Analysis of Joint Scheduling and Power Control for Predictable URLLC in Industrial Wireless Networks

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***Abstract*—Wireless networks are being applied in various industrial sectors, and they are posed to support mission-critical industrial IoT applications which require ultra-reliable, low-latency communications (URLLC). Ensuring predictable per-packet communication reliability is a basis of predictable URLLC, and scheduling and power control are two basic enablers. Scheduling and power control, however, 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 reliability. Towards addressing the gap, we examine the cross-layer design of joint scheduling and power control and analyze the associated challenges. We introduce the Perron–Frobenius theorem to demonstrate that scheduling is a must for ensuring predictable communication reliability, and by investigating characteristics of interference matrices, we show that scheduling with close-by links silent effectively constructs a set of links whose required reliability is feasible with proper transmission power control. 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 the reliability at each time instant and throughput in the long-term. Based on the analysis, we propose a candidate framework of joint scheduling and power control, and we demonstrate how this framework behaves in guaranteeing per-packet communication reliability in the presence of wireless channel dynamics of different time scales. 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.**

I. 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 [1]. Commercial transportation firms are using streaming sensor data from vehicles to identify potential breakdowns and perform preventive and predictive maintenance [2]. 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 [3]. 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[4][5].

Per-packet communication reliability. 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.

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 [6]:

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

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:

$$PDR(\gamma, l) = (1 - BER(\gamma))^{8l}, \quad (2)$$

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

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:

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

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. Based on the formula above, 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.

Joint scheduling and power control. Power control and scheduling are basic enablers of reliable communication at the physical layer and MAC layer of wireless networks respectively [7]. 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 [8][9].

Gupta et al. [10] 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[11]. 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 [12] 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) [13] optimization issue. Due to the NP-hard characteristic, approximation algorithms naturally arise. Wan et al. [8] 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. [9] and Wan et al. [8] also obtained the maximum set of independent links. Magnús M. Halldórsson conducted extensive research on joint scheduling and power control [14]. However, those studies mainly focused on obtaining asymptotic characterization of joint scheduling and power control when using obvious transmission power algorithms [15], and those proposed algorithms are rarely implementable in a distributed way.

Contributions. 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 frameworks 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 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.

Organization. The remaining parts of this paper are organized as follows: Section II analyzes the power control SINR feasibility and proposes a scheduling strategy; Section III presents the contribution of power control; Section IV evaluate the behavior of a candidate framework under different channel dynamics settings; Section V discusses related work; Section VI concludes the paper.

II. 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.

A. Perron-Frobenius Theorem and Need for Scheduling

As denoted in (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 γ. This SINR constraint can be represented in a matrix form as

$$(I - F)P \geq \eta, \text{ with } P > 0, \tag{4}$$

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

$$F_{ij} = \begin{cases} \frac{\gamma g_{ij}}{g_{ii}}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases}, \tag{5}$$

η is the vector of normalized noise power,

$$\eta = (\frac{\gamma n_1}{g_{11}}, \frac{\gamma n_2}{g_{22}}, \ldots, \frac{\gamma n_N}{g_{NN}})^T, \tag{6}$$

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). Let ρ_F be the Perron-Frobenius eigenvalue of F. Then from the Perron-Frobenius theorem and standard matrix theory [16], 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.

B. 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*:

$$f_{ij} = \frac{\gamma g_{ij}}{g_{ii}}, i, j \in \{1, 2, ...N\} \tag{7}$$

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

Definition 1. *The accumulated interference factor is defined as sum of interference from all links normalized by link gain and scaled by target SINR, represented as*

$$I_i = \sum_{i \neq j} \frac{\gamma g_{ij}}{g_{ii}}, i, j \in \{1, 2, ...N\} \tag{8}$$

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 1. *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 [17]. 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 factor 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 $g_{ij} = \frac{c}{d_l^\alpha}$, where c is a constant, d_l 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_l and thus the largest g_{ij}. According to Corollary 1, 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 [18]. 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. [11] 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.

C. 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 proposed scheduling policy. Haenggi et al. [18] 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:

$$P\{SINR_i \geq \gamma\} = P\{\frac{ch_{ii}}{d_{ii}^{\alpha}} \geq \gamma(\sum_{j\in\Phi: d_{ij} > ud_{ii}} \frac{ch_{ij}}{d_l^{\alpha}})\}, \quad (9)$$

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 [18].

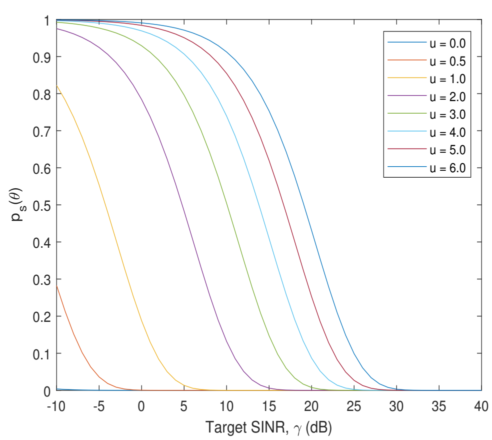


Fig. 1: Comparison of packet delivery rate with different guard area

As shown in Figure 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 still benefit the packet delivery ratio. 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.

III. 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 question of power control is 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 [19] as we discuss next.

A. Characteristics of Foschini-Miljanic's Algorithm

Let's revisit the Perron-Frobenius theory again. According to the Perron-Frobenius theorem, if there exist solutions for the inequality (4), an optimal point can be obtained and denoted as

$$P^* = (I - F)^{-1}\eta. \quad (10)$$

where $P*$ is the minimal transmission power among all feasible solutions, called ***fixed point***. As stated in [20], 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 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.

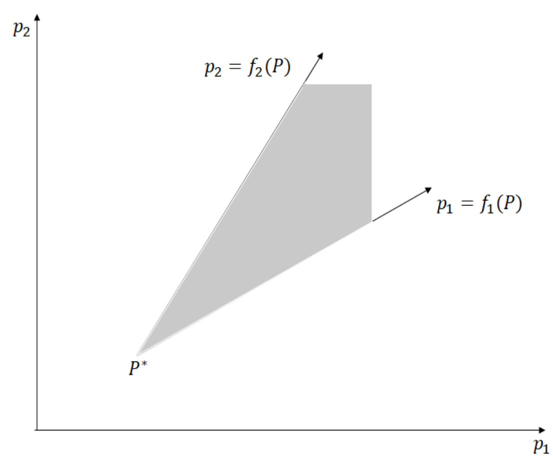


Fig. 2: The fixed point with a set of two links

Based on the theory above, Foschini and Miljanic [19] 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:

$$P(t) = FP(t-1) + \eta, \quad (11)$$

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

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

$$P_i(t) = \frac{\gamma}{\gamma_i(t-1)} P_i(t-1), i = 1, 2, 3, ... \quad (12)$$

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 III-C.

B. 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 experience the same interference power. Thus unbalanced transmission power can help improve concurrency. We can use the following formula to formulate concurrency issue:

$$\max_{X_i, P_i} \sum_{i=1}^{N} X_i \tag{13}$$

Subject to

$$\frac{P_i G_{ii} X_i}{\sum_{j \neq i} P_j G_{ij} X_j + n_i} \geq \beta_i X_i, i = 1 \dots N \tag{14}$$

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 (13) is NP-Hard in general. When it is not easy to obtain optimal transmission power and maximal concurrency, heuristic power control algorithms such as the fractional power control algorithm [21] may be used. In fractional power control, the transmission power is computed as follows:

$$P_i = \frac{P_0}{E[h_{ii}^{-w}]} h_{ii}^{-w}, w \in [0, 1], \tag{15}$$

where h_{ii} is the fading coefficient of the link i, and P_0 is a constant. Jindal et al. [21] have shown that letting $w = 0.5$ tends to minimize communication outage probability.

C. 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) is as follows:

$$F = \begin{bmatrix} 0 & 0.12 & 0.275 & 0.3 \\ 0.24 & 0 & 0.48 & 0.1 \\ 0.12 & 0.55 & 0 & 0.38 \\ 0.09 & 0.21 & 0.79 & 0 \end{bmatrix} \tag{16}$$

[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.

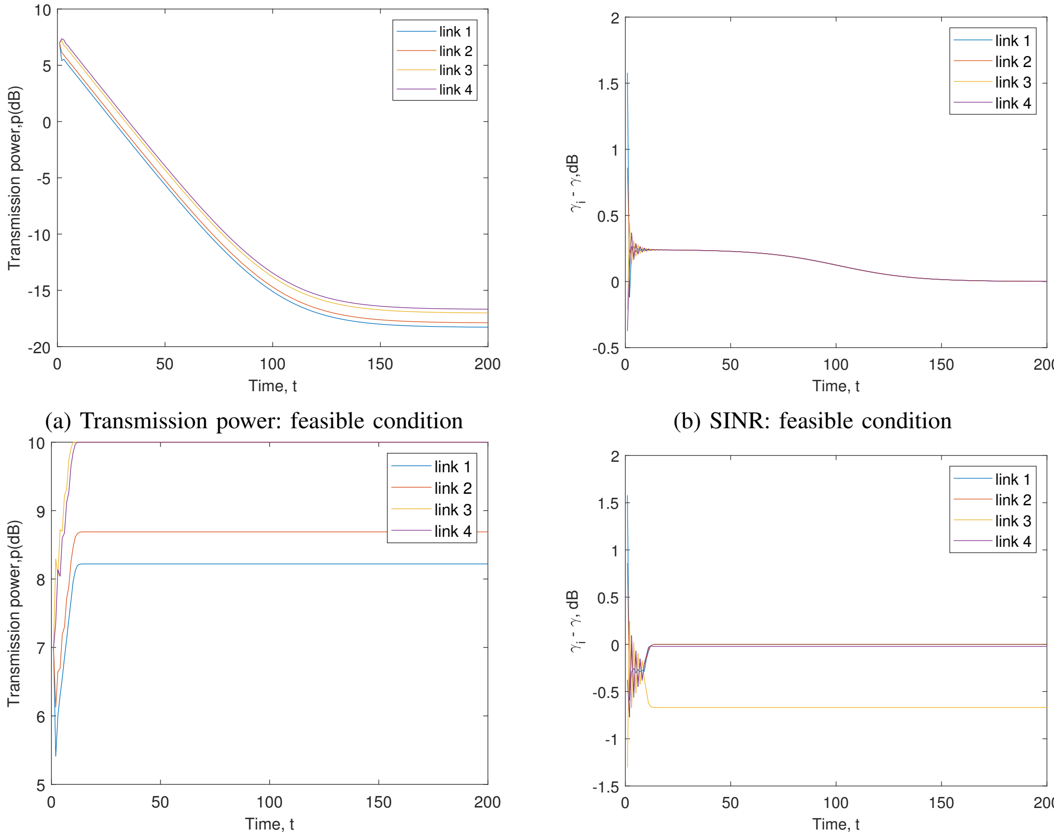
We assume the target SINR threshold $\gamma = 5$ and the normalized noise $\eta = \{0.001, 0.001, 0.001, 0.001\}$. Given the gain matrix, the row sums are $\{0.695, 0.82, 1.05, 1.09\}$. Using the MatLab optimization toolbox, we obtain the Perron root $\rho = 0.9459$ and the optimal transmission power $P* = \{-18.2898, -17.899, -17.0250, -16.6933\}$. 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.

Figure 3 shows the time series of the transmission power and receiver-side SINR of the four links under the feasible condition (Figures 3a and 3b) and infeasible condition (Figures 3c and 3d) respectively. Note that the Y axes of all the subfigures are in logarithmic scale, and the Y axes of Figures 3b and 3d 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 SINR reach γ. Thus, the divergence of Foschini-Miljanic algorithm demonstrates the necessity of scheduling from another perspective. Next section will present the analysis of joint scheduling and power control.

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 (16), and a link's instantaneous channel gain changes across different time slots. Then, we solve Problem (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 show the concurrency for the constant power case and optimal power case respectively, and Figures 4a and 4b show the transmission probability for each single link. We see that, when the optimal transmission power is used, the concurrency has been improved greatly.

IV. Distributed Scheduling and Power Control in Dynamic 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



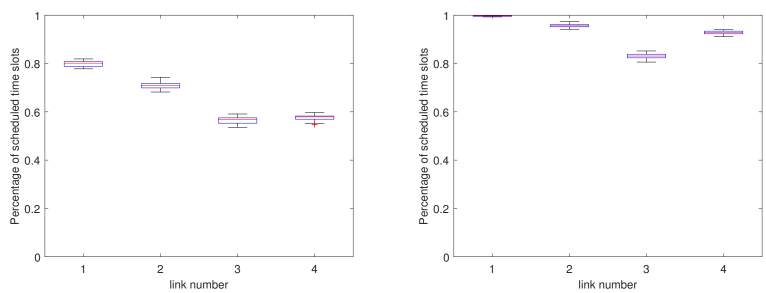
(a) Transmission power: feasible condition

(b) SINR: feasible condition

(c) Transmission power: infeasible condition

(d) SINR: infeasible condition

Fig. 3: Transmission power converges to the fixed point in the feasible condition (see 3a and 3b), and diverges and reaches the maximum value in the infeasible condition (see 3c and 3d).



(a) Transmission probability with constant power

(b) Transmission probability with optimal power

Fig. 4: Transmission probability for each link is improved when optimal transmission power is used.

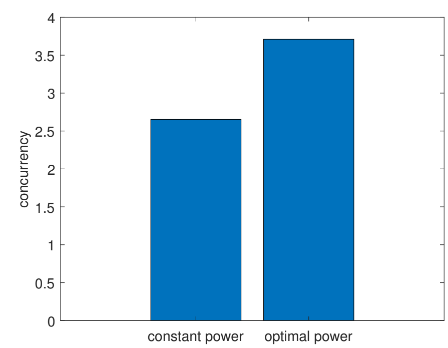


Fig. 5: Concurrency is improved for optimal power under a set of four links

strategy of silencing closing-by links. Power control algorithms such as fractional power control [21] 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.

A. 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

$$p_{rv}(t) = p_{tr}(t)l(t)h(t), \tag{17}$$

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 [22]. 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 [23]. Rayleigh fading is widely used for modeling multi-path fading due to its exponential distribution as follows:

$$h(x,t) = \frac{1}{\Omega_p}\exp\{-\frac{x}{\Omega_p}\}. \tag{18}$$

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

$$R(\tau) = J_0(2\pi f_d \tau) \tag{19}$$

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

$$h_{ii}(t+1) = \sum_{m=1}^{T_c} a_m h_{ii}(t-m-1) + \epsilon(t+1), \tag{20}$$

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

As revealed in [24], to accurately model the Rayleigh fading channel, the AR order R is required to be larger than coherence time. Therefore, in this paper, we consider the time correlation of channel dynamics rather than adopting independent and identically distributions.

B. Distributed Framework 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 [25]. 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.

As presented in Algorithm 1, this framework consists of SINR measurement, PRK-model adaptation [26] and power control, and NAMA scheduling [27]. SINR measurement means that the receiver of each link will measure the SINR of its received signal, and Zhang et al. in [26] 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.

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 1: A distributed framework for joint scheduling and power control

C. Simulation Study

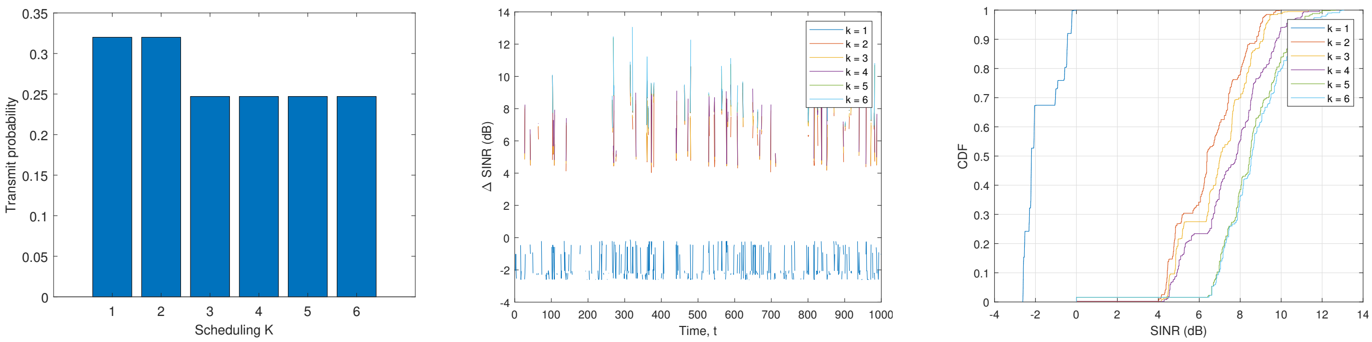
Simulation scenario. We simulate a random network with Poisson Point Process of density $\lambda = 0.01$ in a square area of [100m, 100m], where the number of nodes is 100. Each node is a sender, and its receiver is randomly chosen among all the nodes within 5 meters.

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 7, concurrency has improved from average 30 links to 50 links when the guard area K changes from 6 to 1. However,



(a) Transmission probability (b) SINR: different K (c) SINR CDF: different K

Fig. 6: Behavior of a typical link when different guard zone parameter K is used

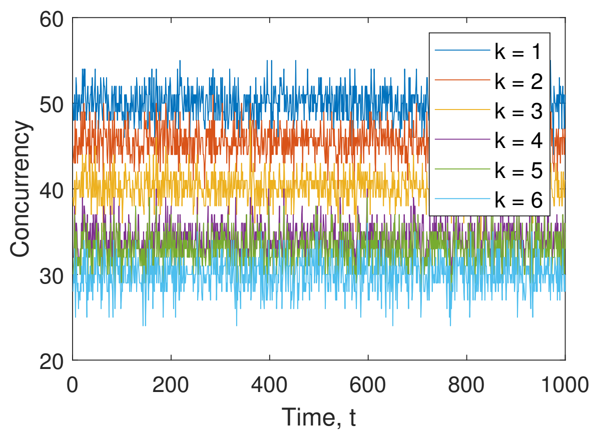
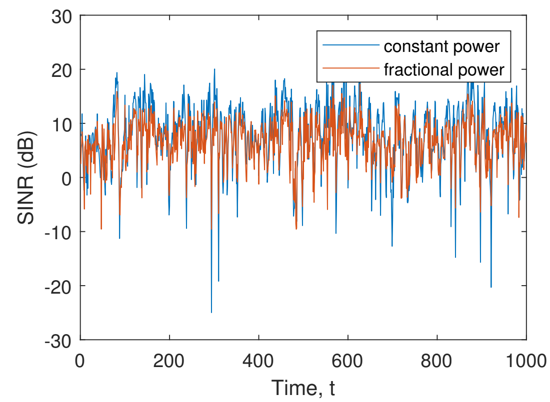
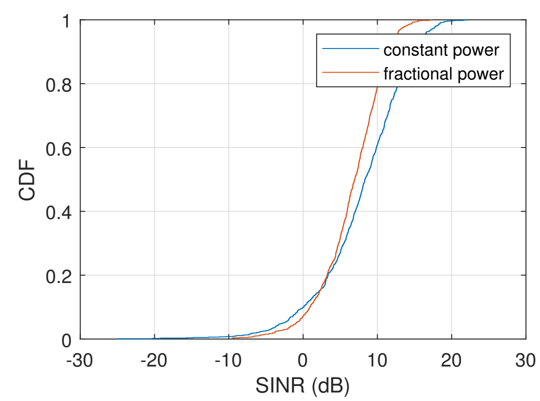


Fig. 7: Currency improvement in large networks under different guard area K



(a) SINR: different power control



(b) SINR CDF: different power control

Fig. 8: Impact of fractional power control on SINR given a fixed guard area

Figure 6a shows an interesting result that, 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 6b and 6c, with the receiver-side SINR increasing with K. However, there is significant variation in SINR for every K configuration, for instance, up to 13dB.

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 8, 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 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 9.

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

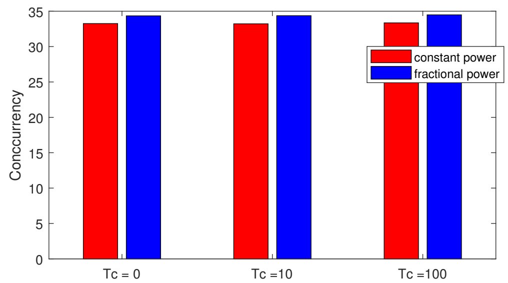


Fig. 9: Slight concurrency improvement with fractional power under channel dynamics

SINR CDF in Figure 10 for a typical link with K = 3. At

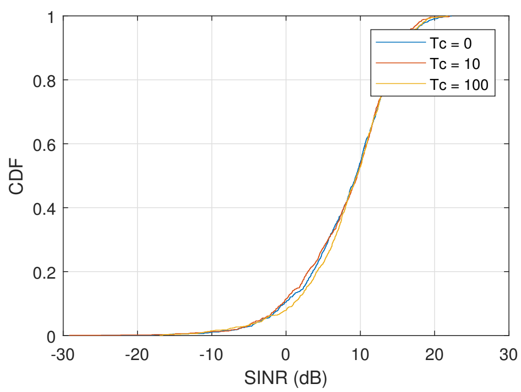


Fig. 10: SINR behavior under channel dynamics

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.

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.

V. Related Work

Gupta et al. [10] presented the system capacity limitation from co-channel interference. Their findings demonstrated that co-channel interference must be mitigated since it doesn't necessarily helps with system capacity and even decreases individual link's reliability and good throughput. Wan et al. [8] 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. Zhang et al. [11] proposed the PRK interference model and a control-theoretic approach to PRK-based scheduling [26] for predictable mean communication reliability and easy field deployment.

Foschini and Miljanic [19] proposed a simple and distributed approach for power control to seek a simple effective means of power control of signals associated with randomly dispersed users in cellular networks. The proposed approach was proved to converge to a fixed point, which is the optimal point on minimizing individual energy consumption. Foschini-Miljanic's approach was widely adopted in wireless sensor networks where distributed implementation is desirable in a mesh topology. Elbatt and Ephremides [12] first introduced joint scheduling and power control framework in wireless ad hoc networks and formulated this issue as a Mixed Integer Linear Programming (MILP) [13] optimization problem. Due to its NP-hardness, approximation algorithms naturally arise. This model disclosed the challenge of joint scheduling and power control in wireless sensor networks. Magnús M. Halldórsson conducted extensive research on joint scheduling and power control [14]. However, those work mainly focuses on obtaining asymptotic characterization of joint scheduling and power control. Meanwhile, they assumed obvious transmission power algorithms [15], such as constant power, power inversion, and those algorithms are rarely implemented in a distributed way.

Channel dynamics is another challenge for reliable packet delivery. Lin et al. [28] 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. Kandukuri and Boyd [29] modeled the impact of channel dynamics on outage probability and built the equation between optimal transmission power and desirable packet delivery ratio. Chiang et al. [7] extended Kandukuri and Boyd's work and can obtain the closed-form transmission power for each link by solving a geometric programming problem. Those algorithms, however, only try to ensure average packet delivery rate without considering per-packet SINR assurance. Holliday et al. [30] attempted to address channel dynamics issue but only obtained average SINR and concluded that FM algorithm may bring SINR overshoot issue.

Wang et al. [25] proposed a distributed scheduling and power control scheme to address channel dynamics. Although their framework obtained a significant improvement in concurrency and satisfied SINR requirements, it mainly accommodates the situation where there is only small variations of channel dynamics and scheduling is rarely adjusted. Under large range of channel dynamics, the problem of ensuring predictable packet delivery reliability for every packet transmission or over a short time interval has not been solved yet.

VI. Concluding Remarks

We have presented an analysis of joint scheduling and power control in guaranteeing predictable per-packet communication reliability. The analysis shows that scheduling is a must and power control can help improve concurrency. In order to obtain these insight, we have introduced the Frobenius-Perron theory and proposed that silencing closing-by links will help regulate co-channel interference to ensure power control SINR feasibility and high transmission concurrency. We then showed that 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 power control SINR feasibility and infeasibility respectively. Building on the insight into scheduling and power control, we have experimentally evaluated the behavior of a distributed framework of joint scheduling and power control, which integrates the scheduling strategy of silencing close-by links with the distributed NAMA scheduling algorithm and classical power control methods. 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.

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