NREL
Transforming ENERGY

Scalable Distributed Model Predictive Control for Building and Renewable Energy Systems

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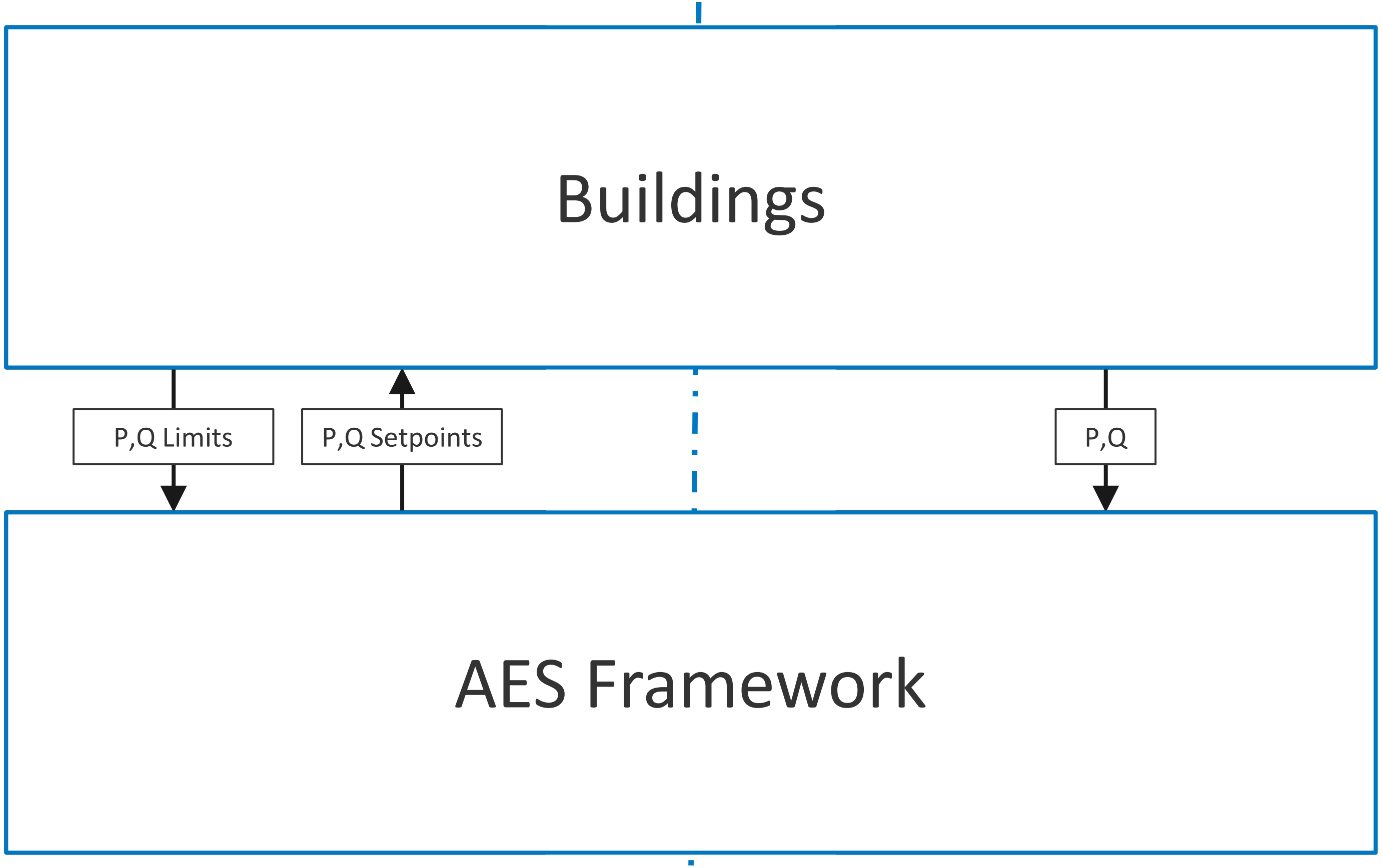
Overview



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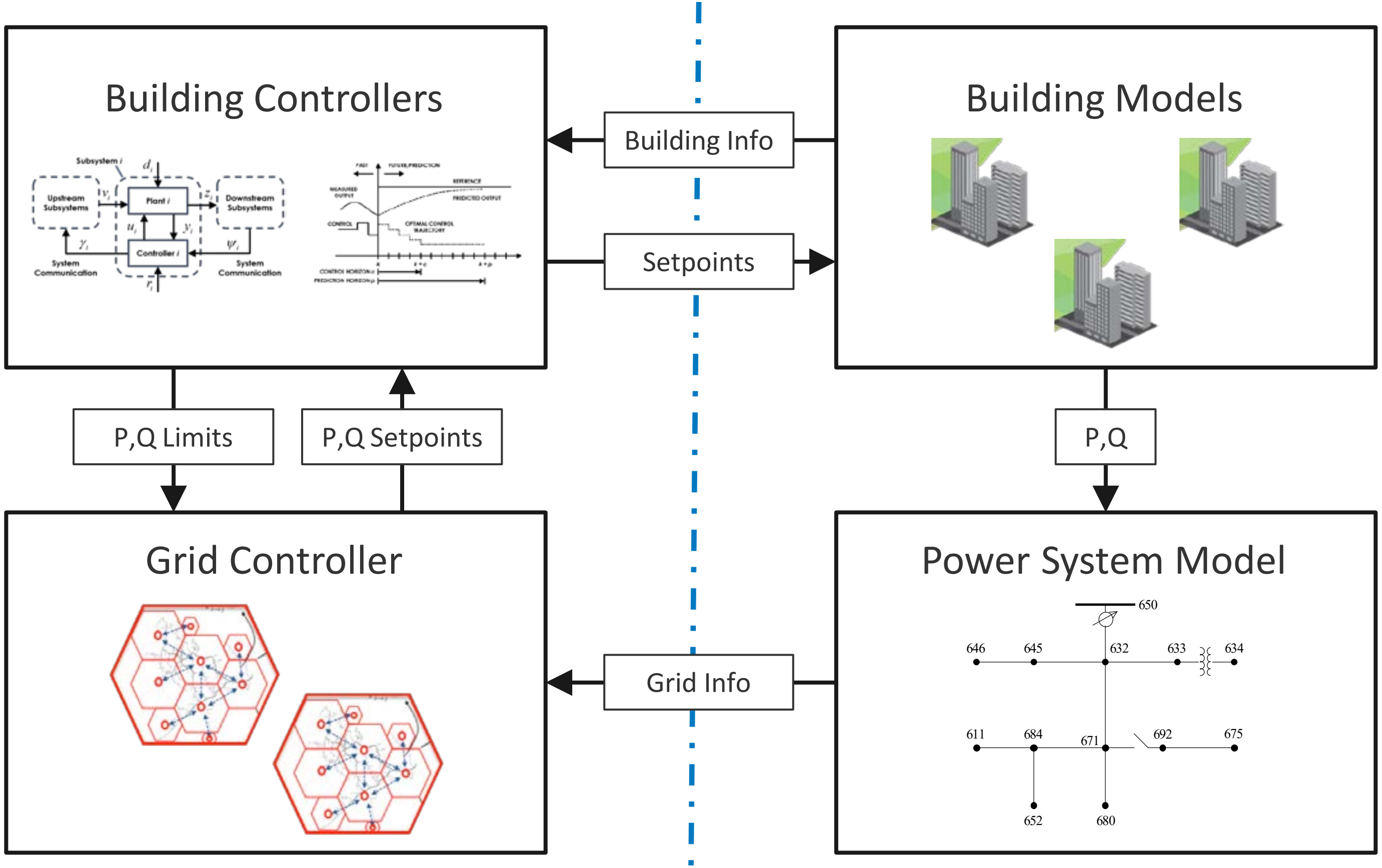

Building Controllers
Building Models
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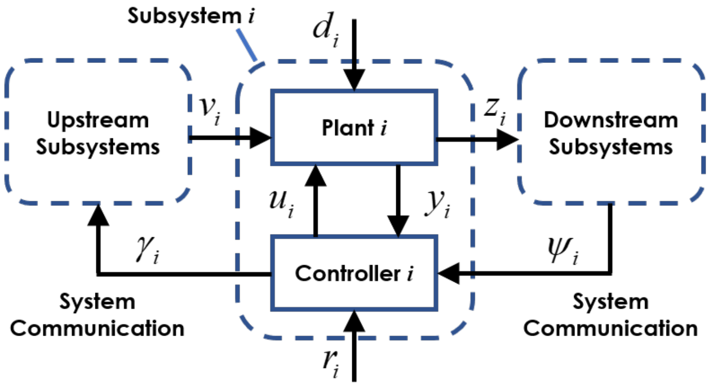
Modeling and Control of Buildings

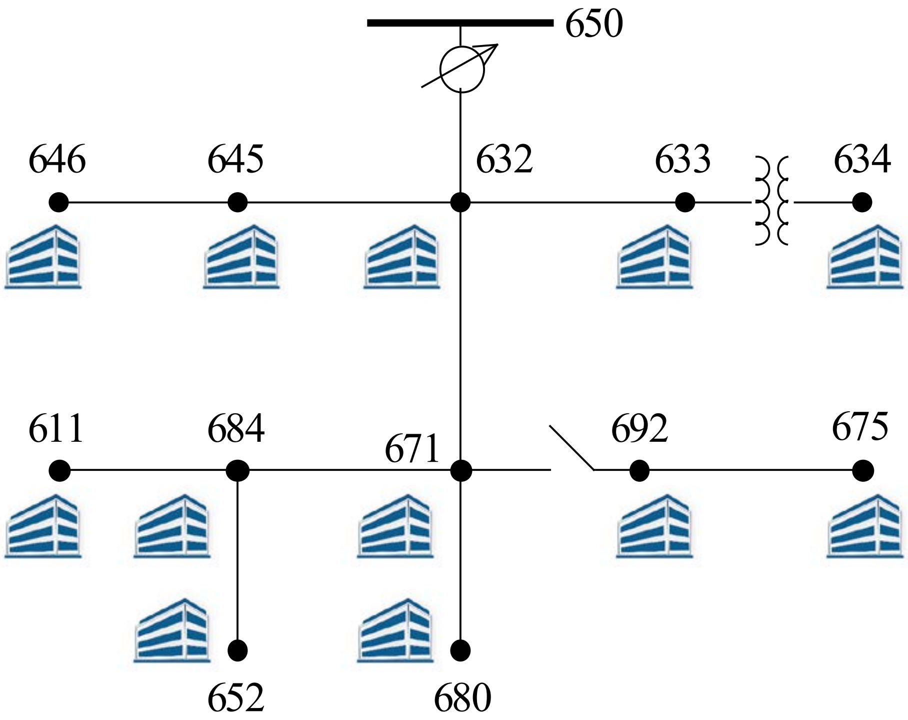
- Building control traditionally focused on energy reduction and occupant comfort
- Need for buildings to provide ancillary services (while keeping people happy)
- Need for coordinating large numbers of building energy systems
- MPC lends itself to a lot of the challenges found in buildings
- Technique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

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

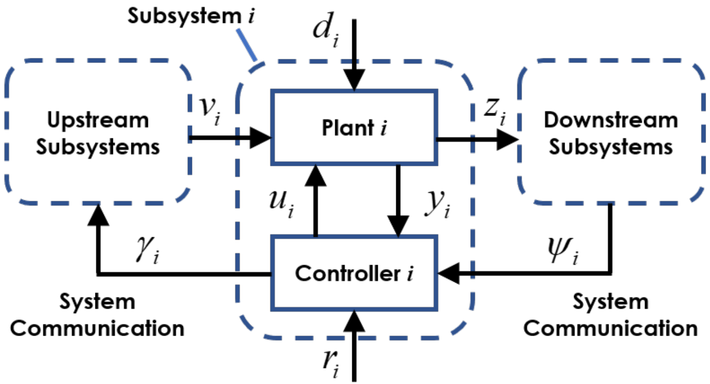


Electrical Connections



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



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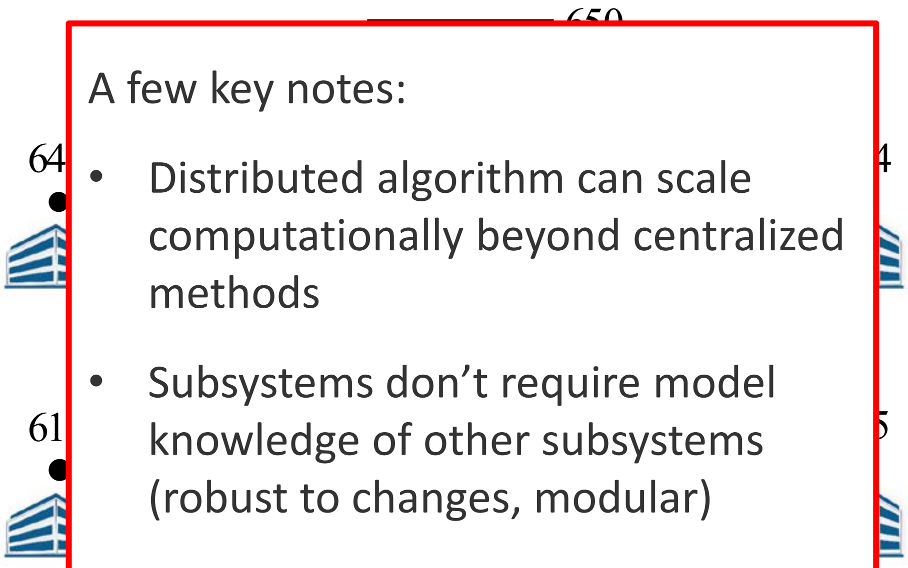
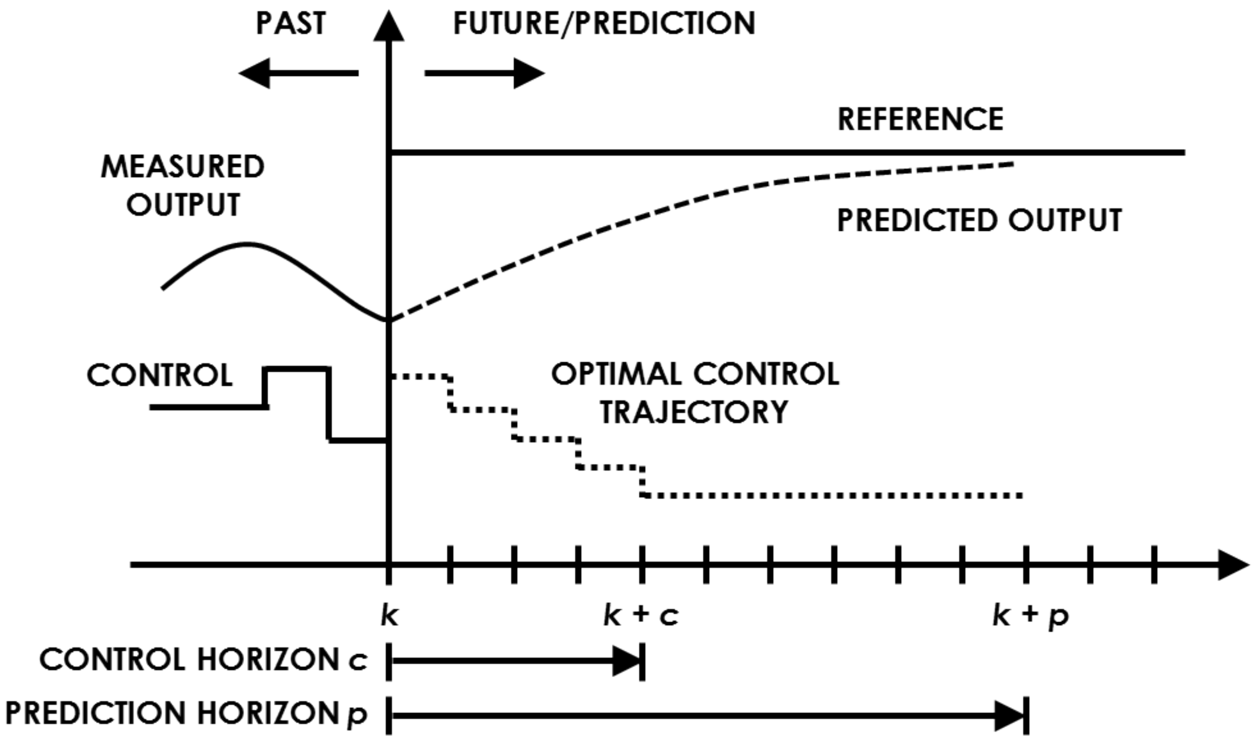


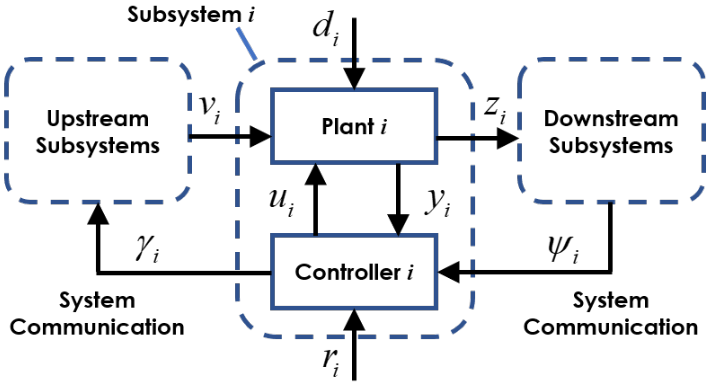
A few key notes:

- 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

$$x_i(k+1) = A_i x_i(k) + B_{u,i}(k) + B_{v,i}(k)$$
$$y_i(k) = C_{y,i} x_i(k) + D_{y,i} u_i(k)$$
$$z_i(k) = C_{z,i} x_i(k) + D_{z,i} u_i(k)$$

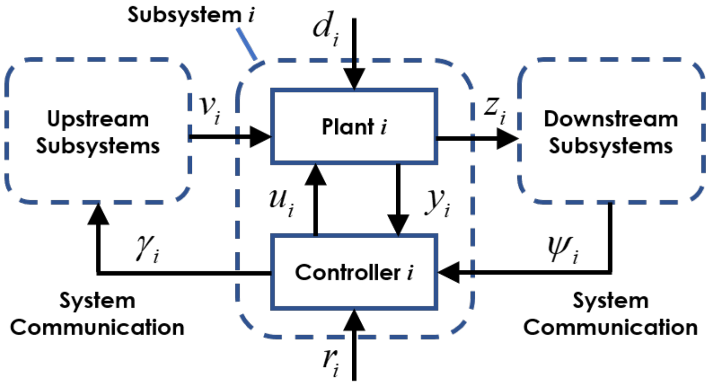
$$Y_i = \left[y_i^T(k+1) \quad y_i^T(k+2) \quad \cdots \quad y_i^T(k+N_{p,i}) \right]^T$$
$$Z_i = \left[z_i^T(k+1) \quad z_i^T(k+2) \quad \cdots \quad z_i^T(k+N_{p,i}) \right]^T$$
$$V_i = \left[v_i^T(k+1) \quad v_i^T(k+2) \quad \cdots \quad v_i^T(k+N_{p,i}) \right]^T$$

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

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

Γ is the interconnection matrix.

LC-DMPC: The method



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

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

$$F_{y,i} = \left[(C_{y,i}A_i)^T \quad (C_{y,i}A_i^2)^T \quad \cdots \quad (C_{y,i}A_i^{N_p})^T \right]^T$$

$$F_{z,i} = \left[(C_{z,i}A_i)^T \quad (C_{y,i}A_i^2)^T \quad \cdots \quad (C_{z,i}A_i^{N_p})^T \right]^T$$

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

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

- 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

LC-DMPC: The optimization

$$\min_{U_i} J_i = \mathrm{e}_i^T \mathrm{Q}_i \mathrm{e}_i + \mathrm{U}_i^T \mathrm{S}_i \mathrm{U}_i + \Psi_i^T \mathrm{Z}_i$$

$$\begin{aligned} \text{s.t. } \mathrm{Y}_i &= F_{y,i} x_{0,i}(k) + M_{y,i} \mathrm{U}_i + N_{y,i} \mathrm{V}_i \\ \mathrm{Z}_i &= F_{z,i} x_{0,i}(k) + M_{z,i} \mathrm{U}_i + N_{z,i} \mathrm{V}_i \\ \mathrm{U}_{i_{\min}} &\le \mathrm{U}_i \le \mathrm{U}_{i_{\max}}. \end{aligned}$$

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

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

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

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

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

$$A_i = diag \begin{pmatrix} I_{i*N_p} \\ -I_{i*N_p} \end{pmatrix}, \qquad B_i = \left[U_{i_{max}}^T \quad U_{i_{min}}^T \right]^T$$

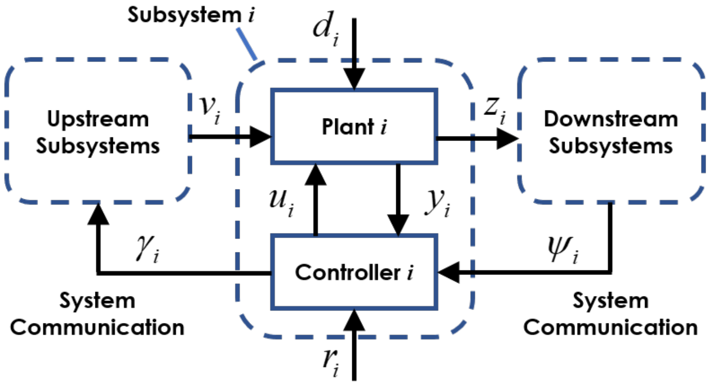
- Objective function has quadratic error and control terms with a linear penalty term
- Local dynamics can be moved into objective function from constraints
- Sensitivities are calculated based on upstream system disturbances

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

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

(Jalal, et al., 2016)

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
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Algorithm 1 LC-DMPC Algorithm

Initialization: Given $x_{0,i}(k)$ & N_a, $\mathrm{V}_i(0), \mathrm{U}_i(0), \Psi_i(0) = 0$.

Step 1: Exchange current information with local agents:

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

Step 2: Solve problem (13) and assign the result as $\mathrm{U}_i{}^{QP}$.

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

$$\mathrm{U}_i(j+1) = \beta \mathrm{U}_i(j) + (1-\beta)\mathrm{U}_i{}^{QP}(j)$$

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

$$\mathrm{Z}_i(j+1) = F_{z,i}x_{0,i}(k) + M_{z,i}\mathrm{U}_i(j+1) + N_{z,i}\mathrm{V}_i(j)$$

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

$$\gamma_i(j+1) = -2N_{y,i}^T \mathrm{Q}_i \mathrm{r}_i(k) + 2N_{y,i}^T \mathrm{Q}_i M_{y,i} \mathrm{U}_i(j+1) + 2N_{y,i}^T \mathrm{Q}_i N_{y,i} \mathrm{V}_i(j) + N_{z,i}^T \Psi_i(j) + 2N_{y,i}^T \mathrm{Q}_i F_{y,i} x_{0,i}(k)$$

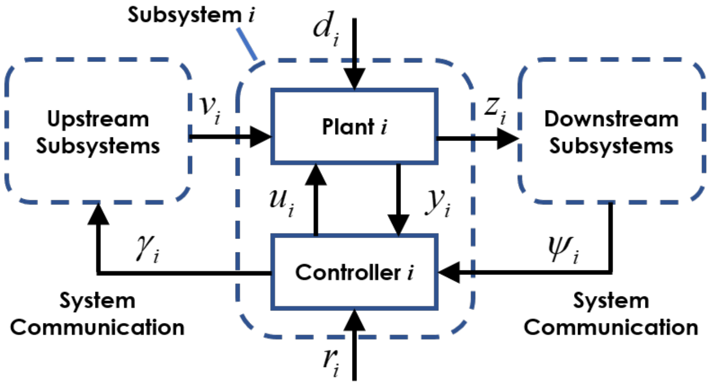
Step 6: If $j \neq N_a$ go to step 1, otherwise go to step 7.

Step 7: Apply the first value of U_i.

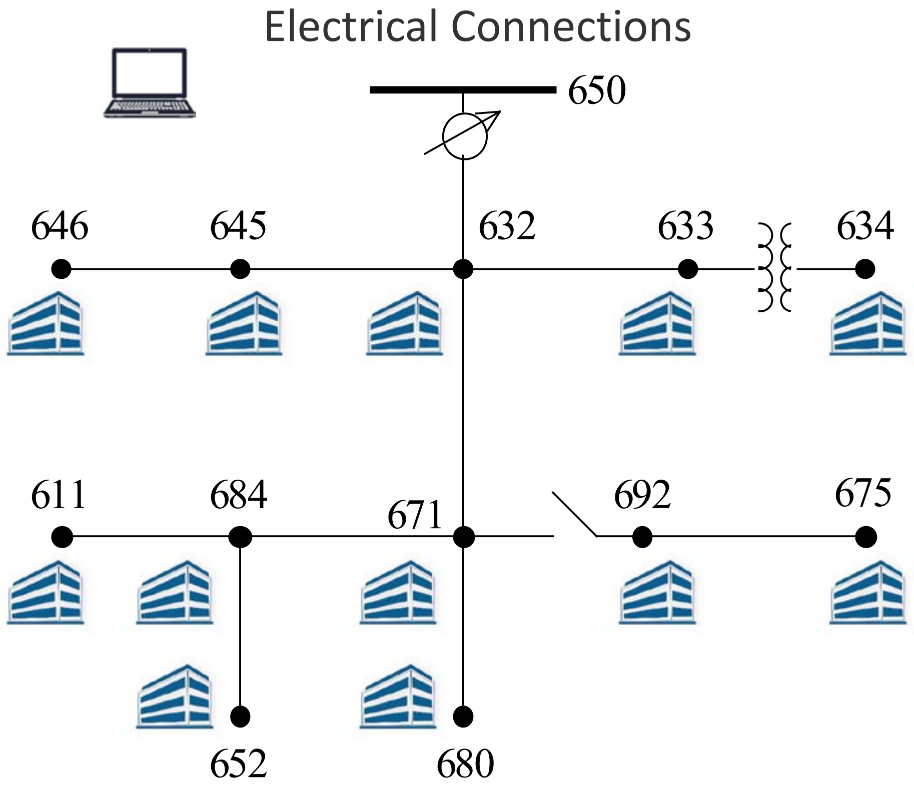
Step 8: Get new measurements for $x_{0,i}$ and go to step 1.

(Jalal, et al., 2016)

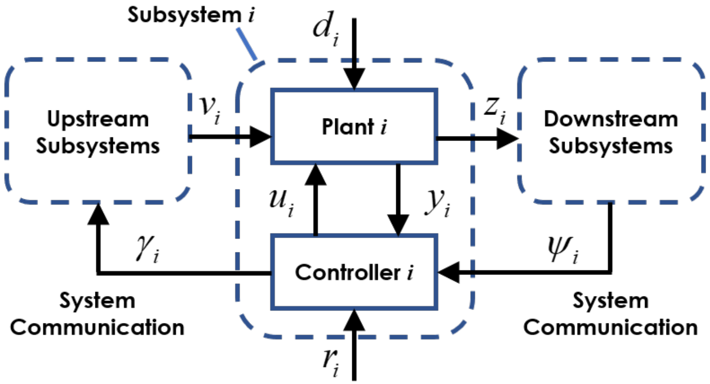
The Model



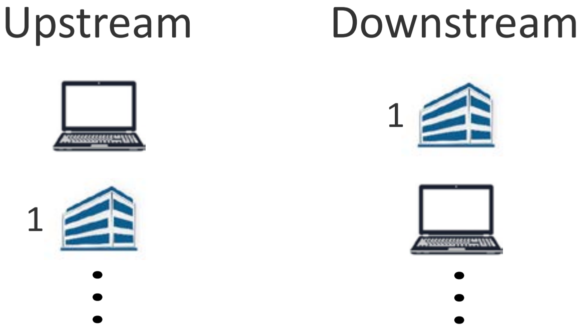
- IEEE 13 Node Test Feeder consisting of building nodes
- Added grid aggregator to distribute reference signal from the grid
- Grid aggregator is at same level as buildings, not hierarchical

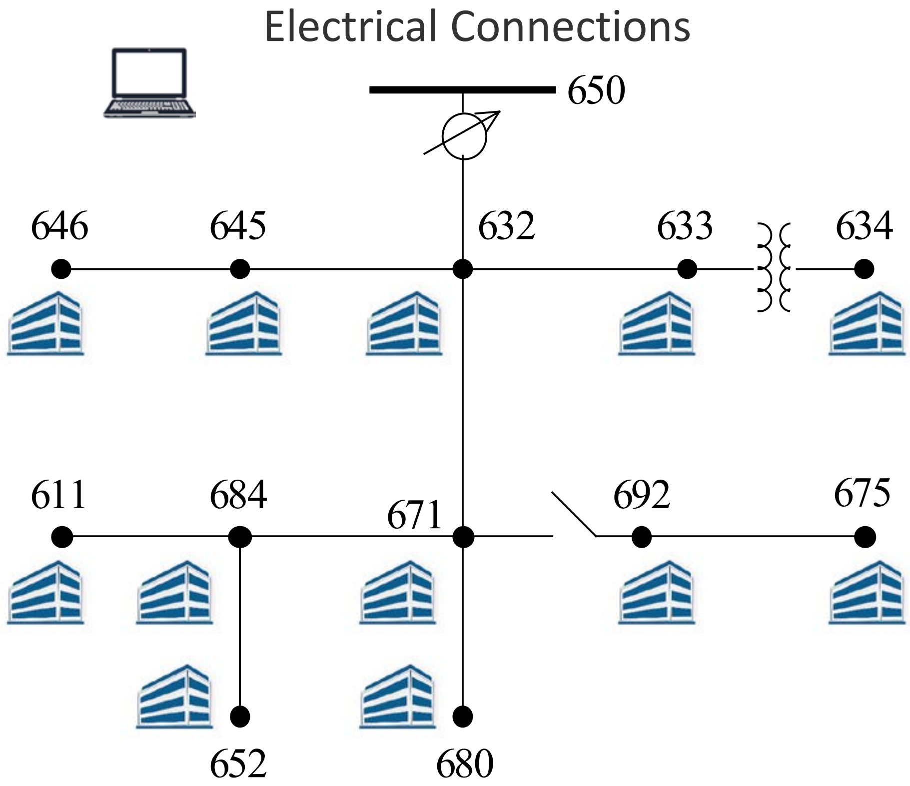


Interconnections



- Grid aggregator is both upstream and downstream to each building





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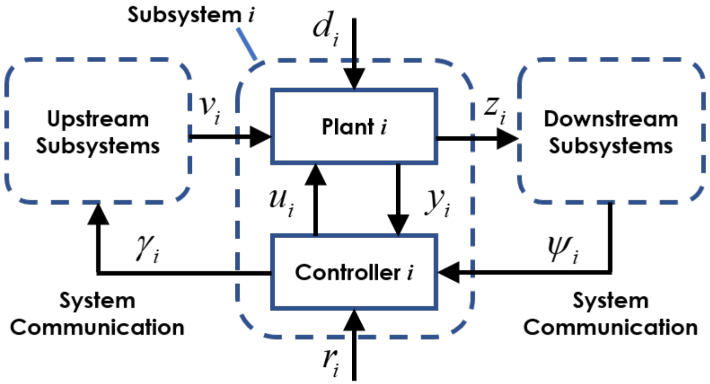
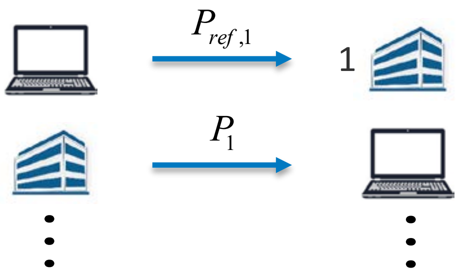
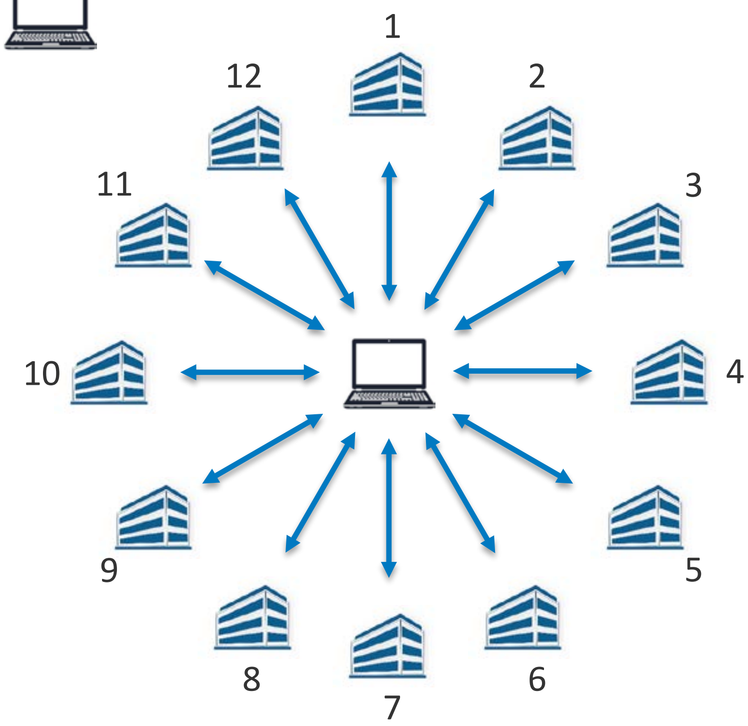


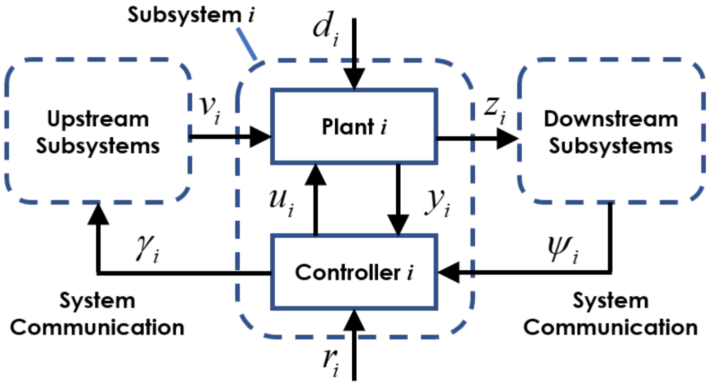
- Grid aggregator is both upstream and downstream to each building

Upstream Downstream

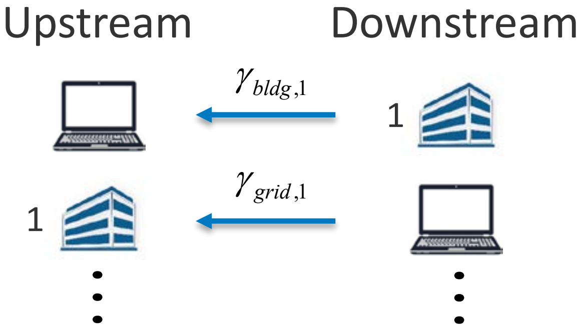




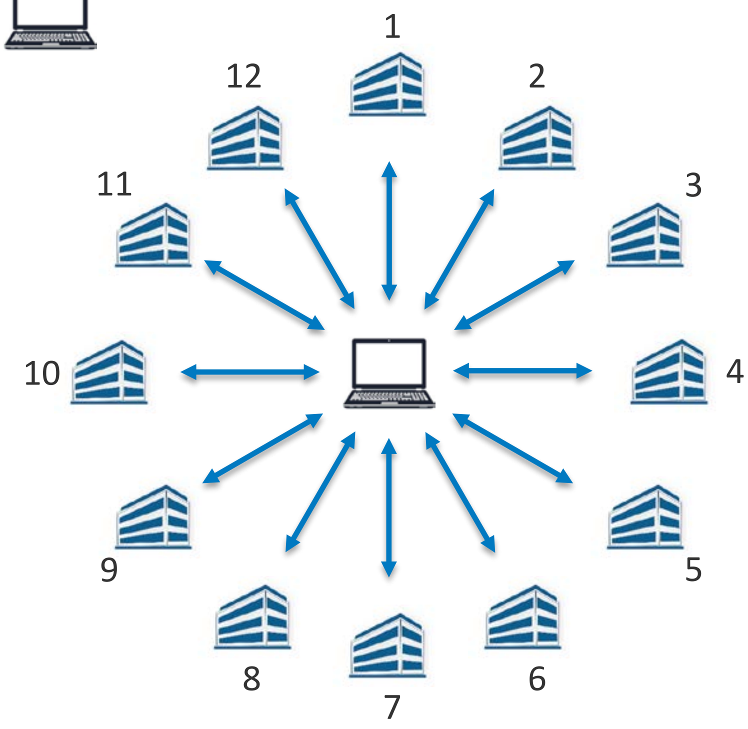
Interconnections



- Grid aggregator is both upstream and downstream to each building



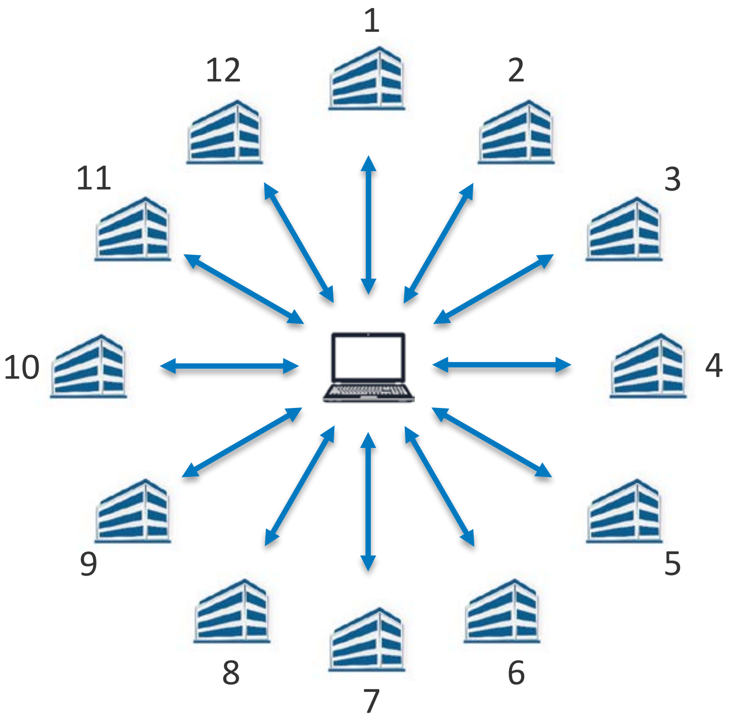
Communication Connections



Grid Aggregator Model

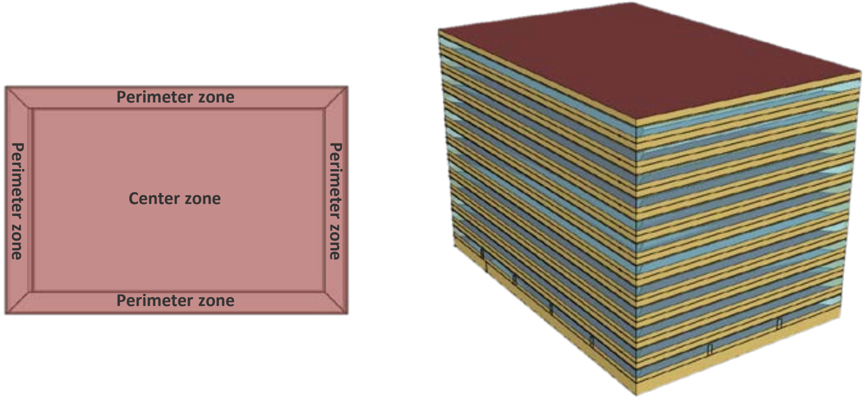
- A bulk reference signal is sent from the grid to the feeder
- The grid aggregator determines power references for the buildings
  - Model includes summation of individual building powers
  - Optimization chooses reference signals such that the reference tracking error is minimized
- Through iterative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

Communication Connections



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

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

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

- 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

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k)$$

- 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

$for\ k = 1{:}\,n_{train}$

$if\ k == 1:$

$x_k := x_{init}$ (Initial state estimates)

$e_{mse-old} = 100$ (Initial state mean squared error)

$else:$

$$e_{mse} = \left(\frac{1}{n_{val}}\right) \cdot \sum_{i=1}^{n_{val}} \left(T_{in}(i + n_{pred}) - Hx_{i+n_{pred}|i}\right)^2$$

$if\ e_{mse} < e_{mse-old}:$

$e_{mse-old} = e_{mse}$

$x_k := x_{k|k}$ (measurement update)

$else:$

$x_k(1{:}2) = x_{k|k}(1{:}2)$ (measurement update only for temperature states)

$x_k := x_{k+1|k}$ (time update)

EKF Matrices and Equations

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

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

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

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

Measurement Update

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

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

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

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

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

Time Update

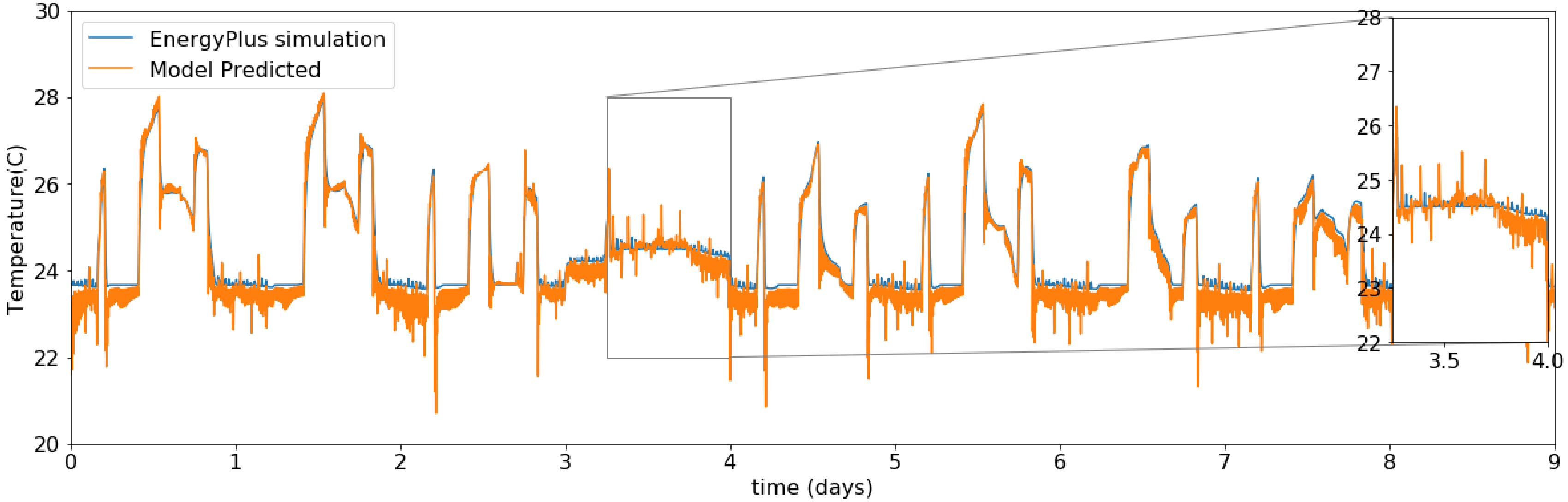
$$x_{k+1|k} = f(x_k, u_k)$$

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

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

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

EKF 4-hour Prediction



- 5 Zone building modeled as a single zone.

Linear Parametric Model for MPC

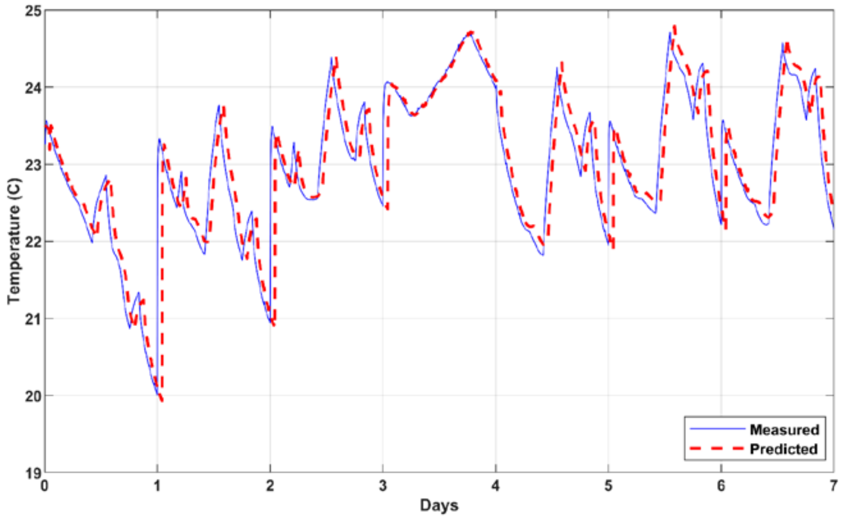
- Linear parametric equation for building envelope modeling
  - —ARX model structure to predict room temperature dynamics

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + \ \dots + a_{n_a} y(k-n_a) + $$
$$b_1 u(k-1) + b_2 u(k-2) + \ \dots + b_{n_b}(k-n_b) + e(t)$$

  - —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

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

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

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

$$a_2 = 0.1403 \qquad a_3 = 0.0086$$

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

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

$\dot{m}_s =$ air mass flow rate

$COP_{HVAC} =$ coeffecient of performance

$T_{ma} =$ mixed air temperature

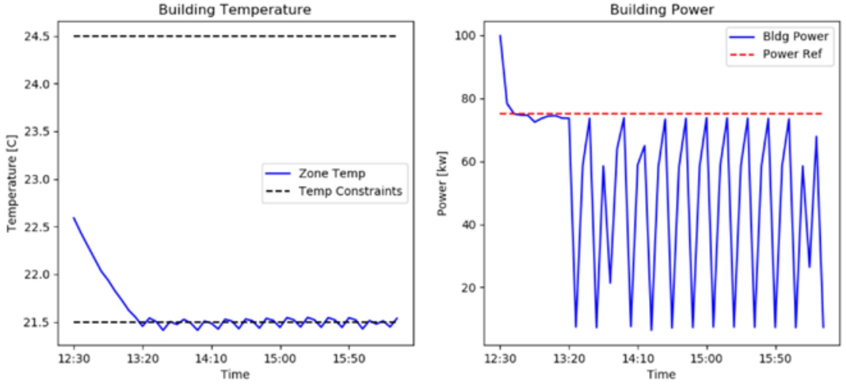
$T_{sa} =$ supply air temperature

$T_z =$ zone temperature

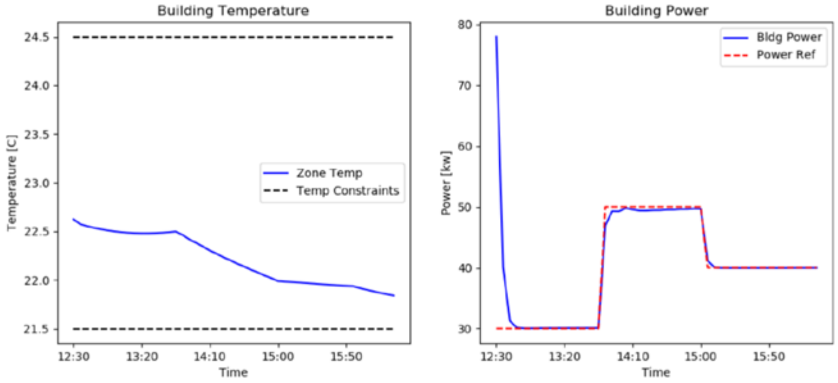
Preliminary Results

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

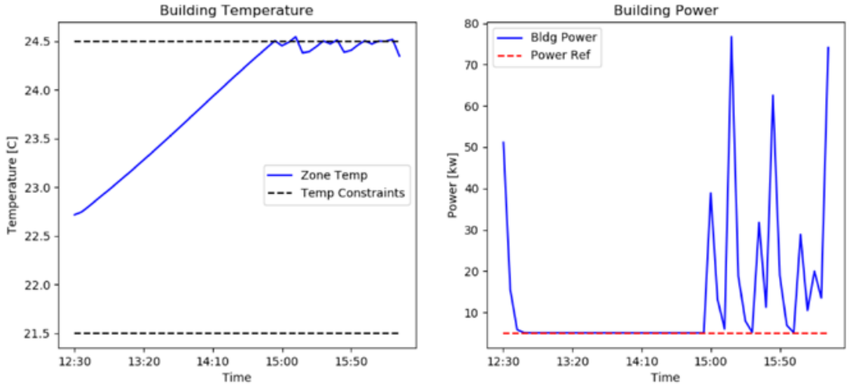
Forcing to Lower Temperature Constraint



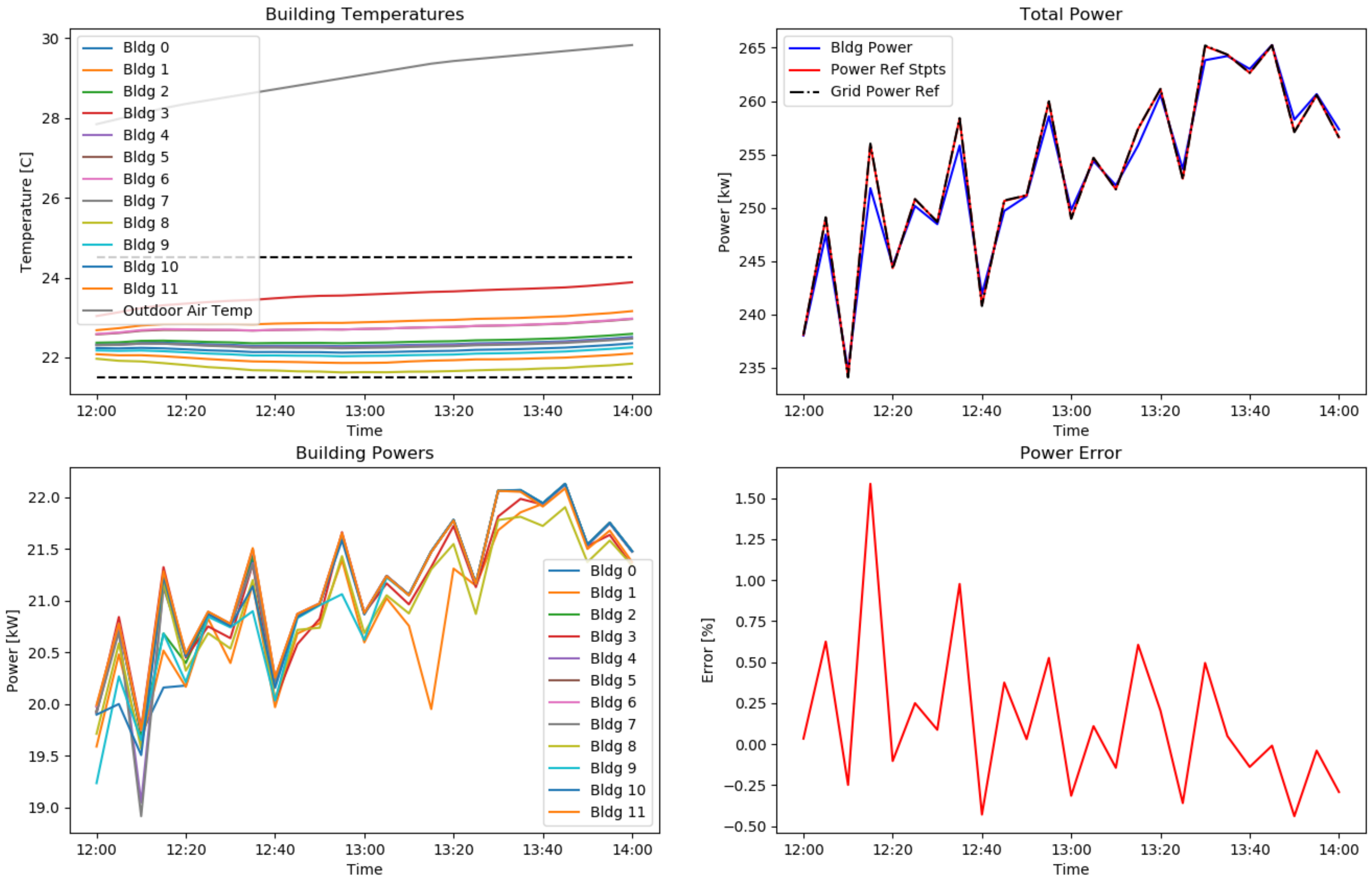
Reference Tracking



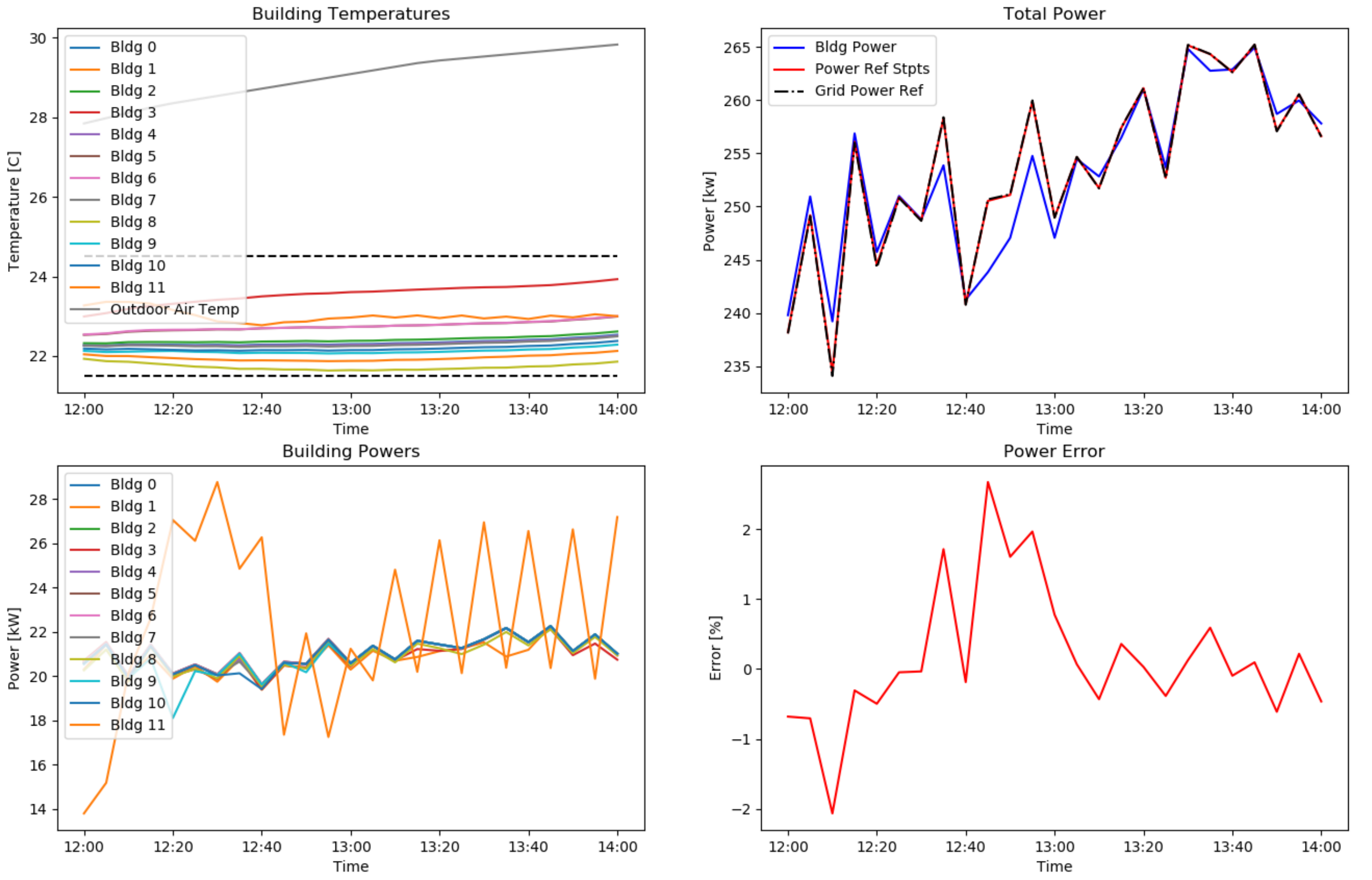
Forcing to Upper Temperature Constraint



Preliminary Results Cont.

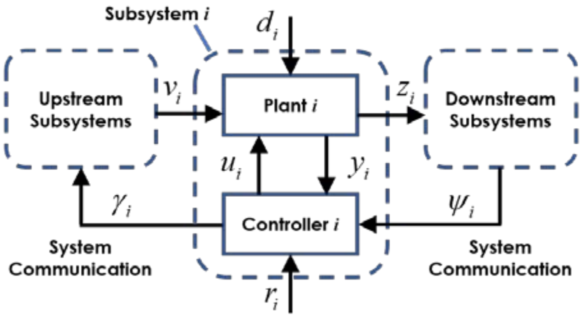


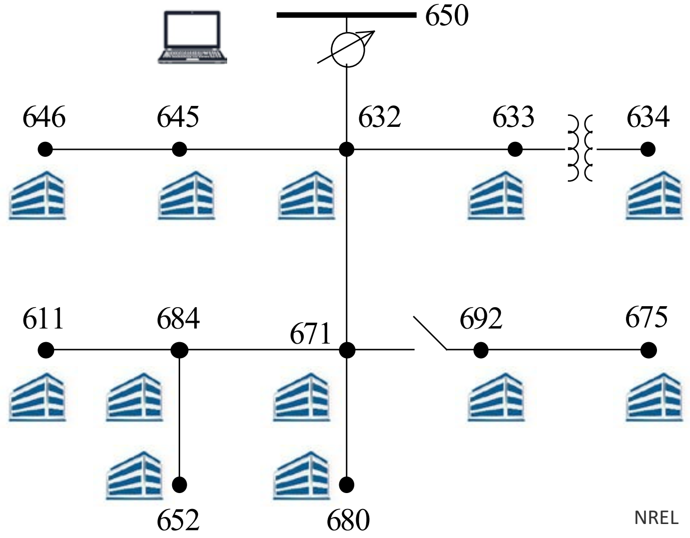
Preliminary Results Cont.



Conclusions

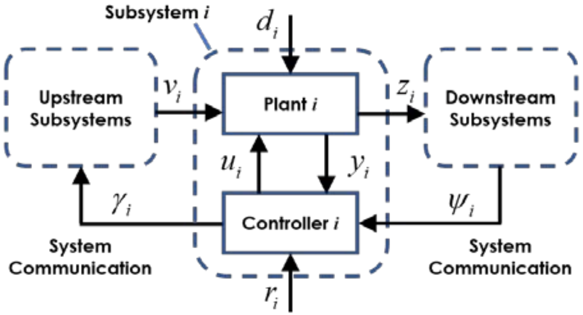
- Grid aggregator allows for buildings to "pushback" with own objectives
- Used novel EKF approach for building model
- LC-DMPC allows for systems to be both upstream and downstream agents (mesh networks)
- Method can be used at different levels of systems

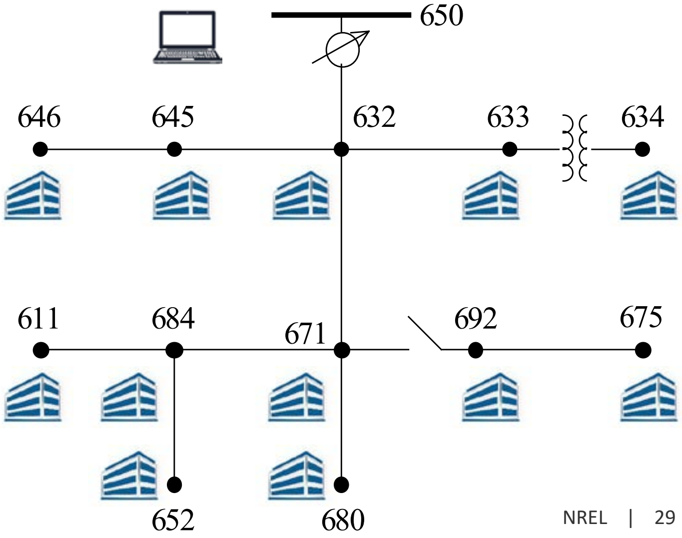




Additional Opportunities/Ongoing Work

- 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





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Questions?

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