

Multi-Source Predictive Distributed Voltage Control (Proof Part)

1 Proof of Theorem 1

We first give a complete statement for Theorem 1

Theorem 1.1 (ISS bound). *Let L_H, μ_H be the maximum and minimum eigenvalue of the Karush-Kuhn-Tucker matrix defined in Lemma 1, and define*

$$\begin{aligned}\alpha_H &:= \left(\frac{L_H^2 - \mu_H^2}{L_H^2 + \mu_H^2} \right)^{-\frac{1}{2}}, \quad \rho_H := \left(\frac{L_H^2 - \mu_H^2}{L_H^2 + \mu_H^2} \right)^{\frac{1}{2}}, \\ \delta_1 &:= \frac{1 + \rho_H}{2}, \quad \Gamma := \sup_{d \in \mathcal{N}} \left(\frac{\rho_H}{\delta_1} \right)^d \mathsf{SE}(d), \\ \beta_1 &:= \frac{L_H \alpha_H \delta_1 \Gamma}{\mu_H^2 (1 - \delta_1)}, \quad \Xi := \frac{2L L_H \alpha_H b_H \Gamma \mathsf{SE}(1)}{\mu_H^2 (1 - \delta_1)}, \\ \beta_2 &:= \frac{2L}{\mu}, \quad \delta_2 := 1 - 2 \left(\sqrt{1 + \beta_2} + 1 \right)^{-1}.\end{aligned}$$

Set $0 < \gamma \leq 1 - \max\{\delta_1, \delta_2\} \in (0, 1)$. For any $i \in \mathcal{N}$, if the locality radius κ and the prediction horizon k such that

$$k \geq \underline{k} = \frac{\ln \frac{2}{\gamma(1-\gamma)}}{\ln \frac{\alpha_H}{1-\gamma}}, \quad \kappa \geq 1 + \frac{\ln(2kLN\beta_1(\beta_2+1))}{\ln \frac{1}{1-\gamma}}$$

where $0 < \gamma < 1$, $N := |\mathcal{N}|$. Then under Assumption 1, 3, 4 (in the main body), the global state \mathbf{x}_t generated by Algorithm 1 (in the main body) satisfies, for all $t \in [T]$,

$$\|\mathbf{x}(t)\| \leq C_x (1 - \gamma)^{\max(t - k, 0)} \|\mathbf{x}(0)\| + \frac{C_e}{\gamma} \sup_{0 \leq s \leq t-1} e_k(s) + \frac{C}{\gamma},$$

where $C_x, C_e, C > 0$ are independent of t , and one of their definition is given in (30). Consequently, the closed-loop system is stable with respect to the weighted prediction error $e_k(s) := \sup_{i \in \mathcal{N}} \sum_{\tau=t}^{\bar{t}} (1 - \gamma)^{\tau - t} \|(\xi(\hat{s}_i(\tau|t)))_{(i,\kappa)} - (\xi(s(\tau)))_{(i,\kappa)}\|$, $s \in [t]$.

Proof Sketch of Theorem 1

We begin the proof of Theorem 1 with a three-step roadmap.

Step 1 Prove exponential-decay gap between the solution to the localized MPC problem (1a) versus the solution to the centralized one (2a). The main idea is to construct an equation 6 using the KKT conditions of both, and to use Lemma 1 to reveal the intrinsic properties of the KKT matrix. Then, the equations are combined to obtain the interim results.

Step 2 By referencing and extending existing error-based theoretical results (Corollary 1.1, Lemma 2, and Lemma 3), we reveal the performance gaps caused by different perturbations $\hat{\mathbf{w}}, \mathbf{w}$.

Step 3 In final step, we prove the upper bound of $\|\mathbf{x}(t)\|$ with respect to initial state $\|\mathbf{x}(0)\|$, weighted summation prediction error $e_k(t)$. The main idea is to construct a induction hypothesis $\|\mathbf{x}(t)\| \leq C_x(1 - \gamma)^{t-k} \|\mathbf{x}(0)\| + \sum_{l=0}^{t+1} C_e(1 - \gamma)^l \sup_{0 \leq s \leq t-1} e_k(s) + \frac{C}{\gamma}$

Now we begin the formal proof.

Step 1 We first recall the localized MPC problem used in Algorithm 1:

$$\Psi_{t,i}^k(\mathbf{x}_{(i,\kappa)}(t), \hat{s}_i(t : \bar{t}|t)) := \arg \min_{\tilde{\mathbf{u}}(0:k-1), \tilde{\mathbf{x}}(1:k)} \sum_{\tau=0}^{k-1} (f_{\tau+t}(\tilde{\mathbf{x}}(\tau)) + g_{\tau+t}(\tilde{\mathbf{u}}(\tau))) + F(\tilde{\mathbf{x}}(k)) \quad (1a)$$

$$\text{s.t. } \tilde{\mathbf{x}}(\tau+1) = \tilde{\mathbf{x}}(\tau) + X_{(i,\kappa)} \tilde{\mathbf{u}}(\tau) + \xi_{(i,\kappa)}(\hat{s}_i(t+\tau|t)) \quad (1b)$$

$$\tilde{\mathbf{x}}(0) = \mathbf{x}_{(i,\kappa)}(t), \quad 0 \leq \tau \leq k \quad (1c)$$

We also use the notation $\Psi(\mathbf{x}_{(i,\kappa)}(t), \hat{s}_i(t : \bar{t}|t), \mathbf{y}_{(i,\kappa)}(t+k)) = \Psi_{t,i}^k(\mathbf{x}_{(i,\kappa)}(t), \hat{s}_i(t : \bar{t}|t))$ in the following content, where $\mathbf{y}_{(i,\kappa)}(t+k)$ denotes the terminal state. Then we construct the corresponding object without any structural sparsity:

$$\Psi_t^k(\mathbf{x}(t), \hat{s}_i(t : \bar{t}|t)) := \arg \min_{\tilde{\mathbf{u}}(0:k-1), \tilde{\mathbf{x}}(1:k)} \sum_{\tau=0}^{k-1} (f_{\tau+t}(\tilde{\mathbf{x}}(\tau)) + g_{\tau+t}(\tilde{\mathbf{u}}(\tau))) + F(\tilde{\mathbf{x}}(k)) \quad (2a)$$

$$\text{s.t. } \tilde{\mathbf{x}}(\tau+1) = \tilde{\mathbf{x}}(\tau) + X \tilde{\mathbf{u}}(\tau) + \xi(\hat{s}_i(t+\tau|t)) \quad (2b)$$

$$\tilde{\mathbf{x}}(0) = \mathbf{x}(t), \quad 0 \leq \tau \leq k \quad (2c)$$

Since the problems are FTOCP, we now investigate the Karush-Kuhn-Tucker (KKT) condition of Ψ_i and Ψ .

Let $\psi := (\tilde{\mathbf{x}}(0), \tilde{\mathbf{u}}(0), \tilde{\mathbf{x}}(1), \dots, \tilde{\mathbf{u}}(T-1), \tilde{\mathbf{x}}(T))$ be the regrouped trajectory of primal variables from Ψ and ψ^c be the same regroup order from ψ ; $J_k(\psi) := \sum_{\tau=0}^{k-1} (f_\tau(\tilde{\mathbf{x}}(\tau)) + g_\tau(\tilde{\mathbf{u}}(\tau))) + F(\tilde{\mathbf{x}}(k))$ denoting the accumulative cost functions, and the constraint Jacobian function:

$$Y(A, B) = \begin{bmatrix} I & & & \\ -A - B & I & & \\ & -A - B & I & \\ & & \ddots & \ddots & \ddots \\ & & & -A - B & I \end{bmatrix}. \quad (3)$$

Let η, η^c denote the trajectory of dual variables in ψ and ψ^c , respectively. It is suffice to write down the KKT condition:

$$\begin{bmatrix} \nabla J_k(\psi) + (Y(I_{(i,\kappa)}, X_{(i,\kappa)}))^\top \eta \\ Y(I_{(i,\kappa)}, X_{(i,\kappa)}) \psi \end{bmatrix} = \underbrace{\begin{bmatrix} 0 \\ \underbrace{\left[\begin{array}{c} \mathbf{x}_{(i,\kappa)}(t) \\ \xi_{(i,\kappa)}(\hat{s}_i(t : t+k-1|t)) \end{array} \right]}_{:=\omega_{(i,\kappa)}} \end{bmatrix}}_{:=\omega_{(i,\kappa)}}, \quad (4)$$

$$\begin{bmatrix} \nabla J_k(\psi^c) + (Y(I, X))^\top \eta^c \\ Y(I, X) \psi^c \end{bmatrix} = \underbrace{\begin{bmatrix} 0 \\ \underbrace{\left[\begin{array}{c} \mathbf{x}(t) \\ \xi(\hat{s}_i(t : t+k-1|t)) \end{array} \right]}_{:=\omega} \end{bmatrix}}_{:=\omega}. \quad (5)$$

By assumption of cost functions that $J_k(\cdot)$ is μ -strongly convex, L -smooth, and twice continuously-differentiable, Lemma 1 in [2] tells us that there exists a symmetric matrix $M(\psi, \psi^c)$ satisfying the condition that $\mu I \preceq M(\psi, \psi^c) \preceq LI$ and $\nabla J_k(\psi) - \nabla J_k(\psi^c) = M(\psi, \psi^c)(\psi - \psi^c)$. Subtracting the left-hand sides of (4) and (5) we get

$$\begin{bmatrix} M(\psi, \psi^c) & (Y(I_{(i,\kappa)}, X_{(i,\kappa)}))^\top \\ Y(I_{(i,\kappa)}, X_{(i,\kappa)}) & 0 \end{bmatrix} \begin{bmatrix} \psi \\ \eta \end{bmatrix} - \begin{bmatrix} M(\psi, \psi^c) & (Y(I, X))^\top \\ Y(I, X) & 0 \end{bmatrix} \begin{bmatrix} \psi^c \\ \eta^c \end{bmatrix} = \omega - \omega_{(i,\kappa)}. \quad (6)$$

We now employ the following lemma to proceed the proof.

Lemma 1 (Theorem A.3 in [4]). *Consider the matrices M and Y defined above, and topology group $\mathcal{G} = (\mathcal{N}, \mathcal{E})$. Then there exist constants $0 \leq \mu_H \leq L_H$ and $b_H \in \mathbb{N}_+$ that the constructed KKT matrix $H := \begin{bmatrix} M & Y \\ Y & 0 \end{bmatrix}$ satisfies a lower-upper bound $\mu_H I \preceq H \preceq L_H I$ and its inverse matrix is bounded by a exponentially decaying form with respect to \mathcal{G} by $\|H_{ij}^{-1}\| \leq \frac{L_H}{\mu_H^2} \left(\frac{L_H^2 - \mu_H^2}{L_H^2 + \mu_H^2} \right)^{\frac{d_{\mathcal{G}}(i,j) - b_H}{2b_H}}$.*

The proof of Lemma 1 is in [4]. Combining this result with (6) yields the following upper bound:

$$\begin{aligned} \|[\psi - \psi^c]_i\| &\leq \left\| \left[\begin{bmatrix} \psi \\ \eta \end{bmatrix} - \begin{bmatrix} \psi^c \\ \eta^c \end{bmatrix} \right]_i \right\| \\ &\leq \left\| \sum_{j \in \mathcal{N}} (H^{c,-1})_{ij} \left((\omega - \omega_{(i,\kappa)})_j - \sum_{\ell \in \mathcal{N}} (H_{j\ell} - H_{j\ell}^c) \begin{bmatrix} \psi \\ \eta \end{bmatrix}_{\ell} \right) \right\| \\ &\leq \frac{L_H}{\mu_H^2} \sum_{j \in (\mathcal{N} - \mathcal{N}_{\mathcal{G}(i)}^\kappa)} \alpha_H \rho_H^{d_{\mathcal{G}}(i,j)} \left(\|\omega - \omega_{(i,\kappa)}\| + 2L \sum_{\ell \in \mathcal{N}_G^{b_H}(j)} \sum_{v \in \mathcal{N}_{\mathcal{G}}^\kappa(i)} \|(H^{-1})_{\ell v}\| \|\omega_{(i,\kappa)}\| \right) \\ &\leq \frac{L_H}{\mu_H^2} \sum_{d \geq \kappa+1} \text{SE}(d) \alpha_H \rho_H^d \left(\|\omega - \omega_{(i,\kappa)}\| + 2Lb_H \text{SE}(1) \sum_{s \leq 2\kappa} p(s) \alpha_H \rho_H^s \|\omega_{(i,\kappa)}\| \right) \\ &\leq \underbrace{\frac{L_H \alpha_H \delta_1 \Gamma}{\mu_H^2 (1 - \delta_1)} \left(\|\omega - \omega_{(i,\kappa)}\| + \frac{2LL_H \alpha_H b_H \Gamma \text{SE}(1)}{\mu_H^2 (1 - \delta_1)} \|\widehat{\omega}_{(i,\kappa)}\| \right)}_{:= \beta_1(\|\mathbf{x}(t)\| + \Xi D_k)} \delta_1^\kappa \end{aligned}$$

where $D_k := \sum_{\tau=0}^{k-1} \|\mathbf{w}(t + \tau)\|$ and

$$\alpha_H := \left(\frac{L_H^2 - \mu_H^2}{L_H^2 + \mu_H^2} \right)^{-\frac{1}{2}}, \quad \rho_H := \left(\frac{L_H^2 - \mu_H^2}{L_H^2 + \mu_H^2} \right)^{\frac{1}{2b_H}}, \quad \Gamma = \sup_{d \in \mathcal{N}} \left(\frac{\rho_H}{\delta_1} \right)^d \text{SE}(d), \quad \delta_1 = \frac{1 + \rho_H}{2}$$

Step 2 In the following content, we will present several auxiliary corollary and lemmas for further proof.

Corollary 1.1. *Let ψ and ψ^* denote the optimal primal solution to $\Psi_{t,i}^k(\mathbf{x}(t), \widehat{\omega})$ and $\Psi_t^k(\mathbf{x}^*(t), \omega)$, and ψ and ψ^* is partitioned by the temporal topology $\mathcal{G}_k := \{\{0, \dots, k-1\}, \{(0, 1), \dots, (k-1, k)\}\}$. Let $\tau = 0, \dots, k-1$, and we have:*

$$\|[\psi - \psi^*](\tau)\| \leq \alpha_H \left(\rho_H^\tau \|\mathbf{x}(t) - \mathbf{x}^*(t)\| + \sum_{l=0}^{k-1} \rho_H^{|l-\tau|} \|\mathbf{w}(t+l) - \widehat{\mathbf{w}}(t+l)\| \right)$$

where α_H and ρ_H follows from the previous content. Specially, if ψ^* is the solution to $\Psi_t^k(0, 0)$, then

$$\|\psi(\tau)\| \leq \alpha_H \left(\rho_H^\tau \|\mathbf{x}(t)\| + \sum_{l=0}^{k-1} \rho_H^{|l-\tau|} \|\widehat{\mathbf{w}}(t+l)\| \right)$$

Proof.

$$\begin{aligned}\|\psi(\tau) - \psi^*(\tau)\| &\leq \left\| \begin{bmatrix} \psi(\tau) \\ \eta(\tau) \end{bmatrix} - \begin{bmatrix} \psi^*(\tau) \\ \eta^*(\tau) \end{bmatrix} \right\| = \| [H^{c,-1}(\widehat{\omega} - \omega)](\tau) \| \\ &\leq \alpha_H \left(\rho_H^\tau \|\mathbf{x}(t) - \mathbf{x}^*(t)\| + \sum_{l=0}^{k-1} \rho_H^{|l-\tau|} \|\mathbf{w}(t+l) - \widehat{\mathbf{w}}(t+l)\| \right).\end{aligned}$$

□

Lemma 2. Under Assumption 4 in the main content, for any state-perturbation groups $(\mathbf{x}, \mathbf{w}, \mathbf{y})$ and $(\mathbf{x}', \mathbf{w}', \mathbf{y}')$ with $0 \leq t \leq T - k$, we have

$$\begin{aligned}\|\Psi(\mathbf{x}, \mathbf{w}, \mathbf{y})_{\widehat{\mathbf{x}}(\tau)} - \Psi(\mathbf{x}', \mathbf{w}', \mathbf{y}')_{\widehat{\mathbf{x}}(\tau)}\| \\ \leq \beta_2 \left(\delta_2^\tau \|\mathbf{x} - \mathbf{x}'\| + \delta_2^{k-\tau} \|\mathbf{y} - \mathbf{y}'\| + \sum_{l=0}^{k-1} \delta_2^{|l-\tau|} \|\mathbf{w}(t+l) - \mathbf{w}'(t+l)\| \right)\end{aligned}$$

where $\beta_2 = \frac{2L}{\mu}$ and $\delta_2 = 1 - 2(\sqrt{1+\beta_2} + 1)$.

This lemma follows directly from Theorem 3.3 in [1], therefore, we omit the proof.

Lemma 3. Suppose the assumption of Theorem 1 hold. We denote \mathbf{w} and $\widehat{\mathbf{w}}$ as the ground-truth disturbance and prediction trajectories over any MPC horizon, respectively. Let $\mathbf{x}(t), \mathbf{x}^*(t)$ be the one-step states updated by localized policy with prediction, and centralized optimal policy, respectively. Then for any $k, \tau \in [T]$ with condition $\tau \leq k$, and $t < T - k$, we have

$$\begin{aligned}\|\Psi_t^{k+1}(\mathbf{x}(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(\tau)} - \Psi_t^k(\mathbf{x}^*(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(\tau)}\| \\ \leq \beta_2^2 \sum_{l=0}^{k-1} \|\varepsilon(t+l-1)\|(1-\gamma)^{\tau+l} \\ + LN\beta_1\beta_2(\|\mathbf{x}(t-1)\| + \Xi D_k)(1-\gamma)^{\tau+\kappa} \\ + \alpha_H \beta_2 \left((1-\gamma)^k (\|\mathbf{x}(t)\| + \alpha_H \rho_H \|\mathbf{x}(t-1)\|) + \frac{6}{1-\rho_H} \sup_{0 \leq l \leq T-1} \|\widehat{\mathbf{w}}(t)\| \right) (1-\gamma)^{k-\tau}\end{aligned}$$

where $\mathbf{x}^*(t) := \Psi_{t-1}^{k+1}(\mathbf{x}(t-1))_{\widehat{\mathbf{x}}(1)}$, $1-\gamma := \max(\delta_1, \delta_2) \in (0, 1)$, and $\varepsilon(t) := \mathbf{w}(t) - \widehat{\mathbf{w}}(t)$.

Proof. We first define that:

$$\mathbf{y} := \Psi_t^{k+1}(\mathbf{x}(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(k)}, \quad \mathbf{y}' := \Psi_t^k(\mathbf{x}(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(k)}, \quad (7)$$

Then it can be observed that

$$\Psi_t^{k+1}(\mathbf{x}(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(\tau)} = \Psi_t^k(\mathbf{x}(t), \widehat{\mathbf{w}}, \mathbf{y})_{\widehat{\mathbf{x}}(\tau)}, \quad \Psi_t^k(\mathbf{x}^*(t))_{\widehat{\mathbf{x}}(\tau)} = \Psi_t^k(\mathbf{x}^*(t), \widehat{\mathbf{w}}, \mathbf{y}')_{\widehat{\mathbf{x}}(\tau)},$$

By Lemma 2, it is straightforward to derive that

$$\begin{aligned}
& \left\| \Psi_t^{k+1}(\mathbf{x}(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(\tau)} - \Psi_t^k(\mathbf{x}^*(t), \widehat{\mathbf{w}})_{\widehat{\mathbf{x}}(\tau)} \right\| \\
&= \left\| \Psi_t^k(\mathbf{x}(t), \widehat{\mathbf{w}}, \mathbf{y})_{\widehat{\mathbf{x}}(\tau)} - \Psi_t^k(\mathbf{x}^*(t), \widehat{\mathbf{w}}, \mathbf{y}')_{\widehat{\mathbf{x}}(\tau)} \right\| \\
&\leq \beta_2 \left(\delta_2^\tau \|\mathbf{x}(t) - \mathbf{x}^*(t)\| + \delta_2^{k-\tau} \|\mathbf{y} - \mathbf{y}'\| \right) \\
&\leq \beta_2 \delta_2^\tau (\|\mathbf{x}^c(t) - \mathbf{x}^*(t)\| + \|\mathbf{x}^c(t) - \mathbf{x}(t)\|) + \alpha_H \beta_2 \delta_2^{k-\tau} \left(\rho_H^k (\|\mathbf{x}(t)\| + \|\mathbf{x}^c(t)\|) + \frac{2}{1-\rho_H} \sup_{0 \leq \tau \leq T-1} \|\widehat{\mathbf{w}}(\tau)\| \right) \\
&\leq \beta_2 \delta_2^\tau \left(\beta_2 \sum_{l=0}^{k-1} \delta_2^l \|\varepsilon(t+l-1)\| + LN \beta_1 (\|\mathbf{x}(t-1)\| + \Xi D_k) (1-\gamma)^\kappa \right) \\
&\quad + \alpha_H \beta_2 \delta_2^{k-\tau} \left(\rho_H^k (\|\mathbf{x}(t)\| + \|\mathbf{x}^c(t)\|) + \frac{4}{1-\rho_H} \sup_{0 \leq \tau \leq T-1} \|\widehat{\mathbf{w}}(\tau)\| \right) \\
&\leq \beta_2^2 \sum_{l=0}^{k-1} (1-\gamma)^{\tau+l} \|\varepsilon(t+l-1)\| + LN \beta_1 \beta_2 (\|\mathbf{x}(t-1)\| + \Xi D_k) (1-\gamma)^{\tau+\kappa} \\
&\quad + \alpha_H \beta_2 \left((1-\gamma)^k (\|\mathbf{x}(t)\| + \alpha_H \rho_H \|\mathbf{x}(t-1)\|) + \frac{6}{1-\rho_H} \sup_{0 \leq \tau \leq T-1} \|\widehat{\mathbf{w}}(\tau)\| \right) (1-\gamma)^{k-\tau}
\end{aligned}$$

where the second, third inequality both employ the result of Corollary 1.1. \square

Step 3 It now suffices to proof the main results of Theorem 1.

Proof of Theorem 1. For $k \leq t+1 \leq T-k$,

$$\begin{aligned}
\|\mathbf{x}(t+1)\| &= \sum_{i=1}^N \|x_i(t+1)\| \\
&\leq \|\Psi_t^k(\mathbf{x}(t))_{\widehat{\mathbf{x}}(1)}\| + \sum_{i=1}^N (\|x_i^*(t+1) - x_i^c(t+1)\| + \|x_i^c(t+1) - x_i(t+1)\|) \\
&\leq \sum_{\tau=0}^{k-2} \left\| \Psi_{t-\tau}^k(\mathbf{x}(t-\tau))_{\widehat{\mathbf{x}}(\tau+1)} - \Psi_{t-\tau-1}^k(\mathbf{x}(t-\tau-1))_{\widehat{\mathbf{x}}(\tau+2)} \right\| + \left\| \Psi_{t-k+1}^k(\mathbf{x}(t-k+1))_{\widehat{\mathbf{x}}(k)} \right\| \\
&\quad + \sum_{l=0}^{k-1} (1-\gamma)^l \|\varepsilon(t+l)\| + LN \beta_1 (\|\mathbf{x}(t)\| + \Xi D_k) (1-\gamma)^\kappa \\
&= \sum_{\tau=0}^{k-2} \left\| \Psi_{t-\tau}^k(\mathbf{x}(t-\tau))_{\widehat{\mathbf{x}}(\tau+1)} - \Psi_{t-\tau}^{k-1}(\mathbf{x}^*(t-\tau))_{\widehat{\mathbf{x}}(\tau+1)} \right\| + \left\| \Psi_{t-k+1}^k(\mathbf{x}(t-k+1))_{\widehat{\mathbf{x}}(k)} \right\| \\
&\quad + \sum_{l=0}^{k-1} (1-\gamma)^l \|\varepsilon(t+l)\| + LN \beta_1 (\|\mathbf{x}(t)\| + \Xi D_k) (1-\gamma)^\kappa \\
&\leq \sum_{\tau=0}^{k-2} \left(\beta_2^2 \sum_{l=0}^{k-1} (1-\gamma)^{\tau+l+1} \|\varepsilon(t-\tau+l-1)\| + LN \beta_1 \beta_2 (\|\mathbf{x}(t-\tau-1)\| + \Xi D_k) (1-\gamma)^{\tau+\kappa+1} \right. \\
&\quad \left. + \alpha_H \beta_2 \left((1-\gamma)^k (\|\mathbf{x}(t-\tau)\| + \alpha_H \rho_H \|\mathbf{x}(t-\tau-1)\|) + \frac{6}{1-\rho_H} \sup_{0 \leq s \leq T-1} \|\widehat{\mathbf{w}}(s)\| \right) (1-\gamma)^{k-\tau-2} \right) \\
&\quad + \alpha_H^k \|\mathbf{x}(t-k+1)\| + \frac{2}{1-\rho_H} \sup_{0 \leq s \leq T-1} \|\widehat{\mathbf{w}}(s)\|
\end{aligned}$$

$$+ \sum_{l=0}^{k-1} (1-\gamma)^l \|\varepsilon(t+l)\| + LN\beta_1 (\|\mathbf{x}(t)\| + \Xi D_k) (1-\gamma)^\kappa. \quad (8)$$

where the second inequality employs the first step's upper bound, and the third inequality employs the result of Lemma 3.

By absorbing $\alpha_H^k \|\mathbf{x}(t-k+1)\|$ into the same structure via

$$\alpha_H^k \|\mathbf{x}(t-k+1)\| \leq \alpha_H^k (1-\gamma)^{-(k+1)} (1-\gamma)^{2k-(k-1)} \|\mathbf{x}(t-k+1)\|,$$

and we define

$$\begin{aligned} C_1 &:= \alpha_H \beta_2 (1-\gamma)^{-2} + \alpha_H^2 \rho_H \beta_2 (1-\gamma)^{-1} + \alpha_H^k (1-\gamma)^{-(k+1)}, \\ C_2 &:= LN\beta_1 \beta_2 (1-\gamma) + LN\beta_1. \end{aligned} \quad (9)$$

Define the length- k sliding-window error

$$\mathbf{e}_k(s) := \sum_{m=0}^{k-1} (1-\gamma)^m \|\varepsilon(s+m)\|. \quad (10)$$

Using time-shift reindexing, one obtains

$$\sum_{\tau=0}^{k-2} \sum_{l=0}^{k-1} (1-\gamma)^{\tau+l+1} \|\varepsilon(t-\tau+l-1)\| \leq \beta_2^2 \sum_{\tau=0}^{k-1} (1-\gamma)^\tau \mathbf{e}_k(t-\tau),$$

and

$$\sum_{l=0}^{k-1} (1-\gamma)^l \|\varepsilon(t+l)\| \leq \sum_{\tau=0}^{k-1} (1-\gamma)^\tau \mathbf{e}_k(t-\tau)$$

and we define

$$C_3 := \beta_2^2 + 1. \quad (11)$$

From the terms involving $\widehat{\mathbf{w}}$ and D_k , we use geometric-series bounds

$$\sum_{\tau=0}^{k-2} (1-\gamma)^{k-\tau-2} \leq \frac{1}{\gamma}, \quad \sum_{\tau=0}^{k-2} (1-\gamma)^{\tau+\kappa+1} \leq \frac{(1-\gamma)^{\kappa+1}}{\gamma},$$

and define

$$\begin{aligned} C_4 &:= \left(\frac{6\alpha_H \beta_2}{1-\rho_H} \cdot \frac{1}{\gamma} + \frac{2}{1-\rho_H} \right) \sup_{0 \leq s \leq T-1} \|\widehat{\mathbf{w}}(s)\| \\ &\quad + LN\beta_1 \beta_2 \Xi D_k \frac{(1-\gamma)^{\kappa+1}}{\gamma} + LN\beta_1 \Xi D_k (1-\gamma)^\kappa. \end{aligned} \quad (12)$$

Then with the definitions (9)–(12), inequality (8) can be compactly written as

$$\|\mathbf{x}(t+1)\| \leq \sum_{\tau=0}^{k-1} (C_1 (1-\gamma)^{2k-\tau} + C_2 (1-\gamma)^{\kappa+\tau}) \|\mathbf{x}(t-\tau)\| + \sum_{\tau=0}^{k-1} C_3 (1-\gamma)^\tau \mathbf{e}_k(t-\tau) + C_4. \quad (13)$$

By shifting the index to start at $\tau = 1$, (13) is equivalently

$$\|\mathbf{x}(t+1)\| \leq \sum_{\tau=1}^k (C_1 (1-\gamma)^{2k-\tau+1} + C_2 (1-\gamma)^{\kappa+\tau-1}) \|\mathbf{x}(t-\tau+1)\| + \sum_{\tau=0}^{k-1} C_3 (1-\gamma)^\tau \mathbf{e}_k(t-\tau) + C_4. \quad (14)$$

It now suffices to proof the results of Theorem 1 by induction. Suppose that for each $\tau \in \{1, \dots, k\}$,

$$\|\mathbf{x}(t - \tau + 1)\| \leq C_x(1 - \gamma)^{t-\tau+1-k} \|\mathbf{x}(0)\| + \sum_{l=0}^{t-\tau} C_e(1 - \gamma)^l \sup_{0 \leq s \leq t-\tau} e_k(s) + \frac{C}{\gamma}. \quad (15)$$

Substituting (15) into (14) yields

$$\begin{aligned} \|\mathbf{x}(t + 1)\| &\leq \sum_{\tau=1}^k \left(C_1(1 - \gamma)^{2k-\tau+1} + C_2(1 - \gamma)^{\kappa+\tau-1} \right) \left[C_x(1 - \gamma)^{t-\tau-k+1} \|\mathbf{x}(0)\| \right. \\ &\quad \left. + \sum_{l=0}^{t-\tau} C_e(1 - \gamma)^l \sup_{0 \leq s \leq t-\tau} e_k(s) + \frac{C}{\gamma} \right] \\ &\quad + \sum_{\tau=0}^{k-1} C_3(1 - \gamma)^\tau e_k(t - \tau) + C_4. \end{aligned} \quad (16)$$

Consider first the term multiplying $\|\mathbf{x}(0)\|$ (by (I)):

$$\begin{aligned} (I) &:= C_x \|\mathbf{x}(0)\| \sum_{\tau=1}^k (C_1(1 - \gamma)^{2k-\tau+1} + C_2(1 - \gamma)^{\kappa+\tau-1})(1 - \gamma)^{t-\tau-k+1} \\ &= C_x(1 - \gamma)^{t-k+1} \|\mathbf{x}(0)\| \sum_{\tau=1}^k (C_1(1 - \gamma)^{2k-\tau+1} + C_2(1 - \gamma)^{\kappa+\tau-1})(1 - \gamma)^{-\tau}. \end{aligned} \quad (17)$$

In Theorem 1, κ and k are chosen to satisfy that

$$\sum_{\tau=1}^k (C_1(1 - \gamma)^{2k-\tau+1} + C_2(1 - \gamma)^{\kappa+\tau-1})(1 - \gamma)^{-\tau} \leq 1. \quad (18)$$

Then from (17),

$$(I) \leq C_x(1 - \gamma)^{t-k+1} \|\mathbf{x}(0)\|. \quad (19)$$

Next, collect all terms involving $e_k(\cdot)$. From (16) we get two contributions. One is from the double sum by (II):

$$(II) := \sum_{\tau=1}^k (C_1(1 - \gamma)^{2k-\tau+1} + C_2(1 - \gamma)^{\kappa+\tau-1}) \sum_{l=0}^{t-\tau} C_e(1 - \gamma)^l \sup_{0 \leq s \leq t-\tau} e_k(s). \quad (20)$$

Since $\sup_{0 \leq s \leq t-\tau} e_k(s) \leq \sup_{0 \leq s \leq t} e_k(s)$, $\sum_{l=0}^{t-\tau} (1 - \gamma)^l \leq \frac{1}{\gamma}$, we have

$$(II) \leq \left(\sum_{\tau=1}^k (C_1(1 - \gamma)^{2k-\tau+1} + C_2(1 - \gamma)^{\kappa+\tau-1}) \right) \cdot \frac{C_e}{\gamma} \cdot \sup_{0 \leq s \leq t} e_k(s). \quad (21)$$

Let us denote the direct error term by (III):

$$(III) := \sum_{\tau=0}^{k-1} C_3(1 - \gamma)^\tau e_k(t - \tau). \quad (22)$$

Using the bound $e_k(t - \tau) \leq \sup_{0 \leq s \leq t} e_k(s)$ and the geometric series sum $\sum_{\tau=0}^{k-1} (1 - \gamma)^\tau \leq \frac{1}{\gamma}$, we have

$$(III) \leq \frac{C_3}{\gamma} \sup_{0 \leq s \leq t} e_k(s). \quad (23)$$

Finally, collect the constant terms (denoted by (IV)):

$$\begin{aligned} \text{(IV)} &:= \left[\sum_{\tau=1}^k \left(C_1(1-\gamma)^{2k-\tau+1} + C_2(1-\gamma)^{\kappa+\tau-1} \right) \right] \frac{C}{\gamma} + C_4 \\ &= \left[\sum_{\tau=1}^k \left(C_1(1-\gamma)^{2k-\tau+1} + C_2(1-\gamma)^{\kappa+\tau-1} \right) (1-\gamma)^{-\tau} (1-\gamma)^\tau \right] \frac{C}{\gamma} + C_4. \end{aligned} \quad (24)$$

From the condition (18), let $\rho := \sum_{\tau=1}^k (C_1(1-\gamma)^{2k-\tau+1} + C_2(1-\gamma)^{\kappa+\tau-1}) (1-\gamma)^{-\tau} \leq 1$. Since $(1-\gamma)^\tau \leq 1-\gamma$ for $\tau \geq 1$, the coefficient of $\frac{C}{\gamma}$ in (24) is bounded by $\rho(1-\gamma) \leq 1-\gamma$. Thus,

$$\text{(IV)} \leq (1-\gamma) \frac{C}{\gamma} + C_4. \quad (25)$$

Combining the bounds for (I) from (19), (II) from (21), (III) from (23), and (IV) from (25), and substituting them back into (16), we obtain:

$$\begin{aligned} \|\mathbf{x}(t+1)\| &\leq C_x(1-\gamma)^{t-k+1} \|\mathbf{x}(0)\| \\ &\quad + \left((1-\gamma) \frac{C_e}{\gamma} + \frac{C_3}{\gamma} \right) \sup_{0 \leq s \leq t} e_k(s) \\ &\quad + (1-\gamma) \frac{C}{\gamma} + C_4. \end{aligned} \quad (26)$$

To satisfy the induction hypothesis form for $t+1$, we define the constants C_e and C such that the coefficients remain bounded. Specifically, we require:

$$(1-\gamma) \frac{C_e}{\gamma} + \frac{C_3}{\gamma} \leq \frac{C_e}{\gamma} \quad \text{and} \quad (1-\gamma) \frac{C}{\gamma} + C_4 \leq \frac{C}{\gamma}.$$

Solving these inequalities yields the conditions:

$$C_e \geq \frac{C_3}{\gamma}, \quad C \geq \frac{C_4}{\gamma}. \quad (27)$$

We define $C_e := C_3/\gamma$ and $C := C_4/\gamma$. Thus, (26) implies that

$$\|\mathbf{x}(t+1)\| \leq C_x(1-\gamma)^{(t+1)-k} \|\mathbf{x}(0)\| + \sum_{l=0}^{t+1} C_e(1-\gamma)^l \sup_{0 \leq s \leq t} e_k(s) + \frac{C}{\gamma}. \quad (28)$$

This completes the induction step.

For $0 \leq t \leq k$, the recursive inequality (13) is unrolled a finite number of times. Since the time horizon is finite, all states are bounded by the initial state, the accumulated error, and the noise terms.

By iterating (13) for t steps (where $t \leq k$), and applying the geometric series bounds (e.g., $\sum_{\tau=0}^{k-1} (1-\gamma)^\tau \leq \gamma^{-1}$), we obtain a uniform finite-time bound:

$$\|\mathbf{x}(t)\| \leq \bar{C}_x \|\mathbf{x}(0)\| + \bar{C}_e \sup_{0 \leq s \leq k} e_k(s) + \bar{C}_c, \quad \forall t \in \{0, \dots, k\}, \quad (29)$$

where $\bar{C}_x, \bar{C}_e, \bar{C}_c > 0$ depend only on the system parameters $(\alpha_H, \beta_1, \beta_2, \rho_H, \gamma, L, N, \Xi, k, \kappa)$ and on $\sup_{0 \leq s \leq T-1} \|\hat{\mathbf{w}}(s)\|$, but are independent of t .

Concretely, one may choose

$$\bar{C}_x := 1 + C_1 \frac{(1-\gamma)^{k+1}}{\gamma} + C_2 \frac{(1-\gamma)^\kappa}{\gamma}, \quad (30)$$

$$\bar{C}_e := \frac{C_3}{\gamma}, \quad (31)$$

$$\bar{C}_c := C_4 + \left(C_1 \frac{(1-\gamma)^{k+1}}{\gamma} + C_2 \frac{(1-\gamma)^\kappa}{\gamma} \right) \cdot \tilde{C}, \quad (32)$$

To ensure the global theorem holds, we simply require the final constants C_x, C_e, C to be large enough to cover this initial transient. We impose the lower bounds: $C_x \geq \bar{C}_x, C_e \geq \bar{C}_e, C/\gamma \geq \bar{C}_c$. Under these conditions, for any $t \leq k$, the bound (29) implies:

$$\begin{aligned} \|\mathbf{x}(t)\| &\leq C_x \|\mathbf{x}(0)\| + C_e \sup_{0 \leq s \leq k} e_k(s) + \frac{C}{\gamma} \\ &= C_x (1 - \gamma)^{\max(0, t-k)} \|\mathbf{x}(0)\| + \sum_{l=0}^t C_e (1 - \gamma)^l \sup_{0 \leq s \leq k} e_k(s) + \frac{C}{\gamma}. \end{aligned} \quad (33)$$

Note that for $t \leq k$, $(1 - \gamma)^{\max(0, t-k)} = 1$. Thus, the form of the inductive hypothesis is satisfied for the initial phase.

Finally, we consider $T - k < t \leq T - 1$. In this case, the summation in the dynamics is truncated because the future horizon $t + k$ extends beyond the available horizon T . Let $Y := T - t < k$. The dynamics are governed by a truncated version of (13):

$$\|\mathbf{x}(t+1)\| \leq \sum_{\tau=1}^Y \Theta_\tau \|\mathbf{x}(t-\tau+1)\| + \sum_{\tau=0}^{Y-1} C_3 (1 - \gamma)^\tau e_k(t-\tau) + C_4^{(Y)}, \quad (34)$$

where $\Theta_\tau := C_1 (1 - \gamma)^{2k-\tau+1} + C_2 (1 - \gamma)^{\kappa+\tau-1}$ denotes the state transition coefficients, and $C_4^{(Y)}$ represents the constant contribution over the truncated horizon Y with

$$\begin{aligned} C_4^{(L)} &:= \left(\frac{6\alpha_H \beta_2}{1 - \rho_H} S_1(L-1, \gamma) + \frac{2}{1 - \rho_H} \right) \sup_{0 \leq s \leq T-1} \|\hat{\mathbf{w}}(s)\| \\ &\quad + LN\beta_1\beta_2\Xi D_k (1 - \gamma)^{\kappa+1} S_1(L-1, \gamma) + LN\beta_1\Xi D_k (1 - \gamma)^\kappa, \end{aligned} \quad (35)$$

and

$$S_1(L-1, \gamma) \leq \frac{1}{\gamma} \Rightarrow C_4^{(L)} \leq C_4.$$

Substituting (15) into (34):

$$\begin{aligned} \|\mathbf{x}(t+1)\| &\leq \sum_{\tau=1}^L \left(C_1 (1 - \gamma)^{2k-\tau+1} + C_2 (1 - \gamma)^{\kappa+\tau-1} \right) \left[C_x (1 - \gamma)^{t-\tau-k+1} \|\mathbf{x}(0)\| \right. \\ &\quad \left. + \sum_{l=0}^{t-\tau} C_e (1 - \gamma)^l \sup_{0 \leq s \leq t-\tau} e_k(s) + \frac{C}{\gamma} \right] \\ &\quad + \sum_{\tau=0}^{L-1} C_3 (1 - \gamma)^\tau e_k(t-\tau) + C_4^{(L)}. \end{aligned} \quad (36)$$

Crucially, the partial sums over L terms are strictly bounded by the sums over k terms used in the main induction step. Specifically:

(a) **Gain Condition:** The sum of state coefficients satisfies

$$\sum_{\tau=1}^L \Theta_\tau (1 - \gamma)^{-\tau} < \sum_{\tau=1}^k \Theta_\tau (1 - \gamma)^{-\tau} \leq 1.$$

(b) **Error Term:** The direct error contribution is

$$\sum_{\tau=0}^{L-1} C_3 (1 - \gamma)^\tau \leq \sum_{\tau=0}^{\infty} C_3 (1 - \gamma)^\tau = \frac{C_3}{\gamma} \leq C_e.$$

(c) **Constant Term:** The truncated constant term satisfies $C_4^{(L)} \leq C_4 \leq C/\gamma$.

Thus, substituting the inductive hypothesis (15) into (36) and following the exact same procedure as in the case of $t+1 \leq T-k$, we confirm that:

$$\|\mathbf{x}(t+1)\| \leq C_x(1-\gamma)^{t+1-k}\|\mathbf{x}(0)\| + \sum_{l=0}^{t+1} C_e(1-\gamma)^l \sup_{0 \leq s \leq t} \mathbf{e}_k(s) + \frac{C}{\gamma}. \quad (37)$$

This completes the proof of Theorem 1. \square

2 Proof of Corollary V.1

The proof contains three steps. First, we show h_t is L_f -smooth by establishing $\|\nabla h_t(\lambda) - \nabla h_t(\lambda')\| \leq L_f \|\lambda - \lambda'\|$ via the properties of mixing model $\xi(\cdot)$ and disturbance $w(t)$, and set $\eta = 1/L_f$. Next, the k -step delayed update yields k number of OGD subsequences with $R_T \leq kD/(2\eta) + \eta T/2(2W_\gamma^2 \omega L_\xi S_\infty)^2$, implying $1/T \sum_{t \in [T]} h_t(\lambda(t-k)) \leq (\varepsilon^\star)^2 + \mathcal{O}(\sqrt{1/T})$. Finally, by ISS Bound in Theorem 1 and Jensen inequality, we complete the proof.

Step 1 Smoothness of $h_t(\lambda(t))$ Recall Algorithm 3, we use a confidence criterion function $h_t(\lambda) = (\epsilon_t(\lambda))^2$, where $\epsilon_t(\lambda) := \sum_{\tau=t-k}^{t-1} (1-\gamma)^{\tau-t+k} \|\xi(\lambda \circ \hat{s}(\tau|t-k)) - w(\tau)\|$. We establish the smoothness constant L_f by analyzing the Lipschitz continuity of the gradient $\nabla h_t(\lambda)$. The gradient is given by $\nabla h_t(\lambda) = 2\epsilon_t(\lambda) \nabla \epsilon_t(\lambda)$. Consider two parameters $\lambda, \lambda' \in [0, 1]^D$. By the triangle inequality:

$$\begin{aligned} \|\nabla h_t(\lambda) - \nabla h_t(\lambda')\| &= 2\|\epsilon_t(\lambda) \nabla \epsilon_t(\lambda) - \epsilon_t(\lambda') \nabla \epsilon_t(\lambda')\| \\ &= 2\|\epsilon_t(\lambda)(\nabla \epsilon_t(\lambda) - \nabla \epsilon_t(\lambda')) + (\epsilon_t(\lambda) - \epsilon_t(\lambda')) \nabla \epsilon_t(\lambda')\| \\ &\leq 2 \underbrace{|\epsilon_t(\lambda)|}_{(a)} \underbrace{\|\nabla \epsilon_t(\lambda) - \nabla \epsilon_t(\lambda')\|}_{(b)} + 2 \underbrace{|\epsilon_t(\lambda) - \epsilon_t(\lambda')|}_{(c)} \underbrace{\|\nabla \epsilon_t(\lambda')\|}_{(d)}. \end{aligned}$$

We bound each term based on the properties of ξ (assumed L_ξ -smooth):

- (a) $|\epsilon_t(\lambda)| \leq 2 \sum_{\tau \geq t} (1-\gamma)^{\tau-t} \omega \leq 2\omega/\gamma$.
- (d) $\|\nabla \epsilon_t(\lambda)\| \leq L_\xi S_\infty / \gamma$.
- (c) $|\epsilon_t(\lambda) - \epsilon_t(\lambda')| \leq L_\xi S_\infty \|\lambda - \lambda'\| / \gamma$.
- (b) $\|\nabla \epsilon_t(\lambda) - \nabla \epsilon_t(\lambda')\| \leq L_\xi S_\infty^2 \|\lambda - \lambda'\| / \gamma$.

Substituting these into the inequality:

$$\begin{aligned} \|\nabla h_t(\lambda) - \nabla h_t(\lambda')\| &\leq 2(2\omega/\gamma)(L_\xi S_\infty^2 / \gamma) \|\lambda - \lambda'\| + 2(L_\xi S_\infty \|\lambda - \lambda'\| / \gamma)(L_\xi S_\infty / \gamma) \\ &= 2S_\infty^2 (2\omega L_\xi + L_\xi^2) \|\lambda - \lambda'\| / \gamma^2. \end{aligned}$$

Thus, $h_t(\lambda)$ is L_f -smooth with $L_f = 2S_\infty^2 (L_\xi^2 + 2\omega L_\xi) / \gamma^2$. Similarly, we get $\|\nabla h_t(\lambda)\| \leq 2\omega L_\xi S_\infty / \gamma^2$.

Step 2: k -Step Delayed Descent Essentially, the update rule $\lambda(t) = \text{Proj}(\lambda(t-k) - \eta \nabla h_t(\lambda(t-k)))$ decouples the learning process into k subsequences. Let the time step set $\mathcal{T}_r = \{t \in [k, T+k-1] \mid t \bmod k = r\}$ for $r \in \{0, \dots, k-1\}$. For each subsequence r , the updates form a standard OGD process on the convex functions $\{h_t\}_{t \in \mathcal{T}_r}$. Applying the standard OGD regret bound in [3]:

$$\sum_{t \in \mathcal{T}_r} (h_t(\lambda(t-k)) - h_t(\lambda^\star)) \leq \frac{D}{2\eta} + \frac{\eta}{2} \sum_{t \in \mathcal{T}_r} \|\nabla h_t(\lambda(t-k))\|^2.$$

Summing over all k subsequences yields the total regret R_T :

$$\begin{aligned} R_T(\lambda) &= \sum_{r=0}^{k-1} \sum_{t \in \mathcal{T}_r} (h_t(\lambda(t-k)) - h_t(\lambda^*)) \\ &\leq \sum_{r=0}^{k-1} \left(\frac{D}{2\eta} + \frac{\eta|\mathcal{T}_r|(2\omega L_\xi S_\infty)^2}{2\gamma^2} \right) \\ &= \frac{kD}{2\eta} + \frac{\eta T (2\omega L_\xi S_\infty)^2}{2\gamma^2}. \end{aligned}$$

Dividing by T and substituting η , the average stage cost is bounded by:

$$\begin{aligned} \frac{1}{T} \sum_{t=0}^{T-1} h_t(\lambda(t-k)) &\leq h(\lambda^*) + \frac{kD}{2\eta T} + \frac{\eta (2W_\gamma^2 \omega L_\xi S_\infty)^2}{2} \\ &= (\varepsilon^*)^2 + \mathcal{O}\left(\sqrt{\frac{1}{T}}\right). \end{aligned} \tag{38}$$

where the equality employs the condition of η .

Step 3: Global ISS Bound Derivation From the proof intermediate (13) underlying Theorem 1, the closed-loop state satisfies, for $t > k$,

$$\begin{aligned} \|\mathbf{x}(t)\| &\leq C_x (1-\gamma)^{\max\{t-k, 0\}} \|\mathbf{x}(0)\| + \frac{C}{\gamma} \\ &\quad + \frac{C_e}{\gamma} \sum_{\tau=k}^{t-1} \gamma(1-\gamma)^{t-\tau} \sqrt{h_\tau(\lambda(\tau-k))}, \end{aligned}$$

where $\sqrt{h_\tau(\lambda(\tau-k))}$ identifies the stage prediction error $\varepsilon(\tau)$ in Theorem 1.

Let $S_t := \sum_{\tau=0}^{t-1} \alpha_{t,\tau} \sqrt{h_\tau(\lambda(\tau-k))}$ with $\alpha_{t,\tau} := \gamma(1-\gamma)^{t-1-\tau}$. By Jensen's inequality,

$$S_t \leq \sqrt{\sum_{\tau=0}^{t-1} \alpha_{t,\tau} h_\tau(\lambda(\tau-k))}. \tag{39}$$

For a horizon $t \in [T]$, Step 2 implies

$$\frac{1}{t} \sum_{\tau=0}^{t-1} h_\tau(\lambda(\tau-k)) = (\varepsilon^*)^2 + \mathcal{O}\left(t^{-1/2}\right), \tag{40}$$

Then the weighted average satisfies $\sum_{\tau=0}^{t-1} \alpha_{t,\tau} h_\tau(\lambda(\tau-k)) = (\varepsilon^*)^2 + \mathcal{O}(t^{-1/2})$ for large time step t . Thus, $S_t = \varepsilon^* + \mathcal{O}(t^{-1/4})$ via $\sqrt{a^2 + b^2} \leq a + b$ for $\forall a, b \geq 0$. Substituting yields

$$\|\mathbf{x}(t)\| \leq \mathcal{O}((1-\gamma)^t) + \frac{C + C_e \varepsilon^*}{\gamma} + \mathcal{O}(t^{-1/4}),$$

as in Corollary V.1. □

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