Supplementary Material for "Battery Dispatch Optimization for Electric Vehicle Aggregators: A Moving Least Squares Approach with Disjunctive Cuts"

Chao Lei, Student Member, IEEE, Siqi Bu, Senior Member, IEEE, Qianggang Wang, Senior Member, IEEE, Zhouyang Ren, Senior Member, IEEE, Lalit Kumar Goel, Fellow, IEEE and Dipti Srinivasan, Fellow, IEEE

I. PROOF OF TIGHTENED FEASIBILITY SPACE

In terms of DCHR, the upper and lower bounds of e_i^t are denoted as $\mathcal{L}_1^{upper} = \lambda_{c,i}^t \overline{E} - \eta_{c,i} P_{c,i}^t (t-1) \Delta T$ and $\mathcal{L}_1^{lower} = \lambda_{d,i}^t \underline{E} + \frac{1}{\eta_{d,i}} P_{d,i}^t (t-1) \Delta T$, respectively. However, according to MIQP-based model (1a)-(1d), we express the upper and lower bounds of e_i^t by $\mathcal{L}_2^{upper} = \overline{E} - \eta_{c,i} P_{c,i}^t (t-1) \Delta T$ and $\mathcal{L}_2^{lower} = \underline{E} + \frac{1}{\eta_{d,i}} P_{d,i}^t (t-1) \Delta T$, respectively. Hence, we achieve the difference in algebra $\mathcal{L}_1^{upper} - \mathcal{L}_2^{upperr} = (\lambda_{c,i}^t - 1) \overline{E}$. Since $\lambda_{c,i}^t \in [0,1]$, this clearly renders $\mathcal{L}_1^{upper} \leqslant \mathcal{L}_2^{upper}$. Similarly, we can also achieve the lower bound subject to $\mathcal{L}_1^{lower} \geqslant \mathcal{L}_2^{lower}$. We have proved that DCHR has tighter relaxation lower and upper bounds than those by MIQP-based model (1a)-(1d) for $\Omega_{op,i}$.

II. PROOF OF THEOREM

Initially, since $\sum_{i=1}^{N} \boldsymbol{p}_{sig,i}^{t*} = \boldsymbol{p}_{ref}^{t}$, we can rewrite \boldsymbol{F}^{*} as

$$m{F}^* = \sum_{t=1}^T \left\| \sum_{i=1}^N (m{c}^T m{x}_i^{t*} - m{p}_{sig,i}^{t*})
ight\|_2 = \sum_{t=1}^T \left\| \sum_{i=1}^N m{lpha}_i^*
ight\|_2 \quad ext{(A-1)}$$

where the optimal auxiliary variable $oldsymbol{lpha}_i^* = oldsymbol{c}^T oldsymbol{x}_i^{t*} - oldsymbol{p}_{sig,i}^{t*}.$

Thus, our goal is to prove that the following two objective functions can get converged over $(\boldsymbol{x}_i^t, \boldsymbol{z}_i^t) \in \mathcal{X}_i, \ \forall i \in \mathcal{E}$, with the same optimal solution $(\boldsymbol{x}_i^{t*}, \boldsymbol{z}_i^{t*})$ for the MIQP-based model (1a)-(1d), namely

$$\underset{(\boldsymbol{x}_{i}^{t}, \boldsymbol{z}_{i}^{t}) \in \mathcal{X}_{i}}{\operatorname{argmin}} \sum_{t=1}^{T} \left\| \sum_{i=1}^{N} \boldsymbol{\alpha}_{i}^{*} \right\|_{2} \iff \underset{(\boldsymbol{x}_{i}^{t}, \boldsymbol{z}_{i}^{t}) \in \mathcal{X}_{i}}{\operatorname{argmin}} \sum_{t=1}^{T} \sum_{i=1}^{N} \left\| \boldsymbol{\alpha}_{i}^{*} \right\|_{2}$$
(A-2)

At time t, when $\left\|\sum_{i=1}^N \alpha_i^*\right\|_2$ can be minimized as a non-zero number, we suppose if there only $\exists \alpha_N^*$ as the minimal non-zero number for the optimal solution $c^T x_i^{t*}$. Then, we have

$$\left\| \sum_{i=1}^{N} \alpha_{i}^{*} \right\|_{2} = \left\| \alpha_{1}^{*} + \alpha_{2}^{*} \dots + \alpha_{N}^{*} \right\|_{2} = \left\| \mathbf{0} + \mathbf{0} + \dots + \alpha_{N}^{*} \right\|_{2} = \alpha_{N}^{*}$$
(A-3)

It is clear that equality (A-3) can be also equivalent to

$$\alpha_N^* = \|\mathbf{0}\|_2 + \|\mathbf{0}\|_2 + \dots + \|\alpha_N^*\|_2 = \sum_{i=1}^N \|\alpha_i^*\|_2$$
 (A-4)

Besides, if the minimal $\left\|\sum_{i=1}^N \alpha_i^*\right\|_2$ is zero, then $\sum_{i=1}^N \|\alpha_i^*\|_2 = \left\|\sum_{i=1}^N \alpha_i^*\right\|_2 = 0$ naturally holds. Based on the above, we can derive (A-5) for $t \in \mathcal{T}$ by

$$\sum_{t=1}^{T} \left\| \sum_{i=1}^{N} \alpha_{i}^{*} \right\|_{2} = \sum_{t=1}^{T} \sum_{i=1}^{N} \left\| \alpha_{i}^{*} \right\|_{2}$$
 (A-5)

Thus, this equality (A-5) indicates that (A-2) can stand at the same optimal solution F^* over the identical feasibility space \mathcal{X}_i , which proves this Theorem.