Electronic Supplementary Material

Data-driven model predictive control for power demand management and fast demand response of commercial buildings using support vector regression

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Appendix

A. Development of the RC model for MPC

According to Figure 4 in the text, the heat exchanges and energy balances between outdoor, indoor and building envelop are presented in Eqs. (a1)–(a5) (Tang and Wang 2019).

$$C_{\mathrm{w,1}}\frac{\mathrm{d}T_{\mathrm{w,ex}}}{\mathrm{d}t}=\frac{T_{\mathrm{out}}-T_{\mathrm{w,ex}}}{R_{\mathrm{w,o}}}-\frac{T_{\mathrm{w,ex}}-T_{\mathrm{w,in}}}{R_{\mathrm{w}}}+Q_{\mathrm{solar,w}} \tag{a1}$$

$$C_{\mathrm{w,2}}\frac{\mathrm{d}T_{\mathrm{w,in}}}{\mathrm{d}t}=\frac{T_{\mathrm{w,ex}}-T_{\mathrm{w,in}}}{R_{\mathrm{w}}}-\frac{T_{\mathrm{w,in}}-T_{\mathrm{in}}}{R_{\mathrm{w,i}}} \tag{a2}$$

$$C_{\mathrm{im,1}}\frac{\mathrm{d}T_{\mathrm{im,1}}}{\mathrm{d}t}=\frac{T_{\mathrm{im,2}}-T_{\mathrm{im,1}}}{R_{\mathrm{i,1}}}+Q_{\mathrm{im,1}} \tag{a3}$$

$$C_{\mathrm{im,2}}\frac{\mathrm{d}T_{\mathrm{im,2}}}{\mathrm{d}t}=\frac{T_{\mathrm{im,1}}-T_{\mathrm{im,2}}}{R_{\mathrm{i,1}}}-\frac{T_{\mathrm{im,2}}-T_{\mathrm{in}}}{R_{\mathrm{i,2}}}+Q_{\mathrm{im,2}} \tag{a4}$$

$$C_{\mathrm{in}}\frac{\mathrm{d}T_{\mathrm{in}}}{\mathrm{d}t}=\frac{T_{\mathrm{im,2}}-T_{\mathrm{in}}}{R_{\mathrm{i,2}}}+\frac{T_{\mathrm{w,in}}-T_{\mathrm{in}}}{R_{\mathrm{w,i}}}+\frac{T_{\mathrm{out}}-T_{\mathrm{in}}}{R_{\mathrm{win}}}+Q_{\mathrm{inter,i}}-Q_{\mathrm{ac}}+Q_{\mathrm{solar,i}} \tag{a5}$$

where, the values of R and C are determined by training historical data by genetic algorithm. T is the temperature. Indoor air, outdoor air, exterior wall, internal wall surface, external wall surface, window, and internal mass are represented by the subscripts of *i*, *out*, *w*, *in*, *ex*, *win* and *im*, respectively. Q_{solar} is the solar heat gain. $Q_{\mathrm{inter,i}}$ is internal heat gain. Q_{im} is the radiation heat. Q_{ac} is the cooling demand provided by the central air-conditioning systems (i.e., Q_{dem}), which is determined by the chiller power demand (P_{ch}) and corresponding COP (coefficient of performance), as shown in Eq. (a11).

$$Q_{\mathrm{solar,w}}=\alpha I_{\mathrm{solar}} \tag{a6}$$

$$Q_{\mathrm{solar,i}}=\beta_i\cdot SHGC\cdot I_{\mathrm{solar}} \tag{a7}$$

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$$Q_{\mathrm{im},1}=Q_{\mathrm{im},2}=b\cdot\left(Q_{\mathrm{solar,im}}+Q_{\mathrm{inter,im}}\right) \tag{a8}$$

$$Q_{\mathrm{solar,im}}=\beta_{\mathrm{im}}\cdot SHGC\cdot I_{\mathrm{solar}} \tag{a9}$$

$$Q_{\mathrm{inter,im}}=\mu\cdot Q_{\mathrm{inter}} \tag{a10}$$

$$Q_{\mathrm{dem}}=P_{\mathrm{ch}}\cdot COP \tag{a11}$$

where, I_{solar} is the global solar radiation, obtained from weather data; β, b, and μ represent the pre-set ratios of split radiative/convective heat gain; α denotes the absorptance of the surface of solar radiation. *SHGC* is solar heat gain coefficient.

The RC model is reformatted as a linear continuous-time state-space model in Eq. (a12), where system state vector $\boldsymbol{x}=[T_{\mathrm{w,ex}}\ T_{\mathrm{w,in}}\ T_{\mathrm{im},1}\ T_{\mathrm{im},2}\ T_{\mathrm{in}}]^{\mathrm{T}}$. Control input vector $\boldsymbol{u}=[\boldsymbol{P}_{\mathrm{ch}}]^{\mathrm{T}}$. Disturbance vector $\boldsymbol{d}=[I_{\mathrm{solar}}\ T_{\mathrm{out}}\ Q_{\mathrm{inter}}]^{\mathrm{T}}$. For online control, the continuous-time state-space model needs to be converted into the discrete-time state-space model (i.e., Eqs.(18)–(19)) based on the sampling time.

$$\frac{\mathrm{d}x}{\mathrm{d}t}=\boldsymbol{a}\cdot\boldsymbol{x}+\boldsymbol{b}\cdot\boldsymbol{u}+\boldsymbol{e}\cdot\boldsymbol{d} \tag{a12}$$

System matrix $\boldsymbol{a}$:

$$\boldsymbol{a}=\begin{bmatrix}\frac{-1}{C_{\mathrm{w},1}R_{\mathrm{w,o}}}+\frac{-1}{C_{\mathrm{w},1}R_{\mathrm{w}}} & \frac{1}{C_{\mathrm{w},1}R_{\mathrm{w}}} & 0 & 0 & 0\\ \frac{1}{C_{\mathrm{w},2}R_{\mathrm{w}}} & \frac{-1}{C_{\mathrm{w},2}R_{\mathrm{w}}}+\frac{-1}{C_{\mathrm{w},2}R_{\mathrm{w,i}}} & 0 & 0 & \frac{1}{C_{\mathrm{w},2}R_{\mathrm{w,i}}}\\ 0 & 0 & \frac{-1}{C_{\mathrm{im},1}R_{\mathrm{i},1}} & \frac{1}{C_{\mathrm{im},1}R_{\mathrm{i},1}} & 0\\ 0 & 0 & \frac{1}{C_{\mathrm{im},2}R_{\mathrm{i},1}} & \frac{-1}{C_{\mathrm{im},2}R_{\mathrm{i},1}}+\frac{-1}{C_{\mathrm{im},2}R_{\mathrm{i},2}} & \frac{1}{C_{\mathrm{im},2}R_{\mathrm{i},2}}\\ 0 & \frac{1}{C_{\mathrm{in}}R_{\mathrm{w,i}}} & 0 & \frac{1}{C_{\mathrm{in}}R_{\mathrm{i},2}} & \frac{-1}{C_{\mathrm{in}}R_{\mathrm{i},2}}+\frac{-1}{C_{\mathrm{in}}R_{\mathrm{w,i}}}+\frac{-1}{C_{\mathrm{in}}R_{\mathrm{win}}}\end{bmatrix}_{5\times5}$$

Input matrix $\boldsymbol{b}$: $\boldsymbol{b}=\begin{bmatrix}0\\0\\0\\0\\ \frac{-COP}{C_{\mathrm{in}}}\end{bmatrix}_{5\times1}$

Disturbance matrix $\boldsymbol{e}$: $\boldsymbol{e}=\begin{bmatrix}\frac{a}{C_{\mathrm{w},1}} & \frac{1}{C_{\mathrm{w},1}R_{\mathrm{w,o}}} & 0\\ 0 & 0 & 0\\ \frac{b\beta_{\mathrm{im}}SHGC}{C_{\mathrm{im},1}} & 0 & \frac{b}{C_{\mathrm{im},1}}\\ \frac{b\beta_{\mathrm{im}}SHGC}{C_{\mathrm{im},2}} & 0 & \frac{b}{C_{\mathrm{im},2}}\\ \frac{\beta_{\mathrm{i}}SHGC}{C_{\mathrm{in}}} & \frac{1}{C_{\mathrm{in}}R_{\mathrm{win}}} & \frac{1-}{C_{\mathrm{in}}}\end{bmatrix}_{5\times3}$.

B. Parameters of the discrete-time state-space model for MPC

Matrix $\boldsymbol{A}_{\mathrm{d}} = \begin{bmatrix} 9.998\times10^{-1} & 1.093\times10^{-5} & 0 & 0 & 0 \\ 1.009\times10^{-5} & 9.989\times10^{-1} & 0 & 0 & 6.948\times10^{-7} \\ 0 & 0 & 9.958\times10^{-1} & 4.191\times10^{-3} & 0 \\ 0 & 0 & 3.796\times10^{-3} & 9.955\times10^{-1} & 2.571\times10^{-6} \\ 0 & 5.789\times10^{-1} & 0 & 2.084\times10^{-1} & 9.403\times10^{-7} \end{bmatrix}_{5\times5}$

Matrix B_{d}: $\boldsymbol{B}_{\mathrm{d}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ -1.003\times10^{-2} \end{bmatrix}_{5\times1}$

Matrix $\boldsymbol{E}_{\mathrm{d}}$: $\boldsymbol{E}_{\mathrm{d}} = \begin{bmatrix} 7.800\times10^{-7} & 1.034\times10^{-5} & 0 \\ 0 & 0 & 0 \\ 1.788\times10^{-6} & 0 & 2.555\times10^{-6} \\ 2.293\times10^{-6} & 0 & 3.276\times10^{-6} \\ 7.808\times10^{-4} & 2.119\times10^{-1} & 1.115\times10^{-3} \end{bmatrix}_{5\times3}$

Matrix $\boldsymbol{C}_{\mathrm{d}}$: $\boldsymbol{C}_{\mathrm{d}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{1\times5}$

Reference

Tang R, Wang S (2019). Model predictive control for thermal energy storage and thermal comfort optimization of building demand response in smart grids. *Applied Energy*, 242: 873–882.