CHAPTER 1

Power Control for Reliable M2M Communication

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From Industrial Automation to connected and automated vehicles, Machine to Machine (M2M) applications pose stringent requirements for reliability and timeliness in wireless communication. For example, networked control systems for industrial automation are required to guarantee control information delivery before a preset deadline. Active vehicle-safety standards suggest message exchange intervals of 100 ms or less. Wireless communication, however, is subject to complex cyber-physical dynamics and uncertainties due to harsh environments and /or mobility. Among all wireless techniques, including MIMO, MAC scheduling, routing, congestion control and etc., which can be jointly designed to support reliability and low latency, power control is one of the most direct way of responding to channel dynamics and guaranteeing link reliability. In this paper, we examine M2M channel characteristics and power control approaches, with a focus on fundamental principles and representative methods. We aim to investigate the possibility of power control in applications of M2M communication systems. We also summarize the literature to illustrate research trends and challenges in the area of power control. Throughout this chapter, we emphasize channel dynamics and narrow down our discussion on enabling reliability in M2M communication systems.

1.1 INTRODUCTION

Power control has been widely used in cellular networks ranging from GSM to LTE. By adjusting the transmission power of individual links in an independent or cooperative manner, power control can be used to optimize network performance including over system throughout and reliability. M2M communication systems are emerging concepts and usually refer to a broad range of application systems that depend on machine to machine communication. They differ from cellular systems in terms of the network architecture and application requirements, but they have a lot in common, for instance, in channel characteristics and co-channel interference model. As in cellular networks, power control will play an important role in M2M communication systems. Thus, we first explore the history of power control in cellular networks.

1.1.1 History of power control in cellular networks

Power control has been playing important roles in cellular networks, ranging from the 2G GSM or CDMA systems, to the 3G networks based on WCDMA or CDMA2000, and to the 4G networks based on LTE or LTE-Advanced. The cellular systems have experienced great changes ranging from user requirements to techniques. Despite those changes, power control has remained a critical mechanism for cellular networks, and power control is a technique that cannot be ignored.

The research on power control in cellular networks dates back to 1990s when GSM systems started to be commercially developed. In order to maintain fixed voice data rate, power control was introduced in GSM systems to compensate channel changes and support overall acceptable voice quality. Around that time, power control has drawn broad attention in the research community. Of all algorithms, Foschini-Miljanic′s distributed power control [12] (usually denoted as DPC) is taken as a canonical power control algorithm. This work first proposed a simple and autonomous method to track average channel variation and regulate interference among users in different cells to meet certain required signal-to-interference-plus-noise-ratios (SINRs). With interference regulated, channel reuse is maximized. Many extensions [30][23][19] have discussed this algorithm′s characteristics and generalized it to a class of algorithms. There are also many variants with special requirements in performance or settings such as base station assignment [6]. The GSM standard [31] implemented a discrete version of DPC, where each user′s transmission power is altered by a fixed step-size update of 2dB or 5dB in extreme situations. The update frequency of transmission power is once every 480 ms, which corresponds to one update every 104 frames. Compared to the cellular systems to be discussed shortly, this update rate is very low.

Power control is a mandatory component in CDMA systems. We can even say that without power control there would not have been the success of CDMA systems. In the early IS-95 system (correspondingly 2G CDMA), the received signals of all links must be equal in order to decode successfully since they are are not perfectly orthogonal. Power control was introduced in all IS-95 systems to solve the well-known near-far problem and ensure insignificant intra-cell interference. The actual power control scheme in IS-95 systems has an open-loop and closed-loop component. The open loop power control scheme (OLPC) [28] estimated the uplink power required by measuring downlink channel strength via a pilot signal. The OLPC scheme was augmented by closed loop power control (CLPC) scheme [13] by adding a 1-bit or 2-bits feedback considering that the uplink and downlink channel typically differ in carrier frequency and are not identical. The update rate of power control in IS-95 systems is set as 800Hz, and the step-size is 1dB.

In addition to voice, 3G and 4G systems support data of varying rates and aim to extend system capacity. Rather than enabling power control to support fixed SINR, power control and rate control are jointly designed to maximize system capacity. In CDMA2000 systems, on the downlink, the transmit power is fixed and the uplink, however, is not scheduled and relies on power control to achieve a required rate. As described in [3], two independent control mechanisms together determine power control scheme of CDMA2000 systems. The first component is the basic power control scheme like CLPC, whose update rate is 600Hz with step-size 1dB. The second control mechanism determines the data rate of transmission. All base stations measure the interference level and set a control bit referred to as ”Reverse Activity Bit”. Each user adjusts their transmission rate by these control bits. The RAB-bits are fed back at the rate of 37.5 Hz. Similarly, LTE systems adjust coding and modulation schemes with the channel strength. In the mean time, fractional power control [20] is adopted in 4G LTE system to increase the overall system throughput. It has been proved in [20] when each link only compensates a part of channel attenuation, the overall system throughput can be maximized.

From GSM to LTE, the philosophy of all power control schemes is similar to the classical DPC scheme. They try to compensate channel attenuation and mitigate co-channel interference. However, their objectives are a bit different. 3G and 4G systems aim to improve system capacity and support QoS while GSM and IS-95 would like to maintain fixed SINR. Moreover, they differ in both update rates and step-sizes. These differences not only depend on specific system architectures but also consider the overall system requirements with a tradeoff between doppler tolerance, robustness, and spectral efficiency.

1.1.2 Objectives

Although we can borrow the ideas and experiences in cellular networks to design M2M communication systems, M2M communication systems are different from cellular networks in a few of respects. Firstly, most M2M communication systems are ad hoc networks. Without the support of central controllers, distributed protocol design is challenging. Secondly, M2M communication systems such as wireless sensing and control networks and vehicular networks may face much harsher network and environmental uncertainties as compared with traditional cellular networks. In supporting safety-critical, real-time applications, in the meantime, they have more stringent requirements for communication reliability and timeliness. Thirdly, different from wireless cellular networks, where system throughput is the main performance metric, packet delivery reliability in M2M networks tends to be critical. For example, industrial wireless networks [39] need to support mission-critical tasks such as industrial process control, and packet delivery is required to be reliable. At the early development stage of wireless ad hoc networks, reliable packet delivery may be able to be guaranteed due to the fact that the traffic load is low and co-channel interference can be controlled by limiting concurrent users. As wireless ad hoc networks develop with dense users, however, the co-channel interference will dominantly affect the packet delivery reliability. The emergence of vehicular networks make the issue even more urgent [12]. The main application of vehicular networks is to support vehicle active safety. The reliable delivery of warning information between vehicles is crucial. Moreover, the broadcast of safety message makes the traffic load high. For most wireless networks, there is a tradeoff between reliability, delay, and throughput. Reliability guarantee of high-load traffic is challenging, especially when the channel is dynamic.

For wireless communication systems, one basic task of the link layer is to address channel variation or channel fading [32]. In addition, an efficient media access control mechanism is required to support as many concurrent links as possible since high system capacity is always desirable and will finally affect the timeliness and decide if the system can work well in a dense network. Rate control, scheduling, and power control are all link-layer mechanisms. Rate control is finally reflected in coding and modulation schemes. Scheduling controls all links′ media access so as to control co-channel interference. Power control is implemented to respond to channel variations by directly adjusting transmission power. However, the optimum transmission power is not simply proportional to individual link′s channel attenuation due to co-channel interference. When all links adjust transmission power by their own channel attenuation, they cannot necessarily transmit successfully. The optimum transmission power is a basis of all power control related topics. Feasibility is another issue. That is, there may not be a transmission power assignment for ensuring the success of the transmissions along all the links. In M2M communication systems, power control schemes tend to be implemented in a distributed way. Thus the time-scale of channel variations becomes a critical factor in power control design. Theoretically, distributed power control should converge much faster than the speed of channel variations. Otherwise, failure in tracking instantaneous channel change would result in channel outage [15].

In this chapter, we will focus on power control theory as well as representative methods. We will analyze the basic mathematical theory behind power control schemes to investigate how power control can affect and support M2M communication systems. We will also briefly discuss rate control and scheduling, but, due to the limitation of space, we will not dive into specific algorithms. In this chapter, we assume TDMA-based scheduling and constant transmission rates unless mentioned otherwise.

1.1.3 Organization

The remaining parts of the chapter will be presented as follows. First, we will describe the system architecture and channel characteristics of M2M communication systems. Then, we will examine the theoretical fundamentals of power control in terms of optimal power control and infeasibility of power control. Next, we will introduce typical power control approaches for constant and fading channels, followed by the discussion on adaptive power control approach for prospective applications in M2M communication systems. We review literature and summarize research topics and challenges in the area of power control. Finally, we will conclude this chapter with open challenges and emerging trends.

1.2 M2M COMMUNICATION SYSTEMS

Machine to machine (M2M) communication distinguishes itself from human-oriented communication, and, unlike traditional cellular networks with specific network architectures, it represents a wide range of networks. In this section, we introduce co-channel interference model and discuss the general network architecture. We assume the ad hoc network architecture for all M2M communication system unless mentioned otherwise. Following this, we discuss the SINR model and the metrics of channel reliability. Then we analyze the origin of channel dynamics and present the statistical models. Lastly, we discuss the time scale of channel variation and the instantaneous characteristics since these metrics are so important for power control design and implementation. This section aims to demonstrate the relationships among channel dynamics, network reliability, and timeliness requirements.

1.2.1 Co-channel interference and network architecture

There is no unified network architecture for M2M communication systems. Different M2M application systems may have different network architectures. For example, wireless sensor networks′ architecture tends to be hierarchical, where the whole network is divided into multiple levels and all nodes in lower levels converge to higher levels and ultimately to a sink. Vehicular networks are currently designed as vehicle-to-vehicle communication network and there are no central control nodes. But it is very likely in the future that vehicular networks will evolve into a mixed and more complicated network architecture with vehicle-to-vehicle and vehicle-to-infrastructure (or vehicle-to-cell) networks coexisting. The vehicle-to-infrastructure networks are more like cluster-based networks just as cellular networks while vehicle-to-vehicle networks are real ad hoc networks. Whatever network architecture, however, we can model the whole network or a part of the whole network as an ad hoc network if we only consider co-channel interference. Indeed, power control is originally used to manage co-channel interference. It is quite reasonable to model all M2M communication systems as ad hoc networks as far as power control is concerned.

Co-channel interference refers to interference from links operating at the same frequency. Due to the scarcity of wireless spectrum, it is impossible that all links transmit at orthogonal frequency bands. Since power control started from cellular networks and there are extensive studies in cellular networks, let′s take cellular networks as an example. In cellular networks, all transmitters in a cell may be designed to ensure orthogonal transmissions. That is, there is no intra-cell interference. However, channel frequency is reused among all cells and the neighboring cells are assigned the same frequency resources. This is indeed the case for CDMA and LTE networks, where any desired downlink signal in a cell receives interference from other base stations and any desired uplink signal received interference from other cellphones in the neighboring cells. If we only consider download links or upload links, all links can form an ad hoc network. Different from the general ad hoc network, the network nodes and links of this ad hoc network will change over time due to the burst of users entering or leaving. Compared to cellular networks, most M2M communication systems have more limited frequency resources and all links interfere with each other. Therefore, similar to cellular networks we can model all M2M communication systems as ad hoc networks.

In Figure 1.1, we show co-channel interference among links and the ad hoc network architecture. To be aware, we only show a partial interfering links in Figure 1.1. For example, link i will receive interference from all links, but we only show the interference from the nearby links such as link 3, 5 and 7. The co-channel interference is the main limiting factor in general wireless systems. Commonly, we call cellular networks as interference-limited system. That is because modern cellular networks′ performance, especially capacity is limited by co-channel interference. The co-channel interference in M2M communication system may be more severe than cellular networks since few M2M communication systems have powerful base stations like cellular networks to assign all frequency resources and temporal resources orthogonally. We investigate the possibility of power control in M2M communication systems for manage interference. We expect that power control can bring a bunch of benefits in terms of link reliability, energy consumption, system throughput, and end-to-end delay.

1.2.2 SINR model and link reliability

Despite decades of research on interference-oriented channel access control, most exiting literature are either based on physical interference model or the protocol interference model [37]. In the protocol model, a transmission from a node S to its receiver R is regarded as not being interfered by a concurrent transmitter C if

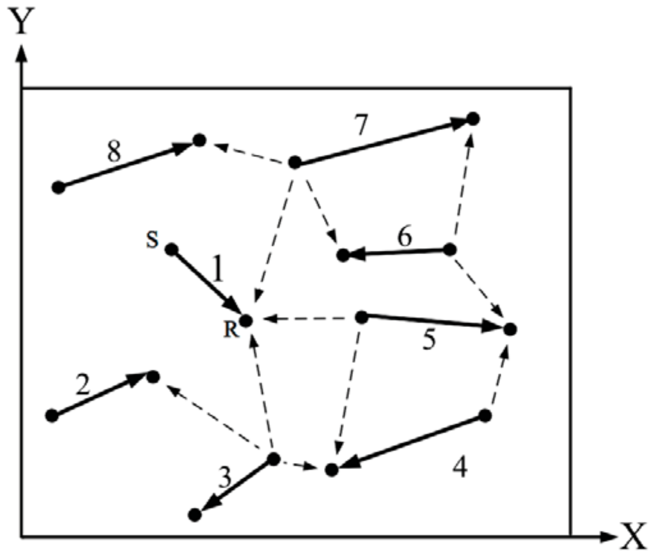

Figure 1.1 Co-channel fading model and ad hoc network architecture

$$D(C, R) \geq K \text{ x } D(S, R) \tag{1.1}$$

where $D(C, R)$ is the geographic distance between C and R, $D(S, R)$ is the geographic distance between S and R, and K is a constant number. In the physical model, a transmitter can send a packet successfully if and only if its receiver′s signal-to-interference-plus-noise rate (SINR) is over a certain threshold. The SINR can be written as

$$SINR = \frac{S}{I + N} \tag{1.2}$$

where, S is received signal, I is the interference, and N is thermal noise.

According to the SINR model, a set of concurrent transmissions is regarded as not interfering with one another if the SINR requirements hold for all links. The physical model is commonly called as SINR model. The SINR model is a high-fidelity interference model in general, but interference relations defined by the physical model are non-local and combinatorial; that is because as we can see from (1.3), whether one transmission interferers with another explicitly depends on all other transmissions in the network. For the consideration of reliability, SINR physical model is a preferred model. Throughout the whole chapter, we use SINR model as reliability reference model unless mentioned otherwise.

Due to the broadcast nature of electromagnetic wave, a transmission signal decays over distance and the received signal is related to transmission power and channel attenuation. Thus we write the SINR model as

$$\frac{P_i G_{ii}}{\sum_{j \neq i} P_j G_{ij} + n_i} \geq \beta_i \tag{1.3}$$

where, P_i is the transmission power of link i; β_i is link i' required SINR threshold; n_i is the noise received by link i. G_{ii} is the path gain between link i's sender and receiver; G_{ij} is the path gain between link i's receiver and link j's sender.

In (1.3), the SINR threshold depends on the modulation scheme, bit error rate (BER) requirement and packet size. Generally, the SINR threshold increases when any one of transmission rate, BER requirement and packet size goes up. The channel gain changes over time in a real system, but we can assume it as a constant or a random variable, which depends on network environment and node mobility. From (1.3), we see once the channel gains change, the SINR requirements are possibly no longer satisfied and packet loss can happen. So we introduce power control to respond to channel variation and guarantee channel reliability.

1.2.3 Channel dynamics and statistical models

From the last part, we have known that channel gain variation is directly related to packet delivery reliability. In this part, we discuss in detail the origin of channel dynamics and obtain a deep understanding of channel dynamics.

A radio link in a network may suffer from signal reflection, diffraction and scattering from surrounding objects when the signal propagates from the transmitter to its receiver. The multipath propagation and aggregation of the original wave is the main factor that results in instantaneous channel variation, usually called multipath fading [32]. Mutipath fading is generally called fading for short. When signal propagates along multiple paths, the differences in delay among different paths will cause distortion of the original sinusoidal signal in terms of amplitude and phase, and most importantly, any tiny change in these path delays can result in significant channel variation. This is why we mention fast channel variation when we mention fading. But whether the fading is fast or not depends on actual node mobility; that is, fast fading is only a relative concept compared with the system requirements.

Let us explain multipath fading with the well-known example where a receiver is moving. If the receiver moves with velocity v, there may exist two waves along two different directions one with a frequency of $f(1 - v/c)$ and experiencing a Doppler shift $D_{min} := -fv/c$, and the other with a frequency of $f(1 + v/c)$ and experiencing a Doppler shift $D_{max} := +fv/c$. The frequency shift

$$f_m = fv/c \tag{1.4}$$

is called the *Doppler shift*. Here, f is the carrier frequency, and $c = 3 \text{ x } 10^8$ m/s is the speed of light. *Doppler spread* is the biggest difference between the Doppler shifts. We can write

$$D_s = D_{max} - D_{min} \tag{1.5}$$

where, D_{max} is the maximum Doppler shift, and D_{min} is the minimum Doppler shift. The frequency of channel variation depends on Doppler spread. The coherence time T_c of a wireless channel is defined as the interval over which the magnitude of signal changes significantly. In [32], $Tc = \frac{1}{4D_s}$. This relation is imprecise and many people instead replace the factor of 4 by 1. Whatever, the important thing is to realize that the coherence time depends on Doppler Spread and the larger the Doppler spread, the smaller the time coherence. Assume $Tc = \frac{1}{4D_s}$, if a mobile is moving at 60 km/h and the carrier frequency $f = 1800$ MHz, the Doppler shift is 100 Hz, and the coherence time is 2.5 ms.

Most of time, we may mistakenly think that multipath fading results from transmitter or receiver's mobility. Actually, the movement of surrounding objects or other changes in propagation path can also result in fading if the propagation path delay or propagation path itself are experiencing time-varying change. That is, a stationary network can have multipath fading. The truth is just because the example of receiver mobility is easier for us to explain and analyze multipath fading, and they also represent the characteristics of multipath fading.

Shadowing is slowly varying fading. The randomness of scatters in the environment makes channel change slowly. This is called shadowing because it is similar to the effect of clouds partly blocking sunlight [32]. The duration of shadowing lasts for multiple seconds or minutes and occurs at a much slower time-scale compared to multipath fading. For convenience, we usually refer to multipath fading as fading and shadow fading as shadowing. Whethert fading or shadowing, the spatial change of scatters or transmitters finally manifest itself as time diversity, and this is why a wireless channel changes over time.

Path loss is due to natural radio energy attenuation. In free space, the path loss is inversely proportional to power 2 of link length. We call the number 2 as *path loss index*. The path loss index depends on the environments. In the urban or suburban areas, path loss indexes are different. Generally, the path index of wireless networks ranges from 2.5 to 6. For analysis and by experimental results, cellular networks usually use 3.5 as the path loss index. Some experimental results can be found in [22].

There are statistical models to represent shadowing and fading. Although statistical models cannot accurately represent actual systems, thanks to these models we have the opportunities to obtain a clearer perspective and understanding of wireless communication systems. In the channel statistical models, we take each link's fading at any time t as an independent and identically distributed (i. i. d) random variable. Shadowing is usually modeled as a random variable with log-normal distribution. Typical fading distributions are Rician fading, Rayleigh fading, and Nakagami fading [29]. When there is a line-of-sight path between transmitter and receiver, or there is a specular path between transmitter and receiver, the channel is represented by a Rician fading model. When there is not a main path component, we can think the channel consisting of many small paths. Rayleigh fading model is the most widely used model. The Nakagami model is known to provide a closer match to some measurement data than either Rayleigh or Rician distributions [4]. The Nakagami model can be used to model the channel which is more or less severe than Rayleigh fading. The Nakagami model defines a Nakagami shape factor m. When $m = 1$, the Nakagami distribution becomes the Rayleigh distribution, and when $m \to \infty$ the distribution approaches an impulse (no fading). The Nakagami model has been recently used in vehicular networks.

The magnitude of the received complex envelop with a Rayleigh distribution can be written as

$$p_\alpha(x) = \frac{x}{b_0}\exp\{-\frac{x^2}{2b_0}\} \tag{1.6}$$

where, b_0 is variation value. The corresponding squared envelop α^2 is

$$p_{\alpha^2}(x) = \frac{1}{\Omega_p}\exp\{-\frac{x}{\Omega_p}\} \tag{1.7}$$

where, $\Omega_p = 2b_0$. We can see that $p_{\alpha^2}(x)$ is an exponential distribution. This distribution is very important. We will discuss it later.

Nakagami fading describes the magnitude of the received complex envelop as

$$p_\alpha(x) = 2(\frac{m}{\Omega_p})^m \frac{x^{2m-1}}{\Gamma(m)}\exp\{-\frac{mx^2}{\Omega_p}\} \tag{1.8}$$

where, $\Gamma(m)$ is Gamma distribution. With Nakagami fading, the squared envelope has the Gamma distribution

$$p_{\alpha^2}(x) = (\frac{m}{\Omega_p})^m \frac{x^{m-1}}{\Gamma(m)}\exp\{-\frac{mx}{\Omega_p}\} \tag{1.9}$$

We plot the Nakagami pdf by Matlab for comparison and analysis as in [29]. From Figure 1.2, we see that Rayleigh distribution (i.e, when $m = 1$) covers a wide range of values while the value of Nakagami distribution is mostly around the mean value. The physical meaning here is Rayleigh channels generally have more frequent fluctuation with larger variation compared to Nakagami fading.

It is easy to confuse the envelop distribution and squared envelop distribution. The

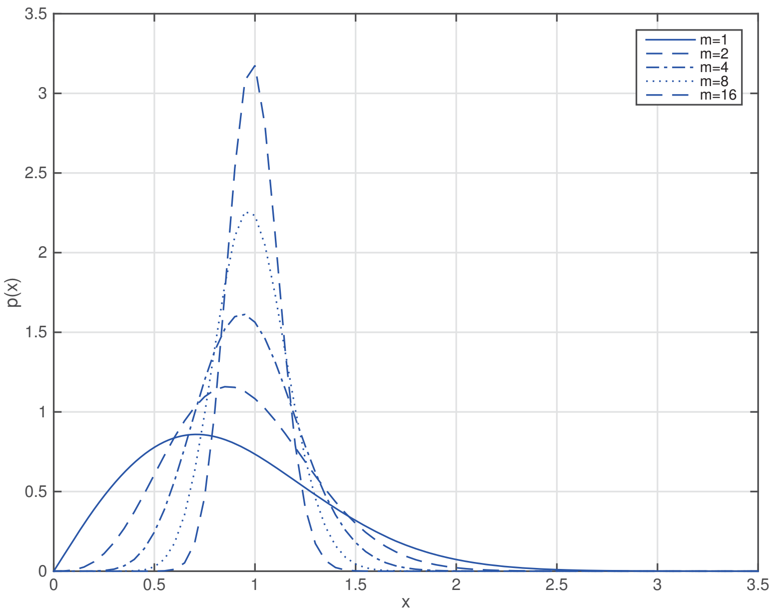

Figure 1.2 The Nakagami pdf with $\Omega_p = 1$

squared envelop is more important for the performance analysis of M2M communication systems because it is proportional to the received signal power and, hence, the received signal-to-interference-plus-noise ratio.

In a M2M communication system with fading, fading changes much faster than shadowing and path loss. Thus we assume that shadowing and path loss represent large-scale path gain $G_{ii}$and can be denoted with a constant, and h_{ii} is an independent and identically distributed (i. i. d) random variable. Compared to (1.3), we add random variable h for fading. The SINR model in fading can be rewritten as

$$\frac{P_i h_{ii} G_{ii}}{\sum_{j \neq i} P_j h_{ij} G_{ij} + n_i} \geq \beta_i \tag{1.10}$$

Without fading, we may be able to find a transmission power for each link to satisfy SINR requirements and guarantee 100% reliability. In the case of fading, it is impossible to guarantee 100% reliability since h is a random variable and can be of a very large value. Thus reliability in this case refers to outage probability or package delivery rate.

1.2.4 Multi-scale and instantaneous characteristics

Many concerns on instantaneous or short-term reliability and delay have risen in M2M communication systems. While channel variations result in the requirements for power control, the time scale of channel variations determine or limit the design and implementation of power control. In this part, we discuss the time scale and instantaneous characteristics of channel dynamics.

The SINR model demonstrates that communication reliability depends on whether wireless channels are constant or dynamic. In real-word networks, however, there are no com-

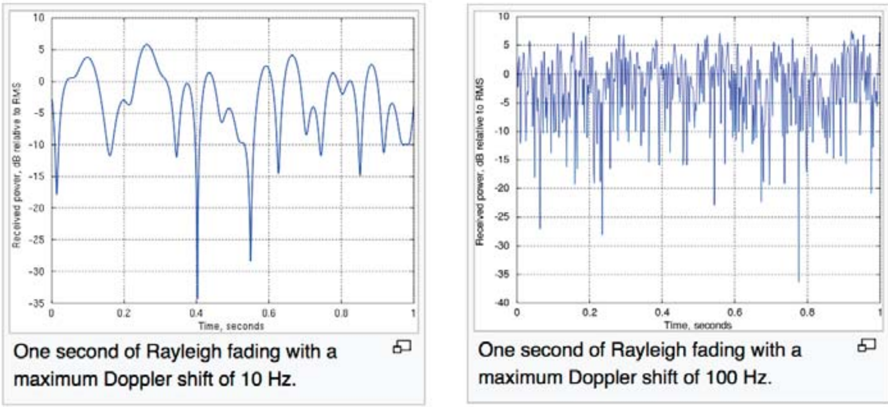

Figure 1.3 Instantaneous channel characteristics with fading

pletely constant channels. Lin et al. in [24] did extensive empirical studies to confirm that the quality of radio communication for low power sensor devices in static wireless sensor networks varies significantly over time and environment. The relative time scales of channel variation and application delay requirement determine the final channel model and power control design. Thus, we discuss the multi-scale and instantaneous characteristics of wireless channels in M2M communications systems.

Two-level time scale exists in many wireless channels. The short time scale is related to fading, and the longer time scale comes from shadowing or path loss change. The multipath fading results in fast channel variation at shorter time scales while shadowing or path loss brings average channel change at longer time scales. The time scale of channel variation from Shadowing or path loss is generally in the order of seconds or minutes, which is much longer than the time scale of fast variation from fading. Figure 1.3 shows instantaneous channel variation and demonstrates the difference between fading with different Doppler shift. From the figure, we can see that the received power with 100 Hz Doppler shift has much faster channel change than that with 10 Hz Doppler shift. These Doppler shifts correspond to velocities of about 60 km/h (40 mph) and 6 km/h (4 mph) respectively at 1800 MHz, one of the operating frequencies for GSM mobile phones [36]. This is the classic shape of Rayleigh fading.

How do these signal variations affect the design of protocols and power control? As it is well known, modern wireless communication systems are discrete systems. Let's first transform the continuous system into discrete format. We use block fading model to represent continuous fading channel. As showed in Figure 1.4, we assume that the channel gain during the coherence time is constant and any two channel gains are independent although the actual channel gain $h(t)$ is correlated and changes over time. Based on the inherent multi-scale channel characteristics, modern communication systems adopt multiple-level time scale design. The multiple-level time scales include symbol time, time slot duration, and frame length. The symbol time is determined by the carrier bandwidth; the selection of time slot duration and frame length depends on channel variation and system delay requirements. Take LTE system as an example. The symbol time of LTE system is 0.0667 ms with the sub-carrier bandwidth 15 kHz; the time slot is 1 ms and the frame length is 10 ms [10]. These parameters are appropriate to meet current LTE requirements. Considering the more stringent delay requirement, however, a scheme on shorter time slot duration has been proposed in future

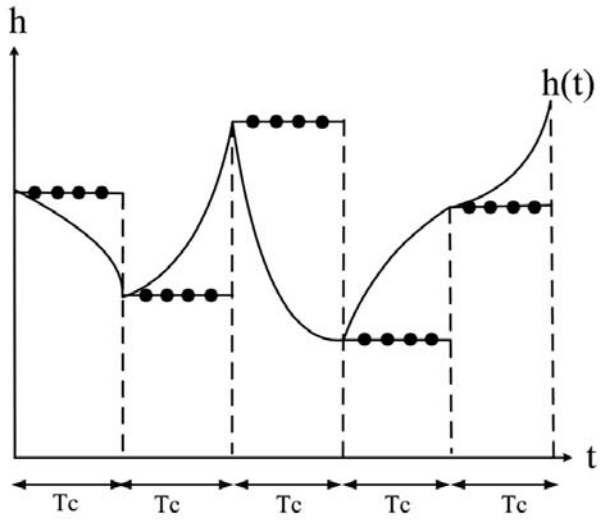

Figure 1.4 Block fading model

5G cellular systems. For vehicular networks, the shorter time slot is also required since the coherence time can be in the order of 5 ms in the case of high vehicle velocity.

In general, if the wireless channels change over a frame (or a few time slots), it is reasonable or feasible to obtain an desirable transmission power; otherwise, it may be difficult to track channel change and guarantee packet delivery rate. We will explain this in the next section by introducing power control theory. In this situation, we can only draw support from other techniques such as interleaved coding or transmission repetition to guarantee reliability. This is the limitation of power control and this fact also tells us the philosophy of wireless communication system design that only when all techniques work together can we obtain a desirable system.

1.3 POWER CONTROL THEORY

The application requirements of cellular networks drive the development of power control approaches. There exist extensive work about power control in the research community and industrial community. Power control is essentially an optimization issue. A minor change in objectives or constraints can generate different problems. However, all power control topics cannot leave the basic SINR model we mentioned in the previous section. Based on the SINR model, power control approaches are not confined in a specific type of network. In fact, many literature don't specify the network type in their power control schemes. Therefore, throughput the whole chapter, we will not specify the network type of given power control methods, and we assume that all power control approaches discussed in this chapter can be used in both cellular networks and M2M communication systems unless mentioned otherwise. In this section, we mainly discuss the feasible and optimal power control and the infeasibility of power control, combining with the mathematical models Linear Programming [8] and Mixed Integer Programming [2]. But one thing should be kept in mind: base stations in cellular networks can centrally do channel measurement and control. Thus power control in M2M communication systems with the ad hoc network architecture tends to be more challenging.

1.3.1 Feasible and optimal power control

Given a set of transmitter-receiver pairs, we would like to find a transmission power for each link to satisfy their SINR requirements. In the SINR requirement model (1.3), each link′s transmission power depends on all other links′ transmission power. To obtain a transmission power for each link, we can transform the SINR model in (1.3) into a matrix form and we have the transformed form

$$P \geq FP + \eta \tag{1.11}$$

and

$$F_{ij} = \begin{cases} \beta_i G_{ij}/G_{ii}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \tag{1.12}$$

and

$$\eta_i = \beta_i G_{ij}/G_{ii} \tag{1.13}$$

where P is a vector of each link′s transmission power. Each entry of F represents the normalized interference multiplied by SINR target. The normalized interference is obtained by dividing each link′s interference by its channel gain. The inequality (1.11) meets the form of Linear Programming. Therefore, we can utilize the theory of Linear Programming to get the solution of all transmission powers. According to Linear Programing, if there exist solutions for the inequality (1.11), all solutions form a cone and the vertex of the cone is the point that lets the equation condition hold. All those solutions are called feasible solutions and the vertex of the cone is usually called *fixed point* [8] by optimization convention. By solving the linear equation, we have the fixed point

$$P^* = (I - F)^{-1}\eta \tag{1.14}$$

P^* is the minimum one among all solutions, so it is the optimal solution in the perspective of power consumption. This characteristic is usually utilized to calculate the minimum power consumption in a given network.

It is theoretically easy to obtain the feasible and optimal transmission power for all links. However, it is challenging to obtain the fixed point in a distributed way. Foschini and Miljanic [12] first proposed the simple and automatous algorithm to obtain the fixed point. The algorithm is as (1.15)

$$P_{t+1}^i = \beta_i P_t^i / r_t^i \tag{1.15}$$

Where, P_{t+1}^i is the transmission power of link i at time $t+1$; P_t^i is the transmission power of link i at time t; β_i is the SINR threshold of link i; r_i is the actual received SINR at time t for link i. Because each link updates its current transmission power only by its previous SINR, this method is easy to implement. Foschini and Miljanic in [12] proved this algorithm can synchronously converge to the fixed point. Most of the following distributed power control are based on this algorithm.

1.3.2 Infeasibility of power control

In contrast, the Linear Programming constraint in (1.11) may have no solutions. That is, we cannot find a transmission power for each link to make sure they can transmit concurrently. We can introduce the Perron-Frobenius Theory [26] to explain the feasibility of the Linear Programming problems.

Theorem 1.1 *[26] if A is a square non-negative matrix, there exists an eigenvalue λ such that*

- *λ is real and non-negative;*
- *λ is larger or equal to any eigenvalue of A.*
- *there exists an eigenvector $x > 0$ such that $Ax = \lambda x$*

Here, λ is the largest eigenvalue of A. We take it as the *spectral radius* of A and we also call it as the *perron root* of A. Applying the Perron-Frobenius theory with the SINR model, we can find if $\lambda(F) < 1$ when $\eta \neq 0$ or $\lambda(F) \leq 1$ when $\eta = 0$, there exists feasible power assignments. The proof can be found in [26].

Once a set of links are infeasible, we need to introduce scheduling to remove a subset of links to ensure remaining links are feasible. Joint scheduling and power control is an important topic in wireless system since a real system almost needs scheduling to remove strong interference. The objective of joint scheduling and power control is to find the active links and their feasible transmission power. We can introduce an indicator variable X_i to represent scheduling, with $X_i = 1$ meaning active and $X_i = 0$ meaning inactive. The mathematical form of joint scheduling and power control can be

$$\text{Maximize } \sum_{i=1}^{N} X_i \tag{1.16}$$

Subject to

$$\frac{P_i G_{ii} X_i}{\sum_{j \neq i} P_j G_{ij} X_j + n_i} \geq \beta_i X_i \tag{1.17}$$

This problem is a mixed integer linear programming (MILP) problem, which is known to be NP-hard. Any NP-hard problems cannot find the solution in a reasonable computation time. Thus most real-world joint scheduling and power control algorithms are approximation methods. One type of heuristic methods use the approaches of adding links one by one and testing its feasibility. These heuristic methods may be helpful for a centralized system, but it is difficult to implement them in a distributed way.

1.4 POWER CONTROL APPROACHES FOR CONSTANT AND FADING CHANNELS

Power control schemes depend on channel variations of wireless networks. In short, power control schemes are totally different in the case of fading or not. Although it is impossible in real-world wireless systems to have constant channels, static networks are usually modeled as constant channels for the purpose of analysis and it is also reasonable since the coherence time is relatively large compared to the communication time. Assume static networks have constant channel and mobile networks such as vehicular networks have fading channels, we discuss power control approaches for constant channels and fading channels. These two approaches are applicable to static and mobile M2M communication systems respectively.

1.4.1 Conflict graph-based power control for constant channels

In a static network, we assume wireless channels don′t change over the communication time. Given a large network with fixed channel gain, power control mainly cares about finding the maximum feasible set and their corresponding optimal transmission power. Just as we discussed in the previous section, such an issue is modeled as joint scheduling and power control, and it is theoretically NP-hard. Therefore, all power control approaches in constant

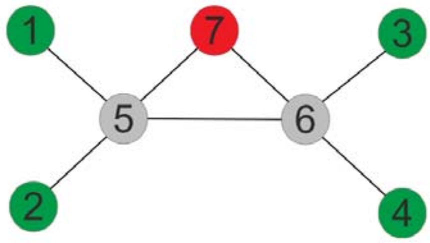

Figure 1.5 Link conflict graph [25]

channels are approximate methods. Most approximate algorithms utilize the fact that the total interference from links beyond a certain distance can be upper bounded [16]. Once the interference is upper bounded, the SINR can be guaranteed and all packets can be delivered successfully.

Given a set of links, if we use simple path loss model, we can calculate the accumulated interference as [16]

$$I = \sum_{d_{ij} > \rho} c/d_{ij}^{\alpha} \tag{1.18}$$

where c is a constant related to path loss and transmission power. Assume all nodes are uniformly distributed in a given area, we can obtain an upper bound of the accumulated interference from nodes within distance ρ away. Furthermore, we can calculate exact ρ by ensuring any specific SINR requirement in (1.3). Given a link, the value of ρ means all links within the distance ρ interfere with the given link. Therefore, each link has a corresponding distance beyond which other links can transmit simultaneously, and all links within which should be disabled as conflict links. We can build a conflict graph to represent the conflict relationship between any two links and then utilize this conflict graph to obtain maximum independent set.

In a conflict graph, a circle represents a link, and all links are vertices of the graph. If two links can transmit at the same time, they are not connected in the conflict graph; otherwise, they are connected. In Figure 1.5, Link 5 is conflict with the link 1, 2, 6 and 7. When Link 5 is transmitting a packet, Link 1, 2, 6 and 7 cannot transmit at the same time with link 5.

There is a disadvantage for conflict graph-based approach. When we build the conflict graph, we mean that a link is conflict with all links within the distance ρ. This implicitly indicates that the conflict links cannot transmit concurrently becasue all links beyond the distance ρ are interfering. But the fact is that there is very small probability that all those links have traffic requirements at the same time in a real-world system and thus the accumulated interference is far less than the upper bounded interference. In this case, two conflict links may be allowed to transmit concurrently. The direct result is big sacrifice in concurrency. Zhang et al. [37] proposed the Physical-Ratio-K (PRK) interference model, which is similar to graph theory but defines a ratio value K to more accurately build the conflict relationship between any two links.

For static networks with constant channels, scheduling and power control is used as a means to guarantee reliability. The performance of conflict graph-based approaches depends on the accuracy of conflict links. A large guard area can bring significant degradation in concurrency while a small guard area may be unable to guarantee reliability. Whatever, all existing algorithms are time consuming. There are few applications of these algorithms in real M2M communication systems.

1.4.2 Geometric programming-based power control for fading channels

For a real-world system, we cannot ignore fading, especially when the system is mobile. Fading is the most important factor that affects the instantaneous packet delivery rate (PDR). If fading is considered, the SINR model will be a bit different. Due to the fact that shadowing changes slowly, most mathematical models don′t consider shadowing. The SINR requirement is as (1.10).

For the random channel, it is impossible to guarantee 100% packet delivery. We use packet delivery rate or outage rate to measure link reliability. For Rayleigh fading, the distribution is an exponential function as we discussed in the previous section and is easy to analyze. Most analytical models assume that channel fading follows the Rayleigh fading model. We can obtain a closed form of outage probability [21]

$$O_i = 1 - \prod_{j \neq i} \frac{1}{1 + \frac{\beta_i G_{ij} P_j}{G_{ii} P_i}} \tag{1.19}$$

where, O_i is the outage probability. We can use some mathematical methods such as Laplace Transform to obtain the results, but Kandukuri and Boyd first gave the conclusion in [21]. We note that the term $\beta_i G_{ij}/G_{ii}$ is exactly the entry of channel gain matrix F. This indicates that the outage probability must be related to static or average channel characteristics. Syod et al. in [1] has proved the relationship between O_i and channel gain matrix F. Here, we define

$$O = \max_i O_i \tag{1.20}$$

We can obtain that

$$\frac{1}{1+\mathrm{CEM}} \leq O \leq 1 - \exp^{-\mathrm{CEM}} \tag{1.21}$$

Where, CEM $= 1/\lambda(F)$. There is a very interesting quantitative result here. If SINR is fixed and $\lambda(F)$ approaches 1, the maximum outage probability can be larger than 50% if we we assume G_{ii} is constant. The physical meaning is that if we don't respond to fading and use fixed transmission power during the process of fading, in the worst case, some feasible links can obtain at most 50% package delivery rate. Obviously, this result is unacceptable. This is the disadvantage of power control with fixed transmission power in fading network. Therefore, this model is usually combined with rate control. Only by adjusting transmission rate, that is, SINR threshold, can the packet delivery rate be guaranteed. The mathematical model can be

$$\text{Maximize } R_i \tag{1.22}$$

$$\text{Subject to}$$

$$O_i \geq O_{i,min} \tag{1.23}$$

$$R_i \geq R_{i,min} \tag{1.24}$$

where, $O_{i,min}$ is the minimum outage requirement and $R_{i,min}$ is the minimum transmission rate requirement. We have $R_i = \log(1 + \beta_i)$ by the well-known Shannon theory [27]. This issue is difficult to solve due to the nonlinear relationship between SINR threshold and transmission rate. If β_i is much larger than 1, however, we can get $R_i = \log\beta_i$. We can use geometric programming to solve it. Due to the limitation of space, we will not introduce geometric programming. But we would like to mention that almost all joint power control and rate control issues are based on this geometric programming model. This model is complex, and it is non-convex especially in the low SINR region. Therefore current effort is focusing on efficiently converting a non-convex issue into convex issue.

1.5 DISCUSSION ON ADAPTIVE POWER CONTROL FOR M2M COMMUNICATION SYSTEMS

In general, the conflict graph-based power control approaches and geometric programming-based power control approach are designed for two different systems. The conflict graph-based power control approach is for static networks with constant channels, and the geometric programming-based power control approach is for mobile networks with fading channels. These two approaches assume that the large-scale channel gain is constant over a long time. There are obvious drawbacks for the above two approaches: time consuming and low concurrency. Thus we suggest adaptive power control in M2M communication systems. Especially in a real-world system, the large-scale channel gain changes over time, we have to adjust to this change even though it may be small. In this section, we will discuss the possibility of adaptive power control and its limitation in M2M communication systems.

Zhang et al. [37] proposed the PRK interference model and the corresponding adaptive scheduling algorithms [38]. The PRK model leverage some inherent characteristics of wireless networks like bounded interference and remove some unreasonable assumptions such as constant channel over time. Although power control has not been completely implemented in the PRK model, Zhang et al.′s method presents the potential application of power control in a real M2M communication systems. The PRK model defined a loose conflict graph. Different from conflict graph in static networks, where conflict graph is based on simple path loss model and is related to the transmitter-receiver pair′s position, this graph does not assume the simple path loss model and the PRK model defined the conflict graph based on the ratio K of the link′ instantaneous received signal to the the instantaneous interference signal.

In the PRK model, a node C' is regarded as not interfering and thus can transmit concurrently with the transmission from another node S to its receiver R if and only if the following holds

$$P(C', R) < \frac{P(S, R)}{K_{S,R,Ts,R}} \tag{1.25}$$

where $P(C', R)$ and $P(S, R)$ is the average strength of signals reaching R from C' and S respectively and K is the minimum real number chosen such that, in the presence of cumulative interference from all concurrent transmitters, the probability for R to successfully receive packets is satisfied. Therefore, K defined the conflict graph between any links. However, PRK-based scheduling can achieve only average or long-term packet delivery rate.

We may be able to consider other potential power control methods. Non-cooperative power control is another type of power control. For these power control schemes, each link′s transmission power depends on their own channel gain. These algorithms have proved that they can obtain an increase in throughput for a random network. It is a potential direction for power control to use simple transmission power that is related to channel gain or received SINR to obtain an increase in throughput and reliability. Here we would like to introduce a few adaptive power control schemes including channel inversion [35], fractional power control [20], step-by-step power control.[18].

Channel inversion sets transmission power inversely proportional to channel gain. If the channel of link i can be represented by h_iG_{ii}, transmission power by channel inversion is

$$P_i = \frac{1}{h_iG_{ii}} \tag{1.26}$$

Therefore, the received power equals to 1 for all links. The main purpose of this approach is to completely compensate the channel attenuation. On the other hand, the transmission power by fraction power control is

$$P_i = \frac{1}{(h_i G_{ii})^\alpha} \tag{1.27}$$

where, α is the fractional number between 0 and 1. Jindal et al. in [20] proved that if h meets Rayleigh fading distribution and the network can be modeled as a Poisson network, any link can obtain the maximum package delivery rate when $\alpha = 0.5$. Fractional power control has been adopted in LTE to improve system capacity. These approaches are common in quickly responding to channel variations. They may be able to obtain long-term packet delivery rate. But obviously there is no any proof that they can guarantee short-time or instantaneous packet delivery rate since most of them only care about their own channel variation.

Another adaptive power control is to use the canonical distributed power control, which is itself an iterative power control method. Tim Holliday et al. [18] have directly applied DPC into fading networks. Applied in a fading channel rather than a constant channel, the algorithm will not converge any more. The authors also consider to adjust transmission power by a fixed step size or adaptive step size and has obtained some experimental results. Those experimental results showed that DPC algorithm can bring great SINR variation and average SINR overshot. The fixed step-size algorithm can perform better. But the issue is how to select the appropriate step size. Moreover, no theoretical analyses have demonstrated the instantaneous SINR characteristics.

So far no power control has achieved short-term reliability in a dynamic system. One main reason is the convergence rate of power control algorithms. To achieve short-term reliability, the convergence rate of power control should be much faster than the channel variation rate. It is challenging in a dynamic system. The scheme which combines fractional power control or its variants with PRK model is under study. We believe these adaptive power control algorithms will build a basis for reliability guarantee and timeless requirement in dynamical M2M communication systems.

1.6 EXTENSIVE STUDIES ON POWER CONTROL

There is extensive research on power control. They mostly focus on performance metrics other than reliability. In this section, we give a summary of studies on power control. We expect to convey a high level idea about the research topics and challenges in the area of power control.

All power control related research started from Foschini and Miljanic' work in [12]. The simple, autonomous, and distributed power control first demonstrated how power control can work to satisfy SINR requirements. Foschini and Miljanic proved that their proposed algorithm can converge to the fixed point. Huang et al. [30] proposed the discrete version where each link updates their transmission by a fixed step and discussed its application in admission control. The convergence property of distributed power control is very important. Thus Leung et al. [23] proposed a general class of power control algorithms and proposed the conditions of convergence. They claimed that any functions that satisfy these conditions can converge. Compared with the convergence property, it is equally important that a power control algorithm can converge quickly to a fixed points or quickly detect the case of infeasibility. Huang and Yates[19] showed that Foschini-Miljanic' algorithm converges to an unique fixed point at a geometric rate. Other than power control alone, there are lots of variants regarding to combined Beamforming and BS assignment. The interested readers can see more algorithms in [6].

The study of power control in wireless ad hoc networks started in the early 2000s. Gupta et al. [14] discussed the system capacity limitation due to co-channel interference and proved that when identical randomly located nodes, each capable of transmitting at bits per second, form a wireless network, the throughput for each node can approach 0. This work told us that it is crucial to mitigate co-channel interference by optimally utilizing power control and scheduling. EIbatt and Ephremides [11] in 2004 introduced power control as a solution to the multiple access problem in contention-based wireless ad-hoc networks. The authors showed that the classical Foschini-Miljanic algorithm [12] in cellular networks is directly applicable to wireless ad hoc networks. Other than this, the general framework of joint scheduling and power control was first proposed. Wan et al. [33] further mathematically formulated the scheduling issue as selecting a maximum set of independent links given a set of links. The authors proved that the cumulative interference beyond a certain distance can be upper bounded. That is, we can guarantee link reliability by removing all links within a distance from the receiver. Leveraging this finding, heuristic methods are mostly used in finding the maximum independent set. These algorithms go through links in a certain order, and all the links are added to form an independent set as in [5] and [33].

Graph theory is used for solving scheduling and power control. Leveraging the finding that the cumulative interference can be bounded, a conflict graph is built to obtain the maximum independent set and any independent set. In the conflict graph, all links are the vertices of the graph. A link can connect to another link if they are far away or satisfy a certain relationship. Magnus M. Halldorsson focuses on the research of joint scheduling and power control, especially their asymptotical properties. In [16], Magnus M. Halldorsson divided all links into subsets with equal link length. Each subset is then scheduled separately through graph coloring. Halldorsson and Tonoyan [17] presented the first-approximation algorithm, which is claimed as the best among oblivious power schemes. Although all these approximation algorithm has an good asymptotical bound, their practical concurrency is very low.

In mobile networks, fading is an inevitable characteristic. Once fading is considered, the theoretical basis of power control makes a bit change, and studies on power control extend to joint power control and rate control. Kandukuri and Boyd [21] proposed optimal power control in interference-limited fading wireless channels with outage-probability specifications, where power control is updated in the time scale of shadowing rather than by fading. Chiang et al. [7] extended Kandukuri and Boyd's work and applied the method into joint power control and rate control in random wireless networks. Of all applications, one is to maximize the overall system throughput while meeting each user′s minimum transmission rate constraint and outage probability constraint. The authors concluded that at the high SINR regimes the issue can be solved by geometric programming (GP) [1] and efficiently solvable for global optimality. The variants of the problem, e.g. a total power consumption constraint or objective function, can be also solved by GP. In the median or low SINR area, the issue is intractable since the Shannon equation cannot be approximated as a linear function between transmission power and transmission rate. However, the successive convex approximation method, which converges to a point satisfying the Kaurush-Kuhn-Tucker (KKT) conditions, can be a good approach as in [7]. Cruz and Santhanam [9] studied joint power control, rate control, and scheduling to minimize total average transmission power with the minimum the average data rate constraints per link in a long term. Cruz and Santhanam formulated the issue as a duality problem via Langrage Multiplier method and decomposed the whole issue into single-slot optimization issue. Cruz and Santhanam concluded that for the optimal policy each node is either not transmitting at all or transmitting at the maximum possible peak power. As for scheduling, the authors recommended a pseudo-random number generator to select which link is activated. The author also mentioned that hierarchical link scheduling and power control, where all links are partitioned into clusters. Links in one cluster are scheduled somewhat independently of links in other clusters. Each cluster is constrained to accommodate a limited number of links. The inter-cluster interference is modeled as static ambient noise. If the desired data rate on links are sufficiently low, the optimal policy activated a large number of clusters. All analyses and conclusions are based on the assumption that the achieved data rate is a linear function of SIR. In fact, this assumption hints that the SIR is high; otherwise, it is unreasonable.

Recent studies mainly care about QoS requirements, especially delay. The system is also toward M2M communication with the coexistence between cellular networks and wireless ad hoc networks. However, when these studies attempt to obtain optimum system design including scheduling, power control, and rate control, they face the curse of dimensionality. So current work mainly focus on turning intractable issues into tractable ones. The computation complexity and the ease of implementation are not the point. Wang et al. [34] considered dynamic power control in Device-to-Device Communications with delay constrained. The D2D networks are similar to wireless ad hoc networks, but the cellular networks can assist D2D networks to make centralized resource allocation. The delay is measured by the ratio of queue length to packet arrival rate. The paper simplified the scheduling process. The scheduling is controlled by a CSMA-like policy, where any two links′ distance must be larger than a constant. The objective of the paper was to minimize the weighted average delay and average power consumption in a long term. The authors formulated the issue as a Markov Decision Process (MDP). In the formulation, the admitted links, the instantaneous channel gain, and the queues size is a ternary state. The action is the transmission power of each link. The transmission probability depends on the each link′s queue size, traffic arrival rate, and channel gain. The problem is an infinite horizon average cost MDP, which is known as a very difficult problem. The authors gave a sufficient condition for optimality by solving the equivalent Bellman-equation. The authors explained that at each stage (time slot), the optimal power has to strike a balance between the current costs and the future cost because the action taken will affect the future evolution of queue size. Similarly, the authors used an approximation method and decomposed the issue into per-stage (one time slot) power control problem. The per-stage issue is similar to the weighted sum-rate optimization subject to the power constraint. From the design, we see that the calculation of the transmit power is very complex.

1.7 OPEN CHALLENGES AND EMERGING TRENDS

There are different perspectives for Internet of Things and M2M communications. It is difficult to reach consensus on the system model and network architecture of M2M communication systems. But based on co-channel interference model, all M2M communication systems (including cellular networks) can be modeled in ways similar to ad hoc networks. In this sense, we can potentially extend power control schemes from cellular system to M2M communication system. But there is a very important difference: base stations in cellular networks can centrally do channel measurement and control. Thus power control in M2M communication systems in the ad hoc network architecture tends to be more challenging.

There are extensive studies on power control in the research community. For static M2M communication systems, the joint scheduling and power control can be used to guarantee reliability. However, most scheduling-related issues are NP-hard, and there are still many open problems. For instance, how to enable distributed scheduling, power control, and rate control in the presence of non-local co-channel interference remains a major challenge. Recent work on high-fidelity and local interference models such as the PRK interference model and related scheduling methods may be leveraged in developing field-deployable solutions. For mobile M2M communication systems, although geometric programming is theoretically feasible, we can see the big degradation in concurrency and its inability in ensuring shorttimescale reliability. Adaptive power control is seen as prospective scheme for future M2M communication systems.

Although there are extensive studies in research community, few power control algorithms have been tested or used in the real-world M2M communication systems. There are reasons from technical aspects and application requirements. For most static wireless sensor networks, the network density is low and the traffic has not reached the system capacity. Without power control, the system can function well. The benefits of power control in energy efficiency and concurrency may be not enough to outweigh the communication overhead power control introduces. Technically, distributed implementation of power control is still challenging. For vehicular networks, we have seen scenario where a large number of vehicles gather together due to traffic congestion such that they pose stringent requirements on communication reliability. Unfortunately, due to inherent challenges of reliability and channel dynamics, power control schemes for vehicular networks are still open challenges.

Power control is an important tool for optimizing network performance. However, the adoption of power control faces the tradeoff between optimization performance and overhead. Moreover, power control alone cannot guarantee communication reliability. Other mechanisms such as packet retransmission and interleaving-coding can be used to further improve the reliability and predictability of wireless communication.

Bibliography

[1] Stephen Boyd, Seung-Jean Kim, Lieven Vandenberghe, and Arash Hassibi. A tutorial on geometric programming. *Optimization and engineering*, 8(1):67–127, 2007.

[2] Stephen Boyd and Lieven Vandenberghe. *Convex optimization*. Cambridge university press, 2004.

[3] Sumantra Chakravarty, Rajesh Pankaj, and Eduardo Esteves. An algorithm for reverse traffic channel rate control for cdma2000 high rate packet data systems. In *Global Telecommunications Conference, 2001. GLOBECOM'01. IEEE*, volume 6, pages 3733–3737. IEEE, 2001.

[4] U Charash. Reception through nakagami fading multipath channels with random delays. *IEEE Transactions on Communications*, 27(4):657–670, 1979.

[5] Xin Che, Hongwei Zhang, and Xi Ju. The case for addressing the ordering effect in interference-limited wireless scheduling. *IEEE Transactions on Wireless Communications*, 13(9):5028–5042, 2014.

[6] Mung Chiang, Prashanth Hande, Tian Lan, and Chee Wei Tan. Power control in wireless cellular networks. *Foundations and Trends® in Networking*, 2(4):381–533, 2008.

[7] Mung Chiang, Chee-Wei Tan, Daniel Pérez Palomar, Daniel O'Neill, and David Julian. Power control by geometric programming. *IEEE Transactions on Wireless Communications*, 6(7):2640–2651, 2007.

[8] E.K.P. Chong and S.H. Zak. *An Introduction to Optimization*. Wiley Series in Discrete Mathematics and Optimization. Wiley, 2011.

[9] Rene L Cruz and Arvind V Santhanam. Optimal routing, link scheduling and power control in multihop wireless networks. In *INFOCOM 2003. Twenty-second annual joint conference of the IEEE computer and communications. IEEE societies*, volume 1, pages 702–711. IEEE, 2003.

[10] Erik Dahlman, Stefan Parkvall, and Johan Skold. *4G: LTE/LTE-advanced for mobile broadband*. Academic press, 2013.

[11] Tamer ElBatt and Anthony Ephremides. Joint scheduling and power control for wireless ad hoc networks. *IEEE transactions on wireless communications*, 3(1):74–85, 2004.

[12] Gerard J Foschini and Zoran Miljanic. A simple distributed autonomous power control algorithm and its convergence. *IEEE transactions on vehicular Technology*, 42(4):641–646, 1993.

[13] K.S. Gilhousen, R. Padovani, and C.E. Wheatley. Method and apparatus for controlling transmission power in a cdma cellular mobile telephone system, October 1991. US Patent 5,056,109.

[14] Piyush Gupta and Panganmala R Kumar. The capacity of wireless networks. *IEEE Transactions on information theory*, 46(2):388–404, 2000.

[15] Martin Haenggi and Radha Krishna Ganti. *Interference in large wireless networks*. Now Publishers Inc, 2009.

[16] Magnús M Halldórsson. Wireless scheduling with power control. *ACM Transactions on Algorithms (TALG)*, 9(1):7, 2012.

[17] Magnús M Halldórsson and Tigran Tonoyan. The price of local power control in wireless scheduling. *arXiv preprint arXiv:1502.05279*, 2015.

[18] Tim Holliday, Andrea Goldsmith, Nick Bambos, and Peter Glynn. Distributed power and admission control for time-varying wireless networks. In *Information Theory, 2004. ISIT 2004. Proceedings. International Symposium on*, pages 352–352. IEEE, 2004.

[19] Ching-Yao Huang and Roy D Yates. Rate of convergence for minimum power assignment algorithms in cellular radio systems. *Wireless Networks*, 4(3):223–231, 1998.

[20] Nihar Jindal, Steven Weber, and Jeffrey G Andrews. Fractional power control for decentralized wireless networks. *IEEE Transactions on Wireless Communications*, 7(12):5482–5492, 2008.

[21] Sunil Kandukuri and Stephen Boyd. Optimal power control in interference-limited fading wireless channels with outage-probability specifications. *IEEE transactions on wireless communications*, 1(1):46–55, 2002.

[22] William CY Lee. *Mobile communications design fundamentals*, volume 25. John Wiley & Sons, 2010.

[23] Kin Kwong Leung, Chi Wan Sung, Wing Shing Wong, and Tat-Ming Lok. Convergence theorem for a general class of power-control algorithms. *IEEE Transactions on Communications*, 52(9):1566–1574, 2004.

[24] Shan Lin, Jingbin Zhang, Gang Zhou, Lin Gu, John A Stankovic, and Tian He. Atpc: adaptive transmission power control for wireless sensor networks. In *Proceedings of the 4th international conference on Embedded networked sensor systems*, pages 223–236. ACM, 2006.

[25] Xiaohui Liu, Yu Chen, and Hongwei Zhang. A maximal concurrency and low latency distributed scheduling protocol for wireless sensor networks. *International Journal of Distributed Sensor Networks*, 2015:153, 2015.

[26] Carl D Meyer. *Matrix analysis and applied linear algebra*, volume 2. Siam, 2000.

[27] Claude Elwood Shannon. A mathematical theory of communication. *ACM SIGMOBILE Mobile Computing and Communications Review*, 5(1):3–55, 2001.

[28] Samir Soliman, Charles Wheatley, and Roberto Padovani. Cdma reverse link open loop power control. In *Global Telecommunications Conference, 1992. Conference Record., GLOBECOM'92. Communication for Global Users., IEEE*, pages 69–73. IEEE, 1992.

[29] Gordon L Stüber. *Principles of mobile communication*. Springer Science & Business Media, 2011.

[30] Chi Wan Sung and Wing Shing Wong. A distributed fixed-step power control algorithm with quantization and active link quality protection. *IEEE Transactions on Vehicular Technology*, 48(2):553–562, 1999.

[31] ETSI TC-SMG. Radio subsystem link control, July 1996.

[32] David Tse and Pramod Viswanath. *Fundamentals of wireless communication*. Cambridge university press, 2005.

[33] Peng-Jun Wan, Xiaohua Jia, and Frances Yao. Maximum independent set of links under physical interference model. In *International Conference on Wireless Algorithms, Systems, and Applications*, pages 169–178. Springer, 2009.

[34] Wei Wang, Fan Zhang, and Vincent KN Lau. Dynamic power control for delay-aware device-to-device communications. *IEEE Journal on Selected Areas in Communications*, 33(1):14–27, 2015.

[35] Steven Weber, Jeffrey G Andrews, and Nihar Jindal. The effect of fading, channel inversion, and threshold scheduling on ad hoc networks. *IEEE Transactions on Information Theory*, 53(11):4127–4149, 2007.

[36] Wikipedia. Rayleigh fading — wikipedia, the free encyclopedia, 2016. [Online; accessed 13-July-2016].

[37] Hongwei Zhang, Xin Che, Xiaohui Liu, and Xi Ju. Adaptive instantiation of the protocol interference model in wireless networked sensing and control. *ACM Transactions on Sensor Networks (TOSN)*, 10(2):28, 2014.

[38] Hongwei Zhang, Xiaohui Liu, Chuan Li, Yu Chen, Xin Che, Feng Lin, Le Yi Wang, and George Yin. Scheduling with predictable link reliability for wireless networked control. In *2015 IEEE 23rd International Symposium on Quality of Service (IWQoS)*, pages 339–348. IEEE, 2015.

[39] R. Zurawski. *The Industrial Communication Technology Handbook*. Industrial Information Technology. CRC Press, 2014.