

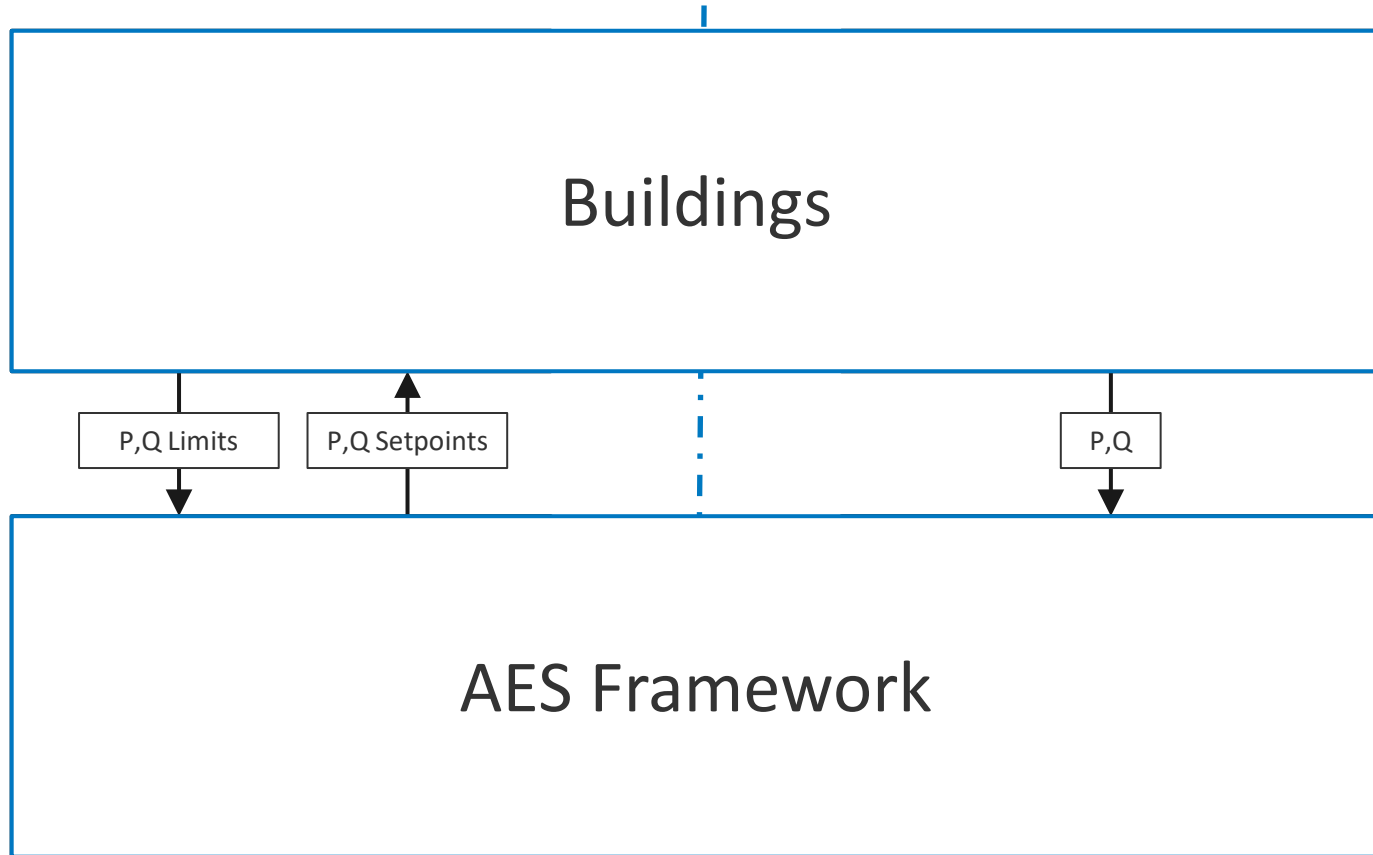


Scalable Distributed Model Predictive Control for Building and Renewable Energy Systems

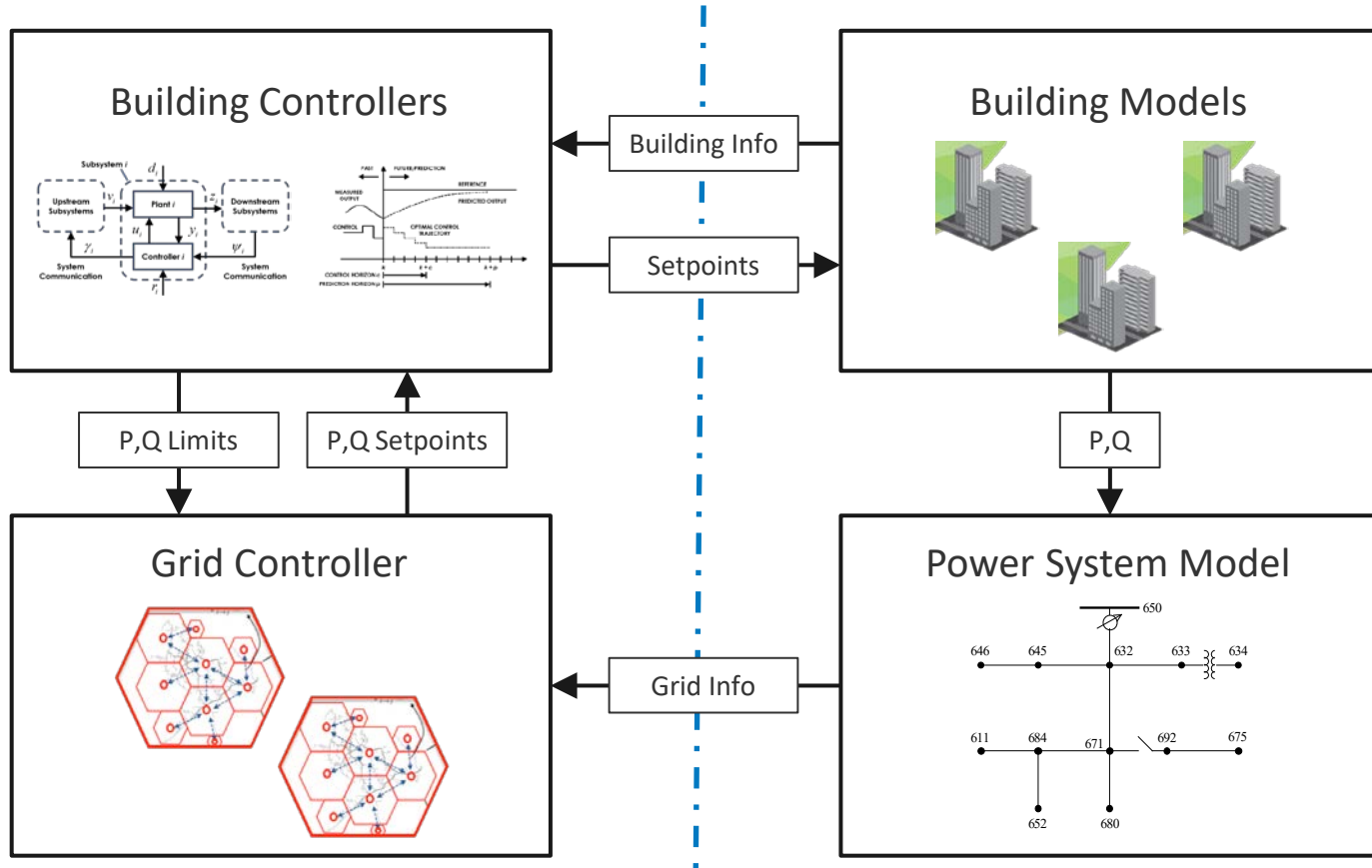
Christopher Bay, Rohit Chintala,
Jennifer King, and Venkatesh Chinde

06.20.2020

Overview



Overview



Modeling and Control of Buildings

- Building control traditionally focused on energy reduction and occupant comfort
- Need for buildings to provide ancillary services (while keeping people happy)
- Need for coordinating large numbers of building energy systems
- MPC lends itself to a lot of the challenges found in buildings
- Technique presented today has also been applied to wind farm control

PARETO OPTIMAL SETPOINTS FOR HVAC NETWORKS VIA ITERATIVE NEAREST NEIGHBOR COMMUNICATION

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Abstract
HVAC systems in large buildings have many overlapping control objectives. This paper presents a distributed control strategy for a network of coupled subsystems based on a set of distributed objectives. According to this strategy, the coupling signals from upstream subsystems and at the same time their neighbors, in concert with local MPC or subsystem setpoints, are used to determine the Pareto optimal setpoints for the entire network. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol.

Introduction
Commercial building energy systems are becoming increasingly complex and widely distributed and individual control strategies are needed. Thus, the optimal building control problem is a large-scale, distributed optimization problem. A typical solution is to use a Model Predictive Control (MPC) or a similar control strategy to control each subsystem. However, this approach is often suboptimal because of the lack of coordination between subsystems. In this paper, we propose a distributed control strategy for a network of coupled subsystems based on a set of distributed objectives. According to this strategy, the coupling signals from upstream subsystems and at the same time their neighbors, in concert with local MPC or subsystem setpoints, are used to determine the Pareto optimal setpoints for the entire network. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol.

Index Terms—Coupled task, predictive control, MPC, Pareto optimal, distributed control.

I. INTRODUCTION
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Chair of Committee, Bryan P. Roe
Committee Members, David A. McAniff, David E. Chaffin, Aniruddha D. S. Jayaraman
Head of Department, Andreas Polydoropoulos

Major Subject: Mechanical Engineering

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LIMITED-COMMUNICATION DISTRIBUTED MODEL PREDICTIVE CONTROL FOR HVAC SYSTEMS

A Dissertation
by
RAWAND EHSAN JALAL

Abstract
This paper presents a distributed control strategy for a network of coupled subsystems based on a set of distributed objectives. According to this strategy, the coupling signals from upstream subsystems and at the same time their neighbors, in concert with local MPC or subsystem setpoints, are used to determine the Pareto optimal setpoints for the entire network. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol.

Active Power Control for Wind Farms Using Distributed Model Predictive Control and Nearest Neighbor Communication

Christopher J. Bay,^{1,2} Jennifer Annoni,¹ Timothy Taylor,¹ Lacy Post,¹ and Kathryn Johnson^{1,2}

Abstract—Wind plant control strategies are becoming increasingly complex and widely distributed and individual control strategies are needed. Thus, the optimal building control problem is a large-scale, distributed optimization problem. A typical solution is to use a Model Predictive Control (MPC) or a similar control strategy to control each subsystem. However, this approach is often suboptimal because of the lack of coordination between subsystems. In this paper, we propose a distributed control strategy for a network of coupled subsystems based on a set of distributed objectives. According to this strategy, the coupling signals from upstream subsystems and at the same time their neighbors, in concert with local MPC or subsystem setpoints, are used to determine the Pareto optimal setpoints for the entire network. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol. The Pareto optimal setpoints are determined iteratively through a nearest neighbor communication protocol.

Steady-State Predictive Optimal Control of Integrated Building Energy Systems Using a Mixed Economic and Occupant Comfort Focused Objective Function

Christopher J. Bay,^{1,2} Rohit Chittala^{1,2} and Bryan P. Rasmussen^{1,2}

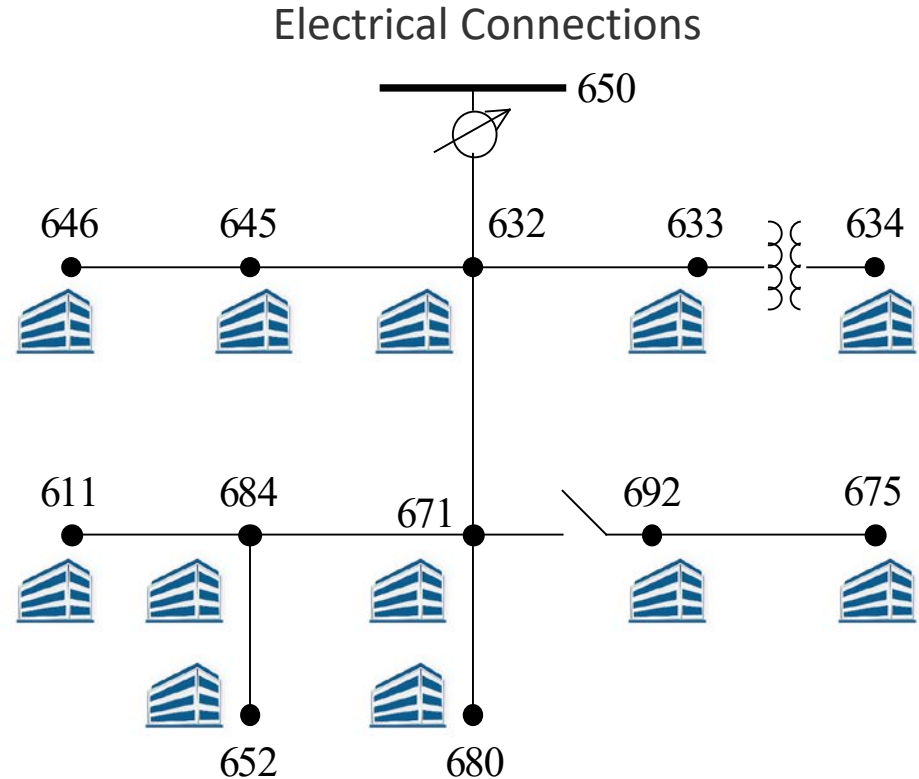
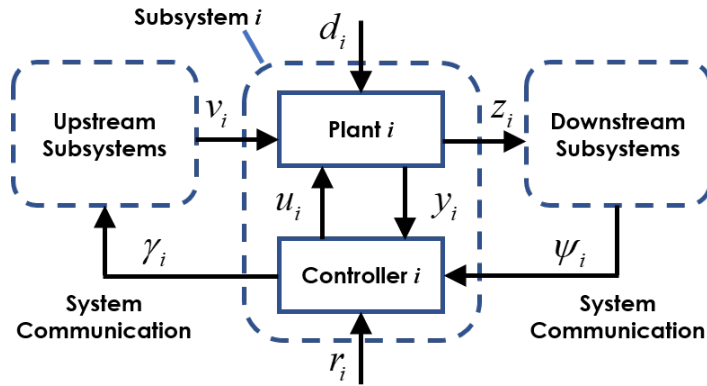
Abstract—Control of energy systems in buildings is an area of expanding interest as the importance of energy efficiency, occupant health, and comfort increases. The objective of this study was to demonstrate the effectiveness of a novel predictive steady-state optimal control method in minimizing the economic costs associated with operating a building. Specifically, the cost of utility consumption and the cost of low productivity due to occupant discomfort were minimized. This optimization was achieved through the use of a steady-state predictive and component level economic objective functions. Specific objective functions were developed and linear models were identified from data collected from a building on Texas A&M University's campus. The building consists of multiple zones and is serviced by a variable air volume, chilled water air handling unit. The proposed control method was then implemented with MATLAB and EnergyPlus to compare against an existing multi-objective, simulation results show improved comfort performance and decreased economic cost over the currently implemented building control, minimizing productivity loss and utility consumption. The potential for more serious consideration of the economic cost of occupant discomfort in building control design is also discussed.

Keywords: energy optimization, steady-state control, building energy control systems, comfort and engineering, building simulation, EnergyPlus and MATLAB

1. Introduction
Energy use and consumption of natural resources has become a pertinent concern for current and future generations. In the U.S. alone, total energy consumption has tripled over the last 65 years from 34.6 quadrillion Btu (quads) in 1950 to 117 quads in 2019 [1]. Of the energy consumed in the U.S., non-renewable energy still represents nearly 90% of energy sources [2]. Many nations have put forth specific renewable energy targets which aim to reduce dependence on non-renewable energy and maintain a competitive edge in the global energy technology market. For example, the European Union's (EU) Renewable Energy Directive has established a goal of 20% final energy consumption from renewable sources by 2020 [3]. The U.S. Department of Energy has set a goal of having 20% electricity sourced from wind energy by the year 2020 [4]. While renewable sources are projected to grow, reductions in energy usage can work to achieve these goals as well.
Moving into the energy consumption practices in the U.S., approximately 40% of all energy goes to building operators in the commercial and residential sectors [5]. The data show that approximately 75% of the energy used in the building sector comes from fossil fuels. As a result, energy usage in buildings accounts for 40% of the total U.S. carbon emissions [6]. Additionally, the building share

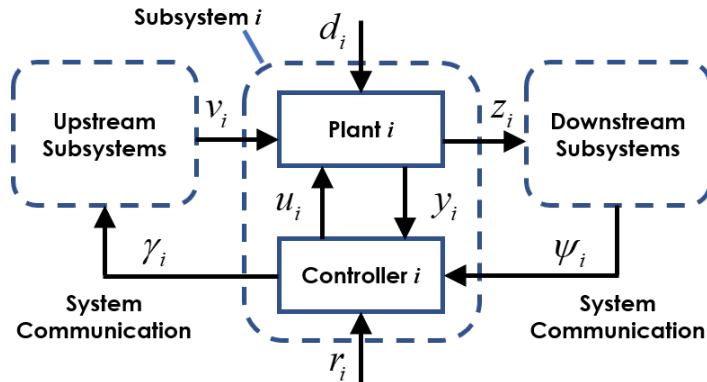
Modeling and Control of Buildings

- Distributed control with the Limited-Communication Distributed MPC method (LC-DMPC)
- IEEE 13 Node Test Feeder consisting of building nodes



Modeling and Control of Buildings

- Distributed control with the Limited-Communication Distributed MPC method (LC-DMPC)
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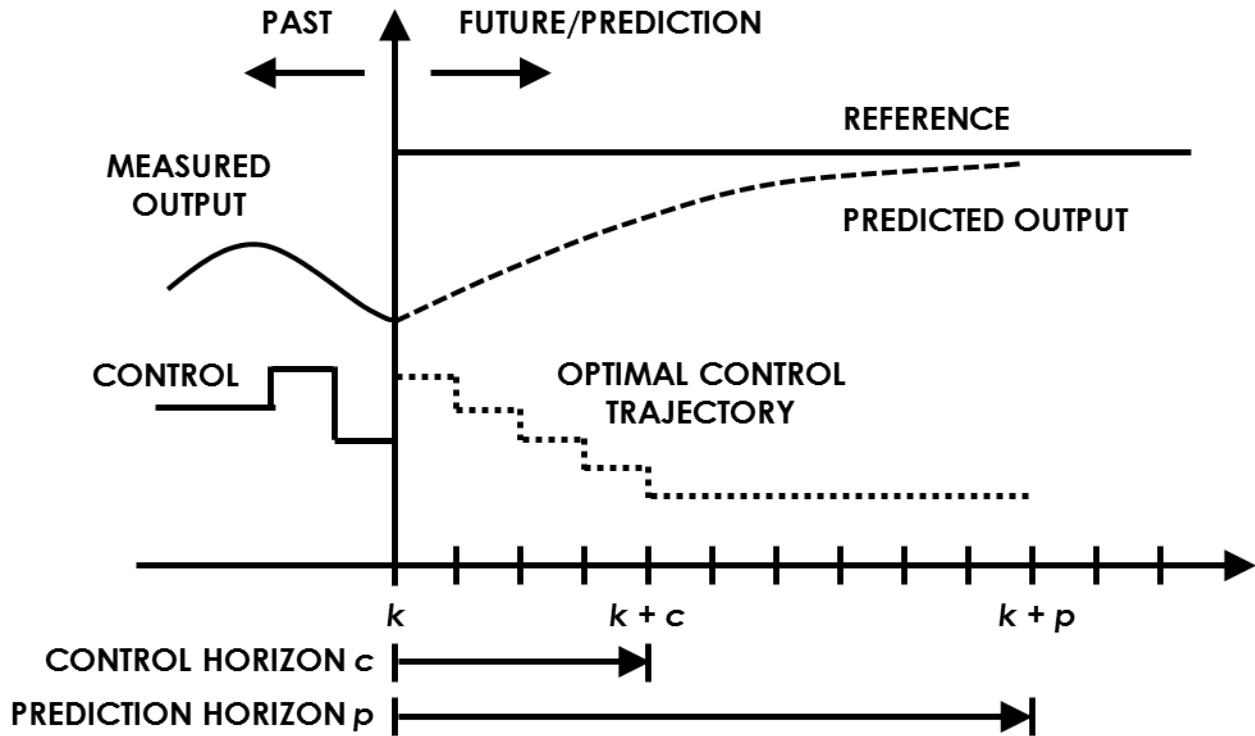


Electrical Connections

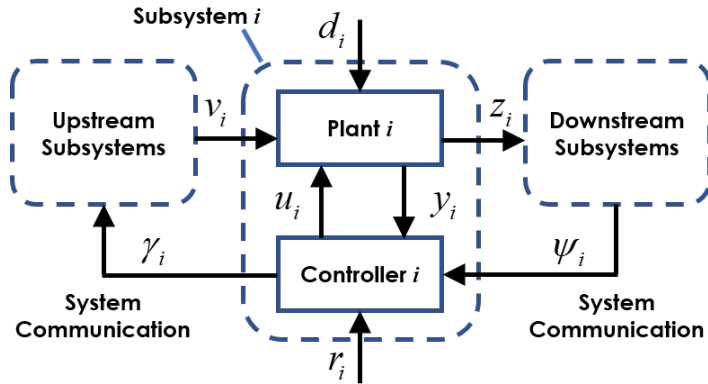
A few key notes:

- Distributed algorithm can scale computationally beyond centralized methods
- Subsystems don't require model knowledge of other subsystems (robust to changes, modular)
- Can be done in hierarchical manner, with local and supervisory setups

Limited-Communication Distributed MPC



LC-DMPC: The method



- Divide system into subsystems with local models
- Establish prediction horizons
- Identify connections between subsystems

$$x_i(k+1) = A_i x_i(k) + B_{u,i}(k) + B_{v,i}(k)$$

$$y_i(k) = C_{y,i} x_i(k) + D_{y,i} u_i(k)$$

$$z_i(k) = C_{z,i} x_i(k) + D_{z,i} u_i(k)$$

$$Y_i = \begin{bmatrix} y_i^T(k+1) & y_i^T(k+2) & \cdots & y_i^T(k+N_{p,i}) \end{bmatrix}^T$$

$$Z_i = \begin{bmatrix} z_i^T(k+1) & z_i^T(k+2) & \cdots & z_i^T(k+N_{p,i}) \end{bmatrix}^T$$

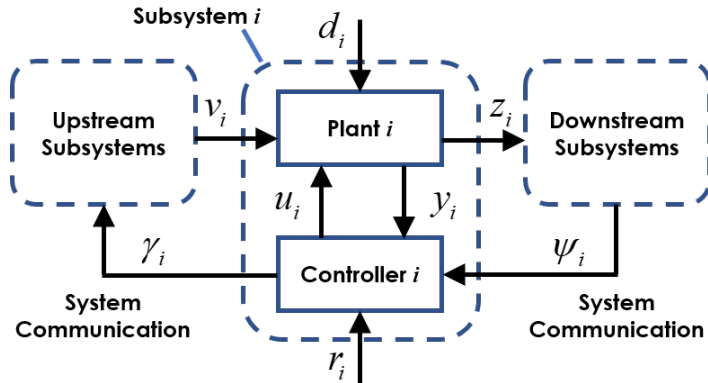
$$V_i = \begin{bmatrix} v_i^T(k+1) & v_i^T(k+2) & \cdots & v_i^T(k+N_{p,i}) \end{bmatrix}^T$$

$N_{p,i}$ is the prediction horizon.

$$\mathbf{V} = \mathbf{\Gamma Z}$$

$\mathbf{\Gamma}$ is the interconnection matrix.

LC-DMPC: The method



- By repeated application of the local model along N_p , the future dynamics for Y and Z can be found
- These prediction matrices are built for each subsystem
- N_y/N_z and P_y/P_z are the same as M_y/M_z with B_u replaced by B_v/B_d

$$Y_i = F_{y,i}x_{0,i}(k) + M_{y,i}U_i + N_{y,i}V_i + P_{y,i}D_i$$

$$Z_i = F_{z,i}x_{0,i}(k) + M_{z,i}U_i + N_{z,i}V_i + P_{z,i}D_i$$

$$F_{y,i} = \begin{bmatrix} (C_{y,i}A_i)^T & (C_{y,i}A_i^2)^T & \cdots & (C_{y,i}A_i^{N_p})^T \end{bmatrix}^T$$

$$F_{z,i} = \begin{bmatrix} (C_{z,i}A_i)^T & (C_{z,i}A_i^2)^T & \cdots & (C_{z,i}A_i^{N_p})^T \end{bmatrix}^T$$

$$M_{y,i} = \begin{bmatrix} D_{y,i} & 0 & \cdots & 0 \\ C_{y,i}B_{u,i} & D_{y,i} & 0 & \vdots \\ \vdots & \cdots & \vdots & 0 \\ C_{y,i}A_i^{N_p-2}B_{u,i} & C_{y,i}A_i^{N_p-3}B_{u,i} & \cdots & D_{y,i} \end{bmatrix}$$

$$M_{z,i} = \begin{bmatrix} D_{z,i} & 0 & \cdots & 0 \\ C_{z,i}B_{u,i} & D_{z,i} & 0 & \vdots \\ \vdots & \cdots & \vdots & 0 \\ C_{z,i}A_i^{N_p-2}B_{u,i} & C_{z,i}A_i^{N_p-3}B_{u,i} & \cdots & D_{z,i} \end{bmatrix}$$

LC-DMPC: The optimization

$$\min_{U_i} J_i = e_i^T Q_i e_i + U_i^T S_i U_i + \Psi_i^T Z_i$$

$$\text{s.t. } Y_i = F_{y,i} x_{0,i}(k) + M_{y,i} U_i + N_{y,i} V_i$$

$$Z_i = F_{z,i} x_{0,i}(k) + M_{z,i} U_i + N_{z,i} V_i$$

$$U_{i_{\min}} \leq U_i \leq U_{i_{\max}}.$$

- Objective function has quadratic error and control terms with a linear penalty term
- Local dynamics can be moved into objective function from constraints
- Sensitivities are calculated based on upstream system disturbances

$$\min_{U_i} J_i = U_i^T H_i U_i + 2U_i^T F_i + V_i^T E_i V_i + 2V_i^T T_i$$

$$\text{s.t. } A_i U_i \leq B_i$$

$$H_i = M_{y,i}^T Q_i M_{y,i} + S_i, \quad E_i = N_{y,i}^T Q_i N_{y,i}$$

$$F_i = M_{y,i}^T Q_i [F_{y,i} x_{0,i}(k) + N_{y,i} V_i + P_{y,i} D_i - r_i(k)] + 0.5 M_{z,i}^T \Psi_i$$

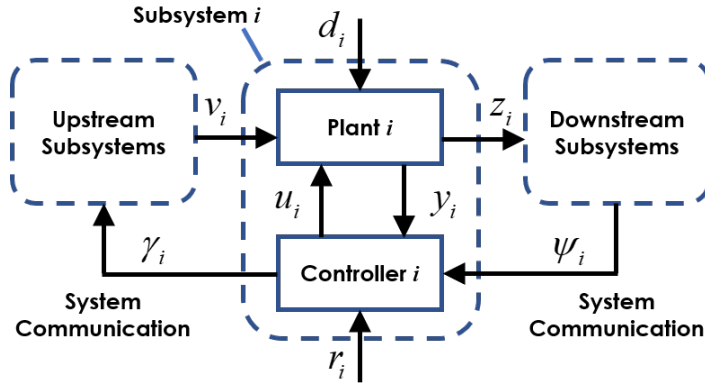
$$T_i = N_{y,i}^T Q_i [F_{y,i} x_{0,i}(k) - r_i(k)] + 0.5 N_{z,i}^T \Psi_i$$

$$A_i = \text{diag} \begin{pmatrix} I_{i^* N_p} \\ -I_{i^* N_p} \end{pmatrix}, \quad B_i = \begin{bmatrix} U_{i_{\max}}^T & U_{i_{\min}}^T \end{bmatrix}^T$$

$$\gamma_{i+1} = \frac{\partial J_{i+1}}{\partial V_{i+1}} = 2 \left[E_i V_{i+1} + T_{i+1} + N_{y,i+1}^T Q_{i+1} M_{y,i+1} U_{i+1} \right]$$

$$\Psi = \left[\Psi_1^T, \Psi_1^T, \dots, \Psi_p^T \right]^T = \Gamma^T \underbrace{\left[\gamma_1^T, \gamma_1^T, \dots, \gamma_p^T \right]^T}_{\gamma} = \Gamma^T \gamma$$

LC-DMPC: The optimization



- Objective function has quadratic error and control terms with a linear penalty term
- Local dynamics can be moved into objective function from constraints
- Sensitivities are calculated based on upstream system disturbances

Algorithm 1 LC-DMPC Algorithm

Initialization: Given $x_{0,i}(k)$ & N_a , $V_i(0)$, $U_i(0)$, $\Psi_i(0) = 0$.

Step 1: Exchange current information with local agents:

$$\mathbf{V}(j+1) = \mathbf{\Gamma}\mathbf{Z}(j), \quad \mathbf{\Psi}(j+1) = \mathbf{\Gamma}^T\mathbf{\Upsilon}(j)$$

Step 2: Solve problem (13) and assign the result as U_i^{QP} .

Step 3: Compute the convex summation for $\beta \in [0,1)$:

$$U_i(j+1) = \beta U_i(j) + (1-\beta)U_i^{QP}(j)$$

Step 4: Use the result from step 3 to compute:

$$Z_i(j+1) = F_{z,i}x_{0,i}(k) + M_{z,i}U_i(j+1) + N_{z,i}V_i(j)$$

Step 5: Use the result from step 3 to compute:

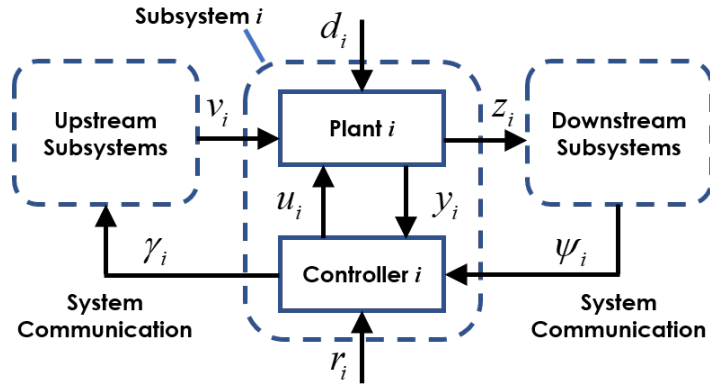
$$\begin{aligned} \gamma_i(j+1) = & -2N_{y,i}^T Q_i r_i(k) + 2N_{y,i}^T Q_i M_{y,i} U_i(j+1) + \\ & 2N_{y,i}^T Q_i N_{y,i} V_i(j) + N_{z,i}^T \Psi_i(j) + 2N_{y,i}^T Q_i F_{y,i} x_{0,i}(k) \end{aligned}$$

Step 6: If $j \neq N_a$ go to step 1, otherwise go to step 7.

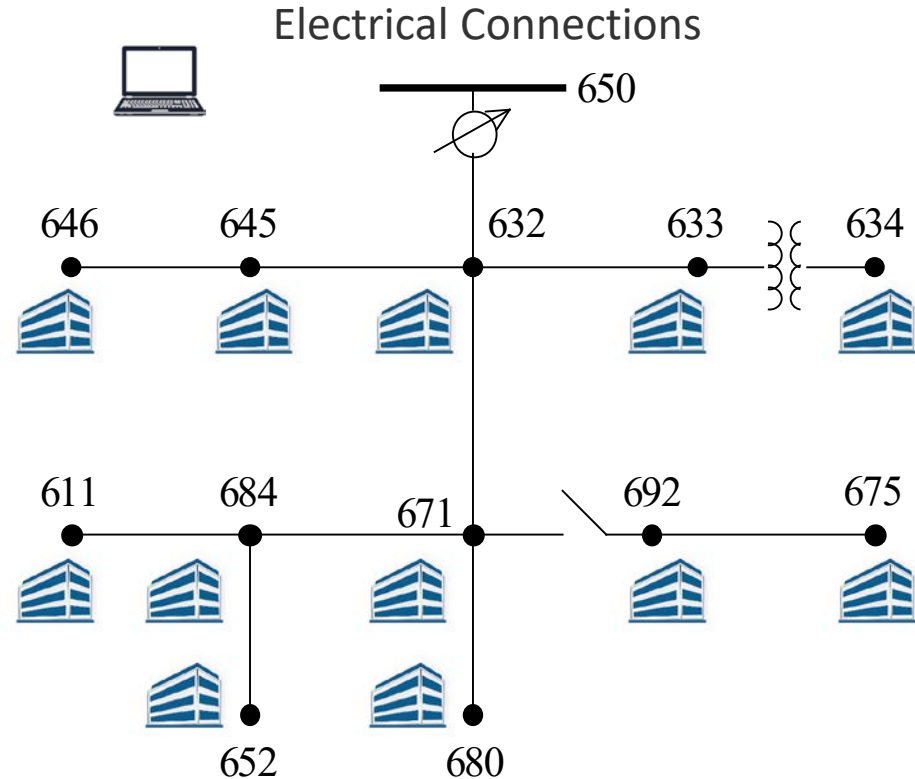
Step 7: Apply the first value of U_i .

Step 8: Get new measurements for $x_{0,i}$ and go to step 1.

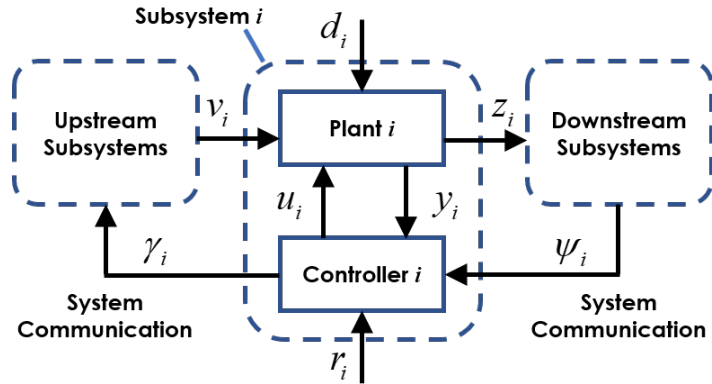
The Model



- IEEE 13 Node Test Feeder consisting of building nodes
- Added grid aggregator to distribute reference signal from the grid
- Grid aggregator is at same level as buildings, not hierarchical



Interconnections

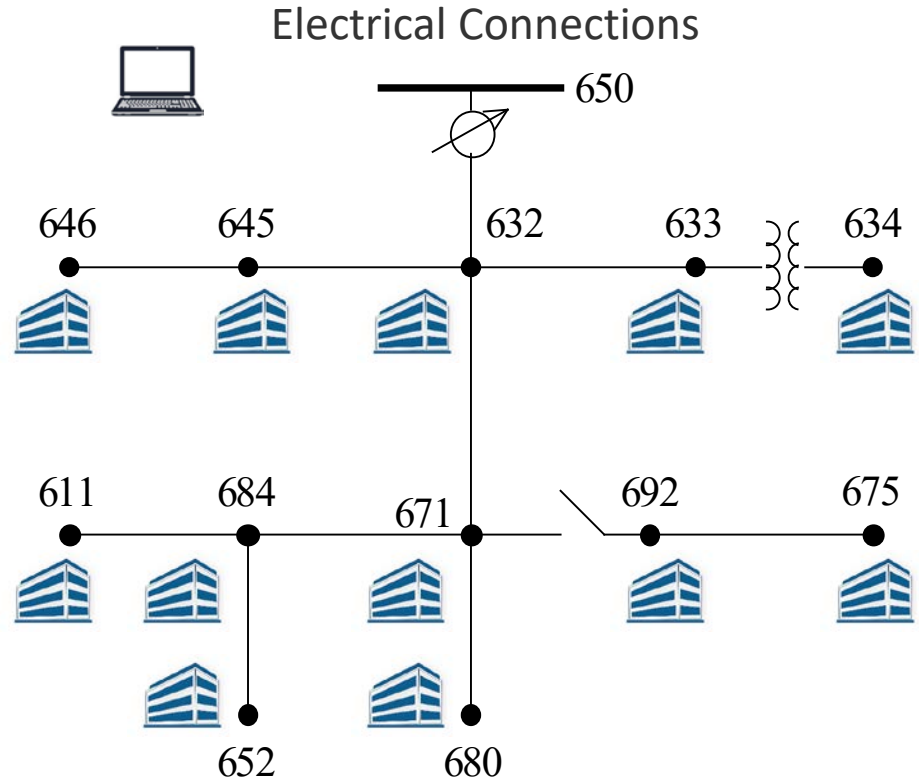


- Grid aggregator is both upstream and downstream to each building

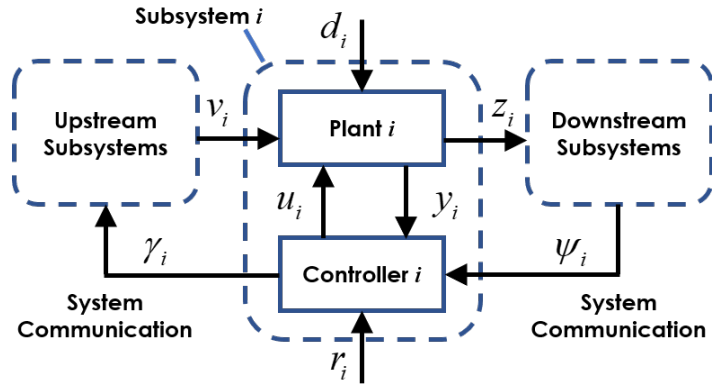
Upstream



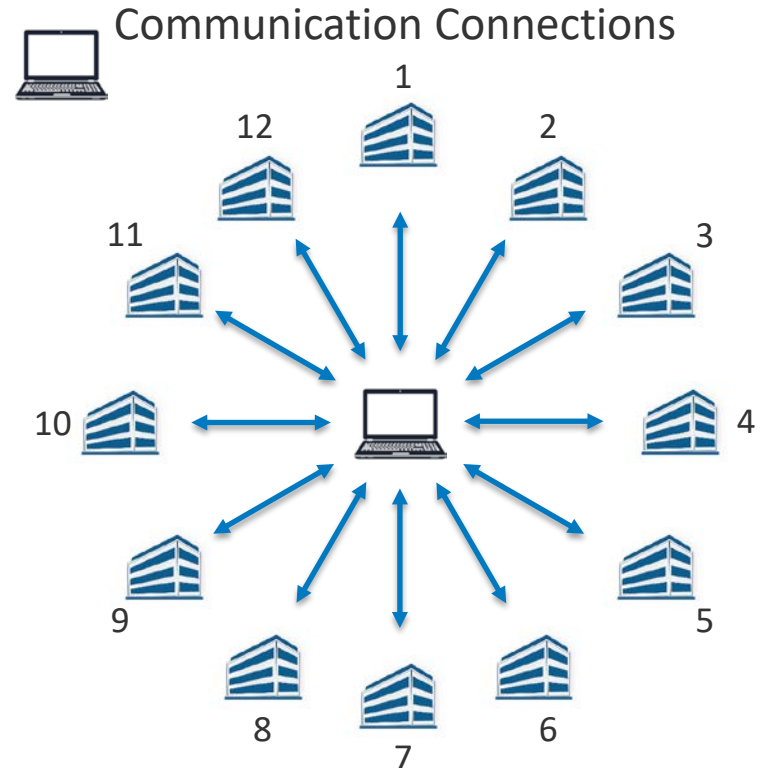
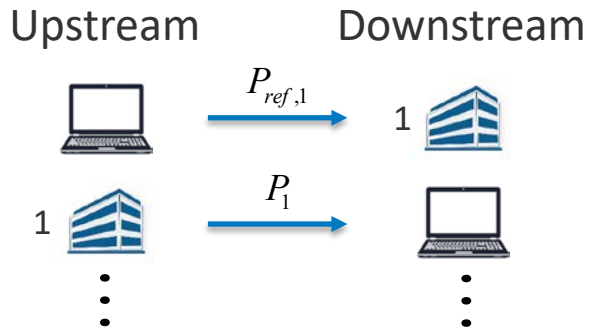
Downstream



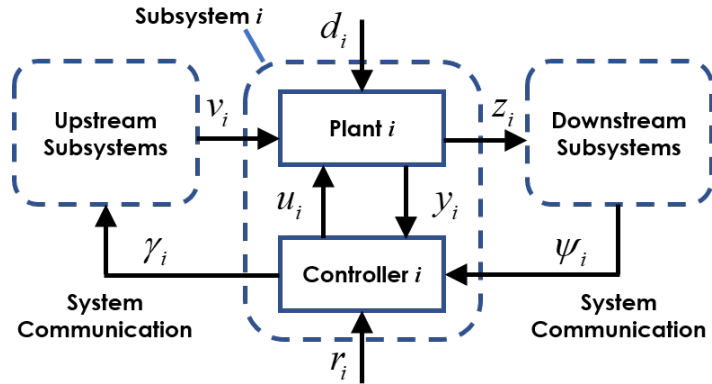
Interconnections



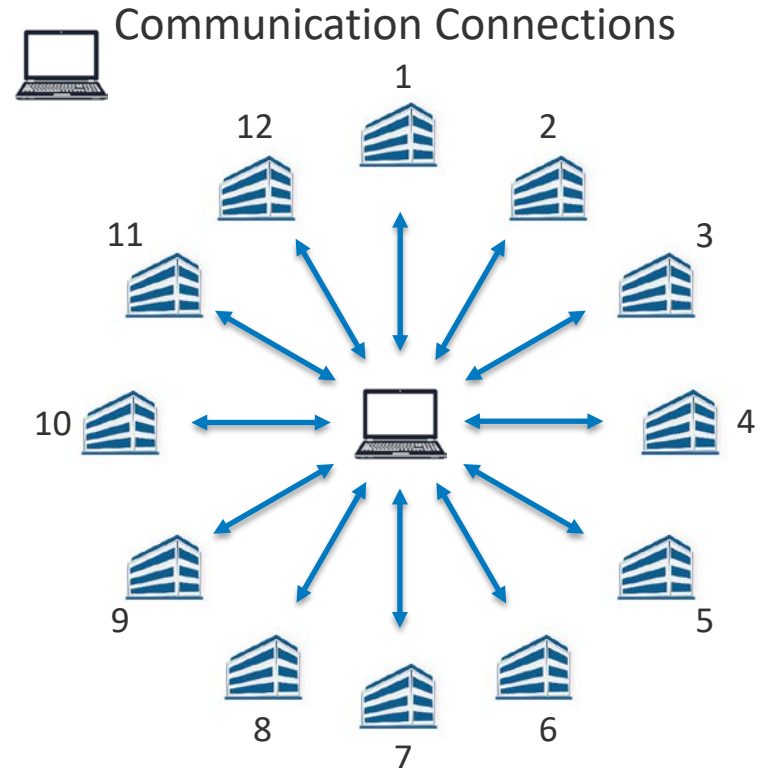
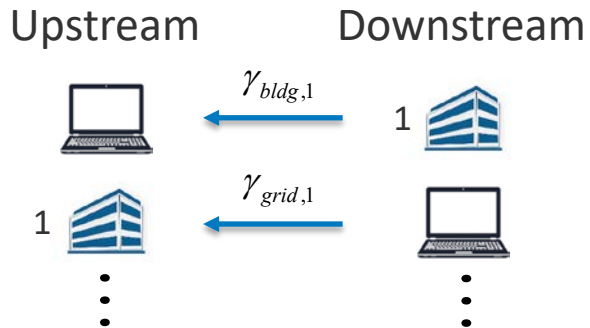
- Grid aggregator is both upstream and downstream to each building



Interconnections

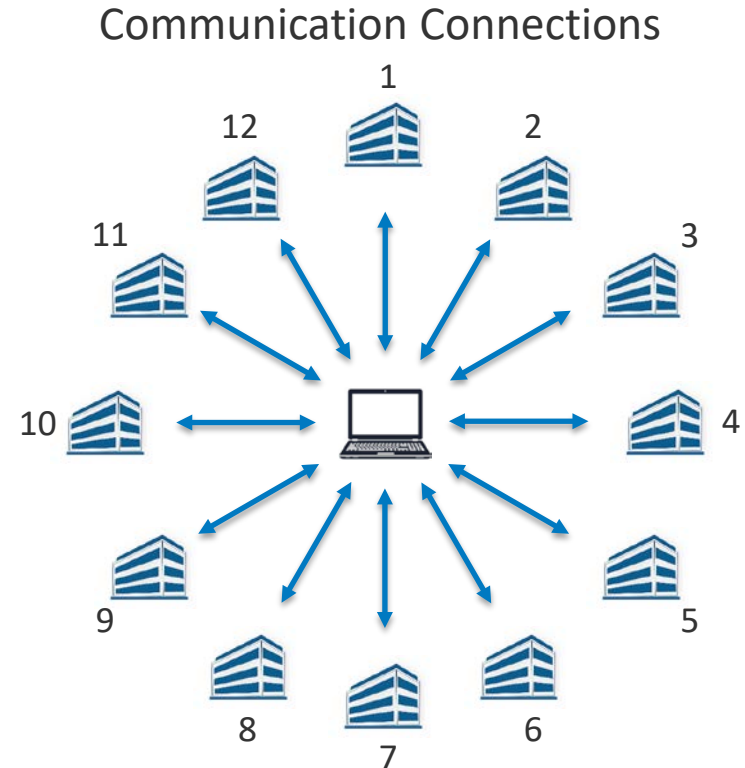


- Grid aggregator is both upstream and downstream to each building



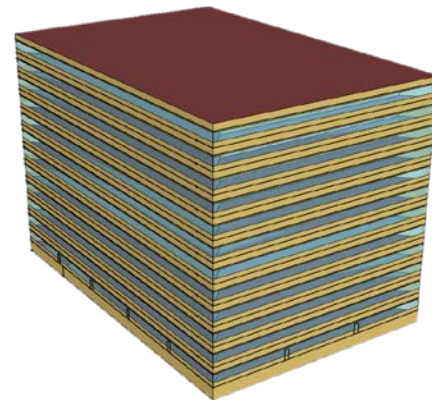
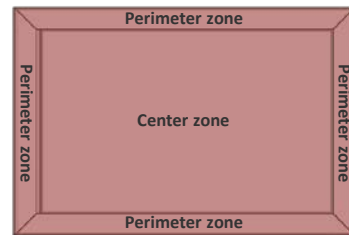
Grid Aggregator Model

- A bulk reference signal is sent from the grid to the feeder
- The grid aggregator determines power references for the buildings
 - Model includes summation of individual building powers
 - Optimization chooses reference signals such that the reference tracking error is minimized
- Through iterative communication, aggregator and buildings come to consensus on control actions



Building Model

- Used DOE Large Office Building Model
- For first implementation, used the ground floor
 - Lumped the 5 zones into 1 zone
 - Equipment consists of 1 AHU
 - Only considered cooling
- Used to generate truth model
- Control model was then identified from the truth model



DOE Large Office Building Model

EKF-based prediction model

EKF-based approach adopted to make RC models feasible for real world implementation

- 3R-2C model used to describe building thermodynamics

$$T_{in}(k + 1) = T_{in}(k) + \frac{t_s}{R_{in,e} \cdot C_{in}} (T_e - T_{in}) + \frac{t_s}{R_{in,a} \cdot C_{in}} (T_a - T_{in}) + \frac{t_s}{C_{in}} (Q_{solar} + Q_{internal} + Q_{hvac} + Q_{inf})$$

$$T_e(k + 1) = T_e(k) + \frac{t_s}{R_{in,e} \cdot C_e} (T_{in} - T_e) + \frac{t_s}{R_{e,a} \cdot C_e} (T_a - T_e) + \frac{t_s}{C_e} (Q_{solar} + Q_{internal} + Q_{hvac} + Q_{inf})$$

- T_{in} - Indoor air temperature
- T_e - Exterior wall temperature
- T_a - Outdoor air temperature
- t_s - Duration of simulation time step
- k – Current time step
- $R_{in,a}, R_{in,e}, R_{e,a}$ - Equivalent resistances
- C_{in}, C_e - Equivalent capacitance values
- Q_{solar} - Solar heat gain through windows
- $Q_{internal}$ - Internal heat gain
- Q_{inf} - Infiltration heat load
- Q_{hvac} - Cooling or heating energy delivered by the HVAC system

EKF-based prediction model

Initial modeling assumptions

- Q_{solar} is assumed to bear a simple relationship with Q_{ghi}

$$Q_{solar} = \alpha \cdot Q_{ghi}$$

- Effect of wind on Q_{inf} is not captured by the model

$$Q_{inf} \propto (T_a - T_{in})$$

- $Q_{internal}$ is known to us.

EKF-based prediction model

EKF algorithm

- State-space representation of the 3R-2C model

$$\begin{aligned}x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k)\end{aligned}$$

- Model parameters are represented as states of the equation

$$x = [T_{in}, T_e, C_{in}, R_{in,e}, R_{in,a}, C_e, R_{e,a}, \alpha]$$

- One-month historical data of indoor air temperature and weather information is used to train the data.
- Discrepancy between measured and predicted values of T_{in} are used to update the initial estimates of the states

EKF Algorithm

EKF Pseudocode

```
for k = 1:ntrain
    if k == 1 :
        xk := xinit (Initial state estimates)
        emse-old = 100 (Initial state mean squared error)
    else:
        emse =  $\left(\frac{1}{n_{val}}\right) \cdot \sum_{i=1}^{n_{val}} (T_{in}(i + n_{pred}) - Hx_{i+n_{pred}|i})^2$ 
        if emse < emse-old:
            emse-old = emse
            xk := xk|k (measurement update)
        else:
            xk(1:2) = xk|k(1:2) (measurement update only
                               for temperature states)
    xk := xk+1|k (time update)
```

EKF Matrices and Equations

$$x = [T_{in}, T_e, C_{in}, R_{in,a}, R_{in,e}, C_e, R_{e,a}, \alpha]$$

$$h = T_{in}, u = [T_{oa}, \dot{Q}_{ghi}, \dot{Q}_{heat}]$$

$$\dot{Q}_{heat} = \dot{Q}_{internal} + \dot{Q}_{inf} + \dot{Q}_{hvac}$$

$$f(x_k, u_k) \equiv \text{derived from 3R2C Model}$$

Measurement Update

$$H = \left. \frac{\partial h(x_k, u_k)}{\partial x} \right|_{x_k, u_k}$$

$$y_k = T_{in}(k) - Hx_{k|k-1}$$

$$K = P_{k|k-1} H^T (HP_{k|k-1} H^T + R)^{-1}$$

$$x_{k|k} = x_{k|k-1} + Ky_k$$

$$P_{k|k} = P_{k|k-1} + Ky_k$$

Time Update

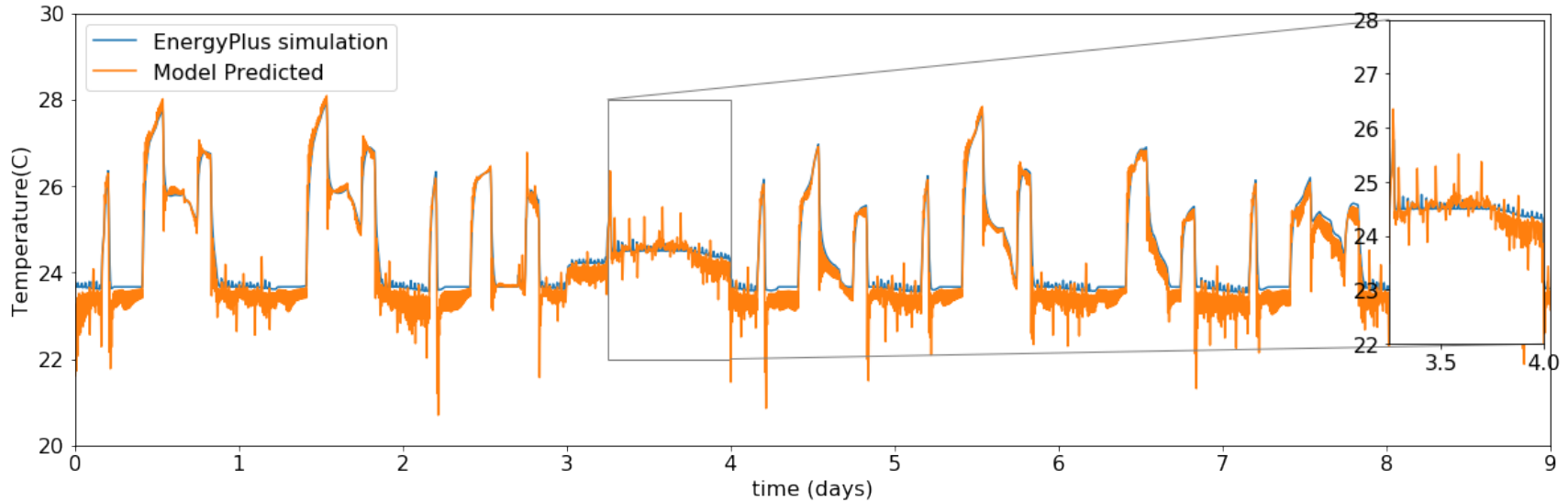
$$x_{k+1|k} = f(x_k, u_k)$$

$$F = \left. \frac{\partial f(x_k, u_k)}{\partial x} \right|_{x_k, u_k}$$

$$V = \left. \frac{\partial f(x_k, u_k)}{\partial u} \right|_{x_k, u_k}$$

$$P_{k+1|k} = FP_{k|k}F^T + VMV^T$$

EKF 4-hour Prediction



- 5 Zone building modeled as a single zone.

Linear Parametric Model for MPC

- Linear parametric equation for building envelope modeling

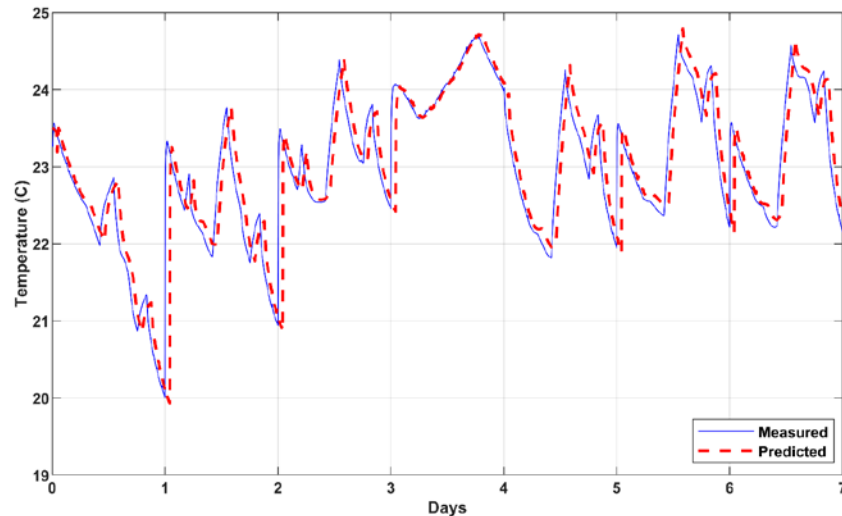
—ARX model structure to predict room temperature dynamics

$$y(k) = a_1y(k-1) + a_2y(k-2) + \dots + a_{n_a}y(k-n_a) + b_1u(k-1) + b_2u(k-2) + \dots + b_{n_b}u(k-n_b) + e(t)$$

—System identification to find the parameters θ of the ARX model.

$$\theta = [a_1, a_2, \dots, a_{n_a}, b_1, b_2, \dots, b_{n_b}]$$

Inputs	Output
T_{oa} (Outside air temperature)	T_{in}
Q_{int} (Internal convective heat gain)	
Q_{ghi} (Solar heat gain)	
Q_{hvac} (Sensible heat from HVAC system)	



Building Power Models

- Building model has 2 power consuming components:
 - AHU Fan
 - Chiller
- Truth model uses non-linear equations shown on the right
- Controller model uses linearized version of the equations around the current operating point

$$P_{bldg} = P_{fan} + P_{chiller}$$

$$P_{fan} = a_0 \cdot \dot{m}_s^3 + a_1 \cdot \dot{m}_s^2 + a_2 \cdot \dot{m}_s + a_3$$

$$a_0 = 0.0029 \quad a_1 = -0.0151$$

$$a_2 = 0.1403 \quad a_3 = 0.0086$$

$$P_{chiller} = \frac{1.005}{COP_{HVAC}} \cdot \dot{m}_s \cdot (T_{ma} - T_{sa})$$

$$T_{ma} = 0.3 \cdot T_{oa} + (1 - 0.3) \cdot T_z$$

\dot{m}_s = air mass flow rate

COP_{HVAC} = coefficient of performance

T_{ma} = mixed air temperature

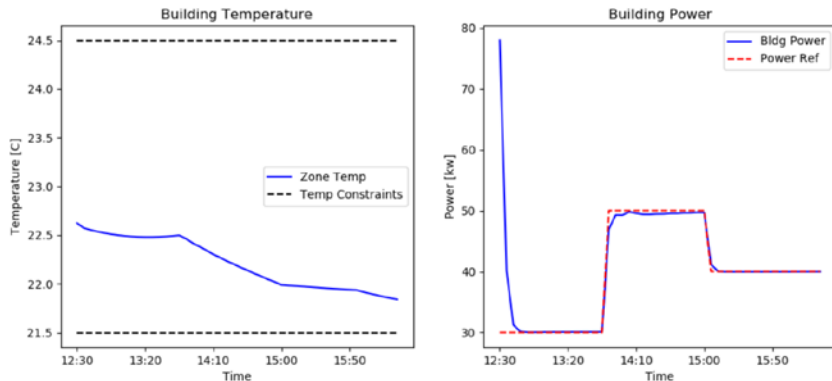
T_{sa} = supply air temperature

T_z = zone temperature

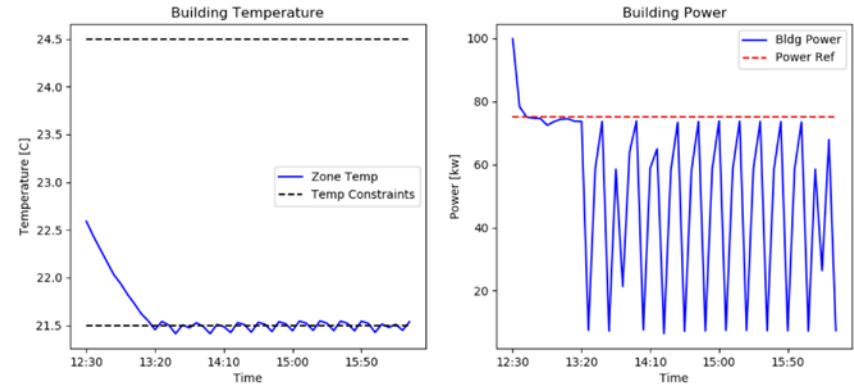
Preliminary Results

- Tested first with one building node tracking a power reference
- Additionally, buildings able to maintain temperature within constraints even when power reference exceeds capabilities

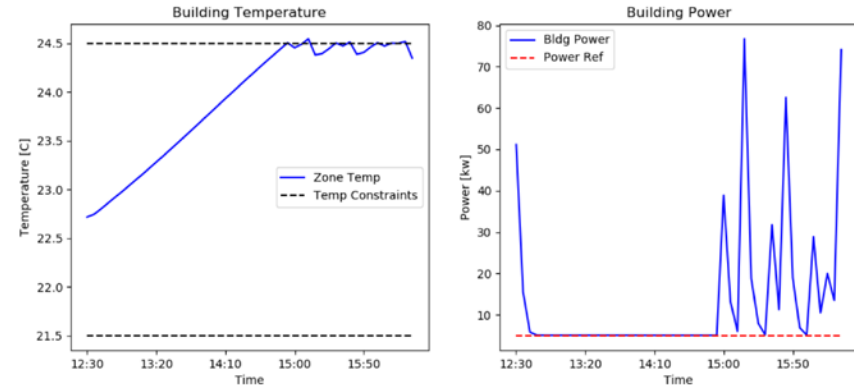
Reference Tracking



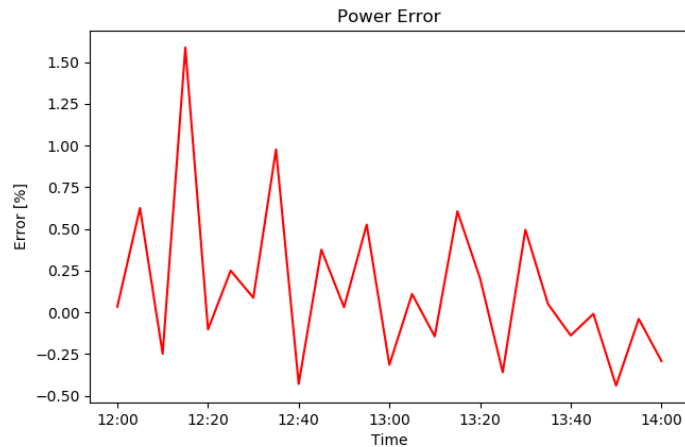
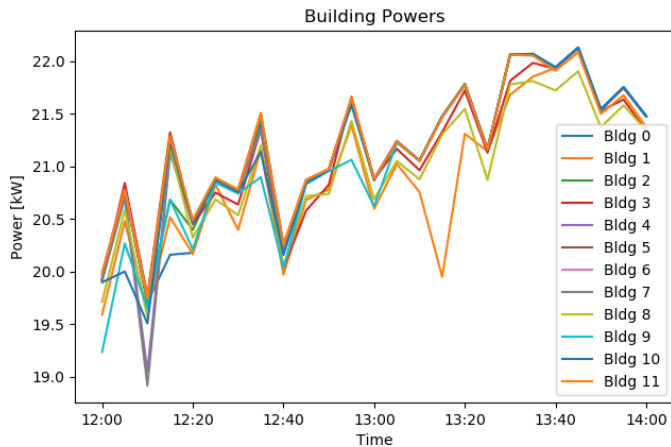
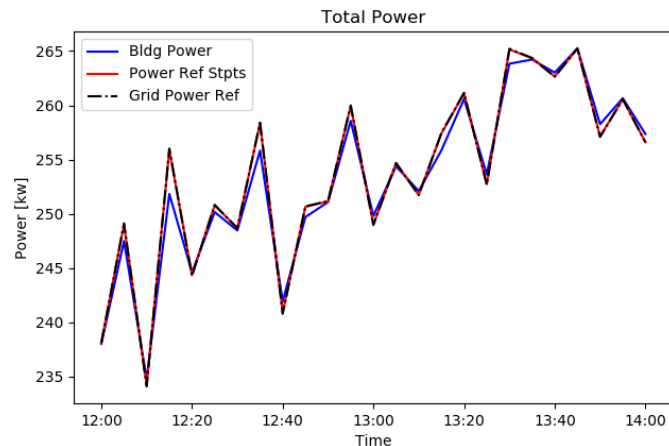
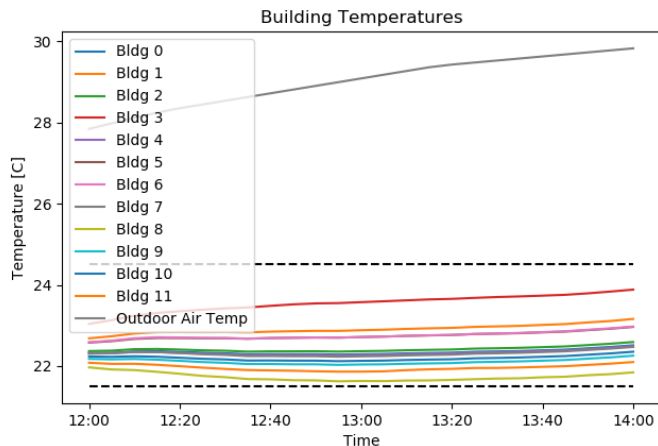
Forcing to Lower Temperature Constraint



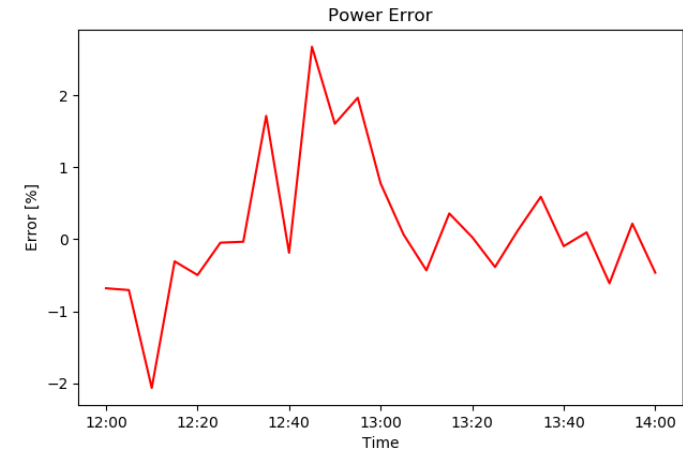
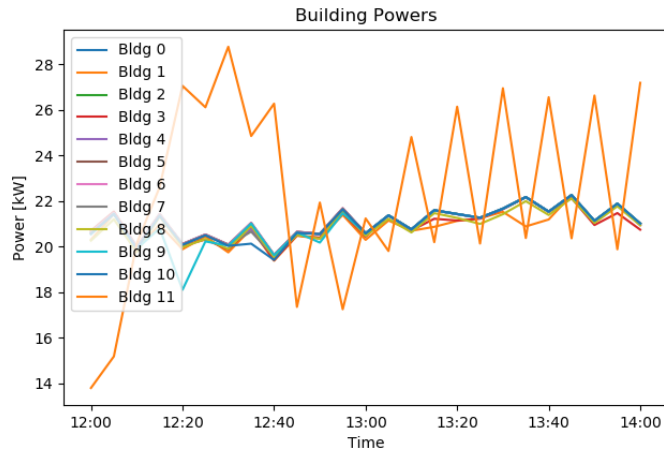
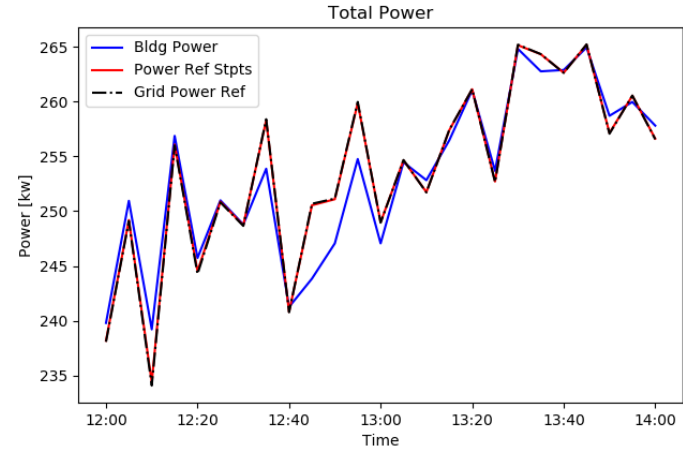
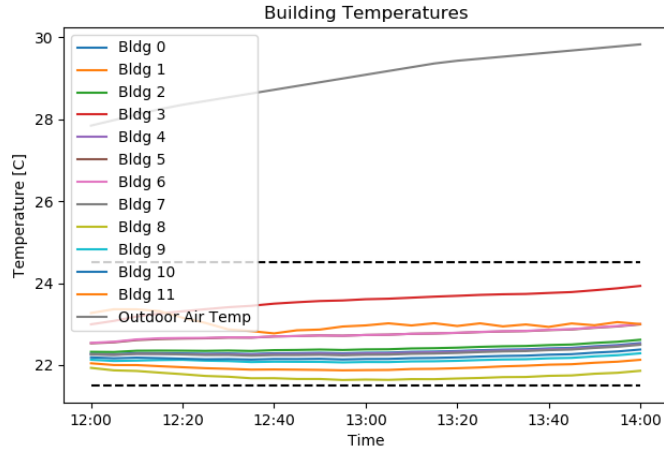
Forcing to Upper Temperature Constraint



Preliminary Results Cont.

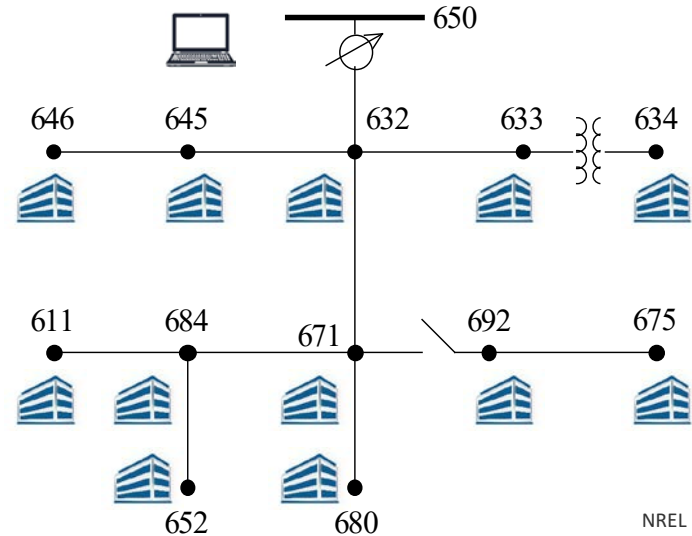
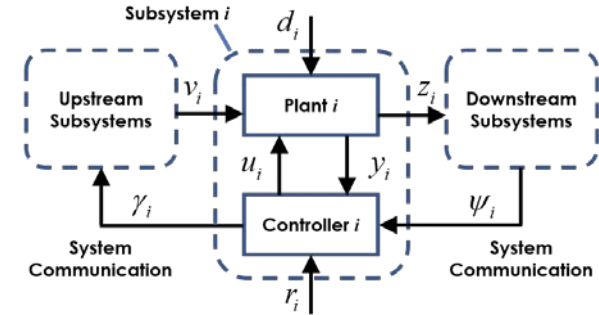


Preliminary Results Cont.



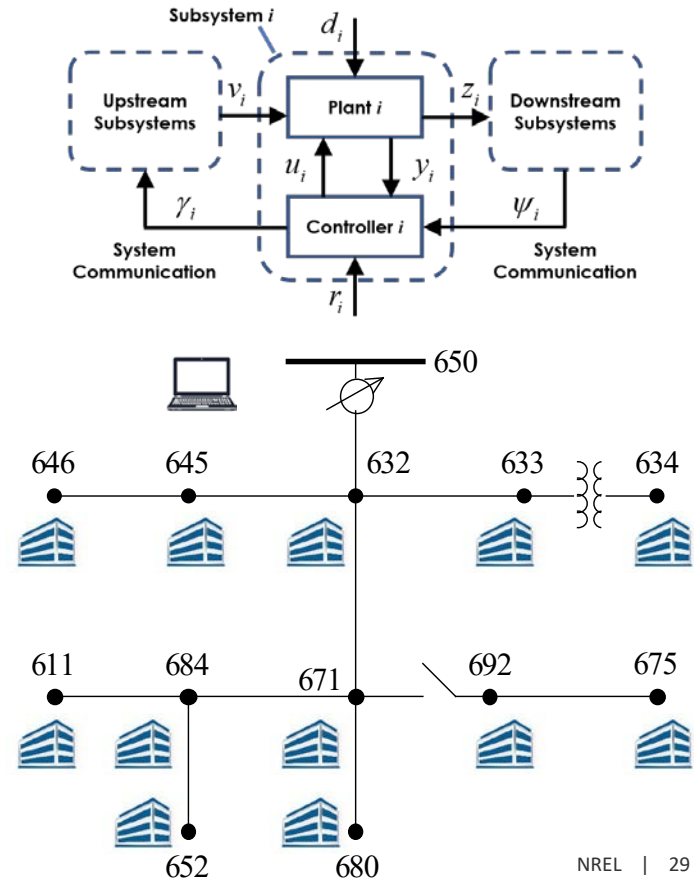
Conclusions

- Grid aggregator allows for buildings to “pushback” with own objectives
- Used novel EKF approach for building model
- LC-DMPC allows for systems to be both upstream and downstream agents (mesh networks)
- Method can be used at different levels of systems



Additional Opportunities/Ongoing Work

- Implement voltage constraints/reactive power
- Convergence studies for communication iterations/beta
- Reduce power model time-step and aggregate control actions to reflect thermodynamics at a larger time-step
- Examine higher fidelity truth modelling; use machine learning/data-driven techniques for control models



References

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Questions?

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