A SUPPLEMENTARY MATERIALS - PROOFS

A.1 Proof of Proposition 3.9

Proposition 3.9[Threshold] There exist a threshold $p_{th} \le 0.5$, such that $B_r(p) > B_p(p) > B_g(p)$ for any $p < p_{th}$.

Proof. First, we prove that there exists an unique intersection point of $B_p(p)$ and $B_g(p)$ within $(0, 1)$. **(i)** We establish the existence by $\lim_{p \to 0^+} B_p(p) > \lim_{p \to 0^+} B_g(p)$ and $\lim_{p \to 1^-} B_g(p) > \lim_{p \to 1^-} B_p(p)$. **(ii)** We prove uniqueness. When $0 < p < 1$, $B_p(p)$ is monotonically decreasing. When $D > 2$, $0 < p \le 0.5$, $B_g(p)$ is monotonically decreasing. When $D > 2$, $0.5 < p < 1$, $B_g(p)$ is monotonically increasing. When $D = 2$, $B_g(p)$ is a constant function. Due to (i) and (ii), $B_p(p)$ and $B_g(p)$ have an unique intersection point within $(0, 1)$. Let p_{pg} be the x-coordinate of the intersection point of $B_p(p)$ and $B_g(p)$.

Similarly, we can prove that if $B_r(0.5) \le B_p(0.5)$, then $B_p(p)$ and $B_r(p)$ have an unique intersection point within $(0, 0.5]$. Let p_{pr} be the x-coordinate of the intersection point of $B_p(p)$ and $B_r(p)$.

Second, we prove that $p_{th} = \min\{p_{pg}, p_{pr}, 0.5\}$ by the graph of $B_p(p)$, $B_g(p)$ and $B_r(p)$. $B_p(p)$ is a quadratic function opening upwards defined on $(0, 1)$, and the axis of symmetry of $B_p(p)$ is larger than 1. when $D > 2$, $B_g(p)$ is a quadratic function opening upwards defined on $(0, 1)$, and the axis of symmetry of $B_g(p)$ is 0.5; when $D = 2$, $B_g(p)$ is a constant function defined on $(0, 1)$. $B_r(p)$ is a function composed of a linear term p and a reciprocal term $1/p$, defined on $(0, 0.5]$. Let $B'_p(p)$, $B'_g(p)$, and $B'_r(p)$ denote the derivative of $B_p(p)$, $B_g(p)$, and $B_r(p)$, respectively. When $0 < p \le 0.5$, $0 \ge B'_g(p) > B'_p(p) > B'_r(p)$. When $0.5 < p < 1$, $B'_g(p) > 0 > B'_p(p)$. After drawing the graph of $B_p(p)$, $B_g(p)$ and $B_r(p)$, we can prove the following two cases. **(i)** $p_{pg} \le 0.5$. If $B_r(0.5) \ge B_p(0.5)$, then $p_{th} = p_{pg}$; if $B_r(0.5) < B_p(0.5)$, then $p_{th} = \min\{p_{pg}, p_{pr}\}$. **(ii)** $p_{pg} > 0.5$. If $B_r(0.5) \ge B_p(0.5)$, then $p_{th} = 0.5$; if $B_r(0.5) < B_p(0.5)$, then $p_{th} = p_{pr}$. Thus, $B_r(p) > B_p(p) > B_g(p)$ for $p < p_{th}$. □

A.2 Proof of Lemma 4.1

Lemma 4.1 Processing capacity vector $\boldsymbol{f}^*$ is the optimal solution to problem (27) only if $\sum_k C_k(f_k^*) = \overline{C}$.

Proof. If $\sum_k C_k(f_k^*) < \overline{C}$, then there always exists a set of small value ϵ_k for k, $\boldsymbol{\epsilon} = \{\epsilon_k, k \in \mathcal{K}\}$, such that $\sum_k C_k(f_k^* + \epsilon_k) \le \overline{C}$ and $\phi(\boldsymbol{f}^* + \boldsymbol{\epsilon}) < \phi(\boldsymbol{f}^*)$. The later inequality leads to the fact that $B(R\phi(\boldsymbol{f}^* + \boldsymbol{\epsilon})) < B(R\phi(\boldsymbol{f}^*))$. This implies a contradiction, so $\boldsymbol{f}^*$ cannot be the optimal solution to problem (27). □

A.3 Proof of Lemma 4.2

Lemma 4.2 Let $\phi_k(f_k) = \frac{S_k D_k E}{f_k} + T_k^{UL} + T_k^{DL}$. Processing capacity vector $\boldsymbol{f}^*$ is the optimal solution only if $\phi_k(f_k^*)$ is identical for $k \in \mathcal{K}$.

Proof. Suppose $\boldsymbol{f}^*$ is the optimal solution and $\phi_k(f_k^*)$ is not identical. Then, there exists an k^- such that $\phi_{k^-}(f_{k^-}^*)$ is the smallest, and another k^+ such that $\phi_{k^+}(f_{k^+}^*)$ is the largest. Let $f_k' < f_k^*$, $\phi_k(f_k') < \phi_{k^+}(f_{k^+}^*)$ and $\boldsymbol{f}' = (f_1^*, ..., f_{k-1}^*, f_k', f_{k+1}^*, ..., f_K^*)$. We can show that $\phi(\boldsymbol{f}') = \phi(\boldsymbol{f}^*)$, according to Eq. (24). Thus, $B(R\phi(\boldsymbol{f}')) = B(R\phi(\boldsymbol{f}^*))$. Meanwhile, since $f_k' < f_k^*$ and $C_k(f_k') < C_k(f_k^*)$, $C(\boldsymbol{f}') < C(\boldsymbol{f}^*) \le \overline{C}$. According to Lemma 4.1, $\boldsymbol{f}'$ cannot be the optimal solution to problem (27). Further, since $\boldsymbol{f}'$ and $\boldsymbol{f}^*$ lead to the same objective value, i.e., $B(R\phi(\boldsymbol{f}')) = B(R\phi(\boldsymbol{f}^*))$, $\boldsymbol{f}^*$ cannot be the optimal solution. This leads to a contradiction. Therefore, Lemma 4.2 must be true. □

A.4 Proof of Proposition 4.3

Proposition 4.3 If τ_2^* is the optimal solution to problem (28), then $f_k^* \triangleq \phi_k^{-1}(\frac{\tau_2^*}{R})$ for $k \in \mathcal{K}$ optimizes problem (27).

Proof. Suppose τ_2^* is the optimal solution to (28), but $f_k^* \triangleq \phi_k^{-1}(\frac{\tau_2^*}{R})$ is not the optimal solution to (27), where $\phi_k^{-1}(\cdot)$ is the inverse function of $\phi_k(\cdot)$. We aim to show contradiction under the two possible cases.

Case 1. There exists a k such that f_k^* is not a feasible solution to problem (27). This cannot be the case, because $\sum_k C_k(\phi_k^{-1}(\frac{\tau_2^*}{R})) = \overline{C}$. That is, $\sum_k C_k(f_k^*) = \overline{C}$ satisfies the constraint.

Case 2. There exists a k such that f_k^* is feasible but cannot minimize the objective function. Then, there exists another $\boldsymbol{f}'$ such that $B(R\phi(\boldsymbol{f}')) < B(R\phi(\boldsymbol{f}^*))$. And $\sum_k C_k(f_k') = \overline{C}$ according to Lemma 4.1. Thus, there exists a $\tau_2' = R\phi(\boldsymbol{f}')$ such that $B(\tau_2') < B(\tau_2^*)$ and $\sum_k C_k(\phi_k^{-1}(\frac{\tau_2'}{R})) = \overline{C}$. Thus, τ_2^* cannot be the optimal solution. This leads to a contradiction. Therefore, Proposition 4.3 must be true. □