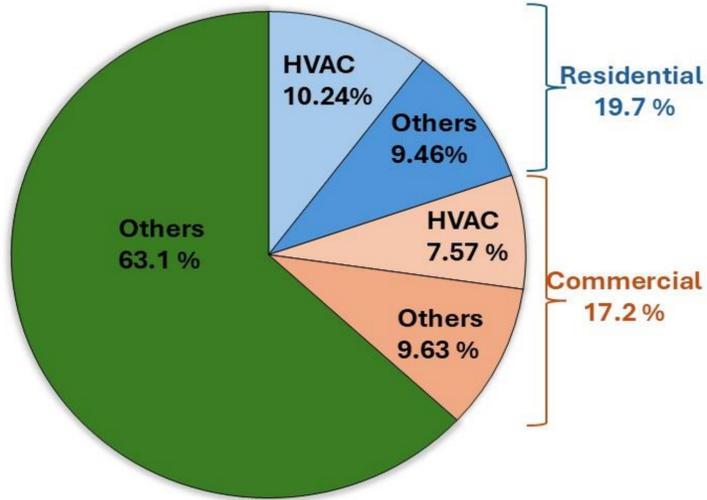


1. BACKGROUND AND MOTIVATION

- Buildings consume 40% of U.S. electricity, with HVAC systems responsible for nearly 45%, making efficient thermal modeling essential.
- Compact and accurate models are needed to enable intelligent HVAC control for grid-edge applications.
- For this purpose, robust models are essential, and we opt for grey-box models as they offer a balance between interpretability, which is lacking in black-box models, and computational efficiency, which is often a challenge in white-box.
- We evaluate Resistance-Capacitance (RC) network models and structured regression models using five parameter estimation techniques: Nonlinear Least Squares (NLS), Batch Estimation (BE), Maximum Likelihood Estimation (MLE) for RC models, and Linear Least Squares (LLS) and Almon Lag Structure (ALS) for regression-based models.
- A structured simulation framework with three testing types is employed to assess model generalization under varying control policies for grid-interactive buildings.

2. ENERGY CONSUMPTION IN USA

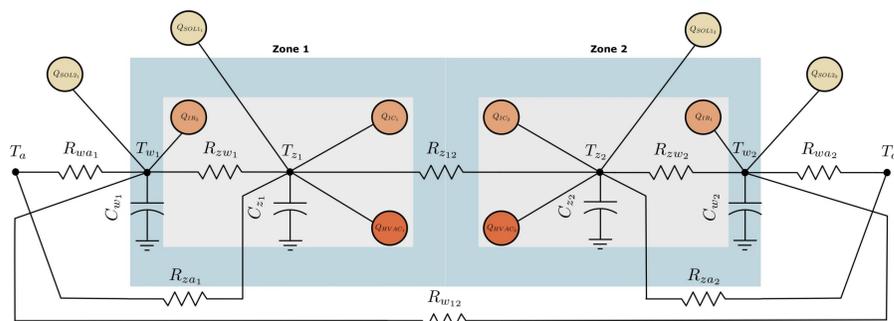
U.S. ENERGY CONSUMPTION 2023



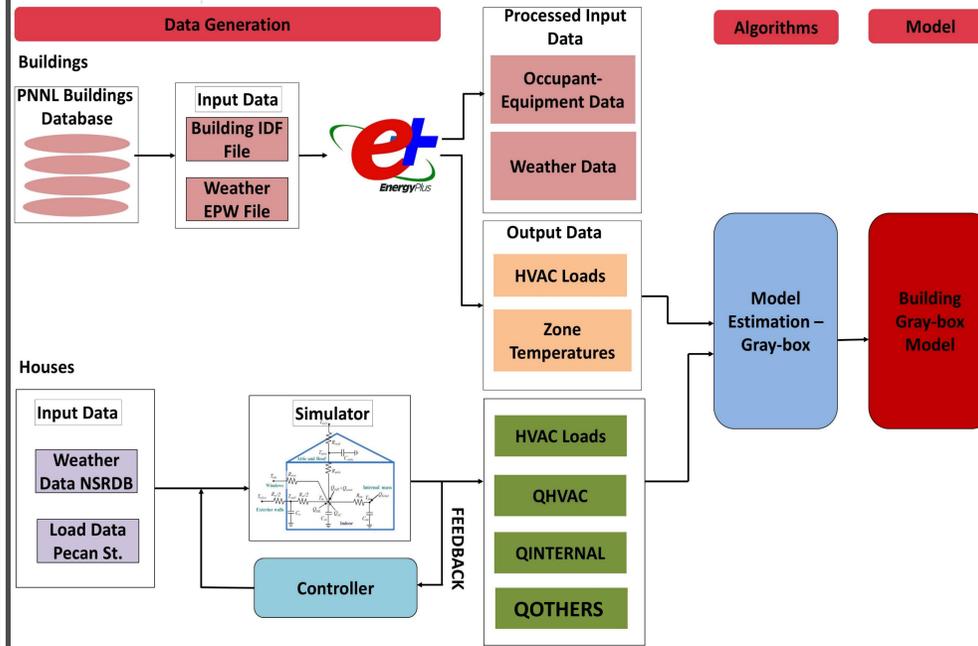
[1] U.S. Energy Information Administration (EIA), "Monthly Energy Review," 2023. [Online]. Available: <https://www.eia.gov/>

3. GREYBOX THERMAL MODELS

Schematic Representation:



4. BUILDING THERMAL MODEL ESTIMATION - WORKFLOW



5. STATE-SPACE FORMULATION OF BUILDING THERMAL DYNAMICS

Model Equations

$$C_{z_i} \dot{T}_{z_i} = \sum_j \frac{A_{ij}}{R_{z_{ij}}} (T_{z_j} - T_{z_i}) + \frac{1}{R_{z_{w_i}}} (T_{w_i} - T_{z_i}) + (Q_{IC_i} - Q_{HVAC_i}) + A_{SOL_i} Q_{SOL1_i}$$

$$C_{w_i} \dot{T}_{w_i} = \sum_j \frac{A_{ij}}{R_{w_{ij}}} (T_{w_j} - T_{w_i}) + \frac{1}{R_{z_{w_i}}} (T_{z_i} - T_{w_i}) + Q_{IR_i} + B_{SOL_i} Q_{SOL2_i}$$

BATCH ESTIMATION

$$\min_{X_1^e, w_1, \dots, w_{N-1}} \left[(X_1^e)^T P_1^{-1} X_1^e + \sum_{k=1}^N (v_k^T R^{-1} v_k) + \sum_{k=1}^{N-1} (w_k^T Q^{-1} w_k) \right]$$

Constraints:

$$v_k = y_k - h(x_k, \theta_k)$$

$$x_k = f(x_{k-1}, \theta_{k-1}, u_{k-1}) + w_{k-1}^x$$

$$\theta_k = \theta_{k-1} + w_{k-1}^\theta$$

ALMON LAG ESTIMATION

$$A(z, l, t, q) = \sum_{i=1}^l \sum_{j=0}^q \omega_{c,j} z(k-i)$$

$$T_z(k+1) = \alpha_0 + A(T_z, l_t, q_t) + A(P_c, j_m, q_p) + A(P_h, j_m, q_p) + A(D_c, n_o, q_d) + A(D_h, n_o, q_d)$$

LEAST SQUARES

$$\min_{\theta} \sum_{k=1}^N [y(k) - \tilde{y}(k)]^2$$

Constraints:

$$\tilde{x}(k+1) = \tilde{x}(k) + t_s [A(\theta)\tilde{x}(k) + B(\theta)u(k)]$$

$$\tilde{y}(k) = C\tilde{x}(k) + Du(k)$$

$$\tilde{x}(k) \in \mathcal{X}$$

$$\theta \in \Theta$$

MAXIMUM LIKELIHOOD ESTIMATION

$$\min_{\theta, e, S, \tilde{x}, P} \sum_{k=0}^N [e_k^T S_k^{-1} e_k] + \log |S_k|$$

Constraints:

$$S_k = C_k P_k C_k^T + R_k$$

$$e_k = y_k - C_k \tilde{x}_k$$

$$\tilde{x}_{k+1} = A_k(\theta) (\tilde{x}_k + P_k C_k^T S_k^{-1} e_k) + B(\theta) u_k$$

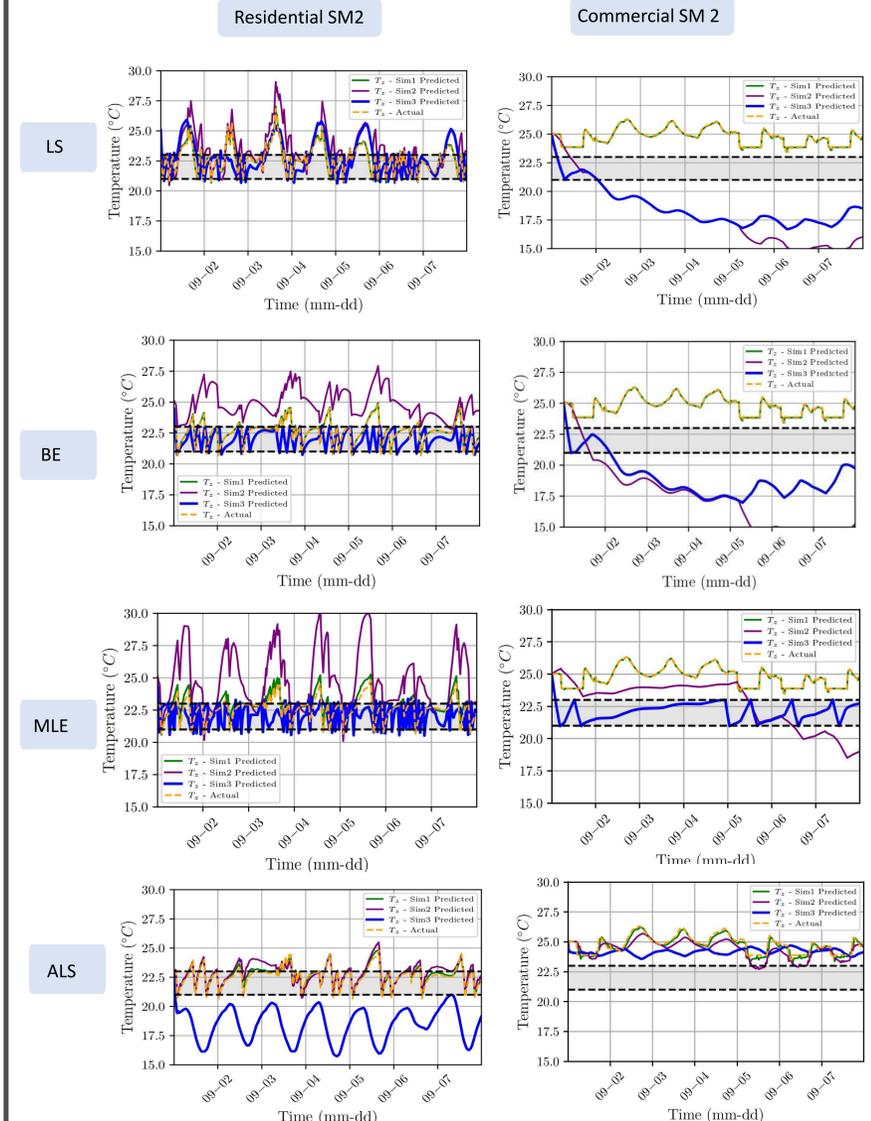
$$P_{k+1} = A_k(\theta) (P_k - P_k C_k^T S_k^{-1} C_k P_k) A_k(\theta)^T + Q_k$$

STATE SPACE REPRESENTATION

$$\dot{x} = A(\theta) x + B(\theta) u + D(\theta) w$$

$$y = C x$$

6. RESULTS



7. CONCLUSION AND FUTURE WORK

- RC-network models of moderate complexity, estimated via BE and MLE, demonstrate superior generalization to varying control policies compared to regression-based models.
- Future work will focus on developing scalable, physics-informed models using Scientific Machine Learning, as larger datasets can improve model learning while GB faces scalability challenges.

8. REFERENCES

- B. Cui, C. Fan, J. Munk, N. Mao, F. Xiao, J. Dong, and T. Kuruganti, "A hybrid building thermal modeling approach for predicting temperatures in typical, detached, two-story houses,"
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