

A companion technical report of “Joint Power and Admission Control: Non-Convex L_q Approximation and An Effective Polynomial Time Deflation Approach”

Ya-Feng Liu, Yu-Hong Dai, and Shiqian Ma

I. PROOF OF LEMMA 1 IN [1]

In this part, we prove Lemma 1 in [1], i.e., for any $q \in [0, 1]$, problem

$$\begin{aligned} \min_{\mathbf{x}} \quad & \|\mathbf{b} - \mathbf{A}\mathbf{x}\|_q^q + \alpha \bar{\mathbf{p}}^T \mathbf{x} \\ \text{s.t.} \quad & \mathbf{0} \leq \mathbf{x} \leq \mathbf{e} \end{aligned} \tag{1}$$

is equivalent to

$$\begin{aligned} \min_{\mathbf{x}} \quad & \|\mathbf{b} - \mathbf{A}\mathbf{x}\|_q^q + \alpha \bar{\mathbf{p}}^T \mathbf{x} \\ \text{s.t.} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{b}, \\ & \mathbf{0} \leq \mathbf{x} \leq \mathbf{e}. \end{aligned} \tag{2}$$

The lemma is a consequence of the special structure of \mathbf{A} and \mathbf{b} .

Before showing the lemma, we first introduce some notations which will be used later. For any subset $\mathcal{I} \subseteq \mathcal{K}$, we use $\mathbf{A}_{\mathcal{I}}$ to denote the matrix formed by the rows of \mathbf{A} indexed by \mathcal{I} . For a vector \mathbf{x} , the notation $\mathbf{x}_{\mathcal{I}}$ is similarly defined. Moreover, for any $\mathcal{J} \subseteq \mathcal{K}$, the notation $\mathbf{A}_{\mathcal{I}, \mathcal{J}}$ will denote the submatrix of \mathbf{A} obtained by taking the rows and columns of \mathbf{A} indexed by \mathcal{I} and \mathcal{J} respectively.

Notice that problem (2) is equivalent to

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{y}} \quad & \|\mathbf{y}\|_q^q + \alpha \bar{\mathbf{p}}^T \mathbf{x} \\ \text{s.t.} \quad & \mathbf{y} = \mathbf{b} - \mathbf{A}\mathbf{x}, \\ & \mathbf{0} \leq \mathbf{x} \leq \mathbf{e}, \mathbf{y} \geq \mathbf{0}. \end{aligned}$$

Thus, to show the equivalence of (1) and (2), it suffices to show that any optimal solution $\tilde{\mathbf{x}}$ of (1) always satisfies $\mathbf{b} - \mathbf{A}\tilde{\mathbf{x}} \geq \mathbf{0}$. For simplicity of notations, let $\tilde{\mathbf{z}} = \mathbf{A}\tilde{\mathbf{x}} - \mathbf{b}$. Next, we show

$$\tilde{\mathbf{z}} = (\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_K)^T \leq \mathbf{0}.$$

Denote $\mathcal{K}^+ = \{k \mid \tilde{z}_k > 0\}$, $\mathcal{K}^0 = \{k \mid \tilde{z}_k = 0\}$, and $\mathcal{K}^- = \{k \mid \tilde{z}_k < 0\}$. We claim $|\mathcal{K}^+| = 0$. Assume the contrary so that $|\mathcal{K}^+| \geq 1$. We will derive a contradiction. Let $\mathcal{I} = \mathcal{K}^+ \cup \mathcal{K}^0$. Then $\tilde{\mathbf{z}}_{\mathcal{I}} = \mathbf{A}_{\mathcal{I}}\tilde{\mathbf{x}} - \mathbf{b}_{\mathcal{I}} \geq \mathbf{0}$, which further implies

$$\mathbf{A}_{\mathcal{I},\mathcal{I}}\tilde{\mathbf{x}}_{\mathcal{I}} - (\mathbf{b}_{\mathcal{I}} - \mathbf{A}_{\mathcal{I},\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c}) \geq \mathbf{0}.$$

Hence, $\tilde{\mathbf{x}}_{\mathcal{I}}$ is a feasible solution to the following linear subsystem in $\mathbf{x}_{\mathcal{I}}$:

$$\mathbf{A}_{\mathcal{I},\mathcal{I}}\mathbf{x}_{\mathcal{I}} - (\mathbf{b}_{\mathcal{I}} - \mathbf{A}_{\mathcal{I},\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c}) \geq \mathbf{0}. \quad (3)$$

Since $\mathbf{A}_{\mathcal{I},\mathcal{I}^c} \leq \mathbf{0}$ (the off-diagonals of \mathbf{A} are nonpositive), it follows that $\mathbf{b}_{\mathcal{I}} - \mathbf{A}_{\mathcal{I},\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c} \geq \mathbf{b}_{\mathcal{I}} > \mathbf{0}$. It can be checked that the other assumptions of Lemma 3.1 in [2] all hold for (3) so that there exists a vector $\bar{\mathbf{x}}_{\mathcal{I}}$ such that $\mathbf{b}_{\mathcal{I}} \leq \bar{\mathbf{x}}_{\mathcal{I}} \leq \tilde{\mathbf{x}}_{\mathcal{I}}$ and $\mathbf{A}_{\mathcal{I},\mathcal{I}}\bar{\mathbf{x}}_{\mathcal{I}} - (\mathbf{b}_{\mathcal{I}} - \mathbf{A}_{\mathcal{I},\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c}) = \mathbf{0}$. Define $\bar{\mathbf{x}}_{\mathcal{I}^c} = \tilde{\mathbf{x}}_{\mathcal{I}^c}$. Then we have

$$\mathbf{A}_{\mathcal{I}}\bar{\mathbf{x}} - \mathbf{b}_{\mathcal{I}} = \mathbf{A}_{\mathcal{I},\mathcal{I}}\bar{\mathbf{x}}_{\mathcal{I}} - (\mathbf{b}_{\mathcal{I}} - \mathbf{A}_{\mathcal{I},\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c}) = \mathbf{0}. \quad (4)$$

Moreover, we have $\mathbf{0} \leq \bar{\mathbf{x}} \leq \tilde{\mathbf{x}} \leq \mathbf{e}$, so $\bar{\mathbf{x}}$ is a feasible power allocation. With this new power allocation $\bar{\mathbf{x}}$, there holds

$$\begin{aligned} \mathbf{A}_{\mathcal{I}^c}\bar{\mathbf{x}} - \mathbf{b}_{\mathcal{I}^c} &= \mathbf{A}_{\mathcal{I}^c,\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c} + \mathbf{A}_{\mathcal{I}^c,\mathcal{I}}\bar{\mathbf{x}}_{\mathcal{I}} - \mathbf{b}_{\mathcal{I}^c} \\ &\geq \mathbf{A}_{\mathcal{I}^c,\mathcal{I}^c}\tilde{\mathbf{x}}_{\mathcal{I}^c} + \mathbf{A}_{\mathcal{I}^c,\mathcal{I}}\tilde{\mathbf{x}}_{\mathcal{I}} - \mathbf{b}_{\mathcal{I}^c} \\ &= \mathbf{A}_{\mathcal{I}^c}\tilde{\mathbf{x}} - \mathbf{b}_{\mathcal{I}^c}, \end{aligned} \quad (5)$$

where the inequality follows from $\mathbf{A}_{\mathcal{I}^c,\mathcal{I}} \leq \mathbf{0}$ and $\bar{\mathbf{x}} \leq \tilde{\mathbf{x}}$. This further implies

$$(\mathbf{b}_{\mathcal{I}^c} - \mathbf{A}_{\mathcal{I}^c}\bar{\mathbf{x}})_+ \leq (\mathbf{b}_{\mathcal{I}^c} - \mathbf{A}_{\mathcal{I}^c}\tilde{\mathbf{x}})_+$$

where $(\cdot)_+$ denotes the projection to the nonnegative orthant. Since $\mathbf{b}_{\mathcal{I}} - \mathbf{A}_{\mathcal{I}}\bar{\mathbf{x}} = \mathbf{0}$ (cf. (4)), it follows that

$$(\mathbf{b} - \mathbf{A}\bar{\mathbf{x}})_+ \leq (\mathbf{b} - \mathbf{A}\tilde{\mathbf{x}})_+ \quad (6)$$

with the inequality holds true *strictly* for entries indexed by \mathcal{K}^+ . Define the function

$$\phi(\mathbf{x}) = \|(\mathbf{b} - \mathbf{A}\mathbf{x})_+\|_q^q + \alpha \bar{\mathbf{p}}^T \mathbf{x}.$$

Clearly, we have

$$\phi(\mathbf{x}) \leq \|\mathbf{b} - \mathbf{A}\mathbf{x}\|_q^q + \alpha \bar{\mathbf{p}}^T \mathbf{x}, \quad \forall \mathbf{x} \geq \mathbf{0},$$

where the equality holds whenever $\mathbf{A}\mathbf{x} - \mathbf{b} \leq \mathbf{0}$. Since $\mathbf{0} \leq \bar{\mathbf{x}} \leq \tilde{\mathbf{x}}$, we can use (6) to obtain

$$\phi(\bar{\mathbf{x}}) = \|(\mathbf{b} - \mathbf{A}\bar{\mathbf{x}})_+\|_q^q + \alpha \bar{\mathbf{p}}^T \bar{\mathbf{x}} < \|(\mathbf{b} - \mathbf{A}\tilde{\mathbf{x}})_+\|_q^q + \alpha \bar{\mathbf{p}}^T \tilde{\mathbf{x}} = \phi(\tilde{\mathbf{x}}).$$

Moreover, it follows from $|\mathcal{K}^+| \geq 1$ that

$$\|\mathbf{A}\bar{\mathbf{x}} - \mathbf{b}\|_0 = K - |\mathcal{I}| = K - |\mathcal{K}^-| - |\mathcal{K}^+| < K - |\mathcal{K}^-| = \|\mathbf{A}\tilde{\mathbf{x}} - \mathbf{b}\|_0.$$

We claim that, without loss of generality, we can assume $\mathbf{A}_{\mathcal{I}^c}\bar{\mathbf{x}} - \mathbf{b}_{\mathcal{I}^c} \leq \mathbf{0}$ so that $\mathbf{A}\bar{\mathbf{x}} - \mathbf{b} \leq \mathbf{0}$. This is because otherwise we can repeat the above steps by replacing the vector $\tilde{\mathbf{x}}$ with $\bar{\mathbf{x}}$ to find a new vector $\mathbf{0} \leq \hat{\mathbf{x}} \leq \bar{\mathbf{x}}$ such that

$$\phi(\hat{\mathbf{x}}) < \phi(\bar{\mathbf{x}}) < \phi(\tilde{\mathbf{x}}) \quad \text{and} \quad \|\mathbf{A}\hat{\mathbf{x}} - \mathbf{b}\|_0 < \|\mathbf{A}\bar{\mathbf{x}} - \mathbf{b}\|_0 < \|\mathbf{A}\tilde{\mathbf{x}} - \mathbf{b}\|_0.$$

Since the ℓ_0 -norm can be reduced at most finitely many times, it follows that by repeatedly applying the above steps we will eventually obtain a power allocation (still denote by $\bar{\mathbf{x}}$) such that

$$\mathbf{0} \leq \bar{\mathbf{x}} \leq \tilde{\mathbf{x}} \leq \mathbf{e}, \quad \phi(\bar{\mathbf{x}}) < \phi(\tilde{\mathbf{x}}), \quad \mathbf{A}\bar{\mathbf{x}} - \mathbf{b} \leq \mathbf{0}.$$

Notice that when $\mathbf{A}\bar{\mathbf{x}} - \mathbf{b} \leq \mathbf{0}$ we have

$$\|\mathbf{A}\bar{\mathbf{x}} - \mathbf{b}\|_q^q + \alpha \bar{\mathbf{p}}^T \bar{\mathbf{x}} = \phi(\bar{\mathbf{x}}) < \phi(\tilde{\mathbf{x}}) \leq \|\mathbf{A}\tilde{\mathbf{x}} - \mathbf{b}\|_q^q + \alpha \bar{\mathbf{p}}^T \tilde{\mathbf{x}}.$$

This contradicts the optimality of $\tilde{\mathbf{x}}$. This completes the proof.

II. GLOBAL MINIMIZER OF PROBLEM (12) IN [1]

In this part, we show that, for any $q \in (0, 1)$, $\mathbf{x}^* = (0.5, 0.5, 0)^T$ is the unique global minimizer of the non-convex optimization problem

$$\begin{aligned} \min \quad & h_q(\mathbf{x}) = (0.5 - x_1 + x_3)^q + (0.5 - x_2 + x_3)^q + (0.5 + x_1 + x_2 - x_3)^q + \alpha \sum_{i=1}^3 x_i \\ \text{s.t.} \quad & 0.5 - x_1 + x_3 \geq 0, \\ & 0.5 - x_2 + x_3 \geq 0, \\ & 0.5 + x_1 + x_2 - x_3 \geq 0, \\ & 0 \leq x_1, x_2, x_3 \leq 1, \end{aligned} \tag{7}$$

where

$$0 < \alpha \leq \bar{\alpha}_q := \min \{1 + (0.5)^q, 2^q\} - (1.5)^q. \tag{8}$$

To show the desired result, let us first introduce the following useful facts.

Fact 1. Suppose $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are concave functions, so is $f(\mathbf{x}) := \min \{f_1(\mathbf{x}), f_2(\mathbf{x})\}$.

Fact 2. Suppose $f(x)$ is an univariate strictly concave function in $x \in [a, b]$, then

$$f(x) > \min \{f(a), f(b)\}, \forall x \in (a, b).$$

Fact 3. For any $q \in (0, 1)$, $\|\mathbf{Ax} + \mathbf{b}\|_q^q$ is concave in $\{\mathbf{x} \mid \mathbf{Ax} + \mathbf{b} \geq \mathbf{0}\}$. Furthermore, it is strictly concave if \mathbf{A} is column full rank.

Fact 4. For any $q \in (0, 1)$, $x_1 \geq 0, x_2 \geq 0$, we have $x_1^q + x_2^q \geq (x_1 + x_2)^q$, where the inequality holds with “=” if and only if at least one of x_1 and x_2 is zero.

From **Fact 3**, we know $h_q(\mathbf{x})$ defined in (7) is strictly concave in its feasible region, and thus is also strictly concave in each of its components. **Fact 4** implies that $\bar{\alpha}_q$ defined in (8) is positive.

We are now ready to show the desired result. It suffices to show that for any feasible set $\mathcal{S} \subseteq \{1, 2, 3\}$, the optimal value of problem

$$\begin{aligned} \min_{\mathbf{x}} \quad & h_{q,\mathcal{S}}(\mathbf{x}) = \sum_{i \notin \mathcal{S}} [\mathbf{b} - \mathbf{Ax}]_i^q + \alpha \mathbf{e}^T \mathbf{x} \\ \text{s.t.} \quad & [\mathbf{b} - \mathbf{Ax}]_i = 0, \quad i \in \mathcal{S}, \\ & [\mathbf{b} - \mathbf{Ax}]_i > 0, \quad i \notin \mathcal{S}, \\ & \mathbf{0} \leq \mathbf{x} \leq \mathbf{e}, \end{aligned} \tag{9}$$

is strictly greater than $h_q(\mathbf{x}^*) = (1.5)^q + \alpha$ except at the point $\mathbf{x} = \mathbf{x}^*$.

It is simple to check that the sets $\{1, 3\}$, $\{2, 3\}$, and (thus) $\{1, 2, 3\}$ are infeasible for problem (9). In the sequential, due to the symmetry of x_1 and x_2 , it is sufficient to consider the following feasible sets (including the empty set):

A: When $\mathcal{S} = \{1, 2\}$, we have $0.5 - x_1 + x_3 = 0$ and $0.5 - x_2 + x_3 = 0$. Therefore,

$$\begin{aligned} h_{q,\mathcal{S}}(\mathbf{x}) &= (0.5 + x_1 + x_2 - x_3)^q + \alpha(x_1 + x_2 + x_3) \\ &= (1.5 + x_3)^q + \alpha + 3\alpha x_3 \\ &\geq h_q(\mathbf{x}^*), \end{aligned}$$

where “=” holds if and only if $\mathbf{x} = \mathbf{x}^*$.

B: When $\mathcal{S} = \{1\}$, we have $x_3 = x_1 - 0.5 \geq 0$ and $x_1 \geq 0.5$. Therefore,

$$\begin{aligned} h_{q,\mathcal{S}}(\mathbf{x}) &= (0.5 - x_2 + x_3)^q + (0.5 + x_1 + x_2 - x_3)^q + \alpha(x_1 + x_2 + x_3) \\ &= (x_1 - x_2)^q + (1 + x_2)^q + 2\alpha x_1 + \alpha x_2 - 0.5\alpha \end{aligned} \quad (10)$$

$$\geq \min \{(1 + x_1)^q + 3\alpha x_1 - 0.5\alpha, x_1^q + 1 + 2\alpha x_1 - 0.5\alpha\} \quad (11)$$

$$\geq \min \{(1.5)^q + \alpha, (0.5)^q + 1 + 0.5\alpha\} \quad (12)$$

$$= h_q(\mathbf{x}^*), \quad (13)$$

where (10) is due to $x_3 = x_1 - 0.5$, (11) comes from the fact that the function in the right hand of (10) is strictly concave in $x_2 \in [0, x_1]$ and **Fact 2**, (12) is due to the fact that the function in the right hand of (11) is increasing in $x_1 \in [0.5, 1]$, and (13) is due to $\alpha \leq \bar{\alpha}_q$ (cf. (8)). Concluding the above analysis, we have $h_{q,\mathcal{S}}(\mathbf{x}) \geq h_q(\mathbf{x}^*)$ and the equality holds true if and only if $\mathbf{x} = \mathbf{x}^*$.

C: When $\mathcal{S} = \{3\}$, we have $x_3 = x_1 + x_2 + 0.5$. Then,

$$\begin{aligned} h_{q,\mathcal{S}}(\mathbf{x}) &\geq (0.5 - x_1 + x_3)^q + (0.5 - x_2 + x_3)^q \\ &= (1 + x_2)^q + (1 + x_1)^q \\ &\geq 2 > h_q(\mathbf{x}^*), \end{aligned}$$

where the last strict inequality is due to the fact $\alpha \leq \bar{\alpha}_q \leq 2^q - (1.5)^q < 2 - (1.5)^q$ (cf. (8)).

D: When $\mathcal{S} = \emptyset$, we further consider the following cases separately.

D1: When $x_1 = 0, x_2 \in [0, 1], x_3 \in [0, 0.5]$, we have

$$\begin{aligned} h_{q,\emptyset}(\mathbf{x}) &= (0.5 + x_3)^q + (0.5 - x_2 + x_3)^q + (0.5 + x_2 - x_3)^q + \alpha(x_2 + x_3) \\ &\geq (0.5 + x_3)^q + \alpha x_3 + \min \{(0.5 + x_3)^q + (0.5 - x_3)^q, 1 + \alpha(0.5 + x_3)\} \end{aligned} \quad (14)$$

$$\geq \min \{(0.5)^q + 1 + 0.5\alpha, 3(0.5)^q, 2 + 0.5\alpha, 2 + 1.5\alpha\} \quad (15)$$

$$> h_q(\mathbf{x}^*), \quad (16)$$

where (14) is due to the fact that $h_{q,\emptyset}(\mathbf{x})$ is strictly concave in $x_2 \in [0, 0.5 + x_3]$ and **Fact 2**, (15) is due to **Fact 1** (the function in the right hand side of (14) is strictly concave in $x_3 \in [0, 0.5]$) and **Fact 2**, and the last strict inequality (16) is due to (8).

D2: Similar as case D1, when $x_1 = 0, x_2 \in [0, 1], x_3 \in [0.5, 1]$, we have

$$\begin{aligned} h_{q,\emptyset}(\mathbf{x}) &= (0.5 + x_3)^q + (0.5 - x_2 + x_3)^q + (0.5 + x_2 - x_3)^q + \alpha(x_2 + x_3) \\ &\geq (0.5 + x_3)^q + \alpha x_3 + \min \{(1.5 - x_3)^q + (x_3 - 0.5)^q + \alpha, 1 + \alpha(x_3 - 0.5)\} \end{aligned} \quad (17)$$

$$\geq \min \{(1.5)^q + 2(0.5)^q + 2\alpha, (1.5)^q + 1.5\alpha + 1, 2 + 1.5\alpha, 2 + 0.5\alpha\} \quad (18)$$

$$> h_q(\mathbf{x}^*), \quad (19)$$

where (17) is due to the fact that $h_{q,\emptyset}(\mathbf{x})$ is strictly concave in $x_2 \in [x_3 - 0.5, 1]$ and **Fact 2**, (18) is due to **Fact 1** (the function in the right hand side of (17) is strictly concave in $x_3 \in [0.5, 1]$) and **Fact 2**, and the last strictly inequality (19) is due to (8).

D3: When $x_1 \in (0, 1), x_2 \in [0, 1], x_3 = 0$, we have

$$\begin{aligned} h_{q,\emptyset}(\mathbf{x}) &= (0.5 - x_1)^q + (0.5 - x_2)^q + (0.5 + x_1 + x_2)^q + \alpha(x_1 + x_2) \\ &\geq (1 - (x_1 + x_2))^q + (0.5 + (x_1 + x_2))^q + \alpha(x_1 + x_2) \end{aligned} \quad (20)$$

$$\geq \min \{(1.5)^q + \alpha, 1 + (0.5)^q\} \quad (21)$$

$$= h_q(\mathbf{x}^*), \quad (22)$$

where (20) is due to **Fact 4**, (21) is due to **Fact 2** and the fact that $x_1 \leq 0.5$ and $x_2 \leq 0.5$, and (22) is due to (8). Hence, $h_{q,\emptyset}(\mathbf{x}) \geq h_q(\mathbf{x}^*)$ for any $x_1 \in (0, 1), x_2 \in [0, 1], x_3 = 0$, and the inequality holds with “=” if and only if $\mathbf{x} = \mathbf{x}^*$.

D4: In a similar fashion as the case D3, when $x_1 \in (0, 1), x_2 \in [0, 1], x_3 = 1$, we can show

$$\begin{aligned} h_{q,\emptyset}(\mathbf{x}) &\geq (1.5 - x_1)^q + (1.5 - x_2)^q + (x_1 + x_2 - 0.5)^q \\ &\geq (3 - x_1 - x_2)^q + (x_1 + x_2 - 0.5)^q \\ &\geq \min \{1 + (1.5)^q, (2.5)^q\} \\ &= (2.5)^q > h_q(\mathbf{x}^*), \end{aligned}$$

where the third inequality comes from the fact that $(3 - (x_1 + x_2))^q + (x_1 + x_2 - 0.5)^q$ is strictly concave in $x_1 + x_2 \in [0.5, 2]$ and **Fact 2**.

D5: The remaining case is $x_1 \in (0, 1), x_2 \in (0, 1), x_3 \in (0, 1)$. Recall that $h_q(\mathbf{x})$ in problem (7) is strictly concave in \mathbf{x} . Combining this, the fact $\mathcal{S} = \emptyset$, and **Fact 2**, we know that the minimum of problem (9) will not lie in this region.

From the above analysis, we conclude that \mathbf{x}^* is the unique global minimizer of problem (7).

REFERENCES

- [1] Y.-F. Liu, Y.-H. Dai, and S. Ma, “Joint power and admission control: Non-convex ℓ_q approximation and an effective polynomial time deflation approach,” accepted for publication in *IEEE Trans. Signal Process.*
- [2] Y.-F. Liu, Y.-H. Dai, and Z.-Q. Luo, “Joint power and admission control via linear programming deflation,” *IEEE Trans. Signal Process.*, vol. 61, no. 6, pp. 1327–1338, Mar. 2013.