Quantile-SMPC for Grid-Interactive Buildings with Multivariate Temporal Fusion Transformers

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CONTRIBUTIONS

Exogenous disturbances such as occupancy and weather strongly affect the performance of grid-interactive buildings, making accurate probabilistic forecasting essential for robust control. We propose a new MQF2-TFT architecture that captures both temporal and cross-variable dependencies for multi-horizon disturbance forecasting. To integrate forecasts into stochastic MPC, we develop a quantile-based sample method that enforces chance constraints despite non-Gaussianity.

CONTROL OF GRID-INTERACTIVE BUILDINGS

Inputs: heat pump, battery charge, battery discharge

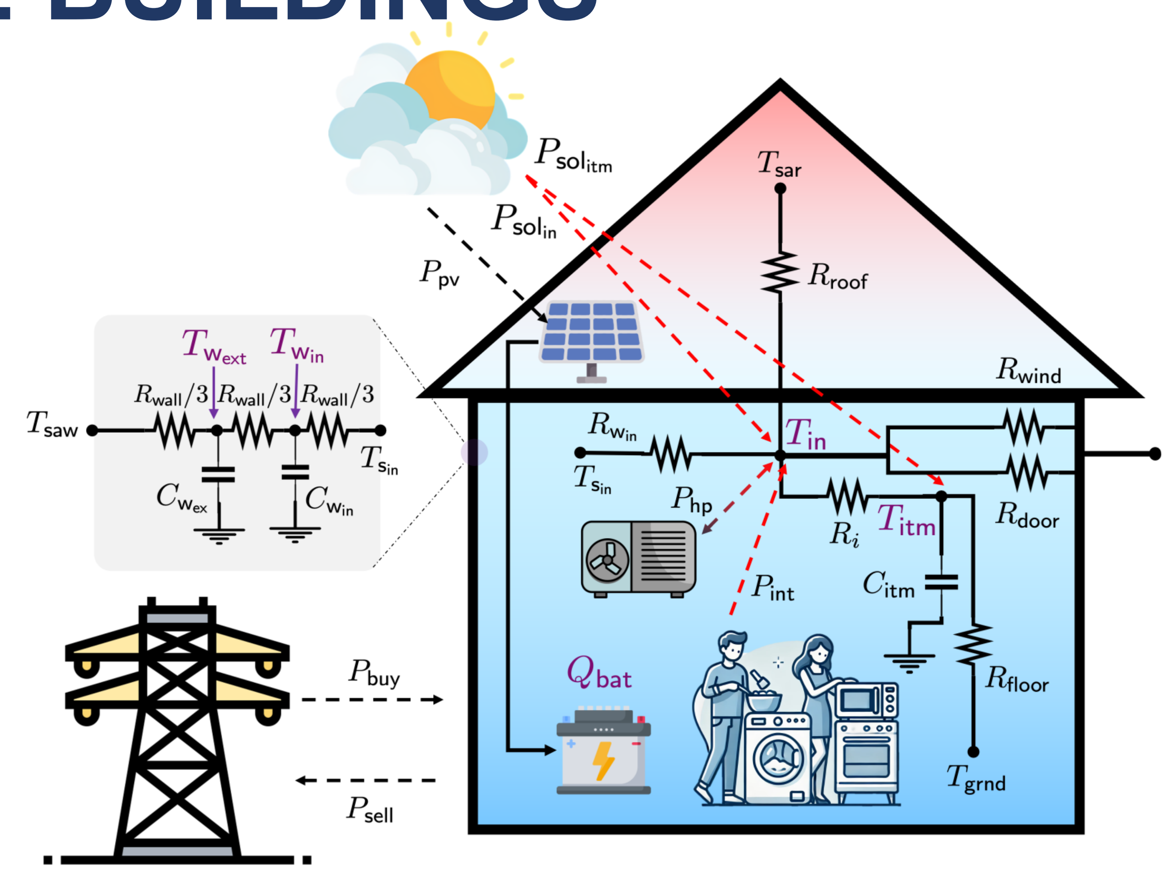
$$u_t = [P_{hp}, P_{bat_{chg}}, P_{bat_{dis}}]$$

States: internal temps $x_t = [T_{in}, T_{itm}, T_{wext}, T_{win}]$

Disturbances: ambient temperature, solar irradiance, internal heat loads $w_t = [T_{amb}, I, P_{int}]$

Comfort Constraints: $T_{in}^{min} \leq T_{in} \leq T_{in}^{max}$

Cost Minimization: aim to minimize power bought from the grid



FORECASTING MODEL

Aim to approximate the disturbance distribution: $\mathbb{P}(w_{t+1:t+H} | w_{1:t}, c_{1:t+H}) \approx f(w_{t+1:t+H}; w_{t-k:t}, c_{t-k:t+H})$

Temporal Fusion Transformer (TFT): TFT backbone provides horizon-specific latent

$$\mathbf{h}_\tau = F_\theta(w_{t-k:t}, c_{t-k:t+\tau}, \hat{w}_{t+1:t+\tau-1}, \tau), \quad \tau = 1, .., H$$

Multivariate Quantile Function Forecastor (MQF2): MQF2 decoder at each horizon generates multi-variate forecasts from latent

$$\hat{w}_{t+\tau} = g_\phi(\mathbf{h}_\tau, \alpha), \quad \alpha \sim U([0,1]^m)$$

QUANTILE-SMPC

Since our forecasting model provides disturbance samples (and not an analytic model), we use *empirical quantiles* to approximate the chance-constraints in SMPC.

Vanilla SMPC

$$\min_{\hat{\mathbf{x}}, \mathbf{u}} \mathbb{E}\left[J(\hat{\mathbf{x}}, \mathbf{u})\right]$$

$$\text{subject to} : \mathbb{P}\left(C\hat{x}_\tau \leq T_{\text{in}}^{\text{max}}\right) \geq p$$

$$\mathbb{P}\left(C\hat{x}_\tau \geq T_{\text{in}}^{\text{min}}\right) \geq p$$

analytic probability

Quantile-SMPC

$$\min_{\hat{\mathbf{x}}, \mathbf{u}} \mathbb{E}\left[J(\hat{\mathbf{x}}, \mathbf{u})\right]$$

$$\text{subject to} : S_\tau^x x_t + S_\tau^u \mathbf{u} + \hat{Q}_{S_\tau^u \hat{\mathbf{w}}}(\Delta) \leq T_{\text{in}}^{\text{max}}$$

$$S_\tau^x x_t + S_\tau^u \mathbf{u} + \hat{Q}_{S_\tau^u \hat{\mathbf{w}}}(1 - \Delta) \geq T_{\text{in}}^{\text{min}}$$

empirical quantiles via disturbance samples

RESULTS

	Winter / Jan 2023		Spring / April 2023		Summer / Jul 2023		Fall / Oct 2023	
Algorithm	TD	Cost	TD	Cost	TD	Cost	TD	Cost
Gaussian	3.26	−16.01	9.66	6.02	21.14	19.48	16.86	14.60
VAR	1.04	−16.90	1.73	−2.39	2.03	10.15	2.90	6.02
Cantelli	**0.10**	−13.98	**0.02**	−1.97	**0.06**	9.78	**0.17**	5.16
Quantile	0.47	**−17.88**	0.43	**−3.33**	0.66	**8.97**	0.36	**3.49**

Gaussian: Computes the SMPC policy with the disturbances taken to be iid Gaussian, with empirical mean and covariance from historical data. **VAR:** Computes the SMPC policy with the disturbances taken to be generated by a vector autoregressive (VAR) model with the same context length as our proposed model. **Cantelli:** Uses the same forecasting model as the proposed approach, but enforces the chance constraints with Cantelli's inequality using the empirical mean and variance of the forecasting samples