

# Proofs: Supplementary Material for paper ‘Enhanced Secondary Frequency Control via Distributed Peer-to-Peer Communication’

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## 1 Condition for Ignoring Ramping Constraints

Under Assumption 3, Theorem 2 shows that if  $\|\Delta P_L(t) - \Delta P_L(t-1)\| \leq \epsilon$ ,  $\forall t \in \mathcal{T}$ , there exists a  $c$ , such that  $\|\lambda_n^t - \lambda^t\| \leq c\epsilon$ . Assumption 3 further guarantees:

$$\begin{aligned} \|u_i(t+1) - u_i(t)\| &\leq \beta \sum_{l \in \Omega_i} \|\lambda_i(t) - \lambda_l(t)\| + \frac{1}{n} \|\Delta P_L(t) - \Delta P_L(t-1)\| \\ &\leq \beta \sum_{l \in \Omega_i} (\|\lambda_i(t) - \lambda(t)\| + \|\lambda(t) - \lambda_l(t)\|) + \frac{1}{n} \epsilon \\ &\leq \left(2\beta c |\Omega_i| + \frac{1}{n}\right) \epsilon. \end{aligned}$$

Thus, as long as

$$\left(2\beta c |\Omega_i| + \frac{1}{n}\right) \epsilon \leq r_i, \forall i \in \Omega,$$

where  $r_i$  is regulation resource  $i$ 's ramping limit, no ramping constraints will be binding. Hence, in such conditions, our relaxation is exact.

## 2 Proof of Theorem 1

**Theorem 1:** *The proposed distributed control scheme satisfies the necessary condition (5).*

*Proof:* At each time  $t \in \mathcal{T}$ , a step load change may happen at the beginning of the time slot, and according to the update rule, we have

$$\sum_{i \in \Omega} u_i(t+1) = \sum_{i \in \Omega} \frac{\tilde{\lambda}_i^{t+1}}{2a_i}, \tag{sp-1}$$

and

$$\sum_{i \in \Omega} \frac{\tilde{\lambda}_i^{t+1}}{2a_i} = \sum_{i \in \Omega} \frac{\tilde{\lambda}_i^t}{2a_i} - \beta \sum_{i \in \Omega} \sum_{l \in \Omega_i} (\lambda_i^t - \lambda_l^t) + \Delta P_L(t+1) - \sum_{i \in \Omega} \Delta P_m^i(t). \tag{sp-2}$$

Note the following facts hold:

$$\sum_{i \in \Omega} \sum_{l \in \Omega_i} (\lambda_i^t - \lambda_l^t) = 0, \forall t \in \mathcal{T}; \quad (\text{sp-3})$$

$$\sum_{i \in \Omega} \frac{\tilde{\lambda}_i^t}{2a_i} = \sum_{i \in \Omega} \Delta P_m^i(t). \quad (\text{sp-4})$$

Combining (sp-3) and (sp-4) with (sp-2), we establish that

$$\sum_{i \in \Omega} u_i(t+1) = \Delta P_L(t+1). \quad (\text{sp-5})$$

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### 3 Proof of Theorem 2

**Theorem 2** *If the communication graph is well connected such that (28) holds,  $\|\Delta P_L(t+1) - \Delta P_L(t)\| < \epsilon$ ,  $\forall t \in \mathcal{T}$ , and Assumption 3 holds, then there exists a constant  $c > 0$  (depending only on the cost parameters and the communication topology) such that control signals ( $u_i$ 's) are  $c\epsilon$ -close to their optimal values given by (13)-(14). More precisely,*

$$\begin{aligned} \|\lambda_i^t - \lambda^t\| &\leq c\epsilon, \quad \forall t \in \mathcal{T}, i \in \Omega, \\ \|u_i(t) - u_i^*(t)\| &\leq c\epsilon, \quad \forall t \in \mathcal{T}, i \in \Omega, \end{aligned}$$

where  $u_i^*(t)$  denotes the solution to (13)-(14).

*Proof:* Using Assumption 3, we know that  $\lambda^t = \tilde{\lambda}^t$ , for all  $t \in \mathcal{T}$ . Thus, the marginal cost updates may be written in vector notation as

$$\Lambda \boldsymbol{\lambda}_{t+1} = (\Lambda - \beta L) \boldsymbol{\lambda}_t + n^{-1} (\Delta P_L(t+1) - \Delta P_L(t)) \mathbf{1}. \quad (\text{sp-6})$$

Since  $\mathbf{1}^T L = \mathbf{0}^T$ , we have

$$\mathbf{1}^T \Lambda \boldsymbol{\lambda}_{t+1} = \mathbf{1}^T \Lambda \boldsymbol{\lambda}_t + (\Delta P_L(t+1) - \Delta P_L(t)). \quad (\text{sp-7})$$

Assumption 3 also leads to

$$\mathbf{1}^T \Lambda \boldsymbol{\lambda}_t = \mathbf{1}^T \Lambda \mathbf{1} \lambda^t. \quad (\text{sp-8})$$

Combining (sp-8) with (sp-7) yields

$$\mathbf{1}^T \Lambda \mathbf{1} \lambda^{t+1} = \mathbf{1}^T \Lambda \mathbf{1} \lambda^t + (\Delta P_L(t+1) - \Delta P_L(t)). \quad (\text{sp-9})$$

By dividing  $\mathbf{1}^T \Lambda \mathbf{1}$  at both sides, we have

$$\lambda^{t+1} = \lambda^t + \frac{\Delta P_L(t+1) - \Delta P_L(t)}{\mathbf{1}^T \Lambda \mathbf{1}}. \quad (\text{sp-10})$$

Therefore,

$$\begin{aligned}
& \boldsymbol{\lambda}_{t+1} - \lambda^{t+1} \mathbf{1} \\
&= (I - \beta \Lambda^{-1} L) \boldsymbol{\lambda}_t + (n\Lambda)^{-1} (\Delta P_L(t+1) - \Delta P_L(t)) \mathbf{1} - \lambda^t \mathbf{1} - \frac{\Delta P_L(t+1) - \Delta P_L(t)}{\mathbf{1}^T \Lambda \mathbf{1}} \mathbf{1} \\
&= (I - \beta \Lambda^{-1} L) (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1}) + \left( (n\Lambda)^{-1} - \frac{1}{\mathbf{1}^T \Lambda \mathbf{1}} \right) (\Delta P_L(t+1) - \Delta P_L(t)) \mathbf{1} \tag{sp-11} \\
&\leq (I - \beta \Lambda^{-1} L) (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1}) + \left\| (n\Lambda)^{-1} - \frac{1}{\mathbf{1}^T \Lambda \mathbf{1}} \right\| \epsilon \mathbf{1}.
\end{aligned}$$

Note that in the second equation of (sp-11), we add a zero term  $\beta \Lambda^{-1} L \lambda^t \mathbf{1}$ . By contradiction, we can show that the largest eigenvalue of the matrix  $I - \beta \Lambda^{-1} L$  is 1. Note that,

$$I - \beta \Lambda^{-1} L = \Lambda^{-\frac{1}{2}} (I - \beta \Lambda^{-\frac{1}{2}} L \Lambda^{-\frac{1}{2}}) \Lambda^{\frac{1}{2}}, \tag{sp-12}$$

$I - \beta \Lambda^{-1} L$  and  $I - \beta \Lambda^{-\frac{1}{2}} L \Lambda^{-\frac{1}{2}}$  are similar matrices with the same eigenvalues. Since the Laplacian  $L$  corresponds to a connected network, one is a simple eigenvalue of the matrix  $I - \beta \Lambda^{-1/2} L \Lambda^{-1/2}$  with corresponding eigenvector  $\Lambda^{\frac{1}{2}} \mathbf{1}$ . By (sp-8), we have

$$(\Lambda^{\frac{1}{2}} \mathbf{1})^T \Lambda^{\frac{1}{2}} (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1}) = \mathbf{1}^T \Lambda (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1}) = 0. \tag{sp-13}$$

Thus,  $\Lambda^{\frac{1}{2}} (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1})$  is orthogonal to the eigenvector corresponding to the eigenvalue 1. Furthermore, the matrix  $\Lambda^{-1/2} L \Lambda^{-1/2}$  is positive semidefinite and hence, by taking  $\beta$  to be small enough, all other eigenvalues of  $I - \beta \Lambda^{-1/2} L \Lambda^{-1/2}$  can be guaranteed to lie in the interval  $[0, 1)$ . Since  $I - \beta \Lambda^{-\frac{1}{2}} L \Lambda^{-\frac{1}{2}}$  is a symmetric matrix, the induced 2-norm coincides with the spectral radius, thus

$$\begin{aligned}
& \|(I - \Lambda^{-1} \beta L) (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1})\| \\
&= \|\Lambda^{-\frac{1}{2}} (I - \beta \Lambda^{-\frac{1}{2}} L \Lambda^{-\frac{1}{2}}) \Lambda^{\frac{1}{2}} (\boldsymbol{\lambda}_t - \lambda^t \mathbf{1})\| \\
&\leq \|\Lambda^{-\frac{1}{2}}\| \|I - \beta \Lambda^{-\frac{1}{2}} L \Lambda^{-\frac{1}{2}}\| \|\Lambda^{\frac{1}{2}}\| \|\boldsymbol{\lambda}_t - \lambda^t \mathbf{1}\| \tag{sp-14} \\
&\leq (1 - \rho) \max_{i \in \mathcal{N}} a_i^{\frac{1}{2}} \max_{i \in \mathcal{N}} (a_i)^{-\frac{1}{2}} \|\boldsymbol{\lambda}_t - \lambda^t \mathbf{1}\|,
\end{aligned}$$

where  $1 - \rho \in [0, 1)$  is the second largest eigenvalue of  $I - \beta \Lambda^{-1} L$ . As long as (28) holds, standard algebraic manipulations now lead to the desired conclusion.  $\blacksquare$