

Research Article

Optimal and Fair Resource Allocation for Multiuser Wireless Multimedia Transmissions

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This paper presents an optimal and fair strategy for multiuser multimedia radio resource allocation (RRA) based on cooperation, which suggests a judicious mixture of competition and cooperation. We formulate the co-opetition strategy as sum utility maximization at constraints from both Physical (PHY) and Application (APP) layers. We show that the maximization can be solved efficiently employing the well-defined Layering as Optimization Decomposition (LOD) method. Moreover, the co-opetition strategy is applied to power allocation among multiple video users, and evaluated through comparing with existing-competition based strategy. Numerical results indicate that, the co-opetition strategy adapts the best to the changes of network conditions, participating users, and so forth. It is also shown that the co-opetition can lead to an improved number of satisfied users, and in the meanwhile provide more flexible tradeoff between system efficiency and fairness among users.

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1. Introduction

Radio resource allocation (RRA) for multimedia services has drawn a lot of attention because of its capability of offering an efficient way to handle the resources. In previous research, much attention has been paid to system efficiency improvement, that is, maximizing system utility [1–8]. It is shown that the Nash Bargaining Solution (NBS), a well-defined notion in game theory, can be used to maximize the sum of Peak Signal-to-Noise Ratios (PSNRs) in rate allocation for collaborative video transmissions [1]. Optimal resource allocation for multiuser wireless transmissions is studied in [2] from an information theoretic perspective, and it is shown that sum rate maximization (SRM) is suboptimal when taking video quality into account. This work has been extended to joint power and subcarrier allocation for multiuser video transmission in multi-carrier systems [3]. In [4], Application (APP), MAC, and Physical (PHY) layers are jointly optimized using Cross-Layer Design (CLD) for streaming video delivery in a multiuser wireless environments, and two objective functions are introduced, that is, minimizing the sum of mean square error (MSE) of all video users, maximizing the sum of PSNRs. As a continuous work

of [4, 5] proposed an application-driven cross-layer optimization strategy and discussed the challenges in CLD for multiuser multimedia services. Two Layering, as Optimization Decomposition (LOD) methods, dual decomposition and gradient projection-based decomposition, are used in [6, 7] for downlink utility maximization (DUM) assuming utility functions at APP layer are concave, increasing, and differentiable. The maximization of weighted sum of data rates in cross-layer resource allocation is addressed in [8], and an improved conjugate gradient method under given power constraint is presented as well.

In the work mentioned above, all the resource allocation methods try to maximize the global utility function. There are also several resource allocations that run in a distributive way, for instance, ReSerVation Protocol (RSVP) was used to allocate bandwidth among multiple multimedia streams over internet based on the Traffic SPECifications (TSPECs) [9]; air time fairness allocates transmission time proportionally to TSPECs to eliminate the passive impact of cross-layer strategies employed in different transmitters [10]. Proportional fairness was introduced [11] to allocate resources based on users' rate requirements, and further applied to rate controlling [12]. In [1], the Kalai-Smorodinsky Bargaining

Solution (KSBS) was used to allocate rates amongst multiple video users such that the utility achieved by each user is proportional to the maximum utility achievable.

Both maximization based and distributive policies work in a competitive way as explained by the following two examples. Utility maximization can actually be viewed as a process in which all users compete for resources according to the criteria that the Highest Quality Improvement the Highest Possibility Resources (HQIHPR) [2]. Using KSBS, users compete for resources to make efficient use of the resource and achieve higher utility. The disadvantage of these competitive policies is that they do not consider user's quality of service (QoS) satisfaction degree, meaning that they are not suitable for multimedia services. To address this disadvantage, we propose an optimal and fair policy for multimedia resource allocation, which introduces a judicious mixture of competition and cooperation, such that user's QoS satisfaction degree is taken into account. The idea behind this judicious mixture is Co-opetition, a concept from economic [13]. Co-opetition has been employed in decentralized resource management [14] and collaborative multimedia resource allocation in our preliminary work [15]. It is shown that co-opetition can provide better tradeoff between system efficiency and fairness.

Main contribution of this paper relies on the proposal of a novel co-opetition strategy for RRA in multimedia services, which is both optimal and fair. In this paper, optimal represents sum utility maximization (SUM) subject to the constraints on individual utility. It is worth to mention that the value of optimal sum utility might be smaller than that achieved by the unconstrained SUM, due to the constraints. Fair is defined to describe that, compared to unconstrained SUM, our strategy can result in fairer resource allocation. The additional fairness from our strategy comes from the individual utility constraint. Recall that the unconstrained SUM allocates resources in a competitive way, which has no constraint on individual utility. Our co-opetition strategy suggests a judicious mixture of competition and cooperation in resource allocation. We formulate the co-opetition strategy mathematically and solve it efficiently using LOD method. This mathematical formulation would help to get a better insight into the essential of competition and cooperation behaviors of users in RRA. We apply our strategy to wireless resource allocation for multiuser video transmissions and evaluate its performance by comparing with existing competition based mechanisms.

The rest of this paper is organized as follows. In Section 2, we formulate the co-opetition strategy, and in Section 3 we implement it by employing LOD method. In Section 4, we apply the co-opetition strategy to power allocation amongst multiple video users together with numerical results for performance evaluation. Conclusion is drawn in Section 5.

2. Problem Setup

We consider RRA over a downlink transmission with N users. We assume that the resource available at PHY layer is denoted by X . Denote $\mathcal{R} \subset \mathcal{R}_{0,+}^N$ as the rate region

achievable at PHY layers, and assume that \mathcal{R} is convex and compact. Convexity assumption means that time-sharing mode is enabled at PHY layer. Let $U_n(r_n), r_n \in \mathcal{R}_{0,+}$ denote the user n 's utility function, which is assumed to be concave, increasing, and differentiable. An example of utility is PSNR for video services [16]. Each user has a minimum desired rate, denoted by r_{0n} , which should be at least guaranteed. That means

$$r_n \geq r_{0n}, \quad (1)$$

otherwise, user n would not be served. A competition strategy should be employed to develop our co-opetition strategy. In this paper, we focus on optimization-based strategy, that is, sum utility maximization (SUM). Investigation based on distributive and competition-based strategies will be accommodated in our future work. For SUM, system utility function $U : \mathcal{R}_{0,+}^N \rightarrow \mathcal{R}_{0,+}$ is defined as

$$U(\vec{r}) = \sum_{n=1}^N U_n(r_n), \quad (2)$$

where $\vec{r} = (r_1, \dots, r_N)$. Hence, SUM can be written as

$$\max_{\vec{r} \in \mathcal{R}} U(\vec{r}), \quad \text{s.t. } r_n \geq r_{0n}. \quad (3)$$

To allow co-opetition, we first define the notion of satisfied user. A user is called satisfied user if its achieved QoS is above or equal to predefined QoS threshold, U_{th} . Then the basic idea of co-opetition can be described as follows. During the process of RRA, in which all users compete for resources to achieve SUM, users who have achieved U_{th} stop competing temporarily, until all resources have been allocated or all users have been satisfied. Denote rate required by user n to achieve U_{th} with $r_{n,th}$, and denote \vec{r}_{th} as $(r_{1,th}, \dots, r_{N,th})$. We distinguish the following two cases.

- (1) If $\vec{r}_{th} \in \mathcal{R}$, co-opetition allocates resources such that the minimum utility of all users is U_{th} , that is, $U_n \geq U_{th}, \forall n$.
- (2) If $\vec{r}_{th} \notin \mathcal{R}$, co-opetition allocates resources such that the maximum utility of all users is U_{th} , that is, $U_n \leq U_{th}, \forall n$.

Thus, our co-opetition strategy reads

$$\begin{aligned} & \max_{\vec{r} \in \mathcal{R}} U(\vec{r}), \\ & \text{s.t. } r_n \geq r_{0n}, \\ & U_n \geq U_{th}, \forall n, \text{ if } \vec{r}_{th} \in \mathcal{R}, \\ & U_n \leq U_{th}, \forall n, \text{ if } \vec{r}_{th} \notin \mathcal{R}. \end{aligned} \quad (4)$$

Introducing U_{th} provides better tradeoff between system efficiency and fairness. For example, for video services in which PSNR is chosen as a QoS metric, U_{th} can be set corresponding to PSNR = 35 dB, above which user could achieve good video quality and user's video satisfaction degree increases very slowly as PSNR increases. In this

case, rate, which can translate to resources at PHY layer, is more important to unsatisfied users. In the following, we investigate how the LOD method is used to solve (4) efficiently.

3. LOD Method

LOD is a well-defined technique for network utility maximization (NUM) by decomposing the NUM into a set of subproblems coupled with each other. Each subproblem is associated with a protocol layer, in which it can be solved separately [17].

3.1. Rewrite Co-competition Strategy. We assume it is known whether \vec{r}_{th} can be achieved or not. In the case of $\vec{r}_{\text{th}} \in \mathcal{R}$, $U_n \geq U_{\text{th}}$ translates into $r_n \geq r_{n,\text{th}}$, and $U_n \leq U_{\text{th}}$ translates into $r_n \leq r_{n,\text{th}}$ otherwise. We also assume that

$$r_{n,\text{th}} > r_{0n} \quad (5)$$

always satisfies. Then constraints in (4) can be rewritten as

$$\begin{aligned} \vec{r}_{\text{th}} \leq \vec{r} \leq \infty, & \quad \text{if } \vec{r}_{\text{th}} \in \mathcal{R}, \\ \vec{r}_0 \leq \vec{r} \leq \vec{r}_{\text{th}}, & \quad \text{if } \vec{r}_{\text{th}} \notin \mathcal{R}, \end{aligned} \quad (6)$$

where $\vec{r} = (r_1, \dots, r_N)$, $\vec{r}_0 = (r_{01}, \dots, r_{0N})$ (In the case of $\vec{r}_0 \notin \mathcal{R}$, total resource available cannot guarantee all users the minimum resource required, and some users will deny to be served. In this paper, we assume the minimum resource of all users can be always guaranteed, that is, $\vec{r}_0 \in \mathcal{R}$). We observe that, no matter $\vec{r}_{\text{th}} \in \mathcal{R}$ or not, the constraint has the same form of

$$\vec{r}_{\text{low}} \leq \vec{r} \leq \vec{r}_{\text{upp}}, \quad (7)$$

with $\vec{r}_{\text{low}} = (r_{11}, \dots, r_{1N})$, $\vec{r}_{\text{upp}} = (r_{u1}, \dots, r_{uN})$. Hence, (4) can be rewritten as

$$\max_{\vec{r} \in \mathcal{R}} U(\vec{r}), \quad \text{s.t. } \vec{r}_{\text{low}} \leq \vec{r} \leq \vec{r}_{\text{upp}}. \quad (8)$$

3.2. Dual Decomposition. To solve (8) with LOD, (8) is firstly modified by introducing an additional variable \vec{s} , then the primal function (8) reads

$$\begin{aligned} \max_{\vec{s}} U(\vec{s}), \\ \text{s.t. } \vec{r}_{\text{low}} \leq \vec{s} \leq \vec{r}, \\ \vec{r} \leq \vec{r}_{\text{upp}}, \\ \vec{r} \in \mathcal{R}. \end{aligned} \quad (9)$$

After introducing the Lagrangian factors

$$\begin{aligned} \vec{\lambda} &= (\lambda_1, \dots, \lambda_N)^T, \\ \vec{\lambda}' &= (\lambda'_1, \dots, \lambda'_N)^T, \end{aligned} \quad (10)$$

the Lagrangian function of (9) is written as

$$L(\vec{s}, \vec{r}, \vec{\lambda}, \vec{\lambda}') = U(\vec{s}) + (\vec{\lambda}'^T, \vec{\lambda}^T)^T \begin{pmatrix} \vec{r} - \vec{s} \\ \vec{s} - \vec{r}_{\text{low}} \end{pmatrix} \quad (11)$$

with $\vec{\lambda} \geq 0, \vec{\lambda}' \geq 0$. Thus, the dual function is

$$g(\vec{\lambda}, \vec{\lambda}') = \sup_{\vec{s}} L(\vec{s}, \vec{r}, \vec{\lambda}, \vec{\lambda}'), \quad (12)$$

The maximization in (9) can be solved by searching the optimum $\vec{\lambda}$ and $\vec{\lambda}'$ such that the dual function is minimized, that is,

$$\min_{\vec{\lambda}, \vec{\lambda}'} g(\vec{\lambda}, \vec{\lambda}'). \quad (13)$$

Based on the analysis afore, (12) can be decomposed into two subproblems as

$$g(\vec{\lambda}, \vec{\lambda}') = g_A(\vec{\lambda}, \vec{\lambda}') + g_P(\vec{\lambda}), \quad (14)$$

where

$$g_A(\vec{\lambda}, \vec{\lambda}') = \max_{\vec{s}} (U(\vec{s}) + (\vec{\lambda}'^T - \vec{\lambda}^T) \vec{s} - \vec{\lambda}'^T \vec{r}_{\text{low}}), \quad (15)$$

$$g_P(\vec{\lambda}) = \max_{\substack{\vec{r} \in \mathcal{R}, \\ \vec{r} \leq \vec{r}_{\text{upp}}}} \vec{\lambda}^T \vec{r}. \quad (16)$$

For given $\vec{\lambda}$ and $\vec{\lambda}'$, the above two-maximization can be solved independently at APP layer for (15) and at PHY layer for (16). So far, we have transformed the original maximization, (8), into its dual problem.

3.3. Solving (13), (15) and (16). As mentioned above, for each fixed $\vec{\lambda}$ and $\vec{\lambda}'$, (15) and (16) have to be solved. Denote $G(\vec{s})$ as the item to be maximized in (15), that is,

$$G(\vec{s}) = U(\vec{s}) + (\vec{\lambda}'^T - \vec{\lambda}^T) \vec{s} - \vec{\lambda}'^T \vec{r}_{\text{low}}. \quad (17)$$

Then $G(\vec{s})$ is continuous and differentiable, and further denote S_0 as set of $\vec{s} = (s_1, \dots, s_N)$ such that

$$S_0 = \left\{ \vec{s} \mid \frac{\partial G(\vec{s})}{\partial s_n} = 0, n = 1, \dots, N \right\}. \quad (18)$$

Then (15) can be solved via efficiently selecting the optimum \vec{s}^* , such that

$$\vec{s}^* = \arg \max_{\vec{s} \in S_0} G(\vec{s}). \quad (19)$$

Maximization of (16) refers to weighted sum rate maximization (WSRMax) at constraint of maximizing individual rate for certain PHY layer setup. $\vec{r} \in \mathcal{R}$ is a general constraint usually corresponding to given power or bandwidth. $\vec{r} \leq \vec{r}_{\text{upp}}$ can be translated into individual constraint. Recall that, \mathcal{R} is

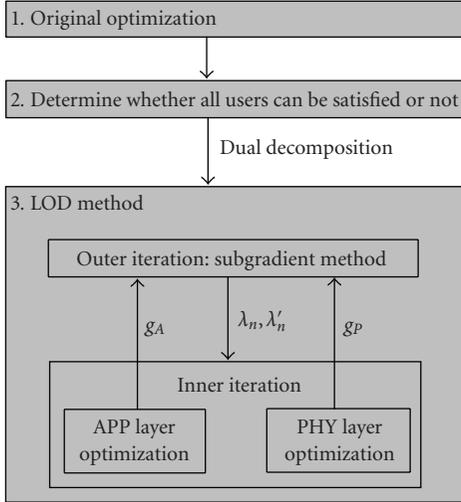


FIGURE 1: Illustration of the implement of co-opetition strategy.

assumed to be convex and compact, thus the domain of (16), denoted with \mathcal{R}' ,

$$\mathcal{R}' = \mathcal{R} \cap \left\{ \vec{r} \mid \vec{r} \leq \vec{r}_{\text{upp}} \right\}, \quad (20)$$

is also convex and compact. WSRMax over \mathcal{R}' is a well-researched problem and there are many efficient solutions for a wide range of PHY layer setups [3, 8, 18].

Hereafter, we assume that for each $\vec{\lambda}$ and $\vec{\lambda}'$, (15) and (16) can be solved efficiently. Then the optimum $\vec{\lambda}$ and $\vec{\lambda}'$ can be determined, for example, using either sub-gradient method, cutting plane method or ellipsoid method [19]. In Section 5, we would show how to solve (13), (15) and (16) more concretely through power allocation.

3.4. Determining Whether $\vec{r}_{\text{th}} \in \mathbf{R}$ or Not. Note that is \vec{r}_{th} not necessarily achievable. Whether $\vec{r}_{\text{th}} \in \mathbf{R}$ or not can be determined by userwisely computing the minimum resource required to achieve \vec{r}_{th} . Fortunately again there are several solutions available for different scenarios. For example, in [20] a generic procedure, CLARA, was presented for cross-layer resource minimization subject to a set of constraints on the overall QoS. [21] proposed an iterative algorithm which monotonically converges to the unique allocation with optimal sum power efficiency. This is actually another hot topic as opposed to utility maximization in this paper, namely, cost minimization to achieve certain QoS.

3.5. Summery of LOD Method. In this Section, we have mapped our co-opetition strategy, (4), to a standard constrained optimization over convex domain, that is, (8). Moreover, importantly, through applying the LOD, many well-researched solutions are available which make our co-opetition strategy more applicable. Finally, since the resource allocation in this paper can be formulated as a convex optimization, the LOD method has worst-case polynomialtime complexity [17]. It will be shown that the LOD method converges within limited iterations. Figure 1

is a brief description to apply the co-opetition strategy. We investigate how co-opetition can be applied to power allocation in detail.

4. RRA Using Co-Opetition

In this Section, we first describe the system scenario, and then illustrate the co-opetition strategy in detail. Finally, numerical results are presented for performance evaluation through comparing with competition-based strategy.

4.1. System Setup. We consider downlink N -user video transmission in a cell with a base-station (BS) which acts as the central spectrum manager (CSM). At APP layer, users transmit same or different video sequences. We choose PSNR as user's utility as it is the only widely accepted video QoS metric and choose the rate-distortion (RD) model proposed in [16] to describe user's average RD behavior as this model applies well to the state-of-the-art video encoder [22]. Then user's utility can be defined as

$$U_n(r_n) = 10 \log \frac{255^2(r_n - R_{0n})}{D_{0n}(r_n - R_{0n}) + \mu_n}, \quad (21)$$

where R_{0n}, D_{0n} and μ_n are sequence parameters, which are dependent on video sequence characteristics, such as spatial and temporal resolution, delay constraints as well as the percentage of INTRA coded macro-blocks [1, 16]. D_{0n} is the minimum rate that should be at least guaranteed for user n , therefore in this work we assume that $r_n > R_{0n}$.

At PHY layer, the BS has limited transmit power, P_{tot} . Let $\vec{P} = (P_1, \dots, P_N)$ represent the power allocated to all the users, thus we have $\sum_{n=1}^N P_n \leq P_{\text{tot}}$. Each user is assumed to experience an AWGN channel, whose capacity, $C_n(P_n)$, is given by

$$C_n(P_n) = B \cdot \log_2 \left(1 + \frac{P_n}{\sigma_{n,n}^2} \right), \quad (22)$$

where B and $\sigma_{n,n}^2$ denote bandwidth available and receiver noise power, respectively.

It is assumed that private information of each user, including $R_{0n}, D_{0n}, \mu_n, \sigma_{n,n}^2$, are sent to CSM, where power allocation is made. Then CSM sends back the decision of power allocated to each user. Note that, more complicated PHY layer setups can also be taken into account, such as multicarrier and multiple antennas systems over Rayleigh fading channels. However, employing simple PHY layer setup would help to highlight the focus of this paper, investigating optimal and fair criteria for RRA. It is worth mentioning that the co-opetition strategy can be easily extended to other scenarios.

4.2. Co-Opetition Strategy.

4.2.1. CO-opetition Formulation. According to the common sense in the field of video signal processing, the PSNR threshold can be set to different values, such as 40 dB,

35 dB, or 32 dB, representing perfect, good and acceptable video quality, respectively. The PSNR threshold can also be set dynamically according to the total resources available, the number of users, and so forth. As an illustration, we choose QoS threshold as PSNR = 35 dB corresponding to good video quality, that is, $U_{\text{th}} = 35$ dB in (4). Denote \vec{P}_{th} as $(P_{1,\text{th}}, \dots, P_{N,\text{th}})$ representing power required by users to achieve PSNR of 35 dB. Using co-opetition strategy, if $\text{sum}(\vec{P}_{\text{th}}) \leq P_{\text{tot}}$ ($\text{sum}(\vec{P}_{\text{th}})$ means calculating the sum of all members in \vec{P}_{th} , i.e., $\sum_{n=1}^N P_{n,\text{th}}$), the lower and upper bounds of achievable PSNR are set at $U_{\text{low}} = 35$ dB and $U_{\text{upp}} = \infty$, respectively, and $U_{\text{low}} = -\infty$ and $U_{\text{upp}} = 35$ dB otherwise. Correspondingly, when we have $\text{sum}(\vec{P}_{\text{th}}) \leq P_{\text{tot}}$, lower and upper bounds of rates are $\vec{r}_{\text{low}} = (r_{1,\text{th}}, \dots, r_{N,\text{th}})$ and $\vec{r}_{\text{upp}} = \infty$, respectively, and $\vec{r}_{\text{low}} = (R_{01}, \dots, R_{0N})$ and $\vec{r}_{\text{upp}} = (r_{1,\text{th}}, \dots, r_{N,\text{th}})$ otherwise. In this paper, it is easy to calculate $P_{n,\text{th}}, r_{n,\text{th}}$ corresponding to PSNR threshold, for both (21) and (22) are invertible and monotonic increasing functions. Thus, given PSNR threshold, $\text{sum}(\vec{P}_{\text{th}}) \leq P_{\text{tot}}$ or not can be easily determined, and consequently, both \vec{r}_{low} and \vec{r}_{upp} are known.

Given each user's utility definition in (21) and (22), system utility writes

$$U_s(\vec{P}) = 10 \sum_{n=1}^N \log \frac{255^2(C_n(P_n) - R_{0n})}{D_{0n}(C_n(P_n) - R_{0n}) + \mu_n}, \quad (23)$$

where $C_n(P_n)$ refers to as r_n . We assume that capacity approaching channel codes is employed at PHY layer. Then our co-opetition strategy writes

$$\begin{aligned} \max \quad & U_s(\vec{P}), \\ \text{s.t.} \quad & \sum_{n=1}^N P_n \leq P_{\text{tot}}, \\ & \vec{r}_{\text{low}} \leq \vec{C} \leq \vec{r}_{\text{upp}} \end{aligned} \quad (24)$$

where $\vec{C} = (C_1(P_1), \dots, C_N(P_N))$. Note that (24) has the same form as (8). The first constraint on the sum of the power (24) corresponds to $\vec{r} \in \mathcal{R}$ in (8).

4.2.2. The Implement of Co-opetition. Using LOD, maximization of (24) can be decomposed into

$$\begin{aligned} \max_{\vec{c}} \quad & \sum_{n=1}^N 10 \log \frac{255^2(c_n - R_{0n})}{D_{0n}(c_n - R_{0n}) + \mu_n} \\ & + \sum_{n=1}^N ((\lambda'_n - \lambda_n)c_n - \lambda'_n r_{n,\text{low}}) \end{aligned} \quad (25)$$

where $\vec{c} = (c_1, \dots, c_N)$, and

$$\begin{aligned} \max \quad & B \sum_{n=1}^N \lambda_n \log_2 \left(1 + \frac{P_n}{\sigma_{n,n}^2} \right), \\ \text{s.t.} \quad & \sum_{n=1}^N P_n \leq P_{\text{tot}} \\ & P_n \leq P_{n,\text{upp}}, \quad \forall n \end{aligned} \quad (26)$$

where $P_{n,\text{upp}}$ is defined as the upper bound of transmit power of user n corresponding to $r_{n,\text{upp}}$.

The optimum variable of (25), $\vec{c}^* = (c_1^*, \dots, c_N^*)$, can be obtained by simply making the partial derivative of g_A and let it equal to 0,

$$D_{0n}(c_n - R_{0n})^2 + \mu_n(c_n - R_{0n}) - \frac{10\mu_n}{(\lambda_n - \lambda'_n)\ln 10} = 0, \quad \forall n. \quad (27)$$

Then we have

$$c_n^* = R_{0n} + \frac{\sqrt{\mu_n^2 + 4D_{0n} \cdot \text{tmp}} - \mu_n}{2D_{0n}}, \quad (28)$$

where $\text{tmp} = 10\mu_n/(\lambda_n - \lambda'_n)$.

As mentioned in Section 3.3, (26) can be solved at PHY layer by the weighted sum rate maximization with the constraints of total and individual power. Note that $C_n(P_n)$ in (22) is concave and increasing with respect to P_n , thus the item to be maximized in (26) is also concave increasing. The domain of (26) is formed by two linear inequalities, each of which forms a convex domain together with $P_n \geq 0, \forall n$. Thus the domain of (26) is also convex, and (26) is accessible to conventional convex optimization techniques, such as feasible direction method and projected gradient method. In this paper the feasible increasing direction method is employed (see the Appendix for details).

So far, given fixed $\vec{\lambda}, \vec{\lambda}'$, two subproblems, (25) and (26), have been solved. We denote the optimal values of them with $g_A^*(\vec{\lambda}, \vec{\lambda}')$ and $g_P^*(\vec{\lambda})$, respectively. In the following, the optimum $\vec{\lambda}, \vec{\lambda}'$, denoted by $\vec{\lambda}^*, \vec{\lambda}'^*$, will be determined such that the sum of $g_A^*(\vec{\lambda}, \vec{\lambda}')$ and $g_P^*(\vec{\lambda})$ is minimized, that is,

$$(\vec{\lambda}^*, \vec{\lambda}'^*) = \arg \min_{\vec{\lambda}, \vec{\lambda}'} g_A^*(\vec{\lambda}, \vec{\lambda}') + g_P^*(\vec{\lambda}). \quad (29)$$

Note that, the dual function might not be differentiable or, in other words, (29) is not accessible to classical computational method, such as steepest descent method. In this paper we employ the sub-gradient method, which applies to both differentiable and nondifferentiable dual functions. Much like the feasible increasing direction method, sub-gradient method also searches the optimal $\vec{\lambda}$ and $\vec{\lambda}'$ iteratively. The main iteration writes

$$\begin{pmatrix} \vec{\lambda}^{k+1} \\ \vec{\lambda}'^{k+1} \end{pmatrix} = \begin{pmatrix} \vec{\lambda}^k \\ \vec{\lambda}'^k \end{pmatrix} - \alpha^k \vec{g}^k, \quad (30)$$

TABLE 1: test video sequences (videoID, video type, temporal level (TL), frame rate).

| ID | Video sequence | μ | D_0 | R_0 |
|----|---------------------------------|----------|-------|-------|
| 1 | Foreman (CIF, TL = 4, 30 Hz) | 5232400 | 0 | 0 |
| 2 | Coastguard (CIF, TL = 4, 30 Hz) | 6329700 | 4.3 | 0 |
| 3 | Mobile (CIF, TL = 4, 30 Hz) | 38230000 | 1 | 44040 |
| 4 | Foreman (QCIF, TL = 4, 30 Hz) | 2653300 | 0 | 19614 |
| 5 | Foreman (CIF, TL = 4, 15 Hz) | 2760000 | 1 | 20720 |
| 6 | Foreman (CIF, TL = 2, 30 Hz) | 4610000 | 3 | 55080 |

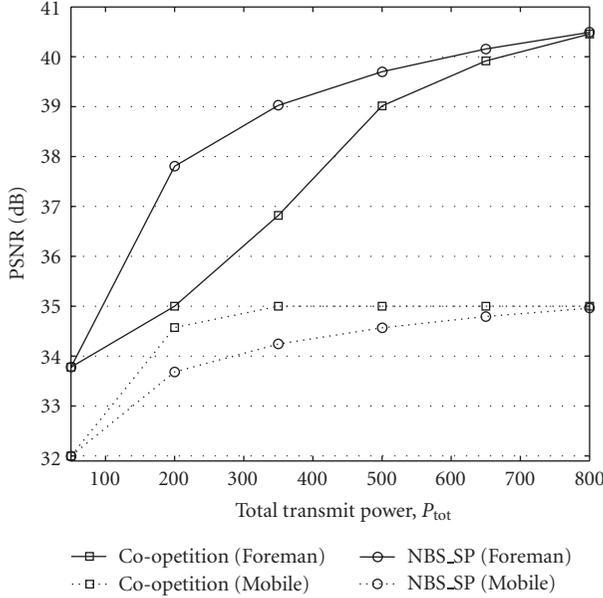


FIGURE 2: Plot of individual PSNRs achieved by the co-opetition, NBS SP. User 1: Foreman (CIF, TL= 4, 30 Hz), user 2: Mobile (CIF, TL = 4, 30 Hz).

where α^k is the step-size which can be set as constant, and \vec{g}^k denotes the sub-gradient at $(\vec{\lambda}^k, \vec{\lambda}'^k)$. Note that, $\vec{P} = (P_1, \dots, P_N)^T$ at $(\vec{\lambda}^k, \vec{\lambda}'^k)$ rightly forms a sub-gradient, so the sub-gradient can be obtained almost without any cost.

4.3. Numerical Results. In this subsection, the proposed co-opetition strategy (co-opetition) is evaluated by comparing with the strategy proposed in [1], which allocates resources using the Nash bargaining Solution of Same bargaining Power (NBS.SP). For the sake of comparison, we use the same test sequences as those in [1], and we list the parameters in Table I for reader's convenience.

4.3.1. Comparison in Terms of Individual PSNR. In this experiment we focus on individual PSNRs in the case of two users. At APP layer, user 1 transmits Foreman sequence of CIF resolution at 30 Hz, and user 2 transmits Mobile sequence of CIF resolution at 30 Hz. At PHY layer, we set the bandwidth to $B = 250$ kHz, and let the receiver noise power to be $\sigma_{n,1}^2 = 50$ and $\sigma_{n,2}^2 = 1$ for user 1 and user 2, respectively.

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1: Set  $k = 1$  and  $P_n^k = 0, \forall n$ , Precision  $\varepsilon = 10^{-4}$ 
Repeat:
2: Determine  $\nabla g_p^k$  using (A.1)
3: Determine  $\vec{d}^k$  according (A.4) and (A.5)
4: Determine  $\alpha^k$  using (A.6)
5: Compute  $\vec{P}^{k+1}$  using (A.8)
Until:  $|(\nabla g_p^k)^T \vec{d}^k| \leq \varepsilon$ .

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ALGORITHM 1: Feasible increasing direction method.

Total transmit power P_{tot} varies from 50 to 800. Figure 2 shows the individual PSNRs achieved by these two schemes. If NBS.SP is employed, user 1 can achieve higher PSNR than user 2 or, in other words, it is very hard for user 2 to achieve satisfying video quality (PSNR ≥ 35). In the case of $P_{tot} \geq 200$, user 1 can always be satisfied. Note in this case, user 1's video satisfaction degree increases very slowly as the PSNR increases, but significantly for user 2. Taking this observation into account, co-opetition imposes individual constraint on each user (see (4)). For example, with $P_{tot} = 200$, which can not satisfy two users simultaneously, co-opetition decreases user 1's PSNR to 35 dB, and consequently, user 2's PSNR achieves an improvement about 1 dB. If have $350 \leq P_{tot} \leq 650$, user 2's PSNR is improved such that user 2 is just satisfied. Note, in these two cases, co-opetition keeps user 1 satisfied, while user 2 either be satisfied or achieve much QoS improvement. It is worth to mention that, under a given total transmit power constraint, NBS.SP can achieve higher total PSNR of two users than that in co-opetition. This is because the NBS.SP maximizes the sum of PSNRs without taking the individual PSNR constraints into account. The co-opetition works in quite a different way. It maximizes the sum of PSNRs under the constraints of individual PSNR. Therefore, the co-opetition is not only optimal (As stated in Section 1, in this paper the optimal means sum utility maximization under certain constraints, differing from unconstrained optimization.), but also fairer than NBS.SP. This argument is further verified with other experiments

4.3.2. Comparison in Terms of the Number of Satisfied Users and Minimum PSNRs. We study a more complicated scenario with nine users, each transmitting a sequence randomly selected from Table 1. They also experience different

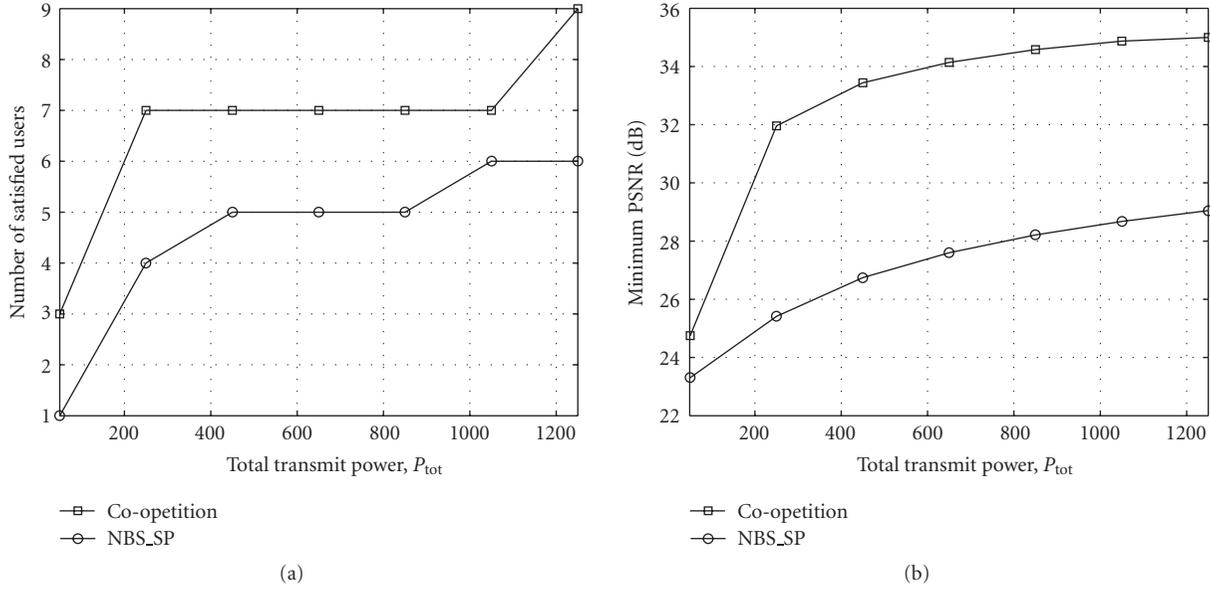


FIGURE 3: Plot of the number of satisfied users (a) and minimum PSNRs (b) achieved by co-opetition and NBS_SP in the case of nine users. Id of sequences transmitted are 3, 6, 1, 3, 5, 1, 3, 2, respectively. These sequences are randomly selected from Table 1. Bandwidth B is set to 400 KHz for all users, and the receiver noise power are set to 16, 7, 5, 1, 19, 12, 24, 12, 11, respectively, again by random generation.

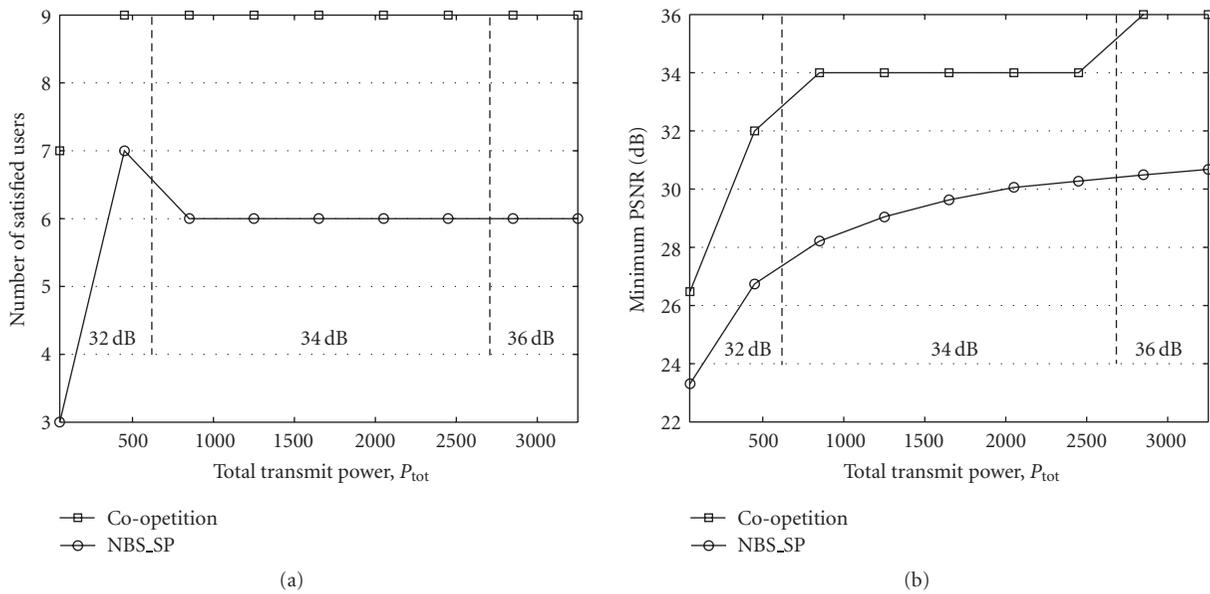


FIGURE 4: Plot of the number of satisfied users (a) and minimum PSNRs (b) achieved by NBS_SP and adaptive co-opetition. System setup is the same as that of Figure 3. 32 dB, 34 dB, and 36 dB refer to PSNR thresholds corresponding to different P_{tot} .

receiver noises randomly generated from 0 to 25. Figure 3 shows the number of satisfied users and the minimum PSNRs achieved by NBS_SP and co-opetition. We observe that, the co-opetition always outperforms the NBS_SP. For example, in the case of $P_{tot} = 1250$, co-opetition can make all users satisfied, but only 6 users satisfied by NBS_SP. With respect to the minimum PSNR, which is an important criteria evaluating system in the worst case, improvement of around 6 dB can be achieved when $P_{tot} \geq 200$. Note that, NBS_SP can only make minimum PSNRs from about 25 dB

to 29 dB, corresponding to poor video quality, while above 32 dB for co-opetition leading to acceptable video quality. Recall that, the co-opetition implies a judicious mixture of competition and cooperation. Through competition, the best system efficiency can be achieved. However, pure competition, for example, NBS_SP, might make very high PSNRs for some users, for example, users transmitting simple video content or having good channel quality, but low PSNRs for the others. This disadvantage is eliminated by co-opetition through introducing cooperation among users.

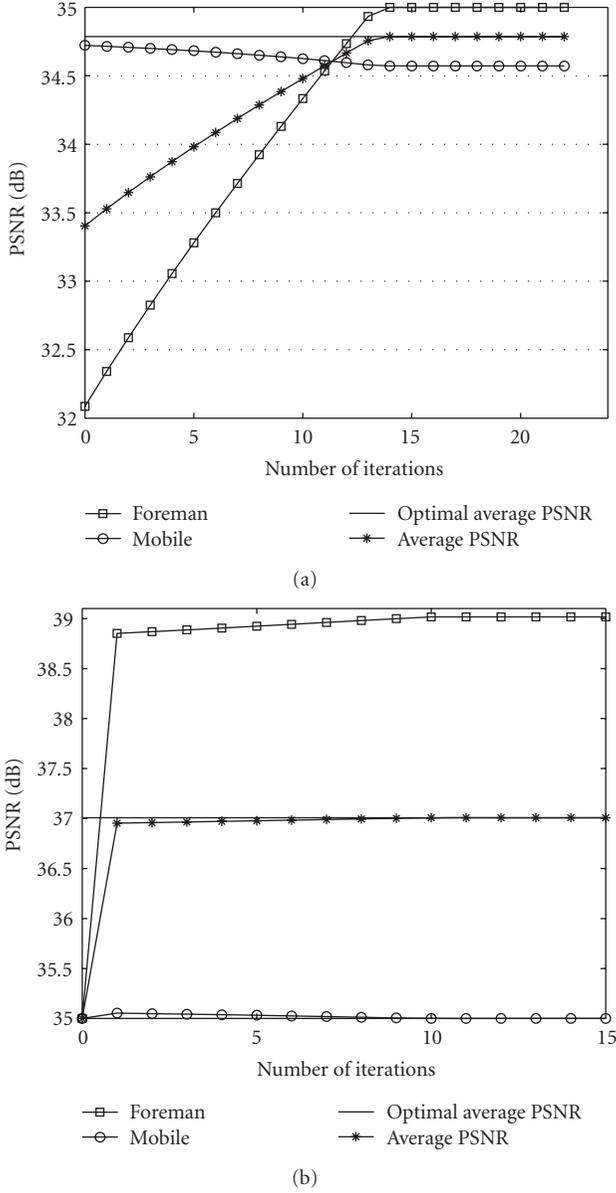


FIGURE 5: Plot of individual PSNRs and average PSNR. User 1: Foreman (CIF, TL = 4, 30 Hz), user 2: Mobile (CIF, TL = 4, 30 Hz). (a): $P_{\text{tot}} = 200$ and (b): $P_{\text{tot}} = 500$.

Again, this experiment indicates that co-opetition provides a good tradeoff between system efficiency and fairness.

4.3.3. Adaptive Co-opetition Strategy. In previous experiments, the threshold PSNR is fixed to be 35 dB. In order to consider more fairness in resource allocation, adaptive threshold can be employed. As an illustration, we present a simple method to set the threshold PSNR. More optimal and fair scheme for determining the threshold PSNR will be investigated in our future work. We employ PSNR = 32 dB, 34 dB and 36 dB to represent acceptable, good and very good quality, respectively. Denote resources required by the three

levels with R_a, R_g, R_v , then threshold PSNR, PSNR_{th} , can be determined as follows

$$\begin{aligned} \text{PSNR}_{\text{th}} &= 32 \text{ dB}, & \text{if } R_{\text{tot}} < R_g, \\ \text{PSNR}_{\text{th}} &= 34 \text{ dB}, & \text{if } R_g \leq R_{\text{tot}} \leq R_v, \\ \text{PSNR}_{\text{th}} &= 36 \text{ dB}, & \text{if } R_g \leq R_{\text{tot}} \leq R_v, \end{aligned} \quad (31)$$

where R_{tot} is denote as total resources available.

Same system setup as that in previous experiment is used. We observe from Figure 4(a) that, co-opetition employing adaptive PSNR_{th} still outperforms the NBS_SP. Moreover, adaptive PSNR_{th} is more concerned with fairness than that using fixed threshold. For example, in the case of low resource, for example, $P_{\text{tot}} \leq 500$, $\text{PSNR}_{\text{th}} = 32$ dB is selected. Consequently, an improvement of about 3 dB and 2 dB can be achieved for the minimum PSNRs compared to NBS_SP and co-opetition using fixed threshold (see Figure 3(b)), respectively. Note, these improvements are significantly important for users having low PSNRs. Although these improvements come from further decreasing the maximum achievable PSNR, it can provide fairer resource allocation. For instance, in Figure 4(a), it is very easy for all users to achieve similar quality level using co-opetition. Moreover, PSNR_{th} can also be set to a very high level, for example, 36 dB in the case of $P_{\text{tot}} > 2500$. An important advantage of this is that all users can be guaranteed high video quality, but cannot by fixed PSNR threshold and NBS_SP.

4.3.4. Optimality Verification. Our co-opetition is also optimal. As stated in Section 1, optimal means sum utility maximization (SUM) under individual constraints. The optimality is verified by experimental analysis in the case of two users. Results of two examples of them are shown in Figure 5(a) and Figure 5(b). System setup is the same as that in Figure 2. The optimal average PSNRs are achieved by exhaustive search. Recall that the LOD method consists of inner and outer iterations. In each inner iteration, the power allocation is initiated corresponding to (R_{01}, R_{02}) for Figure 5(a) and $(r_{1,\text{th}}, r_{2,\text{th}})$ for Figure 5(b). In the outer iteration, the values of λ and λ' are initialized randomly. Figures 5(a) and 5(b) show the results of outer iterations.

From these two figures, we can see that our strategy is optimal under individual constraints. In Figure 2, $P_{\text{tot}} = 200$ cannot satisfy two users simultaneously. Therefore the PSNR of user 1 is pegged at the threshold PSNR = 35 dB. The optimal average PSNR can be achieved after 14 iterations. In Figure 5(b), $P_{\text{tot}} = 500$ can make satisfying PSNR for both the two users. We observe that, user 2's PSNR has only little fluctuation, and converges to the threshold. At the optimal power allocation, both the two users' PSNRs are above or equal to the threshold. All these coincide with the results in Figure 2.

4.3.5. Summarization. To summarize, threshold PSNR plays importantly in adaptive/nonadaptive co-opetition strategies. It provides radio resource allocation (RRA) with more flexible tradeoff between system efficiency and fairness among users.

5. Conclusion

In this paper, we have presented an optimal and fair co-competition strategy for multiuser multimedia RRA. Following contributions and conclusions have been made and drawn

- (1) We formulate the co-opetition strategy as sum utility maximization under constraints from both APP and PHY layers. APP layer constraints imply that co-competition takes the QoS satisfaction degree into account in RRA.
- (2) We show that the co-opetition strategy can be implemented efficiently through applying the LOD method. Therefore the co-opetition strategy can easily apply to real time multimedia services.
- (3) We apply the co-opetition strategy to power allocation among multiple video users. Numerical results indicate that co-opetition can result in an improved number of satisfied users and significant improvement in minimum PSNRs as well. A simple method for adaptively determining threshold PSNR is also presented, such that fairer resource allocation can be achieved.
- (4) We conclude that co-opetition, that is, mixture of cooperation and competition, is more applicable to multiuser multimedia RRA than pure competition based strategy. Co-opetition strategy is not only optimal, but also fair.

Our future work is to design more feasible co-opetition strategy for different system setups, including multicarrier and multiple antennas systems. We also wish to extend our preliminary work to future heterogenous network, in which users not necessarily run in a collaborative way.

Appendix

Feasible Increasing Direction Method

Feasible Increasing direction method iteratively searches the optimum variable, $\vec{P}^* = (P_1^*, \dots, P_N^*)$, by in each iteration selecting a feasible increasing direction and update step size. Denote $\vec{P}^k = (P_1^k, \dots, P_N^k)$ as power allocation in the k_{th} iteration, then \vec{P}^k satisfies the constraints in (26). Denote $\vec{d}^k \in \mathcal{R}^N$, α^k as the direction and step size employed in the k_{th} iteration, then \vec{d}^k , α^k and \vec{P}^{k+1} can be determined as follows.

Denote $g_P(\vec{P})$ as the item to be maximized in (26), then the gradient of $g_P(\vec{P})$ at \vec{P}^k , denoted with ∇g_P^k , writes

$$\nabla g_P^k = \left(\frac{\partial g_P^k}{\partial P_1}, \dots, \frac{\partial g_P^k}{\partial P_N} \right)^T, \quad (\text{A.1})$$

where

$$\frac{\partial g_P^k}{\partial P_n} = \frac{B\lambda_n}{(\sigma_{n,n}^2 + P_n) \ln 2}. \quad (\text{A.2})$$

If \vec{P}^k is strictly feasible, that is,

$$\sum_{n=1}^N P_n < P_{\text{tot}} \quad (\text{A.3})$$

$$P_n < P_{n,\text{upp}}, \quad n \in \{1, \dots, N\}$$

then set

$$\vec{d}^k = \nabla g_P^k. \quad (\text{A.4})$$

Otherwise, denote $\mathcal{I}(\vec{P}^k)$ as set of indexes of active constraints, for example, if $P_n = P_{n,\text{upp}}, 1 \leq n \leq N$, then $n \in \mathcal{I}(\vec{P}^k)$. $0 \in \mathcal{I}(\vec{P}^k)$ refers to $\sum_{n=1}^N P_n = P_{\text{tot}}$. Then \vec{d}^k can be obtained by solving following maximization through linear programming,

$$\begin{aligned} & \max (\nabla g_P^k)^T \vec{d}^k \\ & \text{s.t. } d_n \leq 0, \forall n \in \mathcal{I}(\vec{P}^k), \\ & \sum_{n=1}^N d_n \leq 0, \text{ if } 0 \in \mathcal{I}(\vec{P}^k) \\ & -1 \leq d_n \leq 1, n \in \{1, \dots, N\}. \end{aligned} \quad (\text{A.5})$$

If $(\nabla g_P^k)^T \vec{d}^k = 0$, then \vec{P}^k is optimal. Otherwise, compute α^k by solving following one-dimension maximization,

$$\begin{aligned} & \max \phi(\alpha^k) = g_P(\vec{P}^k + \alpha^k \vec{d}^k) \\ & \text{s.t. } 0 \leq \alpha^k \leq \alpha_{\text{max}}, \end{aligned} \quad (\text{A.6})$$

where

$$\alpha_{\text{max}} = \begin{cases} +\infty, & \text{if } \sum_{n=1}^N d_n \leq 0, d_n^k \leq 0, \forall n, \\ \min \left\{ \frac{P_{\text{tot}} - \sum_{m=1}^N P_m^k}{\sum_{m=1}^N d_m^k}, \frac{P_{n,\text{upp}} - P_n^k}{d_n^k} \right\}, & \text{if } 0, n \notin \mathcal{I}(\vec{P}^k), \\ \min \left\{ \frac{P_{n,\text{upp}} - P_n^k}{d_n^k} \right\}, & \text{if } 0 \in \mathcal{I}(\vec{P}^k), n \notin \mathcal{I}(\vec{P}^k). \end{cases} \quad (\text{A.7})$$

Given \vec{d}^k and α^k , \vec{P}^{k+1} can be set as

$$\vec{P}^{k+1} = \vec{P}^k + \alpha^k \vec{d}^k. \quad (\text{A.8})$$

Then the feasible increasing direction method can be summarized in Algorithm 1.

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