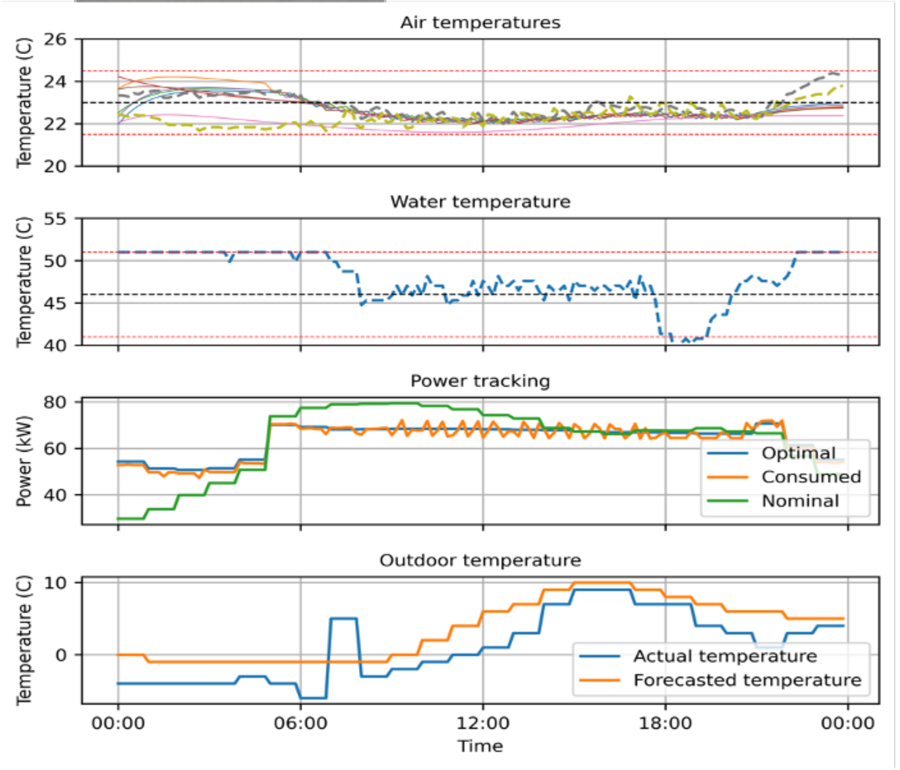


- ORNL Yarnell Station, emulated occupancy
- A 2400 sqft two-story unoccupied residential building with emulated occupancy
  - Two thermal zones
  - A 66-gal water heater
- Seven simulated HVAC and water heater units

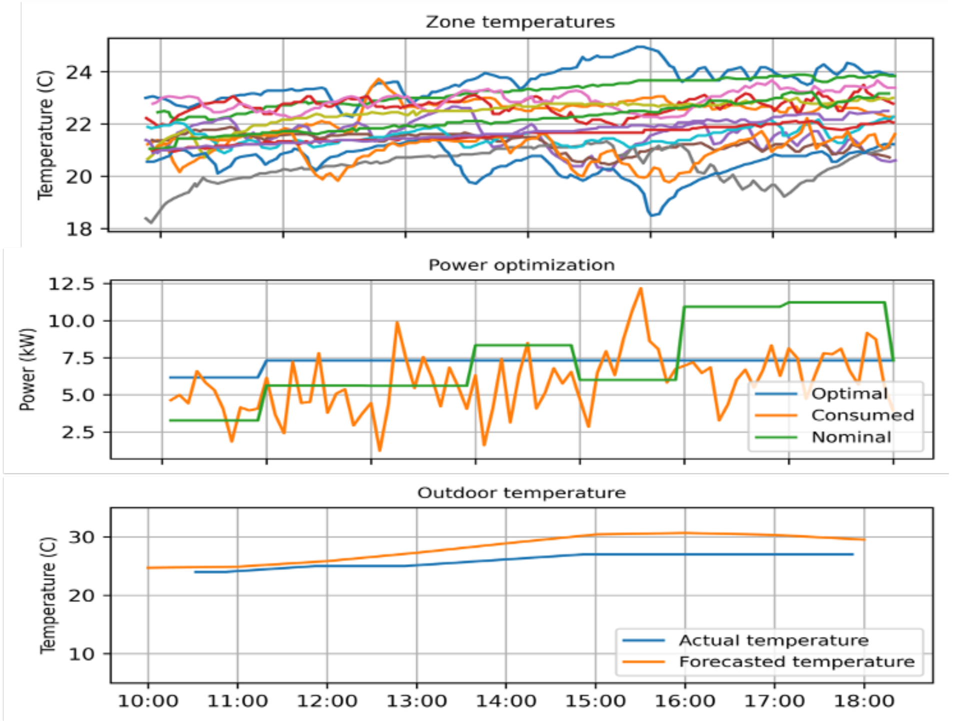
- **Southern Company Smart Neighborhood**
- **Five homes, each having 3 zones**
  - Each home is equipped with smart HVAC and WH
  - A dedicated API providing (named RES) anonymized home device information
  - In home sensor infrastructure for power sub-metering, extra thermal data
  - Cloud-based platform to host and run control applications

Field Testing Results

Jan. 14, 2021



June 23, 2021



	Average time 1 home (s)	Average time 35 homes (s)	Total time spent in computation over 24 hours (s)
MPC	4.13	144.6	20815.2
MFC	0.0007	.025	3.53

5900 times faster (wow)

Impact

- Enable large-scale residential aggregation to engage demand-side flexibility to reliably provide grid services
- Field testing verified that MFC is about 6000 times faster than the conventional MPC. **This will potentially enable many ancillary services that require high frequency computation such as regulation services.**
- Provide a seamless interface between the grid service requests of utilities and the reliable control required by participating buildings
  - No modeling of building loads is required
  - Computationally efficient
  - Guarantee occupants' comfort

Stakeholder Engagement

- **Strategically collaborated with the Southern Company that**
  - Provided feedback about the feasibility and practicality of the proposed approach
  - Provided access and technical support for field testing and validation of the proposed control strategy at their smart neighborhood facility
  - Showed interest in licensing the proposed technology
- **Recently contacted Duke Energy for potential large-scale field testing and validation of the proposed approach**

Remaining Project Work

- **This is a late-stage project that is expected to end by Mar. 31, 2022.**
- **Proposed remaining work:**
  - Develop a stochastic/robust game-theoretic optimization to handle the various uncertainties in the system (e.g., weather forecasts, aggregate nominal demand forecasts, wholesale market prices, etc.)
  - Develop an enhanced model-free controller that can handle practical issues such as communication delays and packet losses.
- **To date, 15 research papers have been published (6 journal papers and 9 conference papers)**

Thank you

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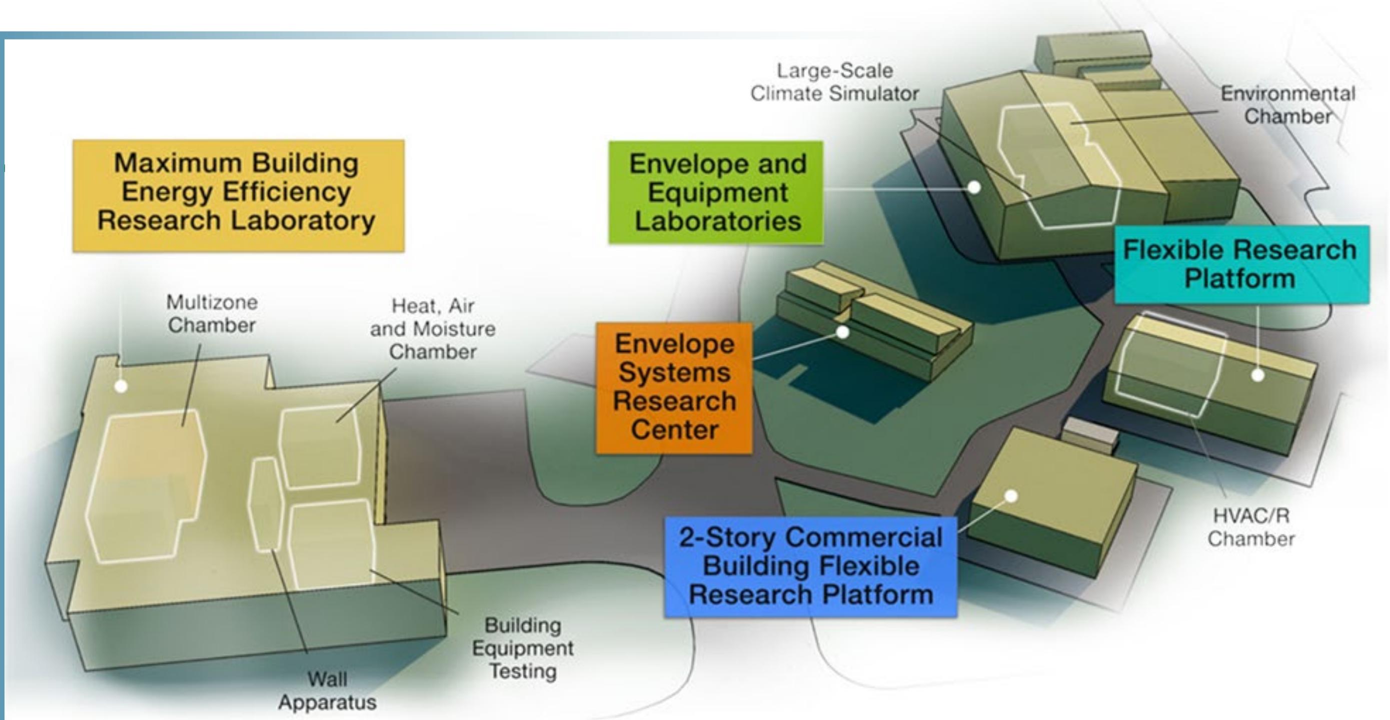


ORNL's Building Technologies Research and Integration Center (BTRIC) has supported DOE BTO since 1993. BTRIC is comprised of 50,000+ ft^2 of lab facilities conducting RD&D to support the DOE mission to equitably transition America to a carbon pollution-free electricity sector by 2035 and carbon free economy by 2050.

Scientific and Economic Results

238 publications in FY20
125 industry partners
27 university partners
10 R&D 100 awards
42 active CRADAs

BTRIC is a DOE-Designated National User Facility

REFERENCE SLIDES

Journal Publications

1) K. Amasyali, Y. Chen, B. Telsang, M. Olama, and S. Djouadi, “Hierarchical Model-free Transactional Control of Building Loads to Support Grid Services,” IEEE Access, vol. 8, pp. 219367-219377, Nov. 2020.

2) B. Telsang, K. Amasyali, Y. Chen, M. Olama, and S. Djouadi, “Power Allocation by Load Aggregator with Heterogeneous Loads using Weighted Projection,” Energy and Buildings, vol. 244, Article ID 110955, Aug. 2021.

3) X. Kou, F. Li, J. Dong, M. Olama, M. Starke, Y. Chen, and H. Zandi, "A Comprehensive Scheduling Framework using SP-ADMM for Residential Demand Response with Weather and Consumer Uncertainties," IEEE Transactions on Power Systems, vol. 36, no. 4, pp. 3004-3016, July 2021.

4) X. Kou, Y. Du, F. Li, H. Pulgar-Painemal, H. Zandi, J. Dong, and M. Olama, “Model-Based and Data-Driven HVAC Control Strategies for Residential Demand Response,” IEEE Open Access Journal of Power and Energy, vol. 8, pp. 186-197, May 2021.

5) Y. Chen, B. Park, X. Kou, M. Hu, J. Dong, F. Li, K. Amasyali, and M. Olama, “A Comparison Study on Trading Behavior and Profit Distribution in Local Energy Transaction Games,” Applied Energy, vol. 280, Article ID 115941, Dec. 2020.

6) X. Kou, F. Li, J. Dong, M. Starke, J. Munk, Y. Xue, M. Olama, and H. Zandi, "A Scalable and Distributed Algorithm for Managing Residential Demand Response Programs using Alternating Direction Method of Multipliers (ADMM)," IEEE Transactions on Smart Grid, vol. 11, no. 6, pp. 4871-4882, Nov. 2020.

Conference Publications

7) K. Amasyali and M. Olama, “Gaussian Process Regression for Aggregate Baseline Load Forecasting,” Annual Modeling and Simulation Conference, July 2021.
8) T. Wu, M. Olama, and S. Djouadi, “Adaptive Control for Residential HVAC Systems to Support Grid Services,” in Proc. of the IEEE Conference on Innovative Smart Grid Technologies (ISGT), Feb. 2021.
9) Y. Chen, M. Olama, X. Kou, K. Amasyali, J. Dong, and Y. Xue, “Distributed Solution Approach for a Stackelberg Pricing Game of Aggregated Demand Response,” in Proc. of the IEEE PES General Meeting, Aug. 2020.
10) A. Melin and M. Olama, “A Comfort Model Simplification for Tight Integration with Grid Services Optimizations,” in Proc. of the IEEE PES General Meeting, Aug. 2020.
11) Y. Chen, X. Kou, M. Olama, H. Zandi, C. Liu, S. Kassaee, B. Smith, A. Abu-Heiba, and A. M. Momen, “Bi-Level Optimization for Electricity Transaction in Smart Community with Modular Pump Hydro Storage,” in Proc. of the ASME 2020 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE 2020), Aug. 2020.
12) K. Amasyali, Y. Chen, and M. Olama, “Genetic Algorithm for Demand Response: A Stackelberg Game Approach,” in Proc. of the 2020 Spring Simulation Conference (SpringSim'20), May 2020.
13) K. Amasyali, M. Olama, and A. Perumalla, “A Machine Learning-based Approach to Predict the Aggregate Flexibility of HVAC Systems,” in Proc. of the IEEE Conference on Innovative Smart Grid Technologies (ISGT), Feb. 2020.
14) B. Telsang, M. Olama, S. Djouadi, J. Dong, and T. Kuruganti, “Stability Analysis of Model-free Control under Constrained Inputs for Control of Building HVAC Systems,” in Proc. of the IEEE American Control Conference (ACC’19), Jul. 2019.
15) Y. Chen, M.M. Olama, T. Rajpurohit, J. Dong, and Y. Xue, “Game-Theoretic Approach for Electricity Pricing Between Distribution System Operator and Load Aggregators,” in Proc. of the 3rd IEEE International Conference on Smart Grid and Smart Cities (ICSGSC’19), Jun. 2019.

Project Budget

Project Budget: $2,100,000.
Variances: None.
Cost to Date: $2,100,000.
Additional Funding: None.

Budget History					
10/01 – FY 2019 (past)		FY 2020 (past)		FY 2021 – 09/30 (current)	
DOE	Cost-share	DOE	Cost-share	DOE	Cost-share
700,000	0,0	700,000	0,0	700,000	0,0

Project Plan and Schedule

Project Schedule												
Project Start: 10/01/2018		Completed Work										
Projected End: 09/30/2021		Active Task (in progress work)										
	◆	Milestone/Deliverable (Originally Planned) use for										
	◆	Milestone/Deliverable (Actual) use when met on time										
	FY2013				FY2014				FY2015			
Task	Q1 (Oct-Dec)	Q2 (Jan-Mar)	Q3 (Apr-Jun)	Q4 (Jul-Sep)	Q1 (Oct-Dec)	Q2 (Jan-Mar)	Q3 (Apr-Jun)	Q4 (Jul-Sep)	Q1 (Oct-Dec)	Q2 (Jan-Mar)	Q3 (Apr-Jun)	Q4 (Jul-Sep)
Past Work												
Q1 Milestone: Development/Collection of dynamic models for the various building loads	◆											
Q2 Milestone: Development of the model-free controller		◆										
Q3 Milestone: Development of the game-theory controller			◆									
Q4 Milestone: Integration of the model-free and game-theory controllers				◆								
Q1 Milestone: Development of system architecture					◆							
Q2 Milestone: Small-scale system-level simulation						◆						
Q3 Milestone: Development of scalable solution							◆					
Q4 Milestone: Large-scale system-level simulation								◆				
Q1 Milestone: SField testing at the ORNL research house									◆			
Q2 Milestone: Field testing preparation at the Southern Company smart neighborhood										◆		
Q3 Milestone: Field testing validation at the Southern Company smart neighborhood											◆	
Current/Future Work												
Q4 Milestone: Final report												◆

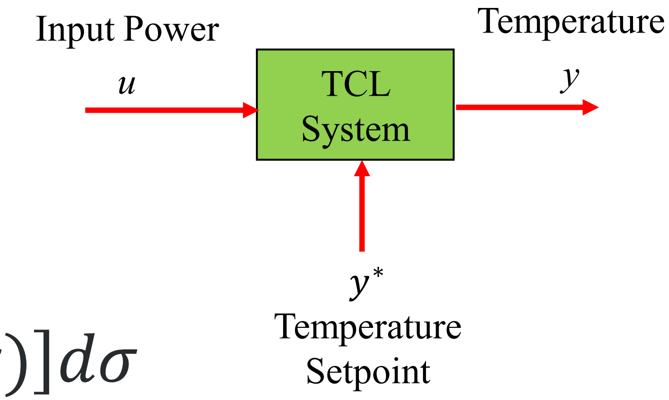
PID vs. MFC vs. MPC

Traditional PID	MFC (Intelligent PID)	MPC
Data driven (model free)	Data driven (model free)	Model based
Control decision is based on the system output (TCL temperature)	Control decision is based on the internal system dynamics as well as the system output (TCL temperature)	Control decision is based on the internal system dynamics, system output, and forecasted disturbances
Tuning the control gain(s) are based on trial and error	The control gain(s) can be explicitly computed	The control gain(s) can be explicitly computed
Straight forward	Simple Approximation (intelligent PID)	Quadratic Programming Optimization
Non-optimal	Sub-optimal (comparable performance to MPC)	Optimal
No guarantee of stability	Asymptotically stable	Stable
Computationally efficient	Computationally efficient	Computationally expensive

Model Free Control: Theoretical Development[1]

- Approximate the unknown system by an **ultra-local** model

$$\dot{y} = F + \alpha\, u$$



- F is **approximated** by a **piecewise constant** function

$$\hat{F} = \frac{-6}{L^3} \int_{t-L}^{t} [(L - 2\sigma)y(\sigma) + \alpha\sigma(L - \sigma)u(\sigma)]d\sigma$$

- An **intelligent proportional controller** is proposed

$$u = -\frac{\hat{F} - \dot{y}^* + K_p(y - y^*)}{\alpha}$$

- The **error** dynamics are governed by $\dot{e} + K_p e = 0$

  where $e = y - y^*$ is the **temperature tracking error**

[1]M. Fliess and C. Join, "Model-free control and intelligent PID controllers: Towards a possible trivialization of nonlinear control?" *IFAC Proc. Volumes,* vol. 42, no. 10, pp. 1531-1550, 2009.

Model Free Control: Stability

- Let t_0 be the initial time, then the solution to error ODE is:

$$e(t) = e(t_0)\exp\left(-K_p(t-t_0)\right), \quad K_p = \frac{log\, e(t_0) - log\, e(t)}{t - t_0}$$

  - The control gain K_p is explicitly computed at every time step using the above equality (it is not a tuning parameter as in the traditional PID)
  - The tracking error asymptotically converges to 0 for $K_p > 0$. This indicates that the MFC strategy is asymptotically stable (in contrast to the traditional PID).
  - We also showed in a recent paper[2] that the system is asymptotically stable even when u is constrained with discrete states (on/off)

[2]B. Telsang, M. Olama, S. Djouadi, J. Dong, and T. Kuruganti, "Stability Analysis of Model-free Control under Constrained Inputs for Control of Building HVAC Systems," in *Proc. of the IEEE American Control Conference (ACC'19)*, Philadelphia, PA, July 2019.

Model Free Control: Power Tracking

- The power tracking (the total power consumed by building TCLs should track a reference load profile) is imposed by the following hard constraint

$$P(t) - \varepsilon \le \sum_{k=1}^{N} u_k(t) \le P(t) + \varepsilon$$

- For discrete on/off TCLs, it is implemented using a rank-based control algorithm. Higher values of local control decision values have higher priorities to be switched on or off.
- Note that in MFC the priorities are determined based on the control decision values instead of temperature deviations as in the conventional priority-based control

Power Tracking/Allocation for Discrete on/off TCLs

- Execute MFC without the power-tracking constraint
- The power tracking is imposed by applying rank-based control based on the local control decisions as described in **Algorithm 1**
- Different weights (importance) can be assigned to the different types of TCLs in a straightforward manner

[3] **Algorithm 1** Power Allocation of TCLs for LA n

1: FOR every time step, t
2: FOR every TCL j with rated power of $P_m(j)$
3: Compute u
4: Sort u values in descending order and get the rank r of TCLs
5: Initialize as $P_{consumed} = 0$ and $r = 1$
6: WHILE $P_{consumed} \leq P_{allocated}$
7: Find the TCL j with the rank of r
8: Turn on the TCL j
9: $P_{consumed} := P_{consumed} + P_m(j)$
10: $r := r + 1$

[3] K. Amasyali, Y. Chen, B. Telsang, M. Olama, and S. Djouadi, "Hierarchical Model-free Transactional Control of Building Loads to Support Grid Services," IEEE Access, vol. 8, pp. 219367-219377, Nov. 2020.