

Appendices

Appendix 1: Proof of Equations (3-4).

Let

$$f = (\mathbf{x}_t - \mathbf{x}_{t-1})' (\mathbf{x}_t - \mathbf{x}_{t-1}) + \lambda' (\boldsymbol{\tau} - \hat{\Psi} \mathbf{y}_t - \hat{\mathbf{B}} \mathbf{x}_t - \hat{\mathbf{C}} \mathbf{x}_{t-1} - \mathbf{a}_t), t \geq 1.$$

Then

$$\frac{\partial f}{\partial \mathbf{x}_t} = 2\mathbf{x}_t' - 2\mathbf{x}_{t-1}' - \lambda' \hat{\mathbf{B}} = \mathbf{0}, \quad (\text{A1})$$

and

$$\frac{\partial f}{\partial \lambda} = \boldsymbol{\tau} - \hat{\Psi} \mathbf{y}_t - \hat{\mathbf{B}} \mathbf{x}_t - \hat{\mathbf{C}} \mathbf{x}_{t-1} - \mathbf{a}_t = \mathbf{0},$$

which leads

$$\boldsymbol{\tau} - \hat{\Psi} \mathbf{y}_t - \hat{\mathbf{B}} \mathbf{x}_{t-1} - \frac{1}{2} (\hat{\mathbf{B}} \hat{\mathbf{B}}') \lambda - \hat{\mathbf{C}} \mathbf{x}_{t-1} - \mathbf{a}_t = \mathbf{0}.$$

That is

$$\lambda = 2 (\hat{\mathbf{B}} \hat{\mathbf{B}}')^{-1} (\boldsymbol{\tau} - \hat{\Psi} \mathbf{y}_t - (\hat{\mathbf{B}} + \hat{\mathbf{C}}) \mathbf{x}_{t-1} - \mathbf{a}_t). \quad (\text{A2})$$

Replacing Equation (A2) in Equation (A1) leads

$$\mathbf{x}_t = \left(\mathbf{I}_{m \times m} - \hat{\mathbf{B}}' (\hat{\mathbf{B}} \hat{\mathbf{B}}')^{-1} (\hat{\mathbf{B}} + \hat{\mathbf{C}}) \right) \mathbf{x}_{t-1} + \hat{\mathbf{B}}' (\hat{\mathbf{B}} \hat{\mathbf{B}}')^{-1} (\boldsymbol{\tau} - \hat{\Psi} \mathbf{y}_t - \mathbf{a}_t).$$

Therefore,

$$\begin{aligned} \mathbf{x}_t - \mathbf{x}_{t-1} &= -\hat{\mathbf{B}}' (\hat{\mathbf{B}} \hat{\mathbf{B}}')^{-1} (\hat{\Psi} + \Omega) (\mathbf{y}_t - \boldsymbol{\tau}) + \hat{\mathbf{B}}' (\hat{\mathbf{B}} \hat{\mathbf{B}}')^{-1} \hat{\Psi} (\mathbf{y}_{t-1} - \boldsymbol{\tau}) \\ &\quad + \left(\mathbf{I}_{m \times m} - \hat{\mathbf{B}}' (\hat{\mathbf{B}} \hat{\mathbf{B}}')^{-1} (\hat{\mathbf{B}} + \hat{\mathbf{C}}) \right) (\mathbf{x}_{t-1} - \mathbf{x}_{t-2}). \end{aligned}$$

Appendix 2: Proof of Lemma 1.

Equations (2) and (3) lead the following equations:

$$\mathbf{a}_{t-1} - \mathbf{a}_{t-2} = \Omega (\mathbf{y}_{t-1} - \hat{\Psi} \mathbf{y}_{t-2} - \hat{\mathbf{B}} \mathbf{x}_{t-2} - \hat{\mathbf{C}} \mathbf{x}_{t-3} - \mathbf{a}_{t-2}) = \Omega (\mathbf{y}_{t-1} - \boldsymbol{\tau}),$$

for $t > 1$, and

$$\mathbf{x}_{t-1} - \mathbf{x}_{t-2} = \begin{cases} -\hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\mathbf{C}}\mathbf{x}_0 - \hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} (\hat{\Psi} + \Omega)(\mathbf{y}_1 - \tau) - \hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\Psi}\tau & t=1, \\ -\hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\mathbf{C}}(\mathbf{x}_{t-2} - \mathbf{x}_{t-3}) - \hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} (\hat{\Psi} + \Omega)(\mathbf{y}_{t-1} - \tau) \\ + \hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\Psi}(\mathbf{y}_{t-2} - \tau) & t > 1. \end{cases}$$

Expressing Equation (1) as a difference equation and using the above results provide the iterative formula for $\mathbf{y}_t - \tau$ as follows:

$$\begin{aligned} \mathbf{y}_t - \tau &= \left(\mathbf{I}_{n \times n} + \Psi - \mathbf{B}\hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} (\hat{\Psi} + \Omega) \right) (\mathbf{y}_{t-1} - \tau) \\ &\quad + \left(-\Psi + \mathbf{B}\hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\Psi} \right) (\mathbf{y}_{t-2} - \tau) \\ &\quad + \left(\mathbf{C} - \mathbf{B}\hat{\mathbf{B}}'(\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\mathbf{C}} \right) (\mathbf{x}_{t-2} - \mathbf{x}_{t-3}) \\ &\quad + (\boldsymbol{\eta}_t - \boldsymbol{\eta}_{t-1}). \end{aligned}$$

Therefore, we have

$$\begin{aligned} \begin{bmatrix} \mathbf{y}_t - \tau \\ \mathbf{y}_{t-1} - \tau \\ \mathbf{x}_{t-1} - \mathbf{x}_{t-2} \end{bmatrix} &= \mathbf{M} \begin{bmatrix} \mathbf{y}_{t-1} - \tau \\ \mathbf{y}_{t-2} - \tau \\ \mathbf{x}_{t-2} - \mathbf{x}_{t-3} \end{bmatrix} + \begin{bmatrix} (1-\mathcal{B})\boldsymbol{\eta}_t \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \\ &= \vdots \\ &= \mathbf{M}^{t-1} \begin{bmatrix} \boldsymbol{\alpha} + \mathbf{B}\mathbf{x}_0 - \tau \\ -\tau \\ \mathbf{x}_0 \end{bmatrix} + \sum_{j=0}^{t-1} (\mathbf{M})^j \begin{bmatrix} (1-\mathcal{B})\boldsymbol{\eta}_{t-j} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}. \end{aligned}$$

Hence,

$$\mathbf{y}_t - \tau = \boldsymbol{\gamma}_{t-1} + \boldsymbol{\xi}_t,$$

where,

$$\boldsymbol{\gamma}_{t-1} = \begin{bmatrix} \mathbf{I} & \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{M}^{t-1} \begin{bmatrix} \boldsymbol{\alpha} + \mathbf{B}\mathbf{x}_0 - \tau \\ -\tau \\ \mathbf{x}_0 \end{bmatrix} = \mathbf{E}_{t-1}\boldsymbol{\gamma}_0 + \mathbf{F}_{t-1}(-\tau) + \mathbf{G}_{t-1}\mathbf{x}_0,$$

and

$$\xi_t = [\mathbf{I} \quad \mathbf{0} \quad \mathbf{0}] \sum_{j=0}^{t-1} (\mathbf{M})^j \begin{bmatrix} (1-\mathcal{B})\boldsymbol{\eta}_{t-j} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} = (\boldsymbol{\eta}_t - \boldsymbol{\eta}_{t-1}) + \sum_{i=1}^{t-1} \mathbf{E}_t (\boldsymbol{\eta}_{t-i} - \boldsymbol{\eta}_{t-i-1}).$$

Note that $\xi_t = 0$, for $t \leq 0$, hence ξ_t can be further expressed as

$$\begin{aligned} \xi_t &= \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \end{bmatrix} (\mathbf{I} - \mathcal{B}\mathbf{M})^{-1} \begin{bmatrix} \mathbf{I}_{n \times n} \\ \mathbf{0}_{n \times n} \\ \mathbf{0}_{m \times n} \end{bmatrix} (1 - \mathcal{B})\boldsymbol{\eta}_t \\ &= [(\mathbf{I}_{(2n+m) \times (2n+m)} - \mathcal{B}\mathbf{M})^{-1}]_{11} (1 - \mathcal{B})\boldsymbol{\eta}_t. \end{aligned} \tag{A3}$$

Appendix 3: Proof of Theorem 1.

If $\rho(\mathbf{M}) < 1$, then

$$\lim_{t \rightarrow \infty} \mathbf{M}^t = \mathbf{0}_{(2n+m) \times (2n+m)}.$$

Therefore, it implies

$$\lim_{t \rightarrow \infty} \mathbf{E}_t = \lim_{t \rightarrow \infty} \mathbf{F}_t = \mathbf{0}_{n \times n}, \quad \lim_{t \rightarrow \infty} \mathbf{G}_t = \mathbf{0}_{n \times m}.$$

Hence, in this case, Equation (12) leads

$$\lim_{t \rightarrow \infty} \mathbf{E}(\mathbf{y}_t) = \lim_{t \rightarrow \infty} \left\{ \boldsymbol{\tau} + \mathbf{E}_{t-1} \boldsymbol{\gamma}_0 + \mathbf{F}_{t-1} (-\boldsymbol{\tau}) + \mathbf{G}_{t-1} \mathbf{x}_0 \right\} = \boldsymbol{\tau}.$$

Now, since $\max_{1 \leq i \leq n} d_i \leq 1$ guarantees $(1 - \mathcal{B})\boldsymbol{\eta}_t$ is stationary, the stability conditions

depend on $\{E_t\}_{i=0}^{t-1}$. To show the covariance matrix of ξ_t is bounded, we first denote

$e_{t,ij}$ as the entry of \mathbf{E}_t . According to Horn and Johnson (1990), since $\lim_{t \rightarrow \infty} \mathbf{E}_t = \mathbf{0}_{n \times n}$,

for arbitrary $\varepsilon > 0$, there exists a positive integer N_ε such that

$$\sqrt{\sum_{i,j} e_{t,ij}^2} < \varepsilon, \quad \forall t > N_\varepsilon,$$

which leads the Euclidean norm $(\|\cdot\|_2)$ of \mathbf{E}_t to be less than ε for large t .

Define $s_t = \sum_{i=0}^t \|\mathbf{E}_i\|_2$. Then

$$s_{n_1} - s_{n_2} = \sum_{i=n_2+1}^{n_1} \|\mathbf{E}_i\|_2 < \varepsilon, \quad \forall n_1 > n_2 > N_\varepsilon.$$

This demonstrates that s_t is a Cauchy sequence. Therefore, the filter relating $(1-\beta)\boldsymbol{\eta}_t$ to $\boldsymbol{\xi}_t$ is stable. According to Reinsel (2003), the process outputs controlled by the dpMEWMA controller satisfy Equations (8) and (9).

Appendix 4: Proof of Equation (17).

From Equation (10), we have

$$\mathbf{I} - \beta\mathbf{M} = \begin{bmatrix} \mathbf{I}_{n \times n} - \beta\mathbf{M}_{11} & -\beta\mathbf{M}_{12} & -\beta\mathbf{M}_{13} \\ -\beta\mathbf{I}_{n \times n} & \mathbf{I}_{n \times n} & \mathbf{0} \\ -\beta\mathbf{M}_{31} & -\beta\mathbf{M}_{32} & \mathbf{I}_{m \times m} - \beta\mathbf{M}_{33} \end{bmatrix}.$$

By the inverse of block matrix (Graybill, page 19), we have

$$[(\mathbf{I} - \beta\mathbf{M})^{-1}]_{11} = \left\{ \mathbf{I}_{n \times n} - \beta\mathbf{M}_{11} - \beta^2 [\mathbf{M}_{12} \quad \mathbf{M}_{13}] \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0} \\ -\beta\mathbf{M}_{32} & \mathbf{I}_{m \times m} - \beta\mathbf{M}_{33} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{I}_{n \times n} \\ \mathbf{M}_{31} \end{bmatrix} \right\}^{-1},$$

where

$$\begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0} \\ -\beta\mathbf{M}_{32} & \mathbf{I}_{m \times m} - \beta\mathbf{M}_{33} \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0} \\ -(\mathbf{I}_{m \times m} - \beta\mathbf{M}_{33})^{-1}(-\beta\mathbf{M}_{32}) & (\mathbf{I}_{m \times m} - \beta\mathbf{M}_{33})^{-1} \end{bmatrix}.$$

Under $\hat{\mathbf{C}} = k\hat{\mathbf{B}}$, we have

$$(\mathbf{I}_{m \times m} - \beta\mathbf{M}_{33})^{-1} = \mathbf{I}_{m \times m} - \frac{k\beta}{1+k\beta} \hat{\mathbf{B}}' (\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\mathbf{B}},$$

and

$$-(\mathbf{I}_{m \times m} - \beta\mathbf{M}_{33})^{-1}(-\beta\mathbf{M}_{32}) = \frac{\beta}{1+k\beta} \hat{\mathbf{B}}' (\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\boldsymbol{\Psi}}.$$

Hence,

$$\begin{aligned} & (1+k\beta) \left\{ \mathbf{I}_{n \times n} - \beta\mathbf{M}_{11} - \beta^2 [\mathbf{M}_{12} \quad \mathbf{M}_{13}] \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0} \\ -\beta\mathbf{M}_{32} & \mathbf{I}_{m \times m} - \beta\mathbf{M}_{33} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{I}_{n \times n} \\ \mathbf{M}_{31} \end{bmatrix} \right\} \\ &= (1+k\beta) \mathbf{I}_{n \times n} - (1+k\beta) \beta\mathbf{M}_{11} - \beta^2 (1+k\beta) [\mathbf{M}_{12} + \mathbf{M}_{13}\mathbf{M}_{31}] \\ & \quad - \beta^3 \left[\mathbf{M}_{13} \hat{\mathbf{B}}' (\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\boldsymbol{\Psi}} - k\mathbf{M}_{13} \hat{\mathbf{B}}' (\hat{\mathbf{B}}\hat{\mathbf{B}}')^{-1} \hat{\mathbf{B}}\mathbf{M}_{31} \right]. \end{aligned}$$

From (A3) in Appendix 2, we have

$$\left(\mathbf{I}_{n \times n} - \Phi_1^* \mathcal{B} - \Phi_2^* \mathcal{B}^2 - \Phi_3^* \mathcal{B}^3\right) \xi_t = (1 + k\mathcal{B})(1 - \mathcal{B}) \eta_t.$$

Appendix 5: The expression of $\sum_{t=1}^{\infty} (\gamma'_{t-1} \gamma_{t-1})$.

From Equation (13), we can re-express γ_{t-1} and $\sum_{t=1}^{\infty} (\gamma'_{t-1} \gamma_{t-1})$ as

$$\gamma_{t-1} = \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \end{bmatrix} \mathbf{M}^{t-1} \begin{bmatrix} \gamma_0 \\ -\tau \\ \mathbf{x}_0 \end{bmatrix},$$

and

$$\sum_{t=1}^{\infty} (\gamma'_{t-1} \gamma_{t-1}) = \begin{bmatrix} \gamma'_0 & -\tau' & \mathbf{x}'_0 \end{bmatrix} \left(\sum_{t=1}^{\infty} (\mathbf{M}')^{t-1} \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{m \times n} & \mathbf{0}_{m \times n} & \mathbf{0}_{m \times m} \end{bmatrix} \mathbf{M}^{t-1} \right) \begin{bmatrix} \gamma_0 \\ -\tau \\ \mathbf{x}_0 \end{bmatrix},$$

respectively. To further simplify the above equation, let

$$\Sigma_{\xi} = \sum_{t=1}^{\infty} (\mathbf{M}')^t \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{m \times n} & \mathbf{0}_{m \times n} & \mathbf{0}_{m \times m} \end{bmatrix} \mathbf{M}^t,$$

then

$$\sum_{t=1}^{\infty} (\gamma'_{t-1} \gamma_{t-1}) = \begin{bmatrix} \gamma'_0 & -\tau' & \mathbf{x}'_0 \end{bmatrix} \Sigma_{\xi} \begin{bmatrix} \gamma_0 \\ -\tau \\ \mathbf{x}_0 \end{bmatrix}.$$

Note that Σ_{ξ} can be viewed as the covariance matrix of the time series ς_t , where

$$\varsigma_t = \mathbf{M}' \varsigma_{t-1} + \varepsilon_t,$$

and ε_t is a vector white noise series with covariance matrix

$$\Sigma_{\varepsilon} = \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{m \times n} & \mathbf{0}_{m \times n} & \mathbf{0}_{m \times m} \end{bmatrix}.$$

Hence, we have

$$\Sigma_{\xi} = \mathbf{M}' \Sigma_{\xi} \mathbf{M} + \begin{bmatrix} \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{0}_{m \times n} & \mathbf{0}_{m \times n} & \mathbf{0}_{m \times m} \end{bmatrix}.$$

Now, by use of procedure in Reinsel (2003, pp 29-30),

$$\Sigma_{\xi} = \text{mat}_{(2n+m) \times (2n+m)} \left(\left(\mathbf{I}_{(2n+m)^2 \times (2n+m)^2} - \mathbf{M}' \otimes \mathbf{M}' \right)^{-1} \text{vec}(\Sigma_{\epsilon}) \right),$$

where $\text{vec}(\cdot)$ is the operator stacking column vectors of a $p \times q$ matrix as a $pq \times 1$

vector; $\text{mat}_{p \times q}(\cdot)$ denotes the operator inversely stacking a $pq \times 1$ column vector as

a $p \times q$ matrix; \otimes denotes the Kronecker product, that is, $\mathbf{A} \otimes \mathbf{C} = (a_{ij} \mathbf{C})_{mp \times nq}$

with $\mathbf{A} = (a_{ij})_{m \times n}$ and $\mathbf{C} = (c_{ij})_{p \times q}$.

Therefore,

$$\sum_{t=1}^{\infty} (\gamma'_{t-1} \gamma_{t-1}) = [\gamma'_0 \quad -\tau' \quad \mathbf{x}'_0] \text{mat}_{(2n+m) \times (2n+m)} \left(\left(\mathbf{I}_{(2n+m)^2 \times (2n+m)^2} - \mathbf{M}' \otimes \mathbf{M}' \right)^{-1} \text{vec}(\Sigma_{\epsilon}) \right) \begin{bmatrix} \gamma_0 \\ -\tau \\ \mathbf{x}_0 \end{bmatrix}.$$

Appendix 6: The expression of ν .

From Equation (17), if η_t is a vector IMA(1,1) process, then ξ_t will follow a stationary vector ARMA(3, 2) process, and the corresponding Yule-Walker equations are

$$\begin{aligned} \Gamma_0 &= \text{Cov}(\xi_t, \xi_t) = \Gamma'_1(\Phi_1^*)' + \Gamma'_2(\Phi_2^*)' + \Gamma'_3(\Phi_3^*)' + \mathbf{H}_0, \\ \Gamma_1 &= \text{Cov}(\xi_t, \xi_{t+1}) = \Gamma_0(\Phi_1^*)' + \Gamma'_1(\Phi_2^*)' + \Gamma'_2(\Phi_3^*)' + \mathbf{H}_1, \\ \Gamma_2 &= \text{Cov}(\xi_t, \xi_{t+2}) = \Gamma_1(\Phi_1^*)' + \Gamma_0(\Phi_2^*)' + \Gamma'_1(\Phi_3^*)' + \mathbf{H}_2, \\ \Gamma_3 &= \text{Cov}(\xi_t, \xi_{t+3}) = \Gamma_2(\Phi_1^*)' + \Gamma_1(\Phi_2^*)' + \Gamma_0(\Phi_3^*)'. \end{aligned}$$

where

$$\mathbf{H}_0 = \Sigma - (\Phi_1^* - \Theta_1) \Sigma \Theta_1' - (\Phi_1^* (\Phi_1^* - \Theta_1) + (\Phi_2^* - \Theta_2)) \Sigma \Theta_2' ;$$

$$\mathbf{H}_1 = -\Sigma \Theta_1' - (\Phi_1^* - \Theta_1) \Sigma \Theta_2' , \text{ and } \mathbf{H}_2 = -\Sigma \Theta_2' ,$$

$$\Theta_1 = \Theta - k \mathbf{I}_{n \times n}, \text{ and } \Theta_2 = k \Theta.$$

Again, by use of procedure in Reinsel (2003, pp 29-30 and 59-60), we obtain

$$\nu = \text{trace}(\Gamma_0) = \text{trace}(\text{mat}_{n \times n}(\mathbf{P}_1^{-1}(\mathbf{P}_3 \mathbf{h}_2 + \mathbf{P}_2 \mathbf{h}_1 + \mathbf{h}_0))),$$

where $\mathbf{h}_i = \text{vec}(\mathbf{H}_i)$, $i = 1, 2, 3$; $\mathbf{P}_1 = \mathbf{Q}_1 - \mathbf{Q}_2 \mathbf{Q}_3 \mathbf{Q}_4$; $\mathbf{P}_2 = \mathbf{Q}_2 \mathbf{Q}_3$, and

$$\mathbf{P}_3 = \mathbf{P}_2 (\Phi_3^* \otimes \mathbf{I}_{n \times n}) \mathbf{S}_{(n,n)} + (\Phi_2^* \otimes \mathbf{I}_{n \times n} + \Phi_3^* \otimes \Phi_1^*) \mathbf{S}_{(n,n)},$$

with

$$\mathbf{Q}_1 = \mathbf{I}_{n^2 \times n^2} - (\Phi_3^* \otimes \Phi_3^*) - (\Phi_2^* \otimes \mathbf{I}_{n \times n} + \Phi_3^* \otimes \Phi_1^*) \mathbf{S}_{(n,n)} (\Phi_2^* \otimes \mathbf{I}_{n \times n});$$

$$\begin{aligned} \mathbf{Q}_2 &= (\Phi_1^* \otimes \mathbf{I}_{n \times n} + \Phi_3^* \otimes \Phi_2^*) \mathbf{S}_{(n,n)} \\ &+ (\Phi_2^* \otimes \mathbf{I}_{n \times n} + \Phi_3^* \otimes \Phi_1^*) \mathbf{S}_{(n,n)} (\Phi_1^* \otimes \mathbf{I}_{n \times n} + (\Phi_3^* \otimes \mathbf{I}_{n \times n}) \mathbf{S}_{(n,n)}); \end{aligned}$$

$$\mathbf{Q}_3 = (\mathbf{I}_{n^2 \times n^2} - (\Phi_2^* \otimes \mathbf{I}_{n \times n}) \mathbf{S}_{(n,n)} - (\Phi_3^* \otimes \mathbf{I}_{n \times n}) \mathbf{S}_{(n,n)} (\Phi_1^* \otimes \mathbf{I}_{n \times n} + (\Phi_3^* \otimes \mathbf{I}_{n \times n}) \mathbf{S}_{(n,n)}))^{-1};$$

$$\mathbf{Q}_4 = \Phi_1^* \otimes \mathbf{I}_{n \times n} + (\Phi_3^* \otimes \mathbf{I}_{n \times n}) \mathbf{S}_{(n,n)} (\Phi_2^* \otimes \mathbf{I}_{n \times n}),$$

and $\mathbf{S}_{(n,n)} = \sum_{i_1=1}^n \sum_{i_2=1}^n \mathbf{E}_{i_1 i_2} \otimes \mathbf{E}'_{i_1 i_2}$ is the permuted identity matrix, with $\mathbf{E}_{i_1 i_2} = (e_{ij})_{n \times n}$ and

$$e_{ij} = \begin{cases} 1 & \text{if } i = i_1 \text{ and } j = i_2, \\ 0 & \text{otherwise.} \end{cases}$$

Appendix 7: Proof of Equation (21).

As $\mathbf{B} = \hat{\mathbf{B}}$, $\mathbf{C} = \hat{\mathbf{C}}$, and $\Psi = \hat{\Psi}$,

$$\mathbf{M} = \begin{bmatrix} \mathbf{I}_{n \times n} - \Omega & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ \mathbf{I}_{n \times n} & \mathbf{0}_{n \times n} & \mathbf{0}_{n \times m} \\ -\mathbf{B}'(\mathbf{B}\mathbf{B}')^{-1}(\Psi + \Omega) & \mathbf{B}'(\mathbf{B}\mathbf{B}')^{-1}\Psi & -\mathbf{B}'(\mathbf{B}\mathbf{B}')^{-1}\mathbf{C} \end{bmatrix}.$$

Hence,

$$\boldsymbol{\gamma}_{t-1}\boldsymbol{\gamma}'_{t-1} = \mathbf{E}_{t-1}\boldsymbol{\gamma}_0\boldsymbol{\gamma}'_0\mathbf{E}'_{t-1},$$

which implies

$$\begin{aligned} \sum_{t=1}^N \text{trace}(\boldsymbol{\gamma}_{t-1}\boldsymbol{\gamma}'_{t-1}) &= \sum_{t=1}^N \text{trace}(\mathbf{E}_{t-1}\boldsymbol{\gamma}_0\boldsymbol{\gamma}'_0\mathbf{E}'_{t-1}) \\ &= \sum_{t=1}^N \boldsymbol{\gamma}'_0\mathbf{E}'_{t-1}\mathbf{E}_{t-1}\boldsymbol{\gamma}_0 \\ &= \sum_{t=1}^N \boldsymbol{\gamma}'_0 \begin{bmatrix} (1-\omega_1)^{2t-2} & 0 & \cdots & 0 \\ 0 & \ddots & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & (1-\omega_n)^{2t-2} \end{bmatrix} \boldsymbol{\gamma}_0 \quad (\text{A4}) \\ &= \sum_{t=1}^N \sum_{i=1}^n (1-\omega_i)^{2t-2} \gamma_{i0}^2 \\ &= \sum_{i=1}^n \frac{1-(1-\omega_i)^{2N}}{\omega_i(2-\omega_i)} \gamma_{i0}^2. \end{aligned}$$

In addition,

$$(\mathbf{I}_{n \times n} - \boldsymbol{\Phi}_1 \boldsymbol{\mathcal{B}}) \boldsymbol{\xi}_t = (\mathbf{I}_{n \times n} - \boldsymbol{\Theta} \boldsymbol{\mathcal{B}}) \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{\Phi}_1 = \mathbf{I}_{n \times n} - \boldsymbol{\Omega} = \text{diag}(1-\omega_1, \dots, 1-\omega_n)$, and then the corresponding

Yule-Walker equations are

$$\begin{aligned} \boldsymbol{\Gamma}_0 &= \text{Cov}(\boldsymbol{\xi}_t, \boldsymbol{\xi}_t) = \boldsymbol{\Gamma}'_1 \boldsymbol{\Phi}'_1 + \mathbf{H}_0, \\ \boldsymbol{\Gamma}_1 &= \text{Cov}(\boldsymbol{\xi}_t, \boldsymbol{\xi}_{t+1}) = \boldsymbol{\Gamma}_0 \boldsymbol{\Phi}'_1 + \mathbf{H}_1, \end{aligned}$$

where

$$\mathbf{H}_0 = \boldsymbol{\Sigma} - (\boldsymbol{\Phi}_1 - \boldsymbol{\Theta}) \boldsymbol{\Sigma} \boldsymbol{\Theta}' \quad \text{and} \quad \mathbf{H}_1 = -\boldsymbol{\Sigma} \boldsymbol{\Theta}'.$$

Setting $\mathbf{g}_i = \text{vec}(\boldsymbol{\Gamma}_i)$ and $\mathbf{h}_i = \text{vec}(\mathbf{H}_i)$ leads

$$\mathbf{g}_0 = (\mathbf{I}_{n \times n} - \boldsymbol{\Phi}_1 \otimes \boldsymbol{\Phi}_1)^{-1} \mathbf{h}_0^*,$$

where $\mathbf{h}_0^* = \text{vec}(\mathbf{H}'_1 \boldsymbol{\Phi}'_1 + \mathbf{H}_0)$.

Let $\mathbf{g}_0 = (g_1^{(0)}, \dots, g_{n^2}^{(0)})$. Since

$$(\mathbf{I}_{n^2 \times n^2} - \mathbf{\Phi} \otimes \mathbf{\Phi})^{-1} = \begin{bmatrix} \frac{1}{1-(1-\omega_1)(1-\omega_1)} & 0 & \dots & \dots & 0 \\ 0 & \ddots & & & \vdots \\ \vdots & & \ddots & & \vdots \\ \vdots & & & \ddots & 0 \\ 0 & \dots & \dots & 0 & \frac{1}{1-(1-\omega_n)(1-\omega_n)} \end{bmatrix},$$

and

$$\mathbf{H}_1' \mathbf{\Phi}_1' + \mathbf{H}_0 = -\mathbf{\Theta} \mathbf{\Sigma} \mathbf{\Phi}_1' + \left(\mathbf{\Sigma} - (\mathbf{\Phi}_1 - \mathbf{\Theta}) \mathbf{\Sigma} \mathbf{\Theta}' \right),$$

we can obtain

$$g_{n(i-1)+i}^{(0)} = \frac{\sigma_{ii} - 2(1-\omega_i) \mathbf{\theta}_i' \mathbf{\sigma}_i + \mathbf{\theta}_i' \mathbf{\Sigma} \mathbf{\theta}_i}{1 - (1-\omega_i)^2}, \quad (\text{A5})$$

where $\mathbf{\sigma}_i = (\sigma_{i1}, \dots, \sigma_{in})'$ and $\mathbf{\theta}_i = (\theta_{i1}, \dots, \theta_{in})'$. Therefore, we can obtain Equation

(21) by Equations (A4) and (A5).

Appendix 8: The process I-O Model used in Section 6

For the CMP dataset, according to Fan et al. (2002), a dynamic process is a better and more realistic model to explain the complicated process. However, the results are addressed only under the case of the SISO process. In the following, adopt this dataset, we obtain a prediction model as follows:

$$\begin{aligned} \hat{\mathbf{y}}_t = & \begin{bmatrix} -0.58 & -0.02 \\ 0.06 & -0.61 \end{bmatrix} \mathbf{y}_{t-1} + \begin{bmatrix} 449.5 \\ 2513.5 \end{bmatrix} + \begin{bmatrix} 31.13 & 107.59 & 34.72 & 57.97 \\ 130.64 & -31.65 & 172.58 & 19.80 \end{bmatrix} \mathbf{x}_{t-1} \\ & + \begin{bmatrix} 10.53 & 41.85 & 12.95 & 18.62 \\ 83.35 & -26.17 & 97.90 & 10.42 \end{bmatrix} \mathbf{x}_{t-2}. \end{aligned}$$

By using Akaike information criterion (AIC), we have AIC(dynamic)=11.19, AIC(static linear model, Tseng et al., 2002)=12.72, AIC(quadratic without interaction term, Castillo and Yeh, 1988)=13.65. Furthermore, the Ljung-Box Portmanteau

statistics for multivariate time series is $Q = 84.69$ when the lag is 20, and the corresponding p -value is 0.34. The test supports that the residuals are white noise. Hence, it demonstrates that the dynamic model together with IMA (1, 1) disturbance is more appropriate for the CMP dataset.

Appendix 9: The derivation of the ST controller.

Considering $\Theta = \mathbf{0}_{n \times n}$, Equation (1) with vector IMA(1,1) disturbance can be reduced as follows:

$$\mathbf{y}_t = \Psi \mathbf{y}_{t-1} + \alpha + \mathbf{B} \mathbf{x}_{t-1} + \mathbf{C} \mathbf{x}_{t-2} + (1-B)^{-1} \boldsymbol{\varepsilon}_t,$$

which leads

$$\mathbf{y}_t - \mathbf{y}_{t-1} = \Psi(\mathbf{y}_{t-1} - \mathbf{y}_{t-2}) + \mathbf{B}(\mathbf{x}_{t-1} - \mathbf{x}_{t-2}) + \mathbf{C}(\mathbf{x}_{t-2} - \mathbf{x}_{t-3}) + \boldsymbol{\varepsilon}_t.$$

In this case, the MMSE controller can be written as follows (Reinsel, 2003):

$$\mathbf{x}_t = \mathbf{x}_{t-1} + (\mathbf{B}'\mathbf{B})^{-1} \mathbf{B}'(\boldsymbol{\tau} - \mathbf{y}_t - \Psi(\mathbf{y}_t - \mathbf{y}_{t-1}) - \mathbf{C}(\mathbf{x}_{t-1} - \mathbf{x}_{t-2})), \quad (\text{A6})$$

where $(\mathbf{B}'\mathbf{B})^{-1}$ denotes the generalized inverse of $\mathbf{B}'\mathbf{B}$.

Let the estimated matrix of model parameters be

$$\Xi_t = [\hat{\Psi}_t | \hat{\mathbf{B}}_t | \hat{\mathbf{C}}_t]$$

and

$$\boldsymbol{\chi}_t = \left[(\mathbf{y}_t - \mathbf{y}_{t-1})' | (\mathbf{x}_{t-1} - \mathbf{x}_{t-2})' | (\mathbf{x}_{t-2} - \mathbf{x}_{t-3})' \right]'$$

In addition, for $t = 1, 2, \dots$, set

$$\mathbf{K}_t = \frac{\mathbf{P}_{t-1} \boldsymbol{\chi}_t}{\lambda + \boldsymbol{\chi}_t' \mathbf{P}_{t-1} \boldsymbol{\chi}_t},$$

$$\Xi_t^{(i)} = \Xi_{t-1}^{(i)} + \mathbf{K}_t' (y_{i,t} - \tau_i - \Xi_{t-1}^{(i)} \boldsymbol{\chi}_t),$$

and

$$\mathbf{P}_t = \left(\mathbf{I}_{(n+2m) \times (n+2m)} - \mathbf{K}_t \boldsymbol{\chi}_t' \right) \mathbf{P}_{t-1} + \frac{\mathbf{I}_{(n+2m) \times (n+2m)} \mathbf{K}_t' \mathbf{P}_{t-1} \boldsymbol{\chi}_t}{n+2m},$$

where $\boldsymbol{\Xi}_t^{(i)}$ is the i -th row of $\boldsymbol{\Xi}_t$ and the initial setting for \mathbf{P}_0 is very close to an identity matrix in practical applications, that is, $\mathbf{P}_0 \approx \mathbf{I}_{(n+2m) \times (n+2m)}$ (Del Castillo and Yeh, 1998). Then modifying Equation (A6) provides the ST controller as follows.

$$\mathbf{x}_t = \mathbf{x}_{t-1} + \left(\hat{\mathbf{B}}_t' \hat{\mathbf{B}}_t \right)^{-1} \hat{\mathbf{B}}_t' \left(\boldsymbol{\tau} - \mathbf{y}_t - \hat{\boldsymbol{\Psi}}_t (\mathbf{y}_t - \mathbf{y}_{t-1}) - \hat{\mathbf{C}}_t (\mathbf{x}_{t-1} - \mathbf{x}_{t-2}) \right).$$