

Chapter 2

Power Allocation Over Fading Channels Under Delay Constraints: A Review

In many wireless communication scenarios, energy management is an important issue for reasons such as extending a device's usable life-time. Since transmission power is one of the main energy consumers in wireless devices, efficient power allocation has been an important challenge, which has attracted significant research interests. Consider a point-to-point communications link over a fading channel with random data arrivals at the source. Due to fading, the channel conditions (and the corresponding instantaneous transmission rates) unpredictably fluctuate over time. Hence, the arriving data might not be transmitted to the destination instantly without delay. To overcome the fading nature of wireless channels, the source uses a buffer to store the data arrivals temporarily, which introduces random queuing delay as a consequence. Intuitively, for power savings, the source can simply defer the packet transmission during 'bad' channel states, and transmit more packets during 'good' channel states, i.e., more power is allocated under more favorable channel conditions. However, such transmission mechanism can lead to long delays for buffered packets since 'bad' channel states can happen often. As a result, delay QoS guarantees cannot be provided as required in order to support delay-sensitive communications. Toward this end, several power allocation schemes over fading channels have been proposed to support delay QoS guarantees as briefly discussed in Chap. 1. In this chapter, we will discuss this topic in greater detail.

2.1 Average Delay Constraint

For delay QoS guarantees, one possible power allocation goal is to minimize the (average) power under a constraint on the (maximum) average delay. Depending on the delay constraint, transmissions can take place even under unfavorable channel conditions since the power allocation is based not only on the channel conditions but also on the current delay of the buffered data. Such design problem has

been addressed in many works, for example, see [1–10] and references therein. The central concept is the optimal power-delay trade-off, i.e., the minimum power required to attain a delay bound [2]. As the delay bound increases implying looser delay constraints, less power is needed since the source can delay transmissions until more favorable channel conditions happening to save power. The structural results of the policies achieving the optimal trade-off (or optimal policies) have been studied in [2, 5, 9]. In general, it is proved that the optimal power allocation increases as the queue length increases, and decreases as the channel state goes from good to bad. It means that the optimal decision is to transmit a certain amount of data at any given instant, where this amount increases with the current queue length and decreases with the channel state. Thus for a fixed channel gain, the greater the queue length the more you transmit, and for a fixed queue length, the better the channel, the more you transmit. Such transmission mechanism, intuitively, can help to reduce the delay and save power simultaneously.

There are several approaches with different complexities and performances to develop power allocation algorithms under average delay constraint, for example, see [11] and references therein. The proposed approaches rely on tools and results in large deviation theory [12], Lyapunov optimization theory [3], or Markov decision process (MDP) and stochastic control theory [2, 4, 5, 8, 9]. While the former two approaches allow potentially simple solutions depending on the channel state information (CSI) only, the resulting policies perform well only for the large delay regime, i.e., asymptotically optimal, where the transmission buffers are assumed to be non-empty. This is because the dynamics of the queue length (or buffer) is not considered when allocating the transmit power. On the other hand, the MDP-based approach achieves optimal performance for all delay regimes at the expense of higher control complexity since it needs to take into account both the CSI and the queue length state, as well as their dynamics when calculating the allocated power. It incorporates the randomness of the channel fading and data arrival processes in the optimal solutions. When the statistical knowledge of the random channel fading and data arrival processes is known, optimal power allocation policies as solutions of the MDP problems can be computed off-line, for instance by using dynamic programming techniques [13]. However, such statistical knowledge is often unavailable in real-life communications, and hence, developing online allocation algorithms without requiring known statistics of the random processes is an important issue [4, 5, 10].

In [1, 2, 4, 5], it is shown that a given delay bound can be attained by allocating a sufficient amount of transmit power. In Chap. 3, we consider a practical scenario where the source is assumed to have a maximum power constraint, which is insufficient to attain the given delay bound. In this case, admission control needs to be applied on random data arrivals to the source buffer to avoid (delay and power) constraint violation. The goal of admission control (jointly with power allocation) is to maximize the average admitted rate, i.e., throughput maximization. In [3], the author proposes the energy constrained control algorithm (ECCA) for joint admission control and power allocation (AC-PA) using Lyapunov optimization theory. While ECCA cannot achieve optimal outcomes, Chap. 3 studies the optimal

AC-PA problem using MDP and stochastic control tools. Unlike the ECCA, the proposed AC-PA algorithm incorporates the dynamics of the buffer as well as the random variations of the channel fading, and data arrivals when computing the admission control and power allocation solution in each transmission time slot. Hence, the proposed algorithm provides higher throughput than ECCA under similar delay and power constraints.

2.2 Delay-Outage Constraint

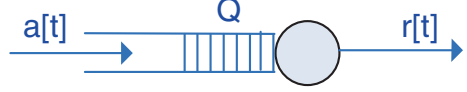
In the above-mentioned works, the resource allocation designs are to provide average delay bound guarantees, which are suitable for applications such as email, file downloading, etc. These applications do not require a specific bounded delay, which is the case for most other delay-sensitive applications such as real-time multimedia streaming, video conference etc. Moreover, it is clear that average delay bound satisfaction do not necessarily guarantee bounded delay requirement. Moreover, due to the random variations of the wireless fading channels with possible deep fades, providing bounded delay guarantees is either infeasible or results in a very high energy consumption or low transmission rate. Fortunately, most real-time multimedia applications can tolerate a certain small probability of delay bound violation. Hence, to support real-time multimedia applications, delay-outage constraint can be employed, where the delay is allowed to exceed a delay bound within a maximum acceptable delay-outage probability [14, 15]. In particular, on the communications over fading channels as described above, we are interested in resource (or power) allocation to maximize the supportable constant data arrival rate to the source transmission buffer under given delay-outage constraint.

To handle the delay-outage constraint, we need to know the (tail) distribution of the delay, which is difficult to derive in general for given arrival and service (or capacity) processes. However, if large delay regime is assumed, we can then employ the asymptotic delay analysis to characterize the tail distribution of the delay using an exponentially decreasing function [16, 17].

2.2.1 Asymptotic Delay Analysis

Consider a time-slotted stable queue with infinite buffer size as in Fig. 2.1. Consider stationary and ergodic arrival process $\{a[t]\}$ and service process $\{r[t]\}$ with the domain, range, and unit being $[0, \infty)$, $t = 1, 2, \dots$, and bits per time-slot, respectively. The processes are assumed to satisfy the Gartner-Ellis limit [17], i.e., for all $\theta \geq 0$, their differential asymptotic logarithmic moment generating functions (LMGFs) $\Omega_a(\theta)$ and $\Omega_r(\theta)$ defined as:

Fig. 2.1 Dynamic queue with arrival and service processes



$$\Omega_a(\theta) = \lim_{t \rightarrow \infty} \frac{1}{t} \log \mathbb{E} \left\{ e^{\theta \sum_{\tau=1}^t a[\tau]} \right\}; \quad \Omega_r(\theta) = \lim_{t \rightarrow \infty} \frac{1}{t} \log \mathbb{E} \left\{ e^{\theta \sum_{\tau=1}^t r[\tau]} \right\} \quad (2.1)$$

exist, where $\mathbb{E}\{\cdot\}$ denotes mathematical expectation operator. Note that for i.i.d. processes $\{a[t]\}$, and $\{r[t]\}$, we have:

$$\Omega_a(\theta) = \log \mathbb{E} \left\{ e^{\theta a[t]} \right\}, \quad \Omega_r(\theta) = \log \mathbb{E} \left\{ e^{\theta r[t]} \right\}.$$

Assume independent processes with $\mathbb{E}\{a[t]\} < \mathbb{E}\{c[t]\}$. If there exists a unique delay exponent $\bar{\theta} > 0$ satisfying the following equation:

$$\Omega_a(\bar{\theta}) + \Omega_r(-\bar{\theta}) = 0, \quad (2.2)$$

then, for sufficiently large x , the tail distribution the steady-state queue-length random variable Q is given as follows [17, Theorem 2.1]:

$$\Pr(Q > x) = e^{-\bar{\theta}x}, \quad (2.3)$$

where $\Pr(Q > x)$ denotes the probability of the event $Q > x$. The rigorous proof based on large deviations principles is presented in [16], and is omitted for brevity. We can see that, under large queue length (or delay) regime, the tail distribution function of the queue length is an exponentially decreasing function with decay rate $\bar{\theta}$. A smaller $\bar{\theta}$ corresponds to a slower decay rate, while a larger $\bar{\theta}$ leads to a faster decay rate.

2.2.2 Effective Capacity

Consider the queue in Fig. 2.1 with constant data arrival process $\{a[t] = \mu\}$ with LMGF $\Omega_a(\theta) = \mu\theta$ instead and some service process $\{r[t]\}$ with LMGF $\Omega_r(\theta)$. Suppose that we impose the following delay-outage constraint in terms of the maximum queue-length-outage probability constraint:

$$\Pr(Q > Q^{\max}) \leq \zeta_Q \quad (2.4)$$

for given queue length bound $Q^{\max} \in (0, \infty)$ and queue-length-outage probability $\zeta_Q \in (0, 1]$. The constraint on a small ζ_Q is applicable to delay QoS requirements, in which the user applications are acceptable as long as the queue length (or delay) does not exceed a threshold Q^{\max} , and ζ_Q indicates how stringent the delay constraint is. For a given Q^{\max} , smaller ζ_Q indicates more stringent delay constraints. As ζ_Q approaches 0, the queue length cannot exceed Q^{\max} , i.e., (deterministic) bounded delay constraint. As ζ_Q approaches 1, we allow unconstrained queue length.

Assume Q^{\max} sufficiently large (but finite) so that the asymptotic delay analysis result (2.3) can be applied. From (2.2) and (2.3), we can see that, in order to meet the constraint (2.4), the arrival rate μ has to satisfy the following conditions:

$$\mu\bar{\theta} + \Omega_r(-\bar{\theta}) = 0; \quad \bar{\theta} \geq \theta^{\text{tar}} \triangleq -\log(\zeta_Q)/Q^{\max} \quad (2.5)$$

for some delay exponent $\bar{\theta} > 0$. This is because from (2.3), we would have: $\Pr(Q > Q^{\max}) = e^{-\bar{\theta}Q^{\max}} \leq \zeta_Q$ as required. Then, it can be seen that the maximum supportable arrival rate μ^{\max} satisfying (2.5) is achieved when $\bar{\theta} = \theta^{\text{tar}}$, and is given by:

$$\mu^{\max} = -\frac{\Omega_r(-\theta^{\text{tar}})}{\theta^{\text{tar}}}. \quad (2.6)$$

μ^{\max} is called the effective capacity (EC) of the service process $\{r[t]\}$ with delay exponent θ^{tar} , which is derived from the delay-outage constraint (2.4).

We shall call the function $-\Omega_r(-\theta)/\theta$ the EC function of the service process $\{r[t]\}$ (with delay exponent θ).

2.2.3 EC-Based Resource Allocation and Performance Analysis

Delay-outage constraint model and EC framework have been employed to analyze the performance and develop many resource allocation schemes for various wireless communications systems. This is because it is particularly convenient for analyzing the delay-outage performance of wireless transmissions where the service process $\{r[t]\}$ is determined by the instantaneous capacity of the wireless fading channel.

As an example, consider power allocation for EC maximization for point-to-point communications system over fading channel with bandwidth B (Hz) [18]. We assume ergodic stationary independent and identically distributed (i.i.d.) block-fading channel with fading duration T (seconds) equal to the transmission frame, i.e., the channel power gains remain unchanged during a frame but vary independently from frame to frame. Denote $h[t]$, and $P[t]$ the instantaneous (normalized) channel gain, and transmit power, respectively, in frame $t = 1, 2, \dots$. Let $r[t]$ denote the corresponding instantaneous transmission rate (or capacity) in frame t , which is given by the Shannon's formula:

$$r[t] = \log_2(1 + P[t]h[t]).$$

From (2.6), the optimal power allocation problem to maximize the effective capacity (with delay exponent θ) under maximum average power constraint can be formulated as:

$$\max_{P[t] \geq 0} -\frac{1}{\theta TB} \log \mathbb{E}\left\{e^{-\theta TB r[t]}\right\} \quad \text{s. t. :} \quad \mathbb{E}\{P^*[t]\} \leq \bar{P}^{\max} \quad (2.7)$$

where \bar{P}^{\max} is the maximum power. Using Lagrangian approach, after some simple manipulations, the optimal power allocation can be shown to be:

$$P^*[t] = \begin{cases} \left(\frac{\hat{\theta}}{\lambda (h[t])^{\hat{\theta}}} \right)^{\frac{1}{1+\hat{\theta}}} - \frac{1}{h[t]}, & h[t] \geq \frac{\lambda}{\hat{\theta}}, \\ 0, & \text{otherwise} \end{cases}$$

where we denote (normalized) delay exponent $\hat{\theta} = \theta TB / \log(2)$, and λ is the Lagrange multiplier satisfying the following condition:

$$\mathbb{E}\{P^*[t]\} = \bar{P}^{\max}.$$

Alternatively, we can consider the power minimization problem subject to the minimum EC constraint. In [19–21], the authors study the power allocation problems for EC or energy efficiency maximization for multi-channel settings, i.e., orthogonal frequency division multiplexing (OFDM). We omit the details here for brevity.

EC framework has also been considered in many other communications scenarios. For example, the effective capacities of multiple-input multiple-output (MIMO) antenna systems, and multiple access channels are analyzed in [22], and [23], respectively. In [24, 25], the authors studied scheduling policies for multi-user cellular networks. In [26, 27], the authors consider sub-channel and power allocation for power minimization for multi-user OFDM systems under minimum effective capacity constraints of the users. In [28], the authors propose a framework to jointly optimize effective spectrum efficiency and effective power efficiency under different delay-outage constraints.

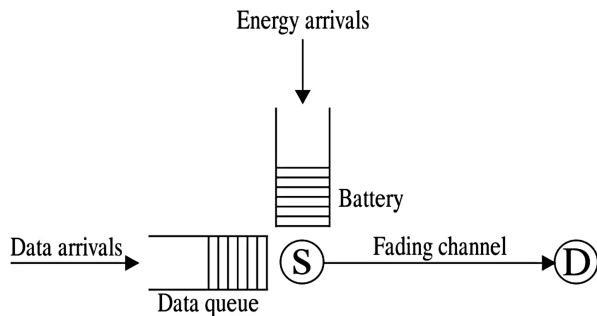
In Chaps. 4, 5, and 6, we will employ the delay-outage constraint and EC notion as criteria to develop resource allocation schemes for two communications systems: (1) A source-destination communications link with energy harvesting; (2) A 3-node source-relay-destination buffer-aided relaying system, where the buffers are employed at both the source and relay. In this case, the delay-outage constraint is imposed on the end-to-end delay, which is the sum of delays at the source and relay buffers.

2.3 Energy Harvesting Communications Systems

We have seen that future wireless communications systems are expected to accommodate an ever increasing number of wireless applications with high capacity demands and/or stringent QoS requirements such as real-time multimedia streaming, connected and autonomous vehicles etc. [29]. Moreover, supporting higher data rates under strict delay QoS requirements increases the energy consumption, which results in a detrimental impact on the environment. A challenge for future wireless system design is to meet the increasing energy demand, while lowering the emission of greenhouse gases for achieving the environment sustainability. Consequently, green communications has attracted significant attention in academia and industry. An efficient and promising technology to tackle this issue is energy harvesting (EH), where wireless EH nodes harvest energy from the renewable sources of their surrounding environment, convert it to electrical energy, and use the electrical energy in order to carry out their functions. In addition to greenhouse gas emission reduction, EH technology is also appealing for communications scenarios when a fixed power supply is not available, and even periodical battery replacement may not be a feasible option for communications devices, for example, in large wireless sensor networks etc. In such cases, EH provides a way of operating the network with a potentially infinite lifetime. EH nodes are particularly suitable for machine-to-machine (M2M), and Internet-of-Things (IoT) communication systems etc. as they are envisaged to be both energy-efficient and self-sustainable [30, 31].

There has been a growing interest in the optimization of EH communication systems, which has to address the challenging issue of instability of renewable energy resources. In particular, power allocation issues for EH communication systems have been investigated [32–37]. Unlike the case of fixed power supply, power allocation for EH transmitters is subject to EH constraints, where in every time slot, each transmitter is constrained to use at most the amount of stored energy currently available, although more energy may become available in the future slots. Consider EH communications systems over fading channels, where the random energy arrivals are stored in battery for data transmission as in Fig. 2.2. In [35],

Fig. 2.2 A source-destination communications link with EH transmitter



the authors study the throughput maximization problem assuming delay-limited communications, where a randomly arriving packet at the source is decided to be either transmitted or dropped without buffering. A learning theoretic approach is introduced, which does not require any statistical information on the random fading channel, energy arrival, and data arrival processes. The works [36, 37] explore various throughput maximization problems assuming data arrivals being stored in a data buffer. However, it is noted that these works do not consider delay constraints. In [38, 39], power allocation schemes for EH systems are proposed to ensure the stability of the data and energy queues (or battery) using Lyapunov optimization theory. In [40], the authors derived the EC for EH systems for given power allocation policies. The derived expressions were then exploited to evaluate commonly used power allocation policies, e.g., greedy policy, constant power policy, etc. assuming the statistical knowledge about the random processes is known.

In Chap. 4, consider the EH system as in Fig. 2.2, we explore optimal stochastic power allocation problems for EH systems as shown in Fig. 2.2 over fading channels under average delay or delay-outage constraints. We develop online power allocation algorithms when the statistical knowledge of the random channel fading, EH processes is unknown, which is typical in real-life communications. The studies provide valuable insights into how to optimally allocate power under different types of delay constraints.

2.4 Buffer-Aided Relaying Communications

The above-mentioned works concern resource allocation for point-to-point communications. In practice, it is not always possible for a source to communicate directly with the destination, for example, due to long distance, or severe shadowing. An example is downlink communications from the base station to the cell-edge users. In such scenarios, wireless relaying provides an efficient means to improve the coverage, throughput, and reliability of wireless networks. Typical situations where wireless relaying is needed are depicted in Fig. 2.3.

Relaying has been adopted by recent wireless communications standards, e.g., 3GPP-Long Term Evolution (LTE) [41]. There has been a great deal of research on the 3-node relay network over the past decades under different configurations, (e.g., with or without direct source-destination link) and relaying schemes, (e.g., decode-and-forward or amplify-and-forward relaying), for example, see [42], and references therein. In these works, the relay receives packets from the source in one time slot, and forwards it to the destination in the next time slot, which is referred to as fixed relaying (or fixed link scheduling) in the sequel. Such fixed relaying schemes may suffer significant performance degradation over fading channels, where the source-relay (S-R) or relay-destination (R-D) link signal strengths can greatly vary with time since the end-to-end transmission rate is dominated by the weaker link of the

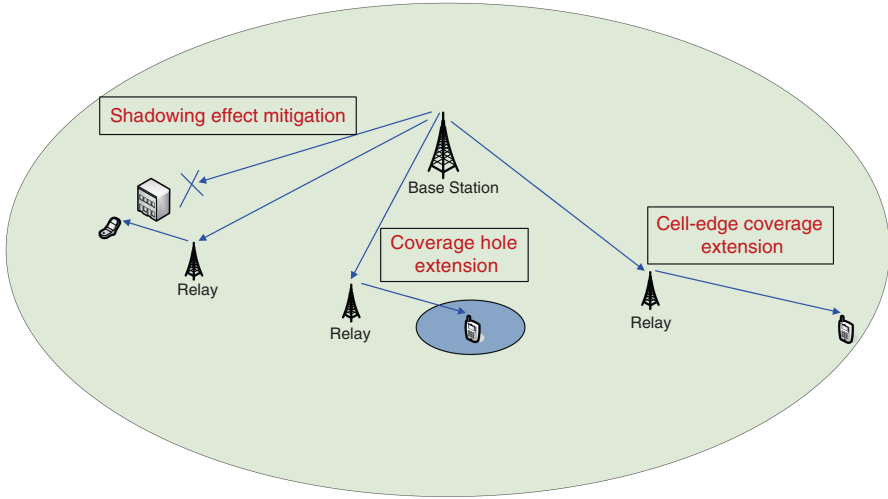


Fig. 2.3 Relaying in wireless cellular communications

two links. For example, for a 3-node decode-and-forward relaying network without a direct S-D link, the capacity is given by the minimum of the S-R and the R-D link capacities [43].

2.4.1 Half-Duplex Relaying with Adaptive Link Selection

Recent works have introduced buffer-aided relaying, where the relay employs buffer to store the received data from the source for future forwarding to the destination [44, 45]. Under buffer-aided relaying, the relay has more transmission flexibility since it might not need to forward the received data to the destination immediately after receiving it as in the case of fixed relaying. Hence, buffer-aided relaying can overcome the fading effects of wireless channels. In general, fixed relaying schemes developed under non-buffer relaying setting can be modified to exploit the relay buffering. However, the resulting relaying schemes may fail to achieve the maximum diversity gain offered by buffer-aided relaying over the non-buffer relaying since the relay still receives and transmits sequentially in every time slot [44, 46–48]. Thus, to exploit the transmission flexibility offered by the relay buffering capability, adaptive link selection relaying must be considered, where the relay transmission and reception schedule is not fixed. Such adaptive relaying efficiently schedules the S-R link and R-D link depending on their channel conditions in each frame. As a result, adaptive relaying can attain significant throughput gains over fixed relaying since it can exploit the link diversity by transmitting over the link with more favorable channel condition [49–51].



Fig. 2.4 Buffer-aided relaying model

One disadvantage of buffer-aided adaptive relaying is that it introduces random queuing delay at the relay, which is not present under non-buffer relaying. Most existing adaptive relaying schemes are developed under the unconstrained delay or average delay constraint settings which are reviewed in the following.

2.4.1.1 Case of Unconstrained Delay

Consider a 3-node buffer-aided relay network in Fig. 2.4. Assume the source always has data to transmit. We assume ergodic stationary i.i.d. block-fading channels with fading duration equal to the transmission frame. Denote $h_1[t]$, and $h_2[t]$ the instantaneous (normalized) channel gains in frame $t = 1, 2, \dots$ of the S-R link and R-D link, respectively. $h_i[t], i = 1, 2$ are assumed to be statistically independent random variables. Let P_1 and P_2 denote the transmit powers of the source and relay, respectively. Similarly, denote $r_i[t], i = 1, 2$ the corresponding instantaneous transmission rates in frame $t = 1, 2, \dots$ of the links:

$$r_i[t] = \log_2(1 + P_i h_i[t]), i = 1, 2.$$

In [50], the authors consider the adaptive link selection relaying problem described as follows. Let $\phi[t] \in \{0, 1\}, \forall t$ denote a binary variable for frame t where we set $\phi[t] = 1$ if the R-D link is active and $\phi[t] = 0$ if the S-R link is active. The adaptive relaying scheme for throughput maximization is shown to have the following form [50]:

$$\phi[t] = \begin{cases} 0, & r_1[t]/r_2[t] \geq \xi, \\ 1, & \text{otherwise} \end{cases} \quad (2.8)$$

where the parameter $\xi > 0$ is determined to maintain the following equality:

$$\mathbb{E}\{(1 - \phi[t])r_1[t]\} = \mathbb{E}\{\phi[t]r_2[t]\}. \quad (2.9)$$

Intuitively, the link scheduling solution ensure equal average arrival rate and departure rate of the relay buffer. We can see that the adaptive link scheduling exploits the link fading diversity by transmitting over a link when the ratio between its rate and rate of the other link is larger than a threshold value ξ . The threshold ξ takes into account the fading statistics and average signal-to-noise power ratios (SNRs) of the S-R and R-D links. Then, the (average) throughput of the adaptive relaying scheme is:

$$\mathcal{T}_{\text{B-ALS}} = \mathbb{E}\{(1 - \phi[t])r_1[t]\}.$$

To show the advantages of adaptive link selection relaying, consider the case that the links have the similar fading distributions with equal average SNRs as an example. The optimal ξ in (2.8) can be easily seen to be 1, i.e., the link with larger instantaneous rate is selected in each slot. The throughput of adaptive link selection relaying can be shown to be:

$$\mathcal{T}_{\text{B-ALS}} = \frac{1}{2} \mathbb{E}\{\max\{r_1[t], r_2[t]\}\}.$$

Consider two non-buffer and buffer-aided relaying schemes with fixed link schedules. With non-buffer relaying, the relay receives a packet in one time slot and transmits it in the next, and the corresponding average throughput is [43]:

$$\mathcal{T}_{\text{N-FLS}} = \frac{1}{2} \mathbb{E}\{\min\{r_1[t], r_2[t]\}\}.$$

With buffer-aided fixed relaying scheme, the relay receives data from the source in the first $N/2$ (N is even) time slots and sends this cumulative information to the destination in the next $N/2$ slots [44]. The corresponding maximum achievable throughput is obtained for $N \rightarrow \infty$ and given by:

$$\mathcal{T}_{\text{B-FLS}} = \frac{1}{2} \min\{\mathbb{E}\{r_1[t]\}, \mathbb{E}\{r_2[t]\}\}$$

We can see that it always holds true that:

$$\mathcal{T}_{\text{B-ALS}} > \mathcal{T}_{\text{B-FLS}} \geq \mathcal{T}_{\text{N-FLS}}.$$

Note that adaptive power allocation in each slot can be considered in addition to the link selection [50].

The work [51] considers the similar buffer-aided relaying model as in [50], and studies two adaptive link scheduling schemes with different requirements regarding the availability of CSIT. In the first scheme, neither the source nor the relay has full CSIT, and consequently, both nodes are forced to transmit with fixed rates. On the other hand, in the second scheme, the source does not have full CSIT and transmits with fixed rate but the relay has full CSIT and adapts its transmission rate accordingly. The optimal link scheduling solutions and the corresponding throughput are derived. We omit the details for brevity.

Buffer-aided adaptive relaying has been considered in other settings too. For example, in [52–54], the authors study the adaptive link scheduling schemes for throughput maximization for two-way relaying. Moreover, buffer-aided adaptive relaying is also employed in 3-hop relay network [55].

We can see that buffer-aided adaptive link selection relaying has significantly improved the performance of non-buffer relaying due to its capability to exploit the

link fading diversity. However, we should emphasize that the QoS-blind adaptive relaying schemes in the aforementioned works introduce unconstrained (or infinite) relaying delay, i.e., the relaying delay can be very large [50, 51]. Hence, in order to support delay-sensitive communications, new adaptive relaying schemes have to be developed.

2.4.1.2 Case of Average Delay Constraint

There have been several attempts to develop buffer-aided adaptive relaying schemes to provide delay QoS guarantees. In particular, several relaying schemes have been developed by heuristically modifying the aforementioned QoS-blind relaying schemes to satisfy maximum average delay constraint [50, 51, 54, 55]. The schemes take into account the instantaneous link conditions and amount of data in the relay buffer based on the observation that the (average) delay can be controlled via the arrival rate and the relay buffer size. Two different approaches to adjust the arrival rate and the queue size are proposed. One approach is to ‘starve’ the buffer by intentionally limiting the arrival rate by choosing a threshold which is strictly smaller than ξ in (2.8). Another approach is to limit the buffer size by forcing the relay to transmit if the relay buffer gets full. We omit the details for brevity. Note that both proposed relaying schemes are heuristic in nature, i.e., sub-optimal schemes.

We have seen that the developed adaptive relaying schemes assume unconstrained delay or average delay constraint. Alternatively, in Chap. 5, we study optimal adaptive relaying scheme under (end-to-end) delay-outage constraint to maximize the EC, i.e., constant supportable arrival rate to the source buffer. Under the proposed design, the link selection solution depends not only on the link conditions as in the case of unconstrained delay but also on the delay constraint. To tackle the delay-outage constraint, we apply the asymptotic delay analysis in Sect. 2.2, to transform the delay-outage constraint into the constraints on the minimum delay exponents at the source and relay buffers. We then derive the relationship between the link selection variables and the delay exponents, which is used to obtain tractable constrained optimization problem. The solution derived under delay-outage constraint is expected to converge to the solution (2.8) derived under unconstrained delay assumption when the delay-outage probability is close to 1.

2.4.2 Full-Duplex Relaying

Under adaptive relaying, the relay can either receive data from the source or transmit data to the destination. Such half-duplex (HD) relaying avoids self-interference (SI) at the expense of low spectral efficiency. Recently, several effective SI mitigation techniques have been developed, based on combinations of antenna, analog, and digital cancellations, e.g., [56–58]. Such results promise a potential full-duplex (FD)

relaying operation, in which a relay can receive and transmit simultaneously to enhance the relay system spectral efficiency [59]. Earlier works on FD relaying, e.g., [60–63] (for one-way relaying) and [64, 65] (for two-way relaying), assumed the *ideal* FD case with *zero* residual SI, which can lead to overestimation of the gains due to FD relaying over HD relaying. The works [66–75] assumed a more practical imperfect SI cancellation with *non-zero* residual SI. Also, in [66–69], the residual SI power is assumed to be proportional with parameter $\beta > 0$ to the relay transmit power, which has been validated by the experiments in [57, 58].

Since the residual SI power depends on the relay transmit power, we can see that source and relay power allocation plays a critical role in improving the performance of FD relaying systems. While power allocation for non-buffer FD relaying systems has been extensively studied as reviewed above, power allocation for buffer-aided FD relaying systems has been under-explored. In [63], a buffer-aided FD relaying scheme is proposed, which provides significant throughput gains compared to non-buffer FD relaying schemes. However, *zero* residual SI and unconstrained relaying delay are assumed. In Chap. 6, we investigate the power allocation problems for buffer-aided FD relaying with imperfect SI cancellation and delay-outage constraint. We investigate two power allocation problems for source arrival rate maximization: (1) Buffer-aided FD relaying with adaptive power allocation when the instantaneous CSI is available at the transmitters (CSIT); (2) Buffer-aided FD relaying with static power allocation when only statistical CSIT is available.

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