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Power control for predictable communication reliability in wireless cyber-physical systems

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Power control for predictable communication reliability in wireless cyber-physical systems

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DEDICATION

To my daughters, my family and my friends for their love and support.

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LIST OF ABBREVIATIONS

2G	Second Generation
3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
ACK	Acknowledgement
ATPC	Adaptive Transmission Power Control
AR	Augmented Reality
BER	Bit Error Rate
BS	Base Station
CDMA	Code Division Multiple Access
CLPC	Closed Loop Power Control
DPC	Distributed Power Control
DSRC	Dedicated Short Range Communications
eMBB	Enhanced Mobile Broadband
FCC	Federal Communications Commission
FM	Foschini-Miljanic
GP	Geometric Programming
GSM	Global System for Mobile Communication
HART	Highway Addressable Remote Transducer
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IS-95	Interim Standard 95
ISA	International Society of Automation

ITS	Intelligent Transportation System
KKT	Karurush-Kuhn-Tucker
LP	Linear Programming
LQI	Link Quality Indicator
LTE	Long Term Evolution
M2M	Machine to Machine
MAC	Media Access Control
MILP	Mixed Integer Linear Programming
MIMO	Multi-input and Multi-output
mMTC	Massive Machine-type Communication
NAMA	Node-Activation Multiple Access
NP-hardness	Non-deterministic Polynomial-time Hardness
PDR	Packet Delivery Ratio
PPP	Poisson Point Process
PRK	Physical-Ratio-K
QoS	Quality of Service
RF	Radio Frequency
RTS	Request to Send
CTS	Clear to Send
RSSI	Received Signal Strength Indicator
SINR	Signal-to-Interference-Plus-Noise Ratio
SIR	Signal-to-Interference Ratio
SNR	Signal-to-Noise Ratio
TDMA	Time-division Multiple Access
URLLC	Ultra-reliable Low-latency Communication
WCDMA	Wideband Code Division Multiple Access

LIST OF SYMBOLS

c	Speed of light
v	Moving speed
f_c	Carrier frequency
D_{min}	Minimum Doppler shift
D_{max}	Maximum Doppler shift
$f_\sigma(.)$	Probability density function
m	Nakagami function shape factor
σ	Multipath fading function standard deviation
σ^2	Multipath fading function variation
∞	Infinity value
$D(x,y)$	Geometric distance between x and y
γ	SINR
$\sum$	Summation function
γ	Signal-to-noise ratio
β_{th}	Target SINR
β_i	Link i's SINR
$\lambda(.)$	Perror root
u	Packet length
S	Received signal
I	Total interference
N	Thermal noise
I_i	Link i interference
η	Vector of thermal noise

η_i	Link i thermal noise
l_{ii}	Link i's shadowing
l_{ij}	Shadowing from Link j's sender to link i's receiver
h_{ii}	Link i's receiver
h_{ij}	Multipath fading from link h's sender to link i's receiver
G_{ii}	Link i's path attenuation
G_{ij}	Path attenuation from link i's sender to link i's receiver
p_i	Transmission power
$p_i^{(.)}$	Link i's transmission power at each iteration
F	Channel gain matrix
F_{ij}	Channel gain matrix entry
d_{ij}	Distance from link j's sender to link i's receiver
$exp(.)$	Exponential function
$\mathbb{E}[.]$	Expectation function
α	Fractional factor
$\in$	Set membership operator
$\Gamma(.)$	Gamma function
$\min(x, y)$	Minimum between x and y
$\max(x, y)$	Maximum between x and y
$\underset{a}{\text{minimum}}(.)$	Minimum of a set or function with respect to a
$\underset{a}{\text{maximum}}(.)$	Maximum of a set or function with respect to a

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ABSTRACT

Wireless networks are being applied in various cyber-physical systems and posed to support mission-critical cyber-physical systems applications. When those applications require reliable and low-latency wireless communication, ensuring predictable per-packet communication reliability is a basis. Due to co-channel interference and wireless channel dynamics (e.g. multi-path fading), however, wireless communication is inherently dynamic and subject to complex uncertainties. Power control and MAC-layer scheduling are two enablers. In this dissertation, cross-layer optimization of joint power control and scheduling for ensuring predictable reliability has been studied. With an emphasis on distributed approaches, we propose a general framework and additionally a distributed algorithm in static networks to address small channel variations and satisfy the requirements on receiver-side signal-to-interference-plus-noise-ratio (SINR). Moreover, toward addressing reliability in the settings of large-scale channel dynamics, we conduct an analysis of the strategy of joint scheduling and power control and demonstrate the challenges.

First, a general framework for distributed power control is considered. Given a set of links subject to co-channel interference and channel dynamics, the goal is to adjust each link's transmission power on-the-fly so that all the links' instantaneous packet delivery ratio requirements can be satisfied. By adopting the SINR high-fidelity model, this problem can be formulated as a Linear Programming problem. Furthermore, Perron-Frobenius theory indicates the characteristic of infeasibility, which means that not all links can find a transmission power to meet all the SINR requirements. This finding provides a theoretical foundation for the Physical-Ratio-K (PRK) model. We build our framework based on the PRK model and NAMA scheduling. In the proposed framework, we define the optimal K as a measurement for feasibility. Transmission power and scheduling will be adjusted by K and achieve near-optimal performance in terms of reliability and concurrency.

Second, we propose a distributed power control and scheduling algorithm for mission-critical Internet-of-Things (IoT) communications. Existing solutions are mostly based on heuristic algorithms or asymptotic analysis of network performance, and there lack field-deployable algorithms for ensuring predictable communication reliability. When IoT systems are mostly static or low mobility, we model the wireless channel with small channel variations. For this setting, our approach adopts the framework mentioned above and employs feedback control for online K adaptation and transmission power update. At each time instant, each sender will run NAMA scheduling to determine if it can obtain channel access or not. When each sender gets the channel access and sends a packet, its receiver will measure the current SINR and calculate the scheduling K and transmission power for the next time slot according to current K, transmission power and SINR. This adaptive distributed approach has demonstrated a significant improvement compared to state-of-the-art technique. The proposed algorithm is expected to serve as a foundation for distributed scheduling and power control as the penetration of IoT applications expands to levels at which both the network capacity and communication reliability become critical.

Finally, we address the challenges of power control and scheduling in the presence of large-scale channel dynamics. Distributed approaches generally require time to converge, and this becomes a major issue in large-scale dynamics where channel may change faster than the convergence time of algorithms. We define the cumulative interference factor as a measurement of impact of a single link's interference. We examine the characteristic of the interference matrix and propose that scheduling with close-by links silent will be still an efficient way of constructing a set of links whose required reliability is feasible with proper transmission power control even in the situation of large-scale channel dynamics. Given that scheduling alone is unable to ensure predictable communication reliability while ensuring high throughput and addressing fast-varying channel dynamics, we demonstrate how power control can help improve both reliability at each time instant and throughput in the long-term. Collectively, these findings provide insight into the cross-layer design of joint scheduling and power control for ensuring predictable per-packet reliability in the presence of wireless network dynamics and uncertainties.

CHAPTER 1. INTRODUCTION

1.1 Wireless Cyber-physical Systems

Cyber-physical systems are physical systems integrated with networks and users, and controlled or monitored by computing process. Cyber-physical systems have applications in a wide variety of areas such as transportation, manufacturing, energy and etc [2][3][4]. Communications between sensors, controllers, and systems still primarily use wired networking today, however, wireless solutions have long been considered a good technical solution due to its reduced costs, easy deployment and improved long-term reliability.

Automotive manufactures are using wireless networks as media to deliver on-board diagnostic data to detect equipment failures, safety risks, and defects [5]. Commercial transportation companies are utilizing sensors from vehicles to identify potential breakdowns and perform preventive and predictive maintenance [6]. For oil and gas producers and refineries, minimizing systems downtime is important, and the industry is using more and more sensors, networks, and analytic tool to generate predictive insight into equipment performance and maintenance. To increase efficiency in factories, wireless technology is essential for communicating with automated mobile equipment, such as shuttle systems, so that they can easily move around the automated storage and retrieval areas. Reliable wireless communication is expected to enable technicians wearing AR head-mount-displays in factories to communicate with remote experts in troubleshooting [7].

Wireless cyber-physical systems are mission-critical and often-times safety-critical. They generally have more strict requirements on reliability and latency compared to human-oriented networks. The low cost, installation benefits and the scaling ability provided by the wireless sensors have increased the interest in the research of process control using short-range wireless technologies, e.g., IEEE 802.15.4. However, new measurements from sensors should arrive at the controller within a specific time interval, sometimes even smaller than 500 ms, to maintain stability of the control loop.

Moreover, a packet delivery ratio/reliability with 99.999% and air-interface delay with 1 ms may be required as well as indicated in [8][9]. Ultra-reliable and low-latency wireless communication are becoming key metrics and challenges to enable large-scale deployment of wireless cyber-physical systems.

1.2 Wireless Communication Reliability

1.2.1 Path loss, shadowing and multipath fading

Wireless communication is inherently dynamic and subject to complex uncertainties. Due to the broadcast characteristic of electromagnetic wave, a radio link in a wireless network may suffer from signal reflection, diffraction, and scattering from surrounding objects when the signal propagates from a transmitter to its receiver. These phenomena result in channel variation and greatly determine wireless communication reliability.

Path loss, or path attenuation, is the reduction in power density (attenuation) of an electromagnetic wave as it propagates through space. Path loss is the main energy attenuation between the transmitter and the receiver for any link. Path loss can be represented by the *path loss exponent*, whose value is normally in the range of 2 to 4 [10]. Some experimental results can be found in [11]. Shadowing as another source of channel variation comes from large obstacles or buildings and is like the effect of clouds partly blocking sunlight [10]. The duration of shadowing lasts for multiple seconds or minutes. The signal radiated by a transmitter may also travel along many and different paths to a receiver simultaneously; this effect is called multipath fading. The differences in delays among different paths will cause distortion of the original sinusoidal signal in terms of amplitude and phase. Multipath fading dominates instantaneous channel variation.

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 $f_c(1 - v/c)$ and experiencing a Doppler shift $D_{min} := -f_c v/c$, and the other with a frequency of $f_c(1 + v/c)$ and experiencing a Doppler shift $D_{max} := +f_c v/c$. The frequency shift $f_m = f_c v/c$ is called Doppler shift. Here, f_c is the carrier frequency, and $c = 3 \times 10^8 m/s$ is the speed of light. Doppler spread is the biggest difference between the Doppler shifts. We can write $Ds = D_{max} - D_{min}$, 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 Tc of a wireless channel is defined as the interval over which the magnitude of signal changes significantly. Assuming a mobile is moving at 60 km/h and the carrier frequency f_c is 1800 MHz, the Doppler shift is round 100 Hz, and the coherence time is approximately 1.25 ms. The Doppler shift and coherence time are important metrics to represent channel variation. What needs to be emphasized is that receiver or transmitter motion is the most important factor for channel variation, but the movement of surrounding objects or other changes in propagation path can also result in multi-path fading if the propagation path delay or propagation path itself is experiencing time-varying change. Fig. 1.1 and Fig. 1.2 show instantaneous channel variation and demonstrate 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.

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 [12]. When there is a line-of-sight path between transmitter and receiver, or there is a specular reflection 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 of 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

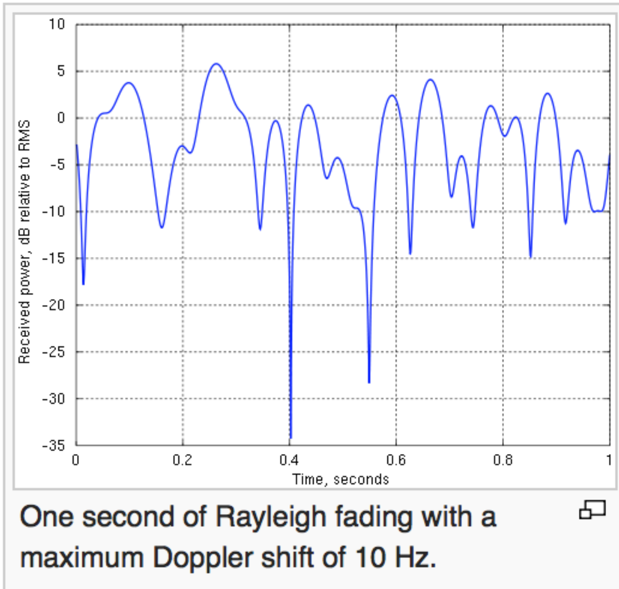

Figure 1.1: Channel variation with 10 Hz Doppler Shift

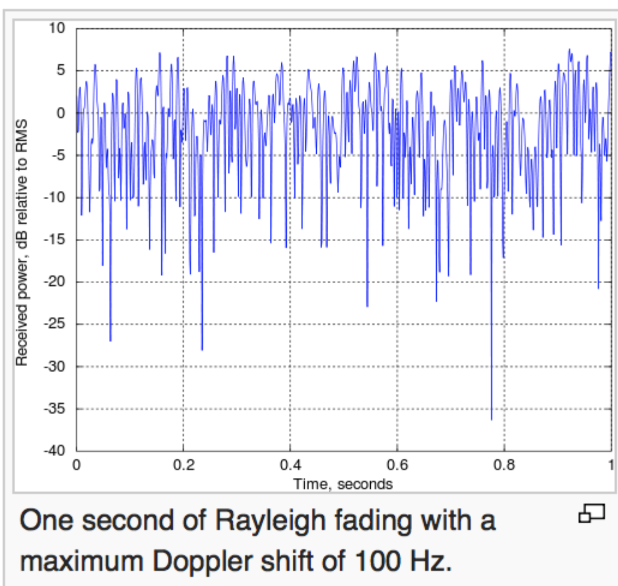

Figure 1.2: Channel variation with 100 Hz Doppler Shift

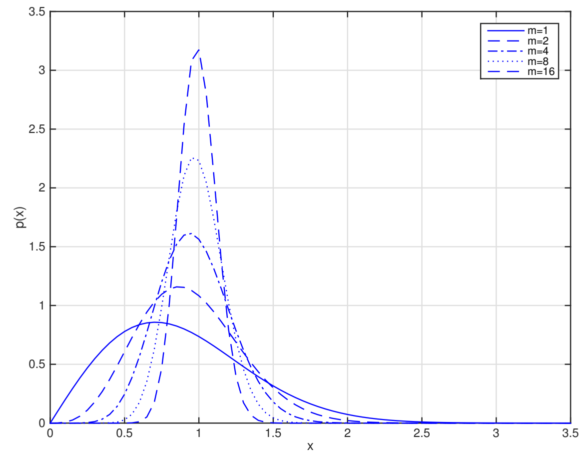

Figure 1.3: The Nakagami pdf with $\Omega_p = 1$.

distributions [13]. The Nakagami model can be used to model the channel which is more or less severe than Rayleigh fading.

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

$$f_\sigma(x) = \frac{x}{\sigma}\exp\{-\frac{x^2}{2\sigma}\} \tag{1.1}$$

where σ is the standard derivation. The corresponding squared envelope is

$$f_{\sigma^2}(x) = \frac{1}{\Omega_p}\exp\{-\frac{x}{\Omega_p}\} \tag{1.2}$$

where $\Omega_p = 2\sigma$. We can see that $f_{\sigma^2}(x)$ 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

$$f_\sigma(x) = 2(\frac{m}{\Omega_p})^m\frac{x^{2m-1}}{\Gamma(m)}\exp\{-\frac{mx^2}{\Omega_p}\}, \quad m \geq 1/2. \tag{1.3}$$

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

$$f_{\sigma^2}(x) = (\frac{m}{\Omega_p})^m\frac{x^{m-1}}{\Gamma(m)}\exp\{-\frac{mx}{\Omega_p}\} \tag{1.4}$$

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. We plot the Nakagami pdf for comparison and analysis as in [12]. From Fig. 1.3, we see that the 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.

The squared envelope is important for the performance analysis because it is proportional to the received signal power and, hence, the received signal-to-interference-plus-noise ratio. Considering path loss, shadowing and multi-path fading we discuss above, the received signal at any receiver in wireless cyber-physical systems would be a random signal and change over time. The effect of path loss, shadowing and multiple-fading can be represented in Fig. 1.4.

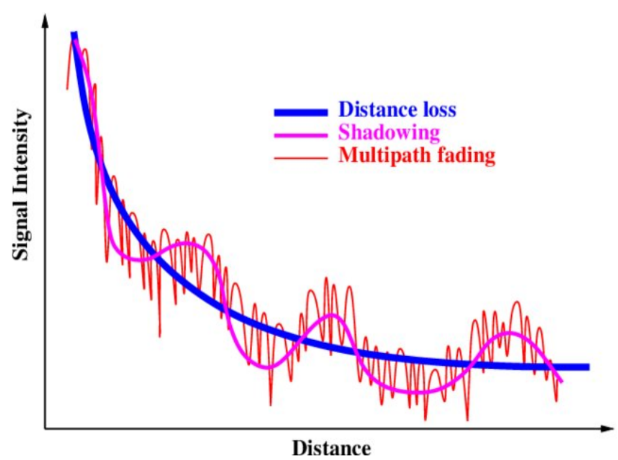

Figure 1.4: The effect of path loss, shadowing and multipath fading

1.2.2 Co-channel interference

There is no unified network architecture for cyber-physical communication systems. Different cyber-physical 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 networks 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. 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 cyber-physical 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 receives interference from other cell phones in the neighboring cells as shown in Fig 1.5. 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 cyber-physical communication systems have more limited frequency resources and all links interfere with each other. Therefore, similar to cellular networks we can model all cyber-physical communication systems as ad hoc networks.

The co-channel interference is the main limiting factor in general wireless systems. Commonly, we call them as interference-limited systems when networks' performance, especially capacity, is

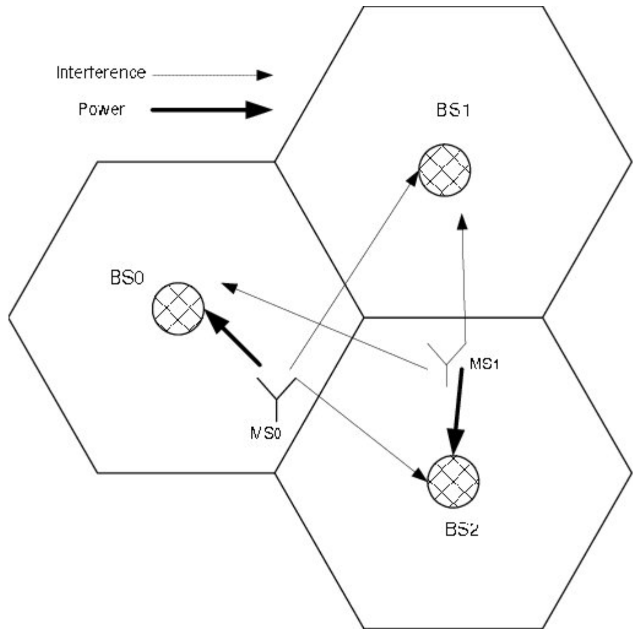

Figure 1.5: Co-channel interference.

limited by co-channel interference. That is because modern cellular networks' performance, especially capacity, is limited by co-channel interference. The co-channel interference in the cyber-physical communication systems may be more severe than cellular networks since few cyber-physical 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 cyber-physical communication systems for managing 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.

1.2.3 SINR model

Despite decades of research on interference-oriented channel access control, there are two widely used models to characterize interference relationship in a wireless network, namely, the protocol model [14] and the physical model. 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 their geographical distance satisfies a certain relationship. The physical model, also known as the SINR model, is based on practical transceiver measurement of communication systems that treat interference as noise. Under the physical model, a transmission is successful if and only if signal-to-interference-and-noise-ratio (SINR) at the intended receiver exceeds a threshold so that the transmitted signal can be decoded with an acceptable bit error probability. The SINR can be written as

$$SINR = \frac{S}{I + N} \tag{1.5}$$

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

In wireless communications, the SINR model is regarded as a high-fidelity interference model in general. Such interference model is considered as a reference model since there exist practical coding schemes to approach its solution in real systems.

However, the difficulty associated with the physical model is its computational complexity in obtaining a solution, particularly when it involves cross-layer optimization in a multihop network environment. This is because SINR calculation is a non-convex function with respect to the transmission powers. As a result, a solution to cross-layer optimization using the physical model is difficult to develop and its computational complexity is likely very high for large-sized networks.

Combining path loss, shadowing and multi-path fading, SINR model can be furthermore represented as in (1.6). Here, p_i represents link transmission power; G_{ii} represents path loss; l_{ii} represents shadowing; h_{ii} represents multipath fading; β_{th} represents SINR threshold.

$$\frac{p_i l_{ii} h_{ii} G_{ii}}{\sum_{j \neq i} p_j l_{ij} h_{ij} G_{ij} + \eta_i} \geq \beta_{th} \tag{1.6}$$

The SINR threshold β_{th}depends on the acceptable BER, detector structure, modulation/demodulation scheme, and channel coding/decoding algorithm. On the other hand, the received SINR depends on the channel attenuation, multiuser interference, antenna gain and transmission power. When any one of the transmission rate, BER requirement, and packet size goes up, the SINR threshold increases as well. The interference relations defined by the physical model are non-local and combinatorial; that is because as shown in (1.6), whether one transmission interferes with another explicitly depends on all other transmissions in the network. That's why addressing the reliability issue in wireless cyber-physical systems would more challenging than expected. We will formulate the SINR requirements of a set of links and demonstrate their relationship later.

1.3 Cross-layer Design for Communication Reliability

There has been a great amount of cross-layer design proposals for wireless networks. A number of researchers have looked at specific aspects of network performance and cross-layer design as mentioned in [15][16][17]. We focus on power control technique through this dissertation.

1.3.1 Power control in cellular networks

Power control provides an intelligent way of determining transmitting power to achieve the quality of service (QoS) goals in wireless channels. Power control has been playing an important role in cellular networks, ranging from 2G GSM and CDMA systems, to 3G networks based on WCDMA or CDMA2000, and to 4G networks based on LTE or LTE-Advanced although there is significant evolution from use experience to supporting techniques.

Power control was first used in the 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 was drawing broad attention in the research community. Of all algorithms, Foschini−Miljanic algorithm [18] (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). There are a great mount research for power control in cellular networks at that time[19][20][21]. Thereafter, Power control became a mandatory component in CDMA systems to address well-known near-far problem and ensure significant intra-cell interference. 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 the 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 [22], two independent control mechanisms together determine the power control scheme of CDMA2000 systems. The first component is the basic power control scheme like CLPC, whose update rate is 600 Hz with step-size 1 dB. 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 meantime, fractional power control [23] is adopted in the 4G LTE system to increase the overall system throughput. It has been proved in [23] when each link only compensates a part of channel attenuation, the overall system throughput can be maximized. A few performance comparison for uplink power control in LTE can be found in [24].

Power control has been utilized to compensate channel attenuation and mitigate co-channel interference. However, 3G and 4G systems aim to improve system capacity and support QoS while GSM and IS-95 would like to maintain fixed SINR. Moreover, power control algorithms are strongly dependent in system architecture and channel variation rates. There is a trade-off between Doppler tolerance, robustness, and spectral efficiency. Distributed power control is of special interest.

1.3.2 The canonical power control

In early cellular systems, the centrally orchestrated control involves added infrastructure, latency and network vulnerability. Successful distributed power control uses only local measurements. J. Zander in [3] reported interesting initial work on distributed power control. Foschini and Miljanic proposed a question:

"Given J deployed users and bases, is it possible to meet the p constraint even with a central controller of power levels? When it is possible, can these same power levels be achieved with a distributed algorithm? If so, how fast can such a distributed power control respond?"

Foschini and Miljanic first proposed a simple and distributed transmission power of the signals for the J users which are evolved to achieve the greatest signal-to-interference ratio are jointly capable of achieving (the same ratio for all J users). The Foschini-Miljanic algorithm can be formulated as follows:

$$P(k+1) = R_0 P(k) + \eta \tag{1.7}$$

where P is a vector of transmission power; R_0 represents channel gain matrix and η represents a vector of thermal noise for each link. This algorithm can be implemented locally as shown in (1.8).

$$p_i^{(k+1)} = \frac{\beta_{th}}{\beta_i} p_i^k \tag{1.8}$$

Each link's current transmission power $p_i^{(k+1)}$ is updated by its previous transmission power, target SINR and current SINR. Since all of them can be measured locally, Foschini-Miljanic algorithm is regarded as a simple and distributed power control algorithm. Assuming the instantaneous channel gain is constant and there exists a fixed point, Foschini-Miljanic algorithm was proved to converge to the fixed point.

The Foschini-Miljanic(FM) algorithm has been regarded as canonical power control algorithm. Although Foschini-Miljanic algorithm builds on an assumption that there exists a fixed point, that is the convergence value, the Foschini-Miljanic algorithm serves as a foundation of all distributed power control algorithms. There are a great amount of variants by relaxing the assumption of constant channel gain or have different settings. Generally, FM algorithm and its variants base their power-control schemes on the observed signal-to-interference ratio (SIR) at the receiver or the knowledge of the gains of all the links. Thus, the implicit assumption made is that the power-control updates are made every time the fading state of the channel changes, i.e., whenever the gain of any link.

1.3.3 Power control in dynamical networks

Traditional power control schemes whether centralized or distributed, assume quasi-stationary of the fading wireless channels. However, a few scenarios have exhibited fast fading where the fades can change within milliseconds (at 900 MHz and mobile traveling at 60 mph). Channel inversion is a method for addressing reliability in fast fading channel which 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

$$p_i = \frac{1}{h_iG_{ii}} \tag{1.9}$$

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

$$P_i = \frac{1}{(h_iG_{ii})^\alpha} \tag{1.10}$$

where α is the fractional number between 0 and 1. Jindal et al. in [23] 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 not any proof that they can guarantee short-time or instantaneous packet delivery rate since most of them only care about their own channel variation.

There is alternative power control scheme in which the transmission power does not need to be updated whenever the channel meanders from one fading state to another. Instead, they explicitly take into account the statistical variation of the SINR of each transmitter/receiver pair and optimally allocate power to minimize probability of fading-induced outage (which occurs when the SINR falls below a threshold). Given the required outage probability for each link, the problem of power allocation that minimizes outage probability is shown to be a convex problem that can be solved globally and efficiently, even when other constraints (such as on individual powers, total power, etc.) are included in the power-allocation problem. However, it is still tough to obtain the optimal transmission power in a distributed way.

Neely et al. in [25] considered dynamic routing and power allocation for a wireless network with time varying channels. The network consists of power constrained nodes which transmit over wireless links with adaptive transmission rates. Packets randomly enter the system at each node and wait in output queues to be transmitted through the network to their destinations. A joint routing and power allocation policy is developed which stabilizes the system and provides bounded average delay guarantees whenever the input rates are within this capacity region. Dulek et al. [26] studied power control issue to minimize outage probability in Gaussian channels and proved that the optimim transmission power strategy involves randomization.

1.3.4 Joint scheduling and power control

For wireless communication systems, one basic task of the link layer is to address channel variation or channel fading [10]. 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.

Although Foschini-Miljanic algorithm builds on an assumption that there exists a fixed point, that is the convergence value, however, in a real network, there may not exist a feasible power control for all links to satisfy the target SINR. The reliability issue can be modelled as joint scheduling and power control. The problem of scheduling non-conflicting transmissions, in order to achieve efficient spatial reuse, TDMA multi-hop packet radio networks has received considerable attention in the literature [27]. In reality, the aggregate interference of a large number of far transmitters could be significant and may cause the SINR to fall below the threshold and, hence, disrupt an ongoing communication.

Definition 1. In TDMA wireless ad hoc networks, a transmission scenario is valid iff it satisfies the following three conditions.

1. A node is not allowed to transmit and receive simultaneously.

2. A node cannot receive from more than one neighbor at the same time.

3. A node receiving from a neighbor should be spatially separated from any other transmitter by at least a distance .

The choice of the parameter affects the amount of interference eliminated via scheduling. If is too small, no spatial separation between simultaneous transmissions is guaranteed and most of the interference will be passed to the power control phase. On the other hand, if it is large, considerable amounts of interference are eliminated via the scheduling phase. For example, to limit multiuser interference to levels comparable to those in channelized cellular systems, the parameter should be equal to the well-known "frequency reuse distance" parameter [37]. The choice of the parameter generally depends on the minimum acceptable SINR levels.

This problem above 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 uses the approach 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.

The joint scheduling and power control approach introduces a cross-layer design framework to the multiple access problem in contention-based wireless ad hoc networks. The power control (physical layer problem) and time-division multiple-access (TDMA) scheduling (multiple access problem) have been largely studied in isolation, namely. The studies have proposed to solve the multiple access problem via two alternating phases that search for an admissible set of users along with their transmission powers. In the first phase, the scheduling algorithm is responsible for coordinating independent users' transmissions to eliminate strong levels of interference inherent to wireless ad hoc networks. In the second phase, power control is executed in a distributed fashion, to determine the "admissible" set of powers that could be used by the scheduled nodes, if one exists. If no set of positive powers can be found, control is transferred again to the scheduling phase to reduce interference via deferring the transmissions of one or more users participating in this scenario. Detailed challenges can be found in [28].

1.4 Dissertation Contribution

This dissertation discusses several issues regarding power control for guaranteeing predictable communication reliability in wireless cyber-physical systems. The contribution of this dissertation can be summarized as follows:

- Chapter 3 has conducted a systematic investigation of power control approaches. It analyzes the theoretical results of power control in a deterministic channel. The normalized interference is directly related to the Perron root and feasibility; when the interference is bounded, the Perron root will be bounded. By this observation, adopting the PRK model and NAMA scheduling as the foundation of the framework, a distributed framework was proposed to do joint scheduling and power control in a distributed way to guarantee communication reliability. The proposed framework is expected to serve as a foundation for distributed scheduling and power control.

- Chapter 4 has aimed to leverage scheduling and power control to support reliable IoT applications. Specifically, it focused on ensuring high concurrency while guaranteeing application-required communication reliability. It adopted the framework proposed in Chapter 3 and employed power control algorithm to update transmission power per SINR feedback. The algorithm improves concurrency by 70% than state-of-art fixed scheduling while ensuring successful SINR tracking over time. This approach is the first distributed scheduling and power control scheme that ensures predictable wireless communication reliability while considering real-world challenges such as fast channel fading, and it is expected to serve as a foundation for real-world deployment of mission-critical IoT systems.

- Chapter 5 has investigated power control approach in addressing large-scale channel dynamics in wireless networks. An analysis of joint scheduling and power control in guaranteeing predictable per-packet communication reliability was presented. The analysis has showed that scheduling is a must and power control can help improve concurrency. A few insights come out for conducting protocol design. Silencing closing-by links will help regulate co-channel interference to ensure SINR feasibility and high transmission concurrency. The Canonical Foschini-Miljanic power control algorithm can help improve transmission concurrency when applied together with scheduling. The numerical results also demonstrated, when using the Foschini-Miljanic power control algorithm, how transmission power changes over time in the case of SINR feasibility and infeasibility respectively. The evaluation results have demonstrated the benefits of joint scheduling and power control even in a real distributed implementation. The results have also demonstrated the challenges in guaranteeing per-packet communication reliability and SINR, for instance, with the randomness in NAMA scheduling introducing non-negligible variations in SINR, and they have suggested future directions of research.

1.5 Dissertation Organization

This dissertation is organized as follows. First, literature review is given in Chapter 2. Then, a general distributed framework is proposed in Chapter 3 and a distributed scheduling and power control for IoT communication reliability is studied in Chapter 4. Chapter 5 introduces analysis of joint scheduling and power control for predictable URLLC in industrial wireless networks. Chapter 6 concludes this dissertation and presents future research.

CHAPTER 2. LITERATURE REVIEW

2.1 A Simple Power Control Algorithm

Jens Zander [29] first analyzed and derived the upper performance bounds for transmitter power scheme in cellular radio system to reduce co-channel interference. Foschini and Miljanic [18] proposed a simple effective means of power control of signals associated with randomly dispersed users in cellular networks. By regulating inter-cell interference and effecting the lowest interference environment, in meeting a required minimum signal-to-interference ratio per user, channel reuse is maximized. The proposed approach can be implemented in a distributed way with only local SINR measurement required and converge to a fixed point, which is the optimal point on minimizing This creative work has been extensively studied and placed a foundation for power control. Huang et al. [30] proposed a discrete version where each link updates their transmission by a fixed step and discussed its application in admission control. When the convergence property of distributed power control is very important, Leung et al. [31] proposed a general class of power control algorithms and proposed the conditions of its 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 point or quickly detect the case of infeasibility. Huang and Yates [30] showed that Foschini−Miljanic algorithm converges to an unique fixed point at a geometric rate. If the system can support all users at the target CIR, iterative power control guarantees convergence to a fixed point at a geometric rate for both fixed base station assignment and minimum power assignment. In the presence of maximum power constraints, geometric convergence to a unique fixed point always occurs. Other than power control alone, there are lots of variants regarding to combine Beamforming and BS assignment [32]. The readers can see more algorithms in [33][34]. Feyzmahdavian et al. [35] introduced counteractive interference functions to analyze a class of power control algorithms that can guarantee the existence and uniqueness of fixed points along with linear convergence of iterates.

2.2 Power Control in Wireless Sensor Networks

The study of power control in wireless ad hoc networks started in the early 2000s. Gupta et al. [36] have discussed the system capacity limitation due to co-channel interference and proved that when n identical randomly located nodes, each capable of transmitting at W bits per second, forms a wireless network, the throughput is only $\Theta(\frac{W}{\sqrt{n}})$ for each node, even in the optimal circumstances. This finding shows that when the number of concurrent nodes in a unit area increases, the throughput for each node can approach 0. This work has indicated that it is crucial to mitigate co-channel interference by optimally utilizing power control and scheduling in wireless sensor networks. Elbatt and Ephremides [37] 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 [18] 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. Kawadia et al. [38] distilled some basic principles on power control. Wan et al. [39] 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 [40] and [39].

Ikram et al. [41] presented a tramsmission power control algorithm to address industrial issues concerning energy consumption. The proposed algorithm assumed a linear approximation between the transmission power and RSSI. When the received RSSI falls beyond estimated value, transmission power control will be triggered.

2.3 Optimization of Joint Scheduling and Power Control

Elbatt and Ephremides [37] first introduced joint scheduling and power control framework in wireless ad hoc networks and formulated this issue as a Mixed Integer Linear Programming (MILP) [42] optimization problem. Due to its NP-hardness, approximation algorithms naturally arise. This model disclosed the optimization challenge of joint scheduling and power control. Leveraging the finding that the cumulative interference can be bounded, graph theory is used for solving scheduling and power control and 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. Magnús M. Halldórsson conducted extensive research on joint scheduling and power control [43]. Those work mainly focuses on obtaining asymptotic characterization of joint scheduling and power control. In [43], Magnús M. Halldórsson divided all links into subsets with equal link length. Each subset is then scheduled separately through graph coloring. Halldórsson and Tonoyan [44] presented the first-approximation algorithm, which is claimed as the best among oblivious power schemes. Although all these approximation algorithms have an good asymptotic bound, their practical concurrency is very low. Meanwhile, they assumed obvious transmission power algorithms [44][45], such as constant power, power inversion, and those algorithms are rarely implemented in a distributed way.

2.4 Address Channel Dynamics using Power Control

Lin et al. [46] has evidenced in their field tests that channel attenuation changes over time and adaptive transmission power control is required to obtain reliable packet delivery over time. They conducted extensive empirical studies and confirmed that the quality of radio communication between low power sensor devices varies significantly with time and environment. This phenomenon indicates that previous topology control solutions, which use static transmission power, transmission range, and link quality, might not be effective in the physical world. This paper presents ATPC, a lightweight algorithm of Adaptive Transmission Power Control for wireless sensor networks. With this model, they employed a feedback-based transmission power control algorithm to dynamically maintain individual link quality over time, and their in-situ experiments revealed the correlation between RSSI/LQI and link quality. They set up a model to predict the proper transmission power, which is enough to guarantee a good packet reception ratio. However, their experiments were designed without congestion and collision.

Kandukuri and Boyd [47] proposed a new method of power control for interference limited wireless networks with Rayleigh fading of both the desired and interference signals. Their method explicitly took into account the statistical variation of both the received signal and interference power, and optimally allocates power subject to constraints on the probability of fading induced outage for each transmitter/receiver pair. They built several results including the equation between optimal transmission power and desirable packet delivery ratio.

Holliday et al. [48] attempted to address channel dynamic issue but only obtained average SINR and concluded that FM algorithm may bring SINR overshoot issue. Previous work in this area has focused on distributed control for ad-hoc networks with fixed channels and the algorithms resulting from such formulations do not accurately capture the dynamics of a time-varying channel. They revealed that he performance of the network in terms of power consumption and generated interference, can be severely degraded when power and admission control algorithms that are designed for deterministic channels are applied to random channels. In order to address these problems, they presented new distributed power and admission control algorithms for ad-hoc wireless networks in random channel environments and a new criterion for optimal transmission power in ad-hoc wireless networks was proposed. A modified version of this algorithm for tracking non-stationary equilibrium was presented, which allows to perform admission control. Ultimately, the iterations of the stochastic approximation algorithms can be decoupled to form fully distributed online power and admission control algorithms for ad-hoc wireless networks with time-varying channels.

2.5 Power Control for System Performance Improvement

Chiang et al. [49] 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) [50] 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 [49].

Cruz and Santhanam [27] studied joint power control, rate control, and scheduling to minimize total average transmission power with the minimum average data rate constraints per link in a long term. Cruz and Santhanam formulated the issue as a duality problem via the Langrage Multiplier method and decomposed the whole issue into a 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 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 rates 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. Rashtchi et al. [51] studied the same issue to determine the data routes, subchannel schedules, and power allocations that maximize a weighted-sum rate of the data.

Dams et. al in [52] studied the convergence of distributed protocols for power control in a non-cooperative wireless transmission scenario. They proposed a framework that uses learning algorithms and iterative discrimination for power control and showed roughly a polynomial number rounds for all links to converge to target SINR. Lee et al. [53] considered a hybrid networks in cellular setting with D2D communication to maximize the sum rate of D2D links using power control. Wang et al. [54] considered the dynamic power control for delay-aware D2D communications.

2.6 Conclusion

In this chapter, related works in the area of power control are presented. Theoretical modelling and approximate approaches of joint scheduling and power control have been well studied. However, distributed approaches have been rarely proposed and are field-deployable in large wireless networks. Accordingly, this dissertation focuses on investigating distributed field-deploy-able power control approaches.

CHAPTER 3. A PHYSICAL-RATIO-K MODEL-BASED POWER CONTROL FRAMEWORK

In this chapter, we investigate power control technique for improving reliability in cyber-physical systems. We model wireless networks in cyber-physical systems as ad-hoc networks and narrow down the reliability issue into addressing co-channel interface and channel dynamics. We propose a distributed power control framework for guaranteeing wireless channel reliability.

3.1 Introduction

We started our study from cellular networks. However, we quickly found that wireless cyber-physical systems are different from cellular networks in a few respects. First, there is an obvious difference in network architecture. For instance, wireless sensor networks' architecture tends to be ad-hoc or 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. Without support of central controllers, such as base stations in cellular networks, the distributed protocol design is challenging. Secondly, wireless networks in cyber-physical systems may face much harsher network and environmental uncertainties as compared with traditional cellular networks. Thirdly, different from wireless cellular networks, where system throughput is the main performance metric, packet delivery reliability in cyber-physical networks tends to be more critical. At the early development stage of wireless networks in cyber-physical systems, 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. In recent years, the emergence of vehicular networks has brought up this issue even more urgent [18] when the main application of vehicular networks is to support vehicle active safety, and the broadcast of safety messages makes the traffic load high. For most wireless networks, there is a trade-off between reliability, delay, and throughput. Reliability guarantee of high-load traffic is challenging, especially when the channel is dynamic. We seek fundamental power control framework to address reliability issue along with channel dynamics.

For wireless communication systems, one basic task of the link layer is to address channel variation or channel fading [10]. 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 the 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 the 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 links. In cyber-physical communication systems, power control schemes tend to be implemented in a distributed way. Thus the timescale 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 [55].

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 cyber-physical communication systems. A general distributed framework is proposed in this chapter.

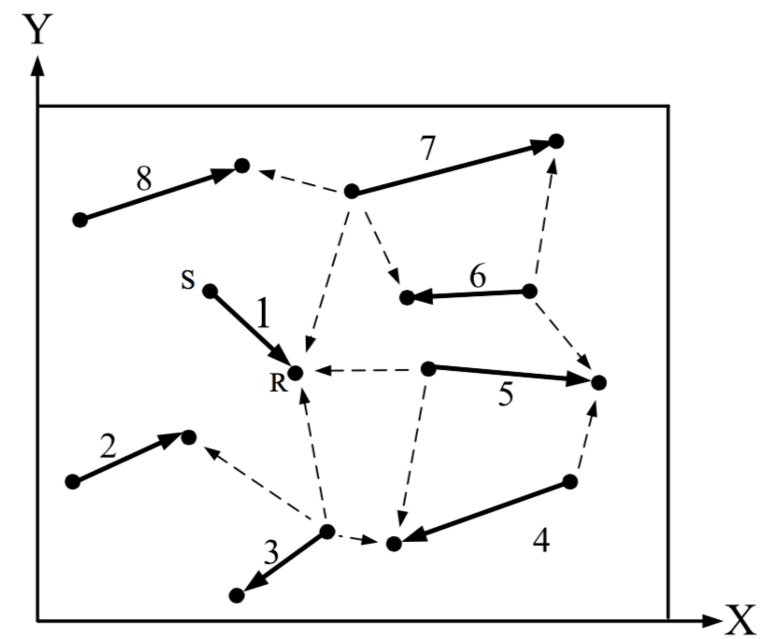

Figure 3.1: The ad hoc network architecture of wireless cyber-physical system

3.2 System Model

We model the wireless network in cyber-physical systems or a partial layer as ad hoc networks if only co-channel interference is considered. It is quite reasonable to model all cyber-physical communication systems as ad hoc networks as far as power control is concidered. We model an ad hoc network and show the co-channel interference characteristic among links in Fig. 3.1. As showed in in Fig. 3.1, for example, link i will receive interference from all links, but for simplicity we only show partial interfering links from the nearby links such as link 3, 5, and 7.

Subject to shadowing and multipath fading, wireless channels change over time. However, wireless channels in static networks are usually modeled as constant channels for the purpose of analysis; it is also reasonable since the coherence time has a relatively larger scale compared to communication time. Given a large network with the fixed channel gain, the problem of power control becomes finding the maximum feasible set of links and their corresponding optimal transmission power. Such an issue can be modeled as joint scheduling and power control, and it is theoretically

NP-hard. 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 receiver-side SINR at a link i ($i = 1, 2, 3...n$) can be represented as (3.1):

$$SINR_i = \frac{p_i h_{ii} g_{ii}}{\sum_{j \neq i} p_j h_{ij} g_{ij} + n_i}, i = 1, 2, 3...N \tag{3.1}$$

where $g_{ij} > 0$ is the power gain from the transmitter of the jth link to the receiver of the ith link, p_i is the power of the ith transmitter, and n_i is the thermal noise power at the ith receiver.

For the random channel, it is impossible to guarantee 100% packet delivery. We use packet delivery rate or outage probability to measure link reliability. Outage probability is an important metric to measure communication reliability in wireless networks. The formal definition of outage probability is as follows

$$O_i = \Pr(\beta_i < \beta_{th}) \tag{3.2}$$

Furthermore, we can rewrite the outage probability as

$$O_i = \Pr(p_{ii} h_i G_{ii} < \beta_{th} \sum_{j \neq i} p_{ij} h_{ij} G_{ij}) \tag{3.3}$$

The general purpose is to find transmission power to have outage probability guaranteed for each link. Through this dissertation, we aim to address this issue with predictable per-packet reliability.

3.3 Key Theoretical Results

3.3.1 Feasible and optimal power control

Let's consider constant channel first. Given a set of transmitter-receiver pairs, we would like to find a transmission power for each link to satisfy their SINR requirements. According to the SINR model, a link would transmit a packet successfully if and only if

$$\frac{p_i G_{ii}}{\sum_{j \neq i} p_j G_{ij} + \eta_i} \geq \beta_{th} \tag{3.4}$$

where p_i is link i's transmission power; G_{ii} is link i's channel gain; G_{ij} is the channel gain from link j's sender to link i's receiver; n_i is link i's receiver-side thermal noise; β_{th} is link i's target SINR.

We assume all links have the same target SINR. As shown in (3.4), individual link's SINR depends on other links' transmission power. To obtain a transmission power for each link, we can transform the SINR model in (3.4) into a matrix form and we have the transformed form

$$P \geq FP + \eta \tag{3.5}$$

and

$$F_{ij} = \begin{cases} \beta_i G_{ij}/G_{ii}, \text{ if } i \neq j \\ 0, \text{ if } i = j \end{cases} \tag{3.6}$$

and

$$\eta_i = \beta_i n_i / G_{ii} \tag{3.7}$$

where P is a vector of each link's transmission power, and n_i is link i's thermal noise. Each entry of F represents the normalized interference multiplied by the SINR target. The normalized interference is obtained by dividing each link's interference by its channel gain. The inequality (3.5) 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 Programming, if there exist solutions for the inequality (3.5), 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* [56] by optimization convention. By solving the linear equation, we have the fixed point

$$P^* = (I - F)^{-1}\eta \tag{3.8}$$

P^* is the minimum value 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 [18] first proposed the simple and autonomous algorithm to obtain the fixed point. The algorithm is as

(3.9)

$$P_{t+1}^i = \beta_i P_t^i / r_t^i \tag{3.9}$$

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_t^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 can be easily implemented. Foschini and Miljanic in [18] proved this algorithm can synchronously converge to the fixed point. Most of the following distributed power control algorithms are based on this algorithm.

3.3.2 In-feasibility of power control

In contrast, the Linear Programming constraint in (3.5) may have no solutions. That is, we cannot find a transmission power for each link to ensure they transmit concurrently. We can introduce the Perron−Frobenius Theory [57] to explain the feasibility of the Linear Programming problems.

Theorem 1. *[57] 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 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 [57].

Lemma 2. *(Feasibility condition [57]) A set of links is feasible if and only if $\lambda(F) \leq 1$ when $\eta = 0$ and $\lambda(F) < 1$ when $\eta \neq 0$.*

Lemma 3. *(Optimum power [57]) If a set of links is feasible, the optimum power is $P^* = (F-I)^{-1}\eta$.*

Once a set of links is 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 systems since a real system almost needs scheduling to remove strong interference. The objective of joint scheduling and power control is to find a set of active links and their feasible transmission power.

The theory above indicates feasibility and optimality of power control in large networks assuming the channel is constant. Actually this theory can be extended into dynamical networks as well. We will discuss later.

3.4 Representative Power Control Schemes

Power control schemes can be significantly different in the situation with the consideration of multipath fading or not. Generally assuming 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.

3.4.1 Conflict graph-based power control for constant channels

In ad hoc networks, it is necessary to suppress transmissions by nodes around the desired receiver in order to achieve successful communication. Hasan and Andrews in [58] first proposed the concept of guard zone. They showed that the size of this exclusion zone has a large impact on the transmission capacity of ad hoc networks, and an optimal guard zone can be found using stochastic geometry. These results provide useful insight in the design of contention resolution algorithms as compared to pure random access in ad hoc networks.

In the real implementation, 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 channels are approximate methods. Most approximate algorithms utilize the fact that the total

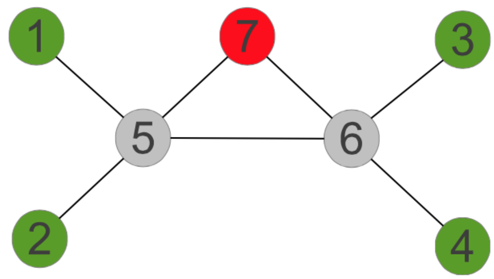

Figure 3.2: Link conflict graph [1].

interference from links beyond a certain distance can be upper bounded [43]. 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 a simple path loss model, we can calculate the accumulated interference as [43]

$$I = \sum_{d_{ij} > \rho} c/d_{ij}^{\alpha} \tag{3.10}$$

where c is a constant related to path loss and transmission power, d_{ij} is the distance from link j's sender to link i's receiver, and α is the path loss index. Assuming 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 in (3.10) by ensuring any specific SINR requirement. 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 a maximal 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 3.2, link 5 is in 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 the conflict graph-based approach as discussed in [59]. When we build the conflict graph, we mean that a link is conflicting with all links within the distance ρ. This implicitly indicates that the conflict links cannot transmit concurrently because 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 a big sacrifice in concurrency.

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 wireless communication systems.

3.4.2 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. It is impossible to guarantee 100% packet delivery. We use packet delivery rate or outage probability to measure link reliability. For Rayleigh fading, its distribution is an exponential function as we discussed in the previous section and is easy to be analyzed. Most analytical models assume that channel fading follows the Rayleigh fading model. We can obtain a closed form of outage probability [47]

$$O_i = 1 - \prod_{j \neq i} \frac{1}{1 + \frac{\beta_i G_{ij} P_j}{G_{ii} P_i}} \tag{3.11}$$

where O_i is the outage probability and P_i is the transmission power. More details about geometric programming can be found in [50]. 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 is always related to static or average channel characteristics. Furthermore, we define the minimum outage probability as

$$O^* = \min_P \max_i O_i, \quad P_i > 0. \tag{3.12}$$

P is a vector of P_i, and O^* is the minimal value of the maximum outage probability among all links. Syod et al. in [50] has proved the relationship between O^* and channel gain matrix F. We have

$$\frac{\lambda}{1+\lambda} \leq O^* \leq 1 - \exp^{-\lambda} \tag{3.13}$$

where λ is the *Perron root* of the constant gain matrix. There is a very interesting quantitative result here. If target SINR is fixed and λ 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 a 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

$$\text{Maximize } R_i \tag{3.14}$$

Subject to

$$O_i \geq O_{i,min} \tag{3.15}$$

$$R_i \geq R_{i,min} \tag{3.16}$$

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 [60]. 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 non-convex especially in the low SINR region. The current effort in the research community is mainly focusing on efficiently converting a non-convex issue into a convex issue.

3.5 The Adoption of Physical-Ratio-K Model

In general, the conflict graph-based power control approach works for static networks with constant channels, and the geometric programming-based power control approach is applicable for mobile networks with fading channels. These two approaches assume that large-scale channel gain is constant over a long time. There are obvious drawbacks for the two approaches: time consuming and low concurrency. Thus we suggest adaptive power control in cyber-physical communication systems should move toward adaptive power control approaches. In this section, we will discuss the possibility of adaptive power control. Neither of approaches above is a good foundation for distributed interference control in the presence of uncertainties[61][62][63].

Zhang et al. [61] proposed the PRK interference model and the corresponding adaptive scheduling algorithms [64]. The PRK model leverages some inherent characteristics of wireless networks like bounded interference and removes 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 the real communication systems. The PRK model defined a loose conflict graph. Different from conflict graph in static networks, where conflict graph is based on a 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 a loose conflict graph based on the ratio K of the link' instantaneous received signal to 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

$$P(C', R) < \frac{P(S, R)}{K_{S,R,Ts,R}} \tag{3.17}$$

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

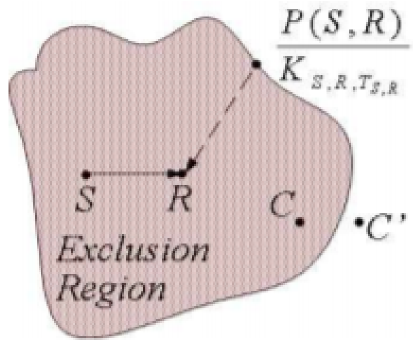

Figure 3.3: The physical-ratio-K (PRK) interference model

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.

The physical-ratio-K(PRK) model [61] is an interference model that defines the conflict relationship between two links. In other words, this model determines whether two links can transmit at the same time or not. According to the PRK model, a link j conflicts with a link i if

$$G_{ij} \geq \frac{G_{ii}}{K_{ii}} \tag{3.18}$$

We find that the parameter K_{ii} of the PRK model is directly related to the feasibility of gain matrix F. For each link, a given K_{ii} would divide all links into conflicting links and concurrent non-interfering links. If K_{ii} is too large, most links will be regarded as conflicting links and sacrifice concurrency; if K_{ii} is too small, the concurrent links are not necessarily non-interfering. Thus finding the exact K_{ii} is very important.

3.6 Proposed Joint Scheduling and Power Control Framework

In this section, we present a distributed framework to obtain near-optimal scheduling and power control.

3.6.1 Observations on Perron Root

It is well known that for a nonnegative matrix A, the smallest row sum of A and the largest row sum of A provide lower and upper bounds, respectively, for the Perron root of A[11]. Furthermore, the increase for any element of A will increase the Perron Root of A [12]. If the distance-based path loss law is adopted, the large element of F corresponds to the link with short interfering link length, which means the close-by links have the most important impact on concurrent transmission. In order to guarantee reliable transmission, the close-by links should not be scheduled at the same time.

According to the perron root theory, we can obtain a few observations.

Corollary 4. *If all row sums of a gain matrix is less than 1, the set of links are feasible.*

Corollary 5. *If all row sums of a gain matrix is larger than 1, the set of links are infeasible.*

Corollary 6. *If a gain matrix has minimal and maximal row sum, respectively s_{min} and s_{max}, $s_{min} <= \lambda <= s_{max}$*

Each entry in the gain matrix means the interference. The row sum is the aggregated interference. Thus if the aggregate interference is bounded, then Perror root is bounded.

Once we find the feasible K for each link and build a conflict relationship, we can use NAMA scheduling [65] to select concurrent links. NAMA scheduling is a distributed approach to channel access scheduling for wireless ad hoc networks. Based on known conflict relationships, each link calculated a priority for itself and all its conflict links. A link would get access to the channel if it has the highest priority among all its conflicting links.

Therefore, back to feasibility condition and PRK model, to ensure reliability becomes finding the feasible K and optimal transmission power for each link. Under channel dynamics, feasibility condition would change and scheduling K (i.e., the parameter K of the PRK model) may change as well. The next section will present how the system converges to an near-optimal K and feasible transmission power over channel variations.

3.6.2 The Framework

This framework consists of the channel measurement module, NAMA scheduling module, SINR measurement module, and PRK adaptation and transmission power update module. For slowly time-varying IoT systems, the channel measurement module will measure average channel at setup stage and update it at a long timescale. All packets are sent in the data channel. At each time slot, each sender will run NAMA scheduling to determine if it can obtain channel access or not. When a sender gets the channel access, it will send a packet, and its receiver will then measure current SINR and send it back to the sender via acknowledgement packet. So the whole system requires ACK feedback. When the sender receives current SINR, it will calculate the scheduling K and transmission power for the next time slot according to current K, transmission power and SINR. This distributed framework will run as shown in Algorithm 1.

Input: P_i^1, K_i^1, β_{th}
Output: p_i^t, x_i^t
$\bar{G}_{i,j}$ = MeasureAverageChannel();
for $t \leftarrow 1$ **to** T **do**
  x_i^t = NAMAScheduling(k_i^t, $\bar{G}_{i,j}$);
  β_i^t = MeasureSINR(p_i^t, x_i^t);
  (p_i^{t+1}, k_i^{t+1}) = UpdateSchedulingKandPower(p_i^t, k_i^t, β_i^t, β_{th});
end

Algorithm 1: A framework of distributed scheduling K and power control

This is an adaptive power control framework that builds iterative scheduling and power control update, which has the flexibility to respond channel dynamics. Depending on scale of channel dynamics, the algorithm of transmission power and scheduling can be finely adjusted.

3.7 Conclusion

In this chapter, we analyzed the theoretical results of power control in deterministic channel. We observed that the normalized interference is directly related to the Perron root and feasibility. Once the interference is bounded, the Perron root will be bounded. By this observation, we adopted the PRK model and NAMA scheduling as the foundation of the framework. We defined the optimum K and proposed a distributed framework to update scheduling and K. In this framework, scheduling and power control will alternatively run. We prove the feasibility of our framework by analytical approach. This adaptive power control framework will be a foundation for distributed power control and scheduling algorithms.

CHAPTER 4. DISTRIBUTED SCHEDULING AND POWER CONTROL FOR IOT RELIABILITY

In this chapter, we further investigate the optimization issue of joint scheduling and power control and focus on adaptive power control algorithm to guarantee SINR for small-scale channel variation. We present a distributed power control and scheduling algorithm and demonstrate the significant improvement in concurrency while guaranteeing reliability.

4.1 Introduction

Wireless networks are stepping into a new era from human-oriented cellular networks to ubiquitous IoT. The emergence of IoT is changing our vision for future wireless networks. Wireless network standards such as ISA100.11a and WirelessHART [66] have facilitated applications of IoT in industrial automation, home intelligence, and health care [67][68][69]. While those standards try to improve wireless communication reliability through mechanisms such as graph routing [70] and packet retransmission, their sacrifice in channel spatial reuse and system capacity have impeded at-scale deployments of IoT. In the meanwhile, Petersen and Aakwag [71] have verified that wireless instrumentation for safety-critical applications in oil and gas industry are still confronted with a serials of issues such as weak RF signals, interference, and multi-path fading [10]. Furthermore, wireless networks in the current IoT practice under star and mesh topology will inevitably suffer from increased co-channel interference from close-by links as network traffic increases and as network scales up. These issues call for new network designs to enhance the reliability and capacity of wireless networks for mission-critical applications.

Uncertainties of wireless networks mainly come from co-channel interference and channel dynamics (e.g., due to shadowing and multi-path fading). It is undoubted that redundant designs such as graph routing and packet re-transmission can improve network reliability to some extent, but they cannot eliminate packet loss from wireless network uncertainties. While cellular networks mitigate co-channel interference through mechanisms such as cell division, CDMA, and TDMA [12], current IoT systems have implemented limited strategies to address co-channel interference. The limitations of traditional CSMA mechanism have propelled the adoption of TDMA in IEEE 802.15.4-based standards [72]; however, current IoT systems including ISA100.11a and WirelessHART only allow one user at each time slot and frequency or allocate dedicated time slots to avoid interference, under which system capacity is underutilized and would potentially lead to inability of high data-rate and delay-sensitive applications such as real-time control. Therefore, improved TDMA scheduling will be desirable. In addition, prior research has confirmed that power control can improve system capacity [10], and many studies have showed the benefits of joint power control and scheduling as well [37][39]. Unfortunately, distributed TDMA scheduling and power control is challenging due to the NP-hardness of optimal scheduling and the fact that there may not always exist a feasible power assignment for every set of concurrent transmissions. Moreover, despite field experiments in [46] evidenced that the received signal strength across links of wireless sensor networks changes over time and suggested that adaptive power control is required to compensate time-varying channel attenuation, many of the existing work on joint scheduling and power control in IoT have overlooked channel dynamics and assumed constant channel gain.

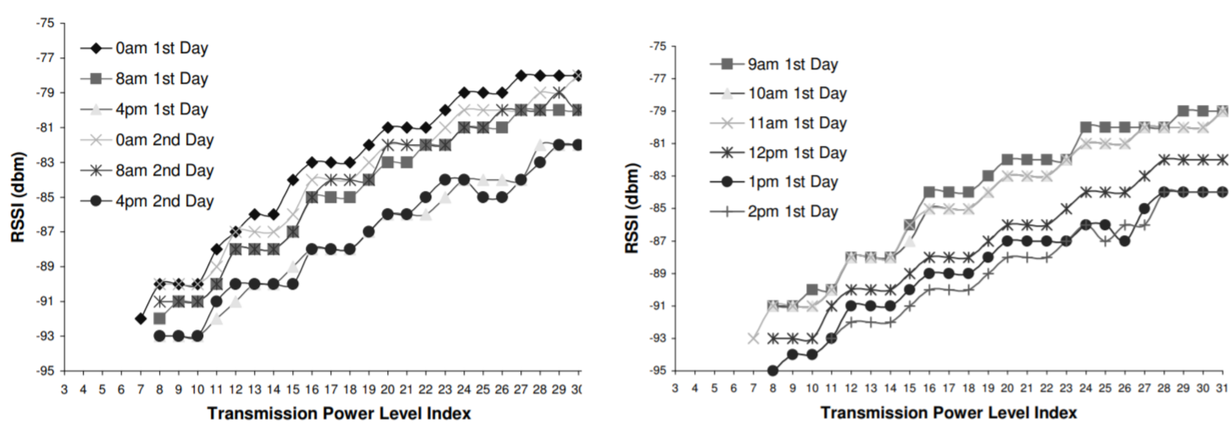

Figure 4.1: Transmission power vs RSSI at different times

Fig. 4.1 demonstrates the RSSI change over time. As showed in Fig. 4.1, received transmission power at different times is different, which indicates power control should be necessary and required to obtain successful packet reception.

In the last chapter, we dived into the Perron-Frobenius theory [57], adopted Physical-Ratio-K (PRK) interference model [61] and NAMA TDMA scheduling algorithm [65] to build the whole distributed framework while both were specifically designed to facilitate distributed scheduling. In this chapter, we aim to develop a field-deployable, joint TDMA scheduling and power control algorithm for supporting reliable wireless networks in IoT systems. This algorithm is designed to implement distributed scheduling and power control with an objective of maximizing concurrency and tracking SINR over channel dynamics. We employed feedback control mechanism to adapt scheduling K and transmission power by current scheduling K and SINR measurement. In a slowly time-varying system, the scheduling K will be expected to change at a large time-scale while transmission power will be updated probably at each time slot depending on the scale of channel variation. We evaluated our algorithm, and the simulation results demonstrated significant improvement in concurrency and successful tracking of target SINRs. To the best of our knowledge, the proposed scheme in this chapter is the first one that can satisfy SINR requirement toward channel dynamics without sacrifice in concurrency. This fundamental design will pave the way for future field deployment of IoT as the development and penetration of IoT expands to a large scale.

The remaining parts of this chapter are organized as follows: Section 4.2 defines the system model and identifies the problem; Section 4.3 introduces preliminary method; Section 4.4 elaborates on the framework and algorithms; Section 4.5 evaluates the design; Section 4.6 concludes the paper.

4.2 System Model and Problem Formulation

Given a set of links in wireless sensor networks, each link's receiver will receive signals from other links' senders due to broadcast nature of electromagnetic wave. The received signals from other links are called *co-channel interference*. According to the SINR model, a link would transmit a packet successfully if and only if

$$\frac{p_i h_i G_{ii}}{\sum_{j \neq i} p_j h_j G_{ij} + n_i} \geq \beta_{th} \tag{4.1}$$

where p_i is link i's transmission power; G_{ii} is link i's channel gain; h_i represents fading; G_{ij} is the channel gain from link j's sender to link i's receiver; n_i is link i's receiver-side thermal noise; β_{th} is link i's target SINR. We assume all links have the same target SINR.

Transform all links$'$ SINR requirements into the matrix form. We have

$$P(t) \geq F(t)P(t) + \eta \tag{4.2}$$

where

$$F_{ij}(t) = \begin{cases} \beta_{th} h_j(t) G_{ij} / h_i(t) G_{ii}, \text{ if } i \neq j \\ 0, \text{ if } i = j \end{cases}$$

and

$$\eta_i = \beta_{th} n_i / G_{ii}$$

Here $P(t)$ is the variant, and $F(t)$ is normalized gain matrix at each time instant. If a solution exist for each time instant, we can claim that (4.2) can be satisfied. In this sense, we define a maximal feasible subset, called *MFS* as a subset into which the addition of any one more link will make it infeasible. Furthermore, we denote all maximal feasible subsets as an union

$$U = \{S_1, S_2, ..., S_m\} \tag{4.3}$$

and their corresponding optimal power as

$$P_i^* = \{P_1^*, P_2^*, ..., P_m^*\} \tag{4.4}$$

In the best case, all scheduled links at each time slot are expected to be a MFS and transmit with optimal power so as to maximize concurrency and guarantee reliability. However, finding these maximal feasible subsets are known as NP-hard. Even in a centralized scheme in which all links' channel information are known, it is almost infeasible to obtain the MFS and their optimal transmission power in reasonable computation time, not to mention that wireless ad hoc networks tend to be distributed. Therefore, we need to figure out a simple way to identify feasible links and remove infeasible links.

4.3 Preliminary Adaptive Power Control

Let's consider adaptive power control. 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 [73], fractional power control [23], and step-by-step power control.[48].

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

$$P_i = \frac{1}{h_i G_{ii}} \tag{4.5}$$

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

$$P_i = \frac{1}{(h_i G_{ii})^\alpha} \tag{4.6}$$

where α is the fractional number between 0 and 1. Jindal et al. in [23] 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 not 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 by itself is an iterative power control method. Tim Holliday et al. [48] 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 adjusting transmission power by a fixed step size or adaptive step size and have obtained some experimental results. Those experimental results showed that the 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.

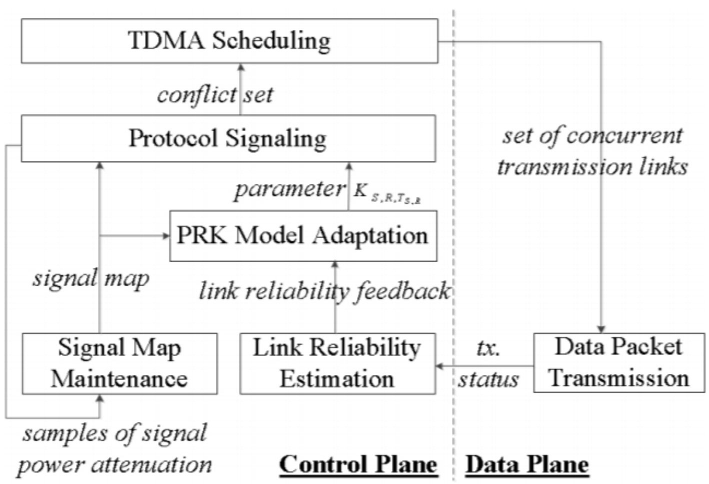

Figure 4.2: The prks architecture

Zhang et. al in [74] has investigated adaptive scheduling algorithm as shown in 4.2. In PRKS, data packet transmissions are executed in the data plane, and their transmission status (i.e., success or failure) serve as the feedback to the control plane which schedules data transmissions to ensure application-required link reliability. In particular, the status of data transmissions are used by individual links to estimate their in-situ link reliabilities, which in turn triggers the PRK model adaptations at individual links. The instantiated PRK model parameters are used together with signal maps to identify interference relations between transmissions, which in turn are used to enable

TDMA scheduling with predictable link reliability. There are a few extensive work in [75][76][77] as well. However, 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 wireless communication systems.

4.4 Proposed Distributed Scheduling K and Power Control

In this section, we present a distributed algorithm to obtain near-optimal scheduling and power control. This algorithm consists of the channel measurement module, NAMA scheduling module, SINR measurement module, PRK adaptation and transmission power update module.

4.4.1 The definition of feasible K

Physical-ratio-K model in [61] is an interference model that defines the conflict relationship between two links. In other words, this model determines whether two links can transmit at the same time or not. According to the PRK model, a link j conflicts with a link i if

$$G_{ij} \geq \frac{G_{ii}}{K_{ii}} \tag{4.7}$$

We find that the parameter K_{ii} of the PRK model is directly related to the feasibility of gain matrix F. For each link, a given K_{ii} would divide all links into conflicting links and concurrent non-interfering links. If K_{ii} is too large, most links will be regarded as conflicting links and sacrifice concurrency; if K_{ii} is too small, the concurrent links are not necessarily non-interfering. Thus finding the exact K_{ii} is very important.

Definition 2. The feasible K for link i, denoted by K_f^i, is the minimum K such that all links satisfying $G_{ij} \leq \frac{G_{ii}}{K_f^i}$ can transmit with link i at the same time under optimum power.

Out of all MFSs, we represent all the MFSs that include i as

$$U_i = \{S_{i1}, S_{i2}, ..., S_{im}\} \tag{4.8}$$

and corresponding transmission power as

$$P_i = \{P_{i1}, P_{i2}, ..., P_{im}\}. \tag{4.9}$$

The links in U_i are those links that can transmit at the same time as i, denoted by N_i. By the definition of K_f^i, we have

$$K_f^i = \min_{j \in N_i} \frac{G_{ii}}{G_{ij}} \tag{4.10}$$

We can prove that K_f^i is the minimum K for link i, that is, the minimum boundary that divides concurrent links and conflict links. If we have $K_{ii} < K_f^i$, there must exist a link which satisfies $G_{ij} = G_{ii}/K_{ii}$ and is allowed to transmit at the same with link i. However, it is not among concurrent links since $G_{ij} = G_{ii}/K_{ii} > G_{ii}/K_f^i$. Allowing this link to transmit simultaneously would not guarantee feasibility. Similarly, letting $K > K_f^i$ will miss some concurrent links. Therefore, K_f^i is the minimum value under optimum power.

Once we find the feasible K for each link and build conflict relationship, we can use NAMA scheduling [65] to select concurrent links. NAMA scheduling is a distributed approach to channel access scheduling for wireless ad hoc networks. Based on known conflict relationships, each link calculated a priority for itself and all its conflict links. A link would get access to the channel if it has the highest priority among all its conflicting links. The priority is calculated as follows

$$p_i^t = \mathbf{Rand}(k \oplus t) \oplus t, \;\; k \in M_i \cup i \tag{4.11}$$

where M_i is a set of links that conflict with link i.

Therefore, back to feasibility condition and PRK model, to ensure reliability becomes finding the feasible K and optimum transmission power for each link. Under channel dynamics, feasibility condition would change and scheduling K(i.e., the parameter K of the PRK model) may change as well. The next section will present how the system converges to an near-optimal K and feasible transmission power over channel variations.

For slowly time-varying IoT systems, the channel measurement module will measure average channel at setup stage and update it at a long timescale. All packets are sent in the data channel. At each time slot, each sender will run NAMA scheduling to determine if it can obtain channel access or not. When a sender gets the channel access, it will send a packet, and its receiver will then measure current SINR and send it back to the sender via acknowledgement packet. So the whole system requires ACK feedback. When the sender receives current SINR, it will calculate the scheduling K and transmission power for the next time slot according to current K, transmission power and SINR. This distributed framework will run as shown in Algorithm 3.

4.4.2 The distributed algorithm

The core part of this algorithm is updating scheduling K and transmission power. To update scheduling K and transmission power, we use iterative approach based on feedback mechanism. Since it is challenging to achieve the exact target SINR and also not necessary, we set a tolerance area as SINR target region, $[\beta_{th}, U\beta_{th}]$, to tolerate any slight variation. We set a reference interval $[K_{lref}, K_{rref}]$. Specifically, $K_{lref} = \beta/(1 + 1/U)$ and $K_{rref} = \beta/(1 - 1/U)$. Despite not all links' feasible K are bound in the reference interval $[K_{lref}, K_{rref}]$, it is a desirable interval for each link considering feasibility condition. Limiting all links' K in this interval would lose a little bit concurrency but the strategy of regulating all links' interference in a range would keep a balanced interference among links and maintain a stable system.

The K reference interval and SINR target region divide $K - SINR$ plane into multiple regions as shown in Figure 4.3. We update K and transmission power by this plane. To decouple the interactive impact of scheduling and power control, we first change K under both overshoot and undershoot of SINR. The rules are as follows:

- **Case 1**. In case that the current SINR is greater than SINR margin $U\beta_{th}$, if $K > K_{rref}$, the scheduling K should be decreased; otherwise, keep K unchanged and decrease transmission power.

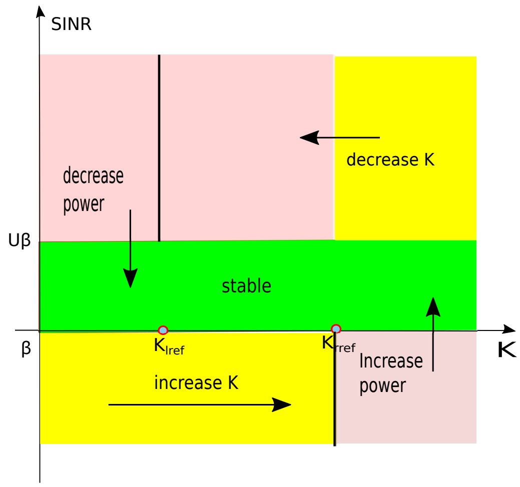

Figure 4.3: The plane of scheduling K and SINR. Transmission power and K will be adjusted by their current location in the plane.

- **Case 2**. In case that the current SINR is smaller than target SINR β_{th}, if $K < K_{rref}$, scheduling K should be increased; otherwise, transmission power should be increased.

The algorithm is as described in Algorithm 2. We now explain how to calculate k_i^{t+1} and p_i^{t+1}. If $\beta_i^t > U\beta_{th}$ and $k_i^t > K_{rref}$, we think k_i^t can be further decreased to tolerate more interference with a benefit in improving concurrency. Expecting $\beta_i^{t+1} = \beta_{th}$, we have

$$I_i^t + \Delta I_i^{t+1} = p_i^{t+1} G_{ii}/\beta_{th} \tag{4.12}$$

where ΔI_i^{t+1} are allowed interference increase from decreasing K. Further,

$$I_i^t/G_{ii} + \sum_{j \in s_i^{t+1}} p_j^{t+1}/k_{ij} = p_i^{t+1}/\beta_{th} \tag{4.13}$$

where $k_{ij} = G_{ii}/G_{ij}$ and s_i^{t+1} is the set of all newly-added links satisfying $k_{ij} \geq k_i^{t+1}$. Because it is difficult to obtain the set s_i^{t+1} and know each link's transmission power, we further relax (4.13) to

$$I_i^t/G_{ii} + p_i^{t+1}/k_i^{t+1} = p_i^{t+1}/\beta_{th} \tag{4.14}$$

Let $I_i^t/G_{ii} = p_i^t/\beta_i^t$ and $\gamma_i^t = \beta_{th}/\beta_i^t$, we obtain $k_i^{t+1} = 1/(1-\gamma_i^t)\beta_{th}$. Since we don't hope k_i^{t+1} changes too much at each time slot to cause system oscillation, we limit $k_i^{t+1} \geq k_{lref}$. It's worthwhile to note that k_i^{t+1} is an approximate value. Further adjustment may be needed before converging to a fixed value.

If $\beta_i^t > U\beta_{th}$ but $k_{lref} < k_i^t < k_{rref}$, we think K is within reference range and doesn't need to change, we only reduce power to satisfy $\beta_i^{t+1} = U\beta_{th}$. Specifically, square root power control is adopted to avoid large transmission power change. If $\beta_{th} < \beta_i^t < U\beta_{th}$ but $k_{lref} < k_i^t < k_{rref}$, K and transmission power will keep unchanged at the next time slot. Once a few links settle down and impact on other links don't change, the whole system will start to converge. In addition, we control the range of power increase at each time step so as to reduce the settle-down links to become unstable.

We can use the same approach above to obtain $k_i^{t+1} = 1/(\gamma_i^t - 1)\beta_{th}$ when $k_i^t < k_{rref}$. If the actual increased k_i^{t+1} is larger than K_{rref}, we will further increase transmission power to ensure expected SINR, $M = U/2$. Let

$$I_i^t/G_{ii} - p_i^t/k_i^{t+1} = \frac{p_i^{t+1}}{M\beta_{th}} \tag{4.15}$$

Replace $k_i^{t+1} = K_{rref}$, we get

$$p_i^{t+1} = M\frac{K_{rref} - \beta_i^t}{K_{rref}}\frac{\beta_{th}}{\beta_i^t}p_i^t \tag{4.16}$$

For wireless sensor networks, SINR overshoot may be acceptable but undershoot is not desirable. So we attempt to satisfy SINR requirements right away by scheduling and further power control when scheduling doesn't work in the case the link gain itself is very small.

The whole system is expected to keep scheduling K constant or change slowly. In the case there is no channel dynamics, scheduling and transmission power converge to the fixed value. The SINR region can be used to tolerate interference variation from random NAMA scheduling. Once variations from channel dynamics are over the system tolerance level and make links infeasible, the system will recalculate scheduling K and transmission power.

4.5 Simulation Results

In this section, we verify the convergence property of the whole framework and algorithms, and evaluate receiver-side SINR variation and concurrency in networks. We use Matlab to simulate

Input: k_i^t, β_i^t, p_i^t, β_{th}
Output: p_i^t, k_i^t

$\gamma_i^t \leftarrow \frac{\beta_{th}}{\beta_i^t}$
if $\gamma_i^t < 1/U$ **then**
  if $k_i^t > K_{rref}$ **then**
    $k_i^{t+1} \leftarrow \max(\frac{1}{1-\gamma_i^t}\beta_{th}, K_{lref})$
  end
  else
    $p(i) \leftarrow max(\frac{p_i^t}{U}, \sqrt{U\gamma_i^t p_i^t})$
    $p(i) = \max(p(i), P_{min})$
    $p(i) = \min(p(i), P_{max})$
  end
end
if $\gamma_i^t > 1$ **then**
  if $k_i^t < K_{rref}$ **then**
    $k_i^{t+1} \leftarrow \frac{1}{\gamma_i^t - 1}\beta_{th}$
    if $k_i^{t+1} >= K_{rref}$ **then**
      $p_i^t \leftarrow \min(Up_i^t, M\frac{K_{rref}-\beta_i^t}{K_{rref}}\gamma_i^t p_i^t)$
      $k_i^{t+1} \leftarrow K_{rref}$
    end
  end
  else
    $p_i^t \leftarrow \min(Up_i^t, \sqrt{M\gamma_i^t p_i^t})$
  end
  $p_i^t = \max(p_i^t, P_{min})$
  $p_i^t = \min(p_i^t, P_{max})$
end

Algorithm 2: Update Scheduling K and Transmission Power a network in a rectangle area with network node density λ, where all senders are randomly and uniformly distributed and their receivers are around the senders with a random distance between d_{min} and d_{max}. The traffic model is a full-buffer model, which means packets are always ready to transmit if they get a chance to access the channel. Constant channel and dynamic channel with Rayleigh multi-path fading are simulated separately. The maximum transmission power and minimum transmission power is 5dBm and -10dBm, respectively. The channel attenuation is in the range $[-70dB, -120dB]$. Each time slot is allocated 5ms. All simulation parameters are showed in Table 4.1.

Table 4.1: Simulation Parameters

Symbol	Parameter	Default value
W	Network width	100 m
L	Network length	100 m
λ	Network density	0.005
d_{min}	Minimum link length	5m
d_{max}	Maximum link length	10 m
α	Path loss exponent	3.5
μ_h	Rayleigh fading mean	0 dB
n_i	Thermal noise	-99 dBm
β_{th}	Target SINR	5 dB
P_{max}	Maximum transmission power	5 dB
P_{min}	Minimum transmission power	-10 dB
P_0	Initial transmission power	0 dB
U	SINR margin	2
T	Timeslot duration	5 ms

4.5.1 Convergence property

Set the default SINR margin $U = 2$, we have $K_{lref} = 2/3\beta_{th}$, $K_{rref} = 2\beta_{th}$. Starting with $K_0 = 3\beta_{th}$ and $P_0 = 0$ dBm, we first observe how scheduling K, transmission power, and SINR change under constant channel. Fig. 4.4 shows that scheduling K for each link will be fixed around 50 time slots, and Fig. 4.5 shows that power control will converge to the fixed value around 100 time slots. These results are as expected while our design has posed a limitation on the adjustment range of transmission power at each time slot to obtain a stable system. As in Fig. 4.8, all links' SINR is over the target value. This suggests that our design ensures tracking and satisfaction of the required target SINR. Our proposed algorithm is inherently a heuristic algorithm. The simulation results

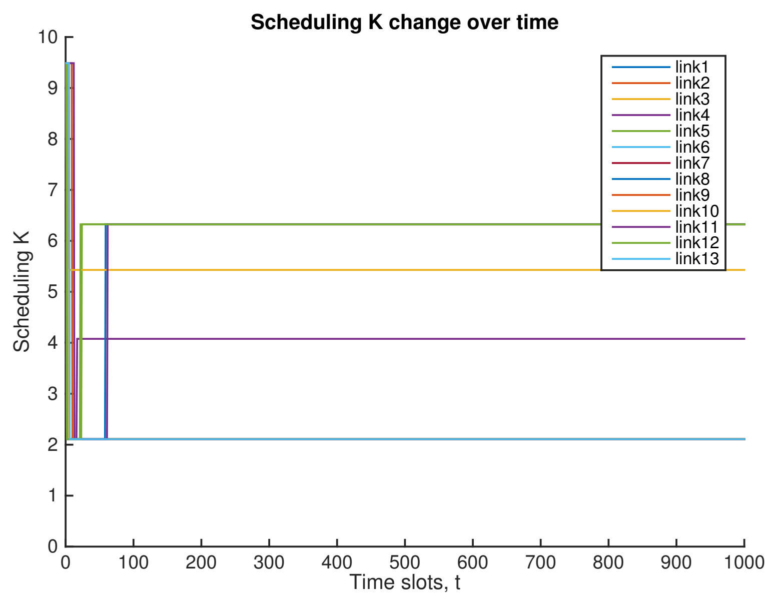

Figure 4.4: Scheduling K converges to a fixed point for each link

have showed fast convergence. The asymptotic analysis of computation complexity shall be a future topic.

4.5.2 Adaptation to dynamic Channels

We model the wireless channel as slowly time-varying channel. Each link's channel gain at current time slot is the average value over channel gains of a few previous time slots and a random Rayleigh fading. The number of dependent slots is set as $W = 20$. Fig. 4.6 indicates that channel variation is around $2dB$. Under this level of channel dynamics, scheduling K is mostly the same as constant channel for the same instance of simulated work, so here we just present the variation of transmission power. As shown in Fig. 4.6, for some links, transmission power is adjusted due to channel dynamics and then keep stable. Fig. 4.8 and Fig. 4.9 are the SINR variation over the

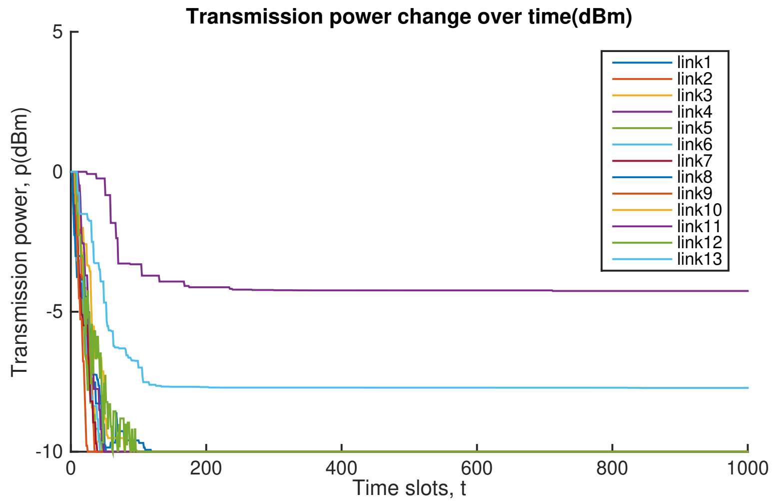

Figure 4.5: Transmission power converges to a fixed point for each link

same network instantiation under constant channel and Rayleigh fading. We can see the difference where SINR has increased and it is a result from transmission power adjustment.

4.5.3 Concurrency

Concurrency is the main performance metric we care about. We compare our schemes with the optimal scheduling and power control and other two typical and state-of-art approaches.

- **ALOHA scheduling with Fractional power control**. ALOHA scheduling is a random scheduling. Each link has an equal chance to transmit or not. For fractional power control [23], each link updates their transmission power by their instantaneous channel gain, $P_{t+1} = P_0/\sqrt{G_{ii}}$.

- **NAMA scheduling with sufficient K and FM control**. We calculate a sufficient K for each link at the first time slot. This sufficient K will ensure all non-conflicting links are feasible under constant power. We then run classical Foschini and Miljanic's distributed power algorithm [18] with $P_{t+1} = \frac{\beta_{th}}{\beta_t} P_t$.

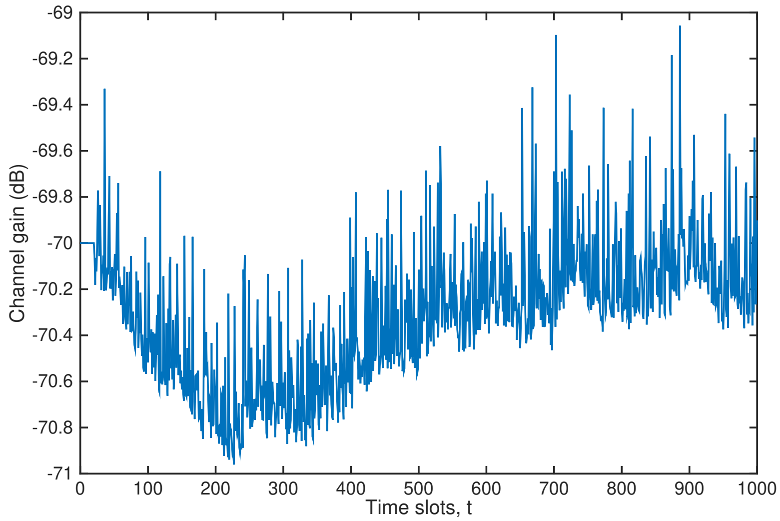

Figure 4.6: Instantaneous channel gain over time slots under Rayleigh fading

- **Optimal scheduling and transmission power**. CPLEX is an optimization tool. We use mixed integer linear programming model in CPLEX and obtain the maximal number of feasible links and their transmission power given the constant gain matrix of a set of links.

We run each scheme 50 times and get the average value. Fig. 5.7 suggests that given a random network, nearly 60% links can transmit simultaneously under optimal transmission power. ALOHA scheduling has the least number of feasible links, which verifies the importance of well-regulating scheduling. Compared to NAMA scheduling with efficient K, our proposed scheme improves concurrency by 70%. This result indicates the benefit of adaptive scheduling.

4.6 Conclusion

In this chapter, we has aimed to leverage scheduling and power control to support reliable IoT applications. Specifically, we have focused on ensuring high concurrency while guaranteeing application-required communication reliability. We have adopted the PRK interference model and NAMA scheduling and proposed our scheduling K and power control framework. We have conducted experiments and verified that this framework enables distributed convergence in joint

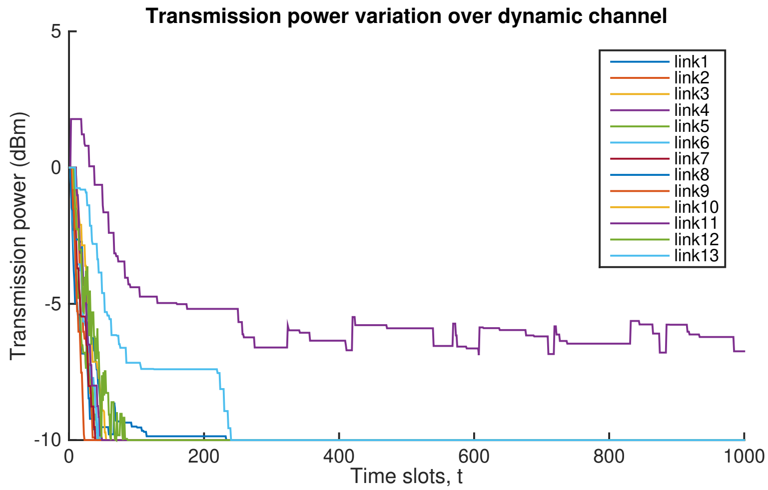

Figure 4.7: Power update for each link over Rayleigh fading

scheduling and power control with advantages in the ease of implementation, significant improvement in concurrency and SINR guarantees. The proposed algorithm is expected to serve as a foundation for distributed scheduling and power control as the penetration of IoT applications expands to scenarios where both the network capacity and communication reliability becomes critical.

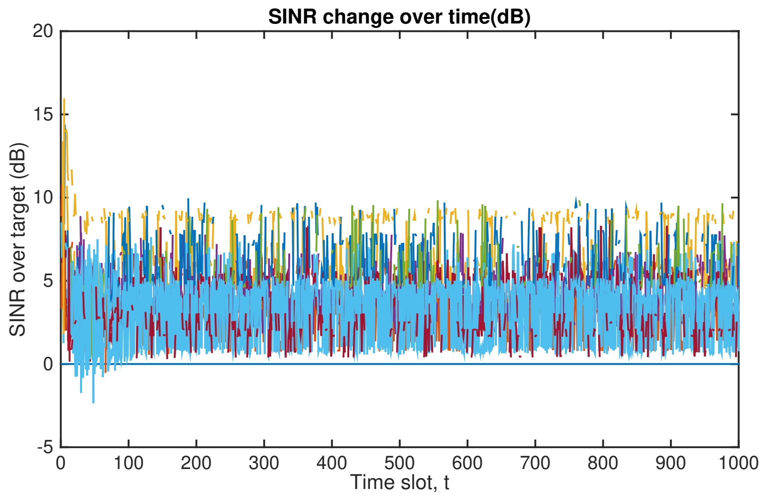

Figure 4.8: SINR variation for each link under constant channel

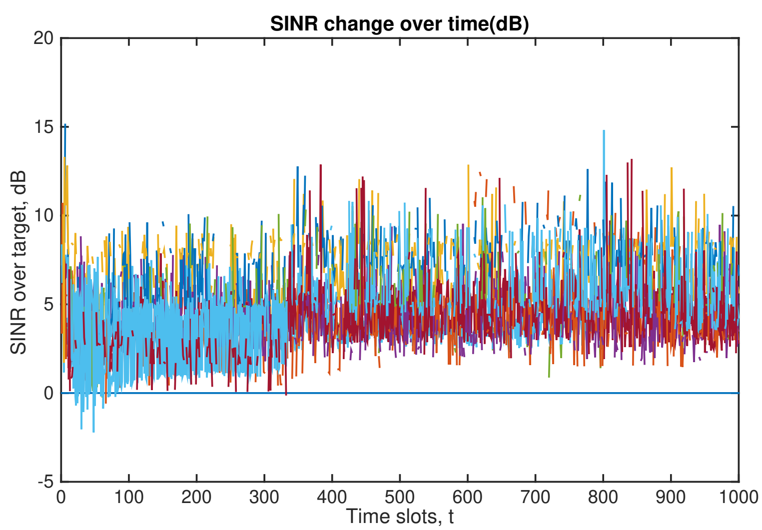

Figure 4.9: SINR variation for each link under Rayleigh fading

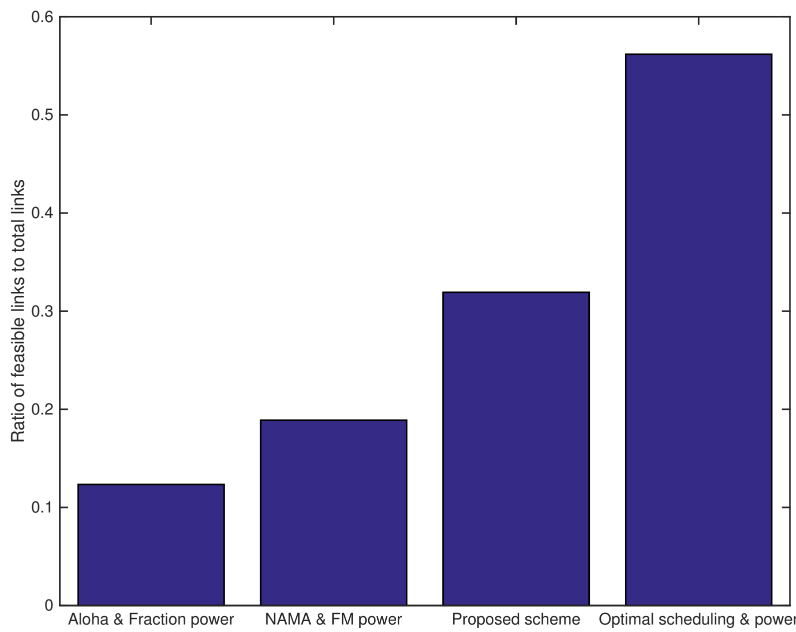

Figure 4.10: Comparison of ratio of concurrent links over total links

CHAPTER 5. ANALYSIS OF JOINT SCHEDULING AND POWER CONTROL FOR PREDICTABLE URLLC IN INDUSTRIAL WIRELESS NETWORKS

In this chapter, we move toward addressing large-scale channel dynamics. We model dynamical wireless channel as AR fading channel and analyze the contribution and limitation of power control in guaranteeing per-packet reliability.

5.1 Introduction

While industrial communications between sensors, controllers, and systems still primarily use wired networking solutions today, wireless solutions have been finding increasingly more applications in mission-critical IoT settings. For instance, to increase efficiency in factories, wireless technology is essential for communicating with automated mobile equipment, such as shuttle systems, so that they can easily move around the automated storage and retrieval areas. For oil and gas producers and refineries, minimizing systems downtime is important, and the industry is using more and more sensors, networks, and analytic to generate predictive insight into equipment performance and maintenance. Automotive manufactures are also using on-board diagnostic data to detect equipment failures, safety risks, and defects [5]. Commercial transportation firms are using streaming sensor data from vehicles to identify potential breakdowns and perform preventive and predictive maintenance [6]. Agricultural and mining companies are using wireless networks to coordinate the movement of equipment in the field, develop driver-less fleets, improve fleet maintenance, and enhance safety. Ultra-reliable, low-latency communication (URLLC) is expected to enable technicians wearing AR head-mount-displays in factories to communicate with remote experts in troubleshooting [7]. Compared to human-oriented cellular networks, industrial IoT applications are mission-critical and often-times safety-critical. Thus they may well require predictable URLLC services, e.g. 99.999% packet delivery ratio/reliability and $1ms$ air-interface delay, respectively[8][9].

Ensuring predictable per-packet communication reliability is a basis of predictable URLLC, since packet loss not only reduces the reliability and increases the latency in communication but also makes communication reliability and latency unpredictable. For predictable per-packet communication reliability, industrial wireless networks need to address co-channel interference and wireless channel dynamics with both small-scale variations and large-scale variations.

More specifically, communication reliability can be characterized by the bit error rate (BER) and the packet delivery rate (PDR) for a receiver in decoding signals with a specific signal-to-interference-plus-noise-ratio (SINR). For instance, for a link with IEEE 802.15.4 radios, the BER for a packet reception is computed as follows [78]:

$$BER(\gamma) = \frac{8}{15} \times \frac{1}{16} \times \sum_{k=2}^{16} (-1)^k \binom{16}{k} e^{(20 \times \gamma \times (\frac{1}{k} - 1)}, \tag{5.1}$$

where γ is the SINR. Assuming the BER of each bit in a packet is independent and identically distributed, the PDR is calculated as follows:

$$PDR(\gamma, l) = (1 - BER(\gamma))^{8l}, \tag{5.2}$$

where l is the packet length. Therefore, for each packet with a received SINR at the receiver side, we can estimate the packet delivery ratio.

Based on SINR model, the receiver-side SINR will be easily affected by other links in the network. Meanwhile, the dynamics of each link will make the variation of SINR more complex and unpredictable. So the challenge is how to enable a predictable SINR at each time instant in the presence of complex dynamics and uncertainties.

Power control and scheduling are basic enablers of reliable communication at the physical layer and MAC layer of wireless networks respectively [49]. Nonetheless, they are subject to challenges such as harsh environments, dynamic channels, and distributed network settings in industrial IoT. Existing solutions are mostly based on heuristic algorithms or asymptotic analysis of network performance, and there lack field-deployable algorithms for ensuring predictable per-packet communication reliability [39][40].

Gupta et al. [36] have proved that when n identical randomly located nodes, each capable of transmitting at W bits per second, forms a wireless network, the throughput is only $\Theta(\frac{W}{\sqrt{n}})$ for each node, even in the optimal circumstances. This finding shows that when the number of concurrent nodes in a unit area increases, the throughput for each node can approach 0. In this sense, it is crucial to mitigate co-channel interference and improve system spatial reuse efficiency. Other than throughput, scheduling is needed to ensure communication reliability. CSMA- and RTS-CTS based channel access control mechanisms may only enable a data delivery ratio of 16.9% and 36.8%, respectively[61]. Therefore, for ultra-reliable communication systems, TDMA scheduling has been widely studied in mission-critical systems.

Joint scheduling and power control have also been studied. Elbatt and Ephremides [37] first introduced the joint scheduling and power control framework in wireless ad hoc networks and formulated this issue as a Mixed Integer Linear Programming (MILP) [42] optimization issue. Due to the NP-hard characteristic, approximation algorithms naturally arise. Wan et al. [39] suggested that the cumulative co-channel interference beyond a certain range can be upper bounded under the link-length-based path loss law and directed the scheduling issue into selecting a maximum set of independent links. Che et al. [40] and Wan et al. [39] also obtained the maximum set of independent links. Magnús M. Halldórsson conducted extensive research on joint scheduling and power control [43]. However, those studies mainly focused on obtaining asymptotic characterization of joint scheduling and power control when using obvious transmission power algorithms [44], and those proposed algorithms are rarely implementable in a distributed way.

Towards developing field-deployable approaches to joint scheduling and power control in ensuring per-packet communication reliability, we analyze the roles of scheduling and power control as well as their interactions in ensuring per-packet communication reliability and high network throughput. Our main contributions are as follows:

- By investigating properties of the interference gain matrix, we for the first time demonstrate the relationship between scheduling and power control SINR feasibility of individual links. The characteristics of gain matrices are such that close-by links have significant impact on the power control SINR feasibility of a link, which suggests that silencing close-by links would be a promising scheduling strategy of ensuring power control SINR feasibility as well as high communication concurrency and throughput.

- We present the exact picture of how power control can help improve transmission concurrency by comparing scheduling with constant transmission power and optimal transmission power respectively in dynamic networks. The significant improvement indicates that there is a big potential for power control to help compensate for the sacrifice that scheduling algorithm usually brings while ensuring reliability.

- We evaluate the behavior of a candidate framework in achieving SINR requirements in different channel dynamics settings. Our evaluation demonstrates the challenges of field-deployable joint scheduling and power control for ensuring predictable per-packet SINR and reliability, for instance, the limited capability of well-known power control algorithms (e.g., constant power and fractional power) in regulating SINR variations. The study suggests a few promising future directions of research, for instance, addressing the randomness of NAMA scheduling.

The remaining parts of this chapter are organized as follows: Section 5.2 analyzes the power control SINR feasibility and proposes a scheduling strategy; Section 5.3 presents the contribution of power control; Section 5.4 evaluate the behavior of a candidate framework under different channel dynamics settings; Section 5.5 concludes the chapter.

5.2 Scheduling with Close-By Links Silent

In this section, we dive into theoretical aspects of joint scheduling and power, and explore strategies of constructing concurrent links while ensuring power control SINR feasibility. We first revisit the gain matrix model and Perron-Frobenius theorem to prove that scheduling is an essential technique in guaranteeing link reliability, and then we show that silencing closing-by links is a promising scheduling strategy which ensures power control SINR feasibility while improving transmission concurrency and throughput.

5.2.1 Need for Scheduling

Let's revist SINR model. In a wireless network with multi-path channel fading, shadowing, and co-channel interference, the receiver-side SINR at a link i $(i = 1, 2, 3...n)$ can be represented as:

$$SINR_i = \frac{p_i h_{ii} g_{ii}}{\sum_{j \neq i} p_j h_{ij} g_{ij} + n_i}, i = 1, 2, 3...N \tag{5.3}$$

where $g_{ij} > 0$ is the power gain from the transmitter of the jth link to the receiver of the ith link, p_i is the power of the ith transmitter, and n_i is the thermal noise power at the ith receiver.

As denoted in (5.3), the quality of each link is determined by the signal to interference plus noise ratio (SINR) at the intended receiver. Based on a given modulation and coding scheme, each link is assumed to have a minimum SINR requirement $\gamma_i > 0$ that represents the ith user's reliability requirements. Since rate control is not considered in this paper, we assume all links have the same modulation and coding scheme, thus the same . This SINR constraint can be represented in a matrix form as

$$(I - F)P \geq \eta, \text{ with } P > 0, \tag{5.4}$$

where F is a gain matrix with each element representing interfering links' channel gain scaled by the SINR constraints and channel gain,

$$F_{ij} = \begin{cases} \frac{\gamma g_{ij}}{g_{ii}}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases}, \tag{5.5}$$

η is the vector of normalized noise power,

$$\eta = (\frac{\gamma n_1}{g_{11}}, \frac{\gamma n_2}{g_{22}}, \ldots, \frac{\gamma n_N}{g_{NN}})^T, \tag{5.6}$$

and $P = (p_1, p_2, ..., p_n)^T$ is the vector of transmission powers.

The gain matrix F has non-negative elements as indicated in (5.5). Let ρ_F be the Perron-Frobenius eigenvalue of F. Then from the Perron-Frobenius theorem and standard matrix theory [57], we have the following equivalent statements:

- $\rho_F < 1$ when $\eta \neq 0$ and $\rho_F \leq 1$ when $\eta = 0$.
- There exists $P > 0$ such that $(I - F)P \geq \eta$.

The above statements demonstrate the conditions for SINR feasibility of power control, which we call *power control SINR feasibility*. That is, in real-world settings with non-zero background thermal noise, a set of links can be scheduled to transmit concurrently while ensuring the required SINR through power control if $\rho_F < 1$; otherwise, when $\rho_F \geq 1$, a subset of links shall be silenced (i.e., not transmitting) since their SINR requirements and communication reliability cannot be satisfied. Therefore, when not considering minimum or maximum transmission power constraints (i.e., any transmission power is available at transmitters), the gain matrix F determines the power control SINR feasibility of a set of links.

When a set of links are determined unfeasible by the gain matrix, scheduling policy must be employed. That's why all networks in real world require an elegantly designed scheduling strategy, such as CSMA or TDMA with responding algorithms.

5.2.2 Strategy of silencing closed-by links

Now we discuss the strategy of among a set of links which link should be transmitted and kept inactive. We start from the investigation of characteristics of the non-negative gain matrix F. To simplify discussion, we first define non-zero entry in the gain matrix F as *effective interference factor*:

$$f_{ij} = \frac{\gamma g_{ij}}{g_{ii}}, i, j \in \{1, 2, ...N\} \tag{5.7}$$

Furthermore, based on the effective interference factor, we define *accumulated interference factor* as follows:

Definition 3. The accumulated interference factor is defined as sum of interference from all links normalized by the link gain and scaled by target SINR, represented as

$$I_i = \sum_{j \neq i} \frac{\gamma g_{ij}}{g_{ii}}, i, j \in \{1, 2, ...N\} \tag{5.8}$$

I_i is inherently the sum of the i-th row of F. Assume $I_i \in (I_{min}, I_{max}), i \in \{1, 2, ...N\}$, where I_{min} and I_{max} are the minimum and maximum row sum, respectively. We have the following conclusion

Corollary 7. *Given a set of links, $I_{min} \leq \rho_F \leq I_{max}$. If any interference factor is removed with $f_{ij} = 0$, ρ_F will be decreased.*

It can be easily approved by the matrix theory in [79]. The statements above indicate that if the accumulated interference factors for all links are larger than 1, the Perron root will be larger than 1; otherwise, the Perron root can be less than 1. In the special case when accumulated interference factors for all links are equal to 1, the Perron root is equal to 1. Then, we have

Proposition 1. Given a set of links in a wireless network with power law signal attenuation, removing closing-by links in scheduling tends to increase transmission concurrency while ensuring power control SINR feasibility.

Proof. According to power law path loss model, the individual link's effective interference factor can be written as $g_{ij} = \frac{c}{d_{ij}^{\alpha}}$, where c is a constant, d_{ij} is the distance from interfering sender to link's receiver, and α is the path loss index. The close-by senders would have the shortest d_{ij} and thus the largest g_{ij}. According to Corollary 7, removing large items in the matrix will help reduce Perron root and make the gain matrix feasible. Meanwhile, removing far links will help reduce gain matrix. However, their impact on the Perron root of gain matrix is much less significant, and removing the large elements in F will be more efficient than removing small elements in reducing Perrron root. □

The strategy of silencing closing-by links coincides with the guard area scheme [55]. For the guard-area scheme, an area around a given link will be set so that all links whose transmitters are within that guard area will not be allowed to transmit packet if the given links is transmitting a packet. Zhang et al. [61] have also proposed the Physical-Ratio-K (PRK) interference model which has the same purpose of mitigating co-channel interference by silencing close-by links in scheduling. Next we evaluate the performance of guard-area based scheduling in time-varying networks.

5.2.3 Guard-area based scheduling in time-varying networks

In this section, we would like to identify the performance of guard-area based scheduling in time-varying networks with random settings and demonstrate the benefits of the proposed scheduling policy. Haenggi et al. [55] considered transmitters distributed in a stationary fashion with homogeneous Poisson point process Φ of constant density λ. Every transmitter is assumed to transmit with a unit power. A guard area is built for each link so that within that area no other links can transmit packets. Assume the power law path loss model, we use u to represent the guard-area, which is the ratio of the maximum distance between the transmitter of any interfering link and the receiver of the data communication link of interest to the length of the data link itself. Since all settings are a random model, packet delivery ratio is considered as the performance metric:

$$P\{SINR_i \geq \gamma\} = P\{\frac{ch_{ii}}{d_{ii}^{\alpha}} \geq \gamma(\sum_{j \in \Phi : d_{ij} > ud_{ii}} \frac{ch_{ij}}{d_l^{\alpha}})\}, \tag{5.9}$$

where c is a constant, u is the guard area radius, d_{ii} and d_{ij} are the link length of link i and the distance from link j's transmitter to link i's receiver, and h_{ii} and h_{ij} are independent Rayleigh fading variables representing the channel fading coefficients of link i and the interference from link j's transmitter to link i's receiver. The noise is negligible here when the interference is dominant over noise. The detailed formula can be found in [55].

As shown in Figure 5.1, when the guard area is larger, packet delivery rate will be higher. Meanwhile, it demonstrates from another perspective that under random networks, scheduling closing-by links will bring benefit for the packet delivery ratio as well. However, the sacrifice would be the decrease in concurrency since larger guard area means that more links will be inactive (i.e., not scheduled to transmit). In regards to concurrency, we will discuss in the next section.

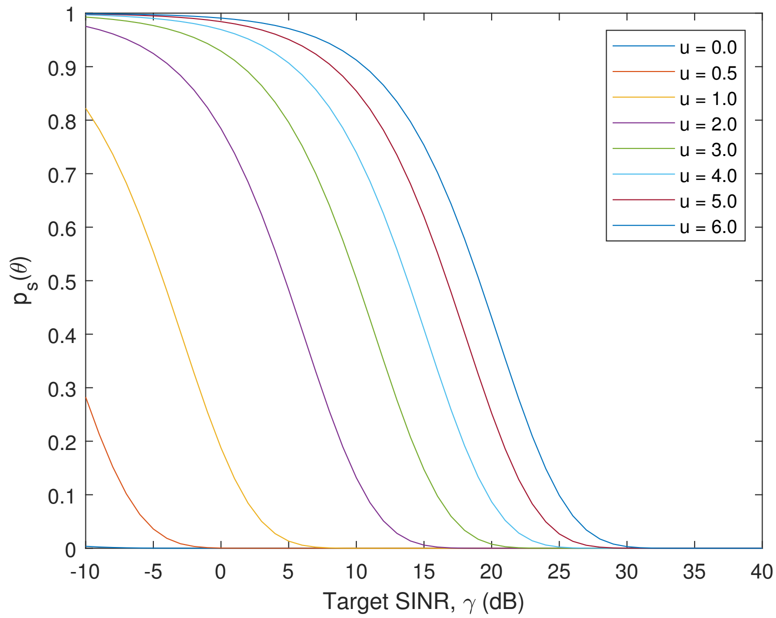

Figure 5.1: Comparison of packet delivery rate with different guard area

5.3 Why Power Control?

For a single link, it's quite intuitive that the transmission power at the sender should adapt to channel attenuation so that the received power at the receiver is greater than a given threshold. For large-scale networks, the problem of power control becomes much more complex. Now we discuss the role of power control in large-scale networks. The analysis has built its ground on the Perron-Frobenius theorem and Foschini-Miljanic's algorithm [18].

5.3.1 Revisit Foschini-Miljanic's algorithm

Let's revisit the Perron-Frobenius theory again. According to the Perron-Frobenius theorem, if there exist solutions for SINR requirement, an optimal point can be obtained and denoted as

$$P^* = (I - F)^{-1}\eta. \tag{5.10}$$

where P^* is the minimal transmission power among all feasible solutions, called ***fixed point***. As stated in [31], all solutions will form a cone in a high-dimension space. For the scenario of two links, we can describe the fixed point in a two-dimensional plane. As shown in Figure 5.2, the line $p_1 = f_1(P)$ represent the SINR requirements for link 1, and $p_2 = f_2(P)$ represents the SINR requirements for link 2. P* exists when two curves exist an intersection.

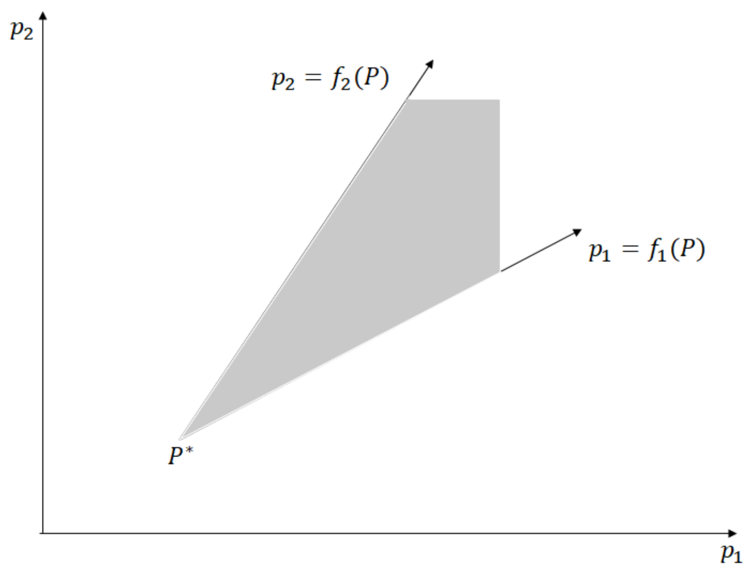

Figure 5.2: The fixed point with a set of two links

Based on the theory above, Foschini and Miljanic [18] proposed a simple distributed power control algorithm where they proved that, given SINR requirements, the optimal transmission power can be obtained through the following iterative computation:

$$P(t) = FP(t-1) + \eta, \tag{5.11}$$

and $\lim_{t\to\infty} P(t) = P^*$. Furthermore, the receiver-side SINR of every link i converges to the desired γ, that is, 27 $\lim_{t\to\infty} \gamma_i(t) = \gamma$.

A significant characteristic is that the algorithm above can be implemented locally as follows

$$P_i(t) = \frac{\gamma}{\gamma_i(t-1)} P_i(t-1), i = 1, 2, 3, ... \tag{5.12}$$

This finding is a breakthrough. It means that each link can change its transmission power by its measured SINR at each time slot. This is a fundamental finding for investigating distributed power control. There are a few valuable characteristics under transmission power constraints and infeasible condition. We would present them in Section 5.3.3.

5.3.2 Concurrency and outage probability improvement by power control

As we have discussed in the last subsection, a set of links can transmit concurrently only when the corresponding Perron root of the gain matrix is less than 1. It doesn't require that all links receive the same interference. Thus unbalanced transmission power can help improve concurrency. We can formulate the concurrency issue as follows:

$$\max_{x_i, p_i} \sum_{i=1}^{N} x_i \tag{5.13}$$

Subject to

$$\frac{p_i G_{ii} x_i}{\sum_{j \neq i} p_j G_{ij} x_j + n_i} \geq \beta_i x_i, i = 1 \ldots N \tag{5.14}$$

where x_i is the indicator variable {0,1}. When $x_i = 1$, it mean that link i is scheduled to transmit; otherwise, link i shall not transmit. This model would help find the maximum set of concurrent links under all conditions with the SINR constraints satisfied. With the maximum concurrency, the transmission power would be optimal as well. In other words, optimal transmission will help increase concurrency.

Problem (5.13) is NP-Hard in general. We can introduce a slack constant Z, as a very large number, and transform this problem into standard Mixed Integer Linear Programming, which can be easily solved with an optimization tool.

$$\min f * X' \tag{5.15}$$

$$\text{Subject to} \tag{5.16}$$

$$AP \leq b \tag{5.17}$$

$$0 \leq P \leq P_{max} * X \tag{5.18}$$

$$\text{variable} \tag{5.19}$$

$$X' = [P \ X] \tag{5.20}$$

where, $A = F - I, b = Z(I_v - X) - \eta$ and $f = -I_v$. I_v represents a vector with all number 1. In the transformed form, we can see that $Z(1 - x_i)$ is introduced for each link. The transmission power can be zero and is constrained by the scheduling variable.

When it is not easy to obtain optimal transmission power and maximal concurrency, heuristic power control algorithms such as the fractional power control algorithm [23] may be used. In fractional power control, the transmission power is computed as follows:

$$P_i = \frac{P_0}{E[h_{ii}^{-w}]} h_{ii}^{-w}, w \in [0, 1], \tag{5.21}$$

where h_{ii} is the fading coefficient of the link i, and P_0 is a constant. Jindal et al. [23] have shown that letting $w = 0.5$ tends to minimize communication outage probability.

5.3.3 Numerical analysis

In this section, we would like to demonstrate the numerical results of power control. Consider a network in a factory with four spatially-separated links.[1] In the first numerical example we will assume every link in the system has constant channel where the gain matrix F (5.5) is as follows:

[1]The purpose of using a small network here is to illustrate the key insight into the behavior of power control without being distracted by complexities of large-scale networks.

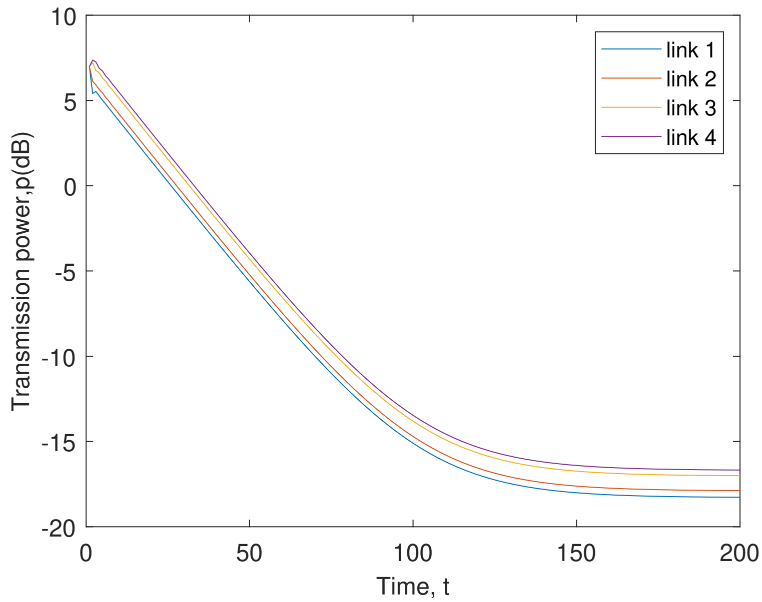

Figure 5.3: Transmission power: feasible condition

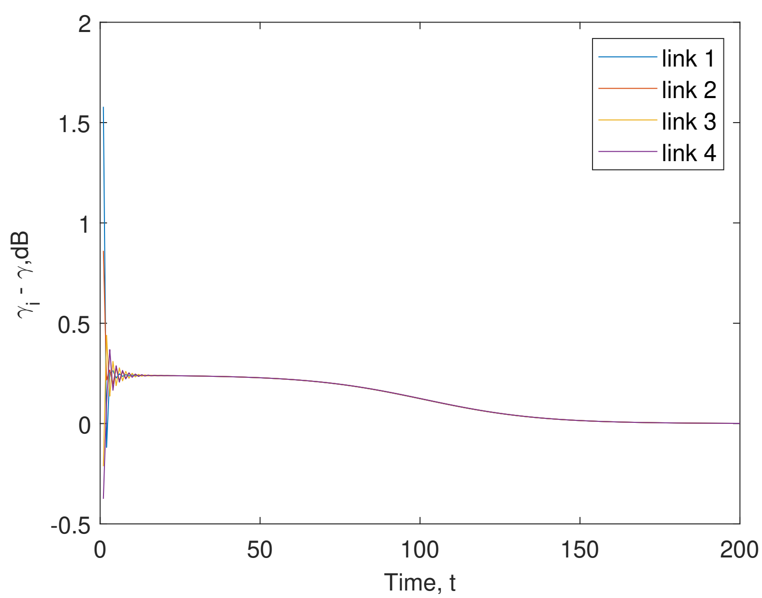

Figure 5.4: SINR: feasible condition

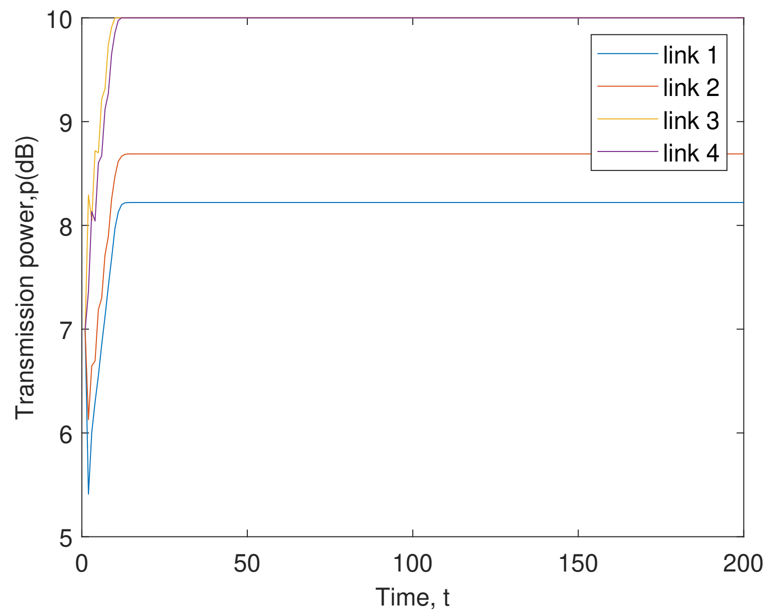

Figure 5.5: Transmission power: infeasible condition

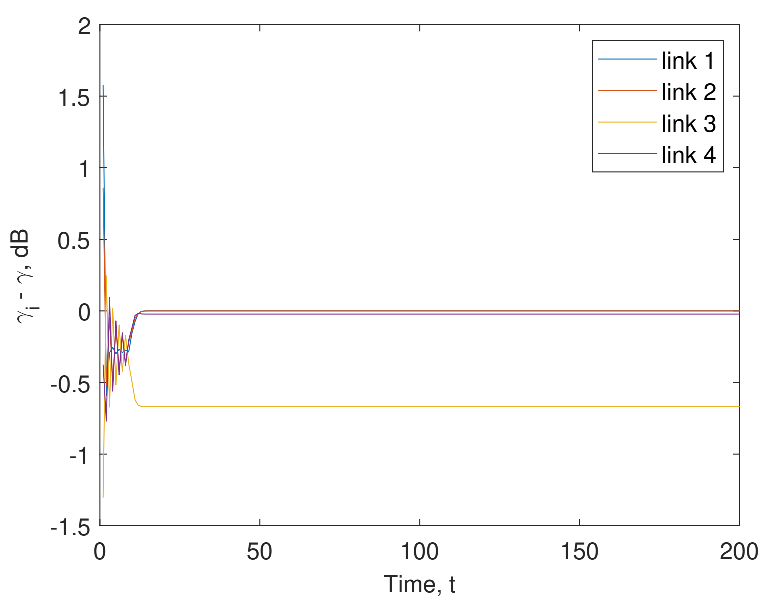

Figure 5.6: SINR: infeasible condition

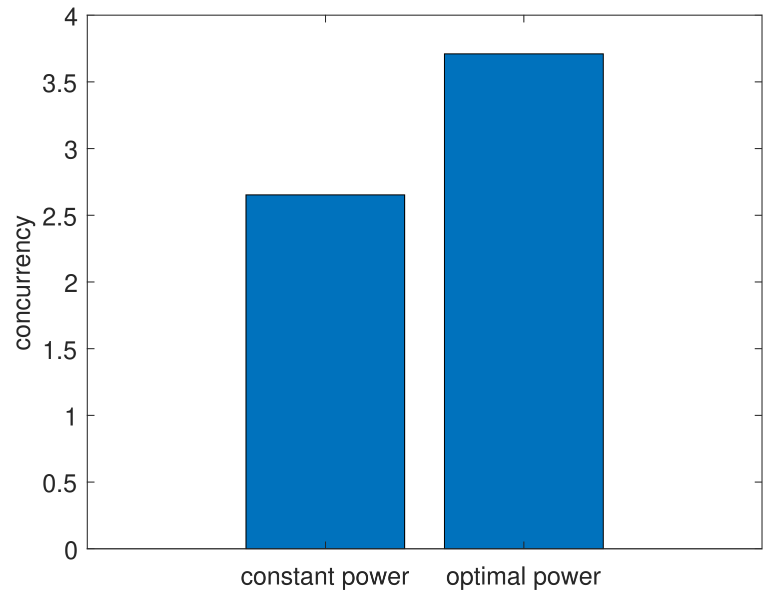

Figure 5.7: Concurrency is improved for optimal power under a set of four links

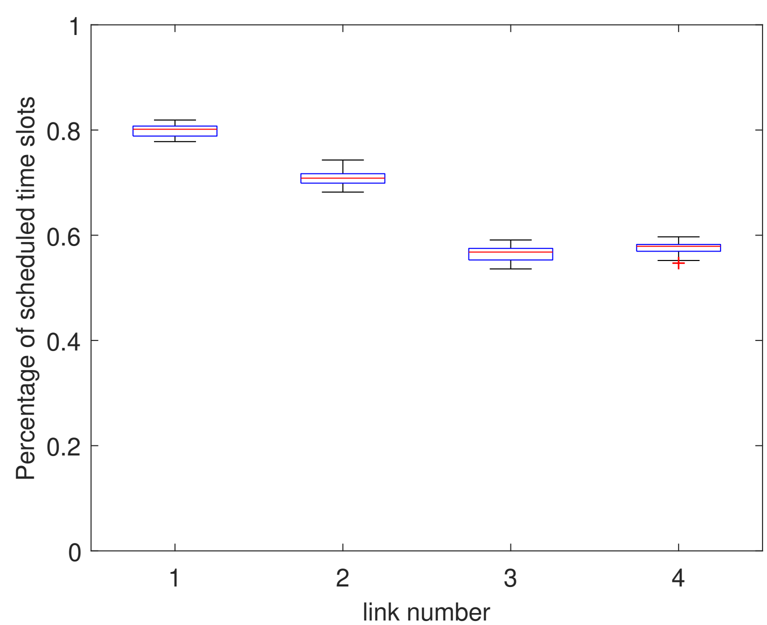

Figure 5.8: Transmission probability with constant power

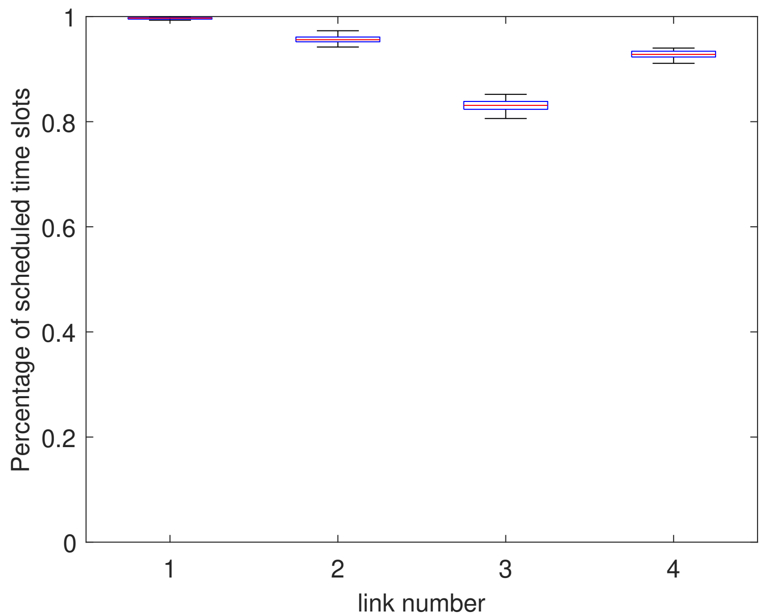

Figure 5.9: Transmission probability with optimal power

$$F = \begin{bmatrix} 0 & 0.12 & 0.275 & 0.3 \\ 0.24 & 0 & 0.48 & 0.1 \\ 0.12 & 0.55 & 0 & 0.38 \\ 0.09 & 0.21 & 0.79 & 0 \end{bmatrix} \tag{5.22}$$

We assume the target SINR threshold $\gamma = 5$ and the normalized noise $\eta = \{0.001, 0.001, 0.001, 0.001\}$. Given the gain matrix, the row sums are $S = \{0.695, 0.82, 1.05, 1.09\}$. Using the MatLab optimization toolbox, we obtain the Perron root $\rho = 0.9459$ and the optimal transmission power $P* = \{-18.2898, -17.899, -17.0250, -16.6933\}$. So we should expect a feasible transmission power solution and the Foschini-Miljanic algorithm would converge stably. Meanwhile, when we change F a little bit and set $F_{23} = 0.68$, we found that $\rho = 1.0668$ and the set becomes infeasible such that link 3 will be unable to transmit while other links still meet the required SINR threshold.

Transmission power converges to the fixed point in the feasible condition (see 5.3 and 5.4), and diverges and reaches the maximum value in the infeasible condition (see 5.5 and 5.6). Note that the Y axes of all the subfigures are in logarithmic scale, and the Y axes of Figures 5.4 and 5.6 show the actual receiver-side SINR minus the target SINR. In the feasible condition, all links' transmission power will converge to the fixed point. The SINR will first converge to a point equal to γ/ρ and then to the target point γ. In the case of infeasibility where link 3 has the maximum receiver-side interference, link 3 will reach out to its maximum transmission power and keep unchanged. Once the transmission power of link 3 reaches its maximum, other links will converge quickly and reach their target SINR γ. Thus, the divergence of Foschini-Miljanic algorithm demonstrates the necessity of scheduling from another perspective.

Now we evaluate the concurrency benefit of power control. We assume the gain of every link in the system is an independent exponentially-distributed random variable with the expected gain matrix as (5.22), and a link's instantaneous channel gain changes across different time slots. Then, we solve Problem (5.13) for the case when all links transmit with a constant transmission power irrespective of the channel gains, as well as the case when all the links transmit with an optimal transmission power based on the instantaneous channel gain. We run the study for 1,000 time slots. For each link, we calculate the percentage of time slots when it is scheduled to transmit while having its required SINR met, and denote it as the transmission probability. We repeat the study for 10 times and obtain statistical results for each link. Figure 5.7 show the concurrency for the constant power and optimal power respectively, and Figures 5.8 and 5.9 show the transmission probability for each single link. We see that, when the optimal transmission power is used, the concurrency has been improved greatly.

5.4 Distributed Scheduling and Power Control in Dynamical Networks

We now discuss the effect and limitation of joint scheduling and power control in dynamic networks. For comparison, we introduce a general framework of distributed scheduling and power control. In this framework, we adopt the scheduling strategy of silencing closing-by links. Power control algorithms such as fractional power control [23] are used to evaluate their performance in responding to channel dynamics. But before diving into more details, we would like to investigate the characteristics of channel dynamics.

5.4.1 Channel dynamics

Shadowing and multi-path fading are main sources of channel dynamics. For the purpose of analysis, statistical models are generally used. Although statistical models cannot perfectly represent actual systems, these models allow us to obtain a clearer perspective and understanding of wireless communication systems. In statistical models, shadowing and multi-path fading are generally modeled by two independent variables. Under this model, we can have the received power as

$$p_{rv}(t) = p_{tr}(t)l(t)h(t), \tag{5.23}$$

Where p_{tr} and p_{rv} are the transmission power and reception power respectively, $l(t)$ denotes shadowing, and $h(t)$ denotes multi-path fading. Shadowing is usually modeled as a random variable with log-normal distribution. Typical fading distributions are Rician fading, Rayleigh fading, and Nakagami fading [12]. Different models are applicable to different scenarios. When there is a line-of-sight path between the transmitter and receiver, or there is a specular path between the transmitter and receiver, the channel is represented by a Rician fading model. When there is no main path component, we can think of the channel consisting of many small paths, and the Rayleigh fading model is the most widely used model in this case. The Nakagami model is known to provide a closer match to some measurement data than Rayleigh and Rician distributions do [13]. Rayleigh fading is widely used for modeling multi-path fading due to its exponential distribution as follows:

$$h(x,t) = \frac{1}{\Omega_p}\exp\{-\frac{x(t)}{\Omega_p}\}. \tag{5.24}$$

In the model above, the distribution is modeled as i.i.d over time t. However, in reality, the measured fading in each time instant is correlated. For the Rayleigh multi-path fading channel, the variability over time is reflected in its auto-correlation function (ACF) and the corresponding normalized (unit variance) continuous-time function are as follows

$$R(\tau) = J_0(2\pi f_d \tau) \tag{5.25}$$

where $J_0(.)$ is the zero-order bessel function, f_d is the maximum Doppler frequency in Hertz, and τ is the time delay.

The coherence time can be computed as $T_c = 2.4/f_d$ if considering the first zero point of $J_0(.)$. In a time-division system, auto-regression (AR) model can be be used to approximate Rayleigh fading channel as follows

$$h_{ii}(t+1) = \sum_{m=1}^{T_c} a_m h_{ii}(t-m-1) + \epsilon(t+1), \tag{5.26}$$

where T_c is the AR order, a_m is the auto-correlation coefficient, and $\epsilon(t+1)$ is the variance of Gaussian White Noise with mean value 0.

As revealed in [80], to accurately model the Rayleigh fading channel, the AR order R is required to be larger than coherence time. In this paper, we consider the time correlation of channel dynamics rather than adopting independent and identically distributions.

5.4.2 Distributed approach for joint scheduling and power control

We now introduce a distributed framework for joint scheduling and power control. This framework was first proposed for guaranteeing instantaneous SINR in the settings of slight channel variations [81]. Here we use the framework to explore the behavior and challenges of joint scheduling and power control for ensuring per-packet SINR and reliability in settings of large/complex channel variations.

Input: P_i^1, K_i^1, γ
Output: p_i^t, x_i^t
$\bar{G}_{i,j}$ = MeasureAverageChannel();
for $t \leftarrow 1$ **to** T **do**
  γ_i^t = MeasureSINR(p_i^t, x_i^t);
  (p_i^{t+1}, k_i^{t+1}) = UpdateSchedulingKandPower(p_i^t, k_i^t, γ_i^t, γ);
  x_i^t = NAMAScheduling(k_i^t, $\bar{G}_{i,j}$);
end

Algorithm 3: A distributed framework for joint scheduling and power control

As presented in Algorithm 3, this framework consists of SINR measurement, PRK-model adaptation [82], power control, and NAMA scheduling [65]. SINR measurement means that the receiver of each link will measure the SINR of its received signal. Zhang et al. in [82] presented a detailed method of how the receiver's SINR can be measured. NAMA scheduling is a simple approach to channel access scheduling for wireless networks. It calculates a priority for each link at each time slot. The link with the highest priority among a set of conflicting links will be scheduled to transmit at each time slot. So once we have the PRK model parameter K for each link (which specifies a guard area around receiver of each link), we can build the conflict graph, and then the NAMA scheduling will determine which links can transmit. First we have the initial scheduling K and run NAMA scheduling to determine if a link can transmit. Then the SINR measurement will obtain the current SINR. Based on the measured SINR, scheduling and power control will obtain a guard area specified by the PRK model parameter K and update the transmission power. Based on the guard-area parameters, each link will be able to build a conflict graph and run the NAMA scheduling again. The process repeats to schedule data transmissions over time.

5.4.3 Simulation study

Simulation scenario. We simulate a random network with Poisson Point Process of density $\lambda = 0.01$ in a square area of [100m, 100m], where the number of nodes is 100. Each node is a sender, and its receiver is randomly chosen among all the nodes within 5 meters.

Channel settings. We adopt the power law pass loss model and the path loss index is set as $\alpha = 3.5$. The multi-path fading is modelled as correlated Rayleigh fading with AR order set as $T_c = 0, 10, 100$. $T_c = 0$ means that the channel is i.i.d.

Scheduling algorithm. We consider the impact of guard area. To facilitate the experimental analysis, the scheduling K doesn't adjust on the fly. We set the scheduling K as different fixed values $K = 1, 2, 3, 4, 5, 6$ and study their impact.

Power control algorithm. We adopt the strategies of constant transmission power and fractional power control algorithm for this study, with fractional power control widely used in existing cellular networks.

Simulation results. First, we discuss the impact of scheduling. We set the transmission power as constant. As shown in Figure 5.10, concurrency has improved from average 30 links to 50 links when the guard area K changes from 6 to 1. However, Figure 5.11 shows an interesting result that,

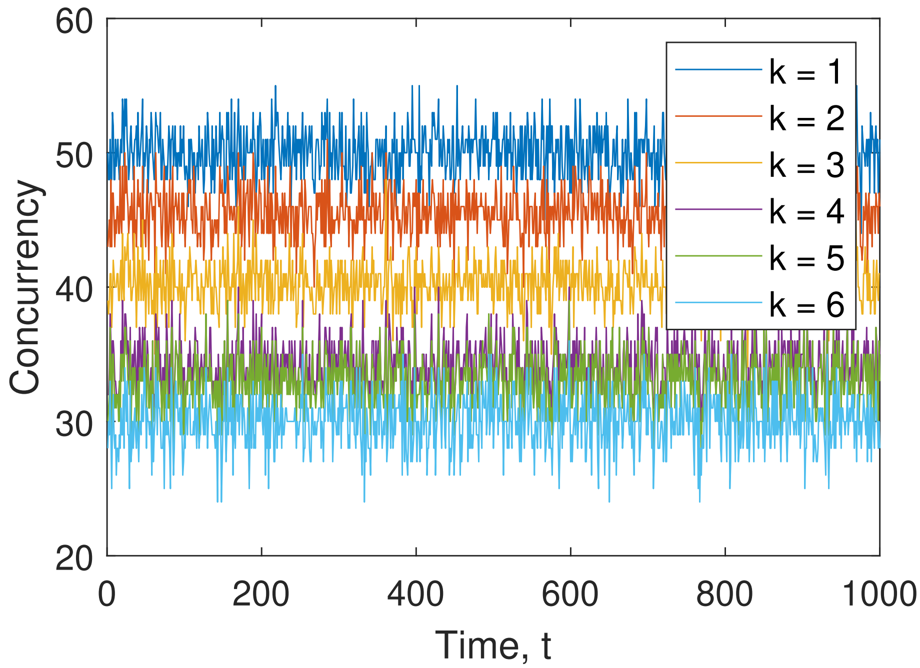

Figure 5.10: Currency improvement in large networks under different guard area K

for a typical link, its transmission probability (or percentage of time slots when the link is scheduled to transmit) may not change for some Ks such as 3, 4, 5, and 6. That is because, even though the overall transmission probability across the network nodes decreases as K increases, the set of interfering links in the guard zone around a specific link may not change for every change of K. In addition, scheduling K significantly affects a link's instantaneous SINR as shown in Figures 5.12 and 5.13, with the receiver-side SINR increasing with K. However, there is significant variation in SINR for every K configuration, for instance, up to 13dB. In addition, we have observed that given the network setting, it can take around two minutes to obtain the optimal solution. In contrast, our distributed approach can obtain the scheduling K in a much faster way.

Next, we focus on the case of $K = 3$ and discuss the impact of power control. We compare constant power and fractional power since optimal power is unavailable in a distributed scheme. As shown in Figure 5.14 and 5.15, the fractional power helps make SINR variation smaller as compared with constant transmission power. However, the SINR variation is still non-negligible in the case

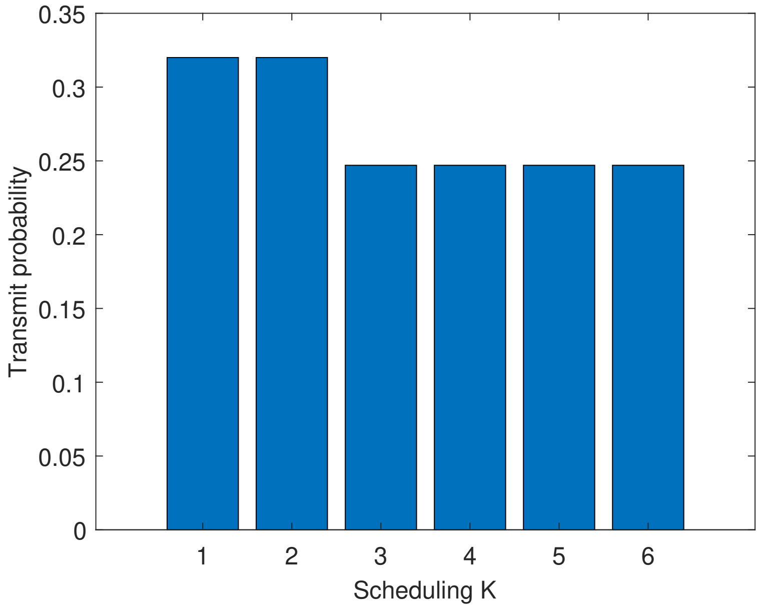

Figure 5.11: Transmission probability

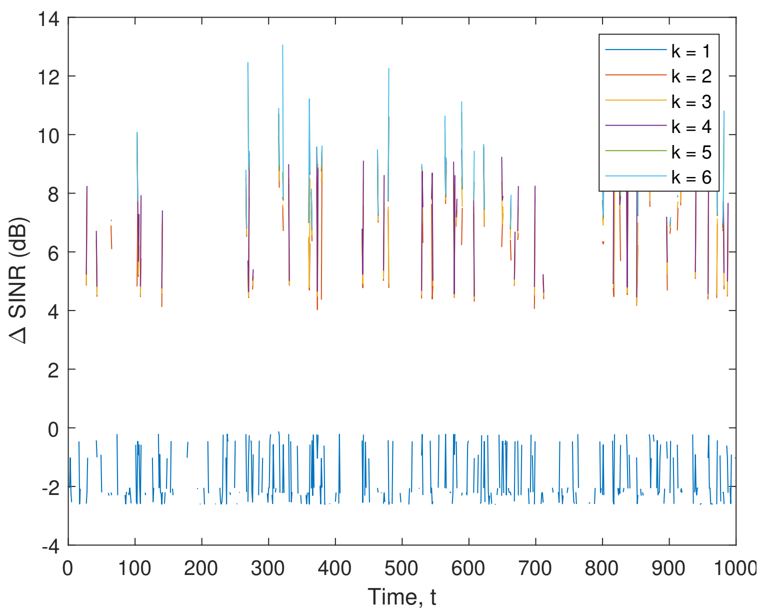

Figure 5.12: SINR: different K

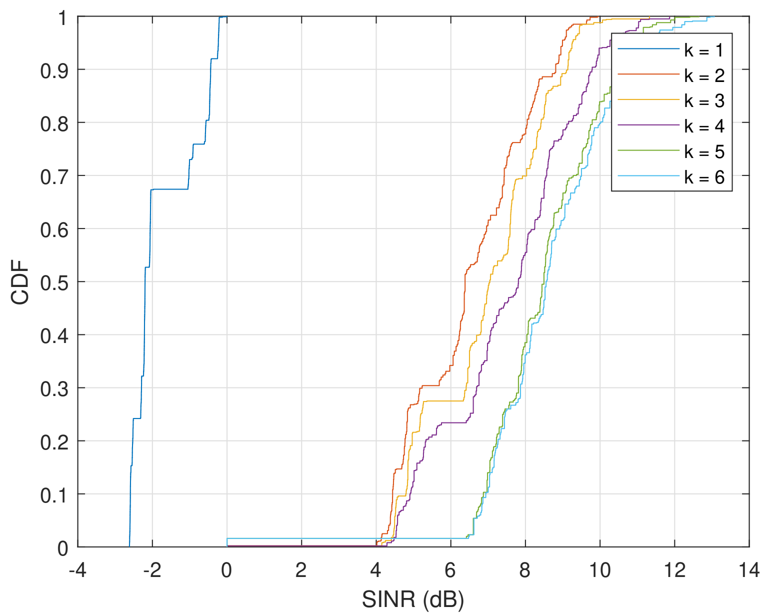

Figure 5.13: SINR CDF: different K

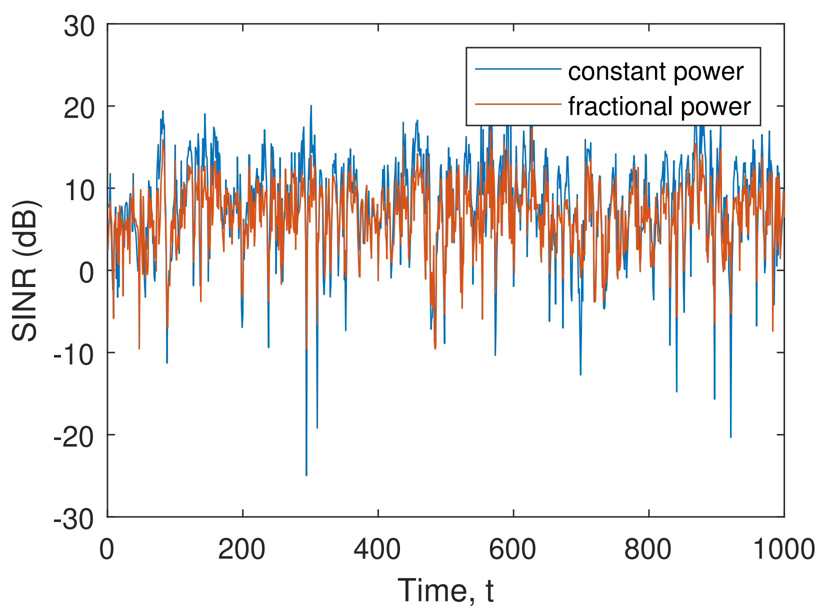

Figure 5.14: SINR: different power control

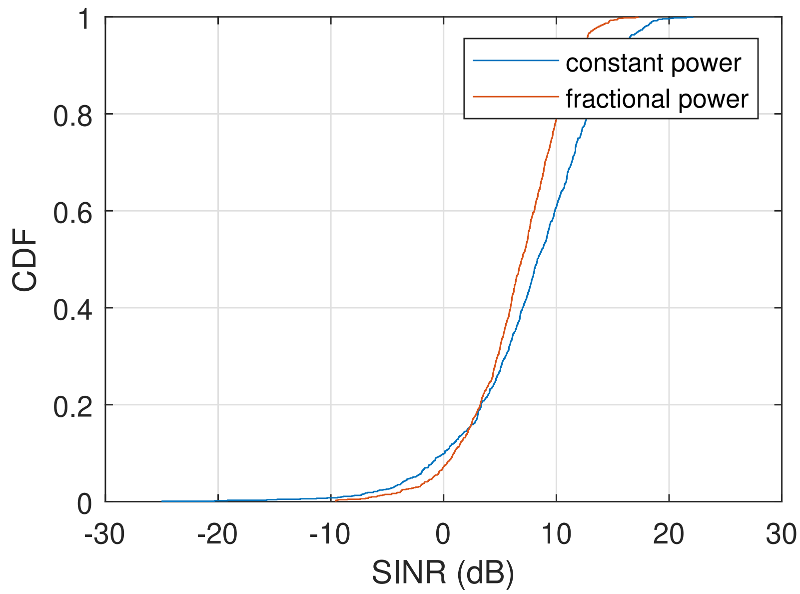

Figure 5.15: SINR CDF: different power control

of fractional power control. This is in part because fractional power control only adapts to channel attenuation and doesn't target to regulate SINR. In terms of concurrency, fractional power control also enables slight improvement over constant power, as shown in Figure 5.16.

Lastly, we discuss SINR changes under different time scales of channel dynamics in the case of fractional power control. We find only slight differences in SINR are observed for different time scales of channel dynamics as presented by the SINR CDF in Figure 5.17 for a typical link with K = 3.

At first sight, this result is beyond our expectation. However, it becomes reasonable when we find that the channel variations are still large even when $Tc = 100$. This result exposes the challenges of distributed scheduling and power control. When the channel variation is large, current power control algorithms cannot regulate the SINR to a small range. Meanwhile, due to the randomness of NAMA scheduling, the spatial distribution and number of interfering links can change significantly, leading to significant variations in the accumulated receiver-side interference and SINR.

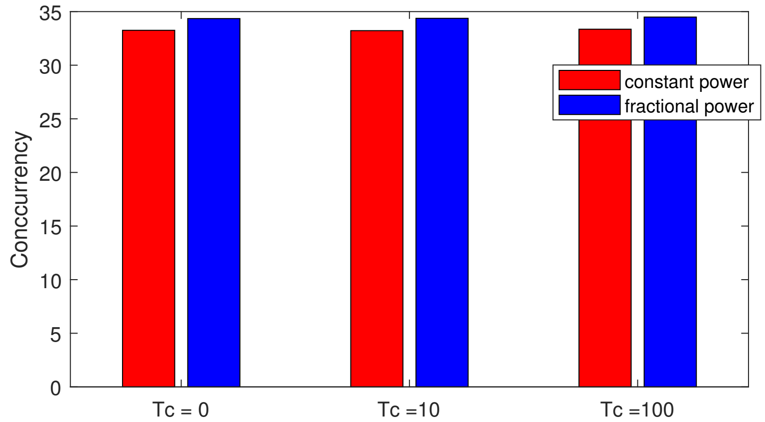

Figure 5.16: Slight concurrency improvement with fractional power under channel dynamics

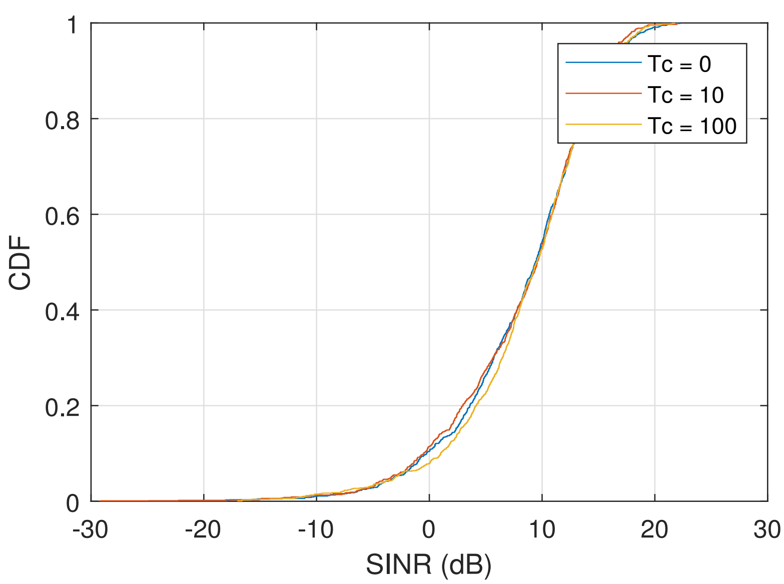

Figure 5.17: SINR behavior under channel dynamics

In summary, sacrificing concurrency (e.g., by expanding the guard area) can help increase receiver-side SINR. For more precise control of receiver-side SINR to smaller variations, mechanisms shall be designed to regulate the impact of the large variations in channel gains and to mitigate the randomness in NAMA scheduling. Detailed study of these will be good avenues for future research.

5.5 Conclusion

Towards developing field-deployable approaches to joint scheduling and power control in ensuring per-packet communication reliability, we analyze the roles of scheduling and power control as well as their interactions in ensuring per-packet communication reliability and high network throughput, and we evaluate a candidate framework of distributed implementation. Our main contributions are as follows:

- By investigating properties of the interference gain matrix, we for the first time demonstrate the relationship between scheduling and power control, and SINR feasibility of individual links. The characteristics of gain matrices are such that close-by links have significant impact on the power control SINR feasibility of a link, which suggests that silencing close-by links would be a promising scheduling strategy of ensuring power control SINR feasibility as well as high communication concurrency and throughput.
- We present the exact picture of how power control can help improve transmission concurrency by comparing scheduling with constant transmission power and optimal transmission power respectively in dynamic networks. The significant improvement indicates that there is a big potential for power control to help compensate for the sacrifice that scheduling algorithm usually bring to ensure reliability.
- We evaluate the behavior of a candidate framework in achieving SINR requirements in different channel dynamics settings. Our evaluation demonstrates the challenges of field-deployable joint scheduling and power control for ensuring predictable per-packet SINR and reliability, for instance, the limited capability of well-known power control algorithms (e.g., constant power

and fractional power) in regulating SINR variations. The study suggests a few promising future directions of research, for instance, addressing the randomness of NAMA scheduling.

CHAPTER 6. CONCLUSION AND FUTURE RESEARCH

6.1 Conclusions

In this dissertation, power control technique and reliability issue in cyber-physical systems have been studied. We started our investigation from cellular networks and explore all power control techniques that have been adopted in commercial cellular networks, like 2G, 3G and 4G. We found that power control techniques in cellular networks are applicable to cyber-physical systems but new challenges are observed as well, such as the ad-hoc architecture and harsh channel environments. Through this dissertation, we have focused our research on addressing channel dynamics and conduct distributed implementation of joint power control and scheduling.

First, we considered to build a system model and distributed power control framework to address channel dynamics and guarantee reliability. The theoretical results of power control in deterministic channel have been analyzed. We observed that the normalized interference is directly related to the Perron root and feasibility. Once the interference is bounded, the Perron root will be bounded. By this observation, we adopted the PRK model and NAMA scheduling as the foundation of the framework. In this framework, scheduling and power control will alternatively run. The feasibility of the proposed framework has been proved by analytical approach. This adaptive power control framework will be a foundation for distributed power control and scheduling algorithms.

Secondly, given the adaptive framework, we proposed a distributed implementation algorithm considering small-scale channel variation, where scheduling K and transmission power will be adapted over time. We have conducted experiments and verified that this algorithm enables distributed convergence in joint scheduling and power control with advantages in the ease of implementation, significant improvement in concurrency and SINR guarantees. The proposed algorithm is expected to serve as a foundation for distributed scheduling and power control as the penetration of IoT applications expands to scenarios where both the network capacity and communication reliability are critical.

Furthermore, we considered the reliability issue in large-scale channel dynamics. We found that power control is limited in solving large-scale channel dynamics, which means that channel variation may be fast and the scale is large beyond a couple of dbm in mobile settings. By investigating properties of the interference gain matrix, we for the first time demonstrated the relationship among scheduling, power control and SINR feasibility of individual link. We have suggested that silencing close-by links would be a promising scheduling strategy of ensuring power control SINR feasibility as well as high communication concurrency and throughput. We presented the exact picture of how power control can help improve transmission concurrency by comparing scheduling with constant transmission power and optimal transmission power respectively in dynamic networks. The significant improvement indicates that there is a big potential for power control to help compensate for the sacrifice that scheduling algorithm usually bring to ensure reliability. Our evaluation demonstrates the challenges of field-deployable joint scheduling and power control for ensuring predictable per-packet SINR and reliability, for instance, the limited capability of well-known power control algorithms (e.g., constant power and fractional power) in regulating SINR variations. The study suggests a few promising future directions of research, for instance, addressing the randomness of NAMA scheduling.

6.2 Future Work

In general, 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. 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. The use of reinforcement-learning to solve joint power control and rate control problem would be another direction.

While 5G networks are trying to build a ubiquitous network (including supporting cyber-physical systems), how to ensure predictable communication reliability remains an open question, and many of the issues studied in this dissertation will apply, even though in the context of the cellular architecture instead of ad-hoc network architecture.

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