Distributed Scheduling and Power Control for Predictable IoT Communication Reliability

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***Abstract*—Mission-critical IoT applications such as wireless-networked industrial control require reliable wireless communication. 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. Joint scheduling and power control has been explored for reliable wireless communication, but existing solutions are mostly centralized or do not consider real-world challenges such as fast channel fading. Towards a foundation for mission-critical IoT communication, we develop a distributed, field-deployable approach to joint scheduling and power control that adaptively regulates co-channel interference and ensures predictable IoT communication reliability in the presence of wireless communication dynamics and uncertainties. Our approach effectively leverages the Perron-Frobenius theory, physical-ratio-K (PRK) interference model, and feedback control for PRK model adaptation and transmission power update. Through simulation analysis, we have shown that our approach improves concurrency by 70% than state-of-art fixed scheduling while ensuring successful SINR tracking over time. To the best of our knowledge, our 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.**

I. 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 [1] have facilitated applications of IoT in industrial automation, home intelligence, and health care. While those standards try to improve wireless communication reliability through mechanisms such as graph routing [2] 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 [3] 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 [4]. Furthermore, wireless networks in the current IoT practice under star and mesh topologies 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 enhace 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 undoubtable that redundant designs such as graph routing and packet retransmission 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 [5], 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 [6]; 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 [4], and many studies have showed the benefits of joint power control and scheduling as well [7][8]. 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 [9] evidence that the received signal strength across links of wireless sensor networks changes over time and suggeste 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.

In this paper, we aim to develop a field-deployable, joint TDMA scheduling and power control framework for supporting reliable wireless networks in IoT systems. This framework is designed to implement distributed scheduling and power control with an objective of maximizing concurrency and tracking SINR over channel dynamics. We dived into the Perron-Frobenius theory [10] and formulated our problem. We adopted Physical-Ratio-K (PRK) interference model [11] and NAMA TDMA scheduling algorithm [12] to build the whole distributed framework while both were specifically designed to facilitate distributed scheduling. 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 framework and algorithms, 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 paper 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 paper are organized as follows: Section III defines the system model and identifies the problem; Section IV elaborates on the framework and algorithms; Section V evaluates the design; Section II highlights related work and findings; Section VI concludes the paper.

II. Related work

Foschini and Miljanic's work in [13] has been widely considered as a canonical algorithm in the field of power control. This simple, autonomous, and distributed power control, where each link updates their transmission power only from their received SINR, was proved to converge to a unique fixed point at which the total energy consumption is minimized under SINR constraints. Debasis Mitra [14] extended the Foschini and Miljanic's algorithm and verified the asynchronous convergence. Bambos et al. [15] and Huang et al. [16] have considered fixed-step power adjustment algorithms for admission control, but those algorithms do not ensure convergence to the fixed point. Yates [17] proposed concepts of standard interference function and standard power control and reveals the convergence conditions for general power control algorithms. While Foschini and Miljanic's algorithm has guided the study on distributed power control, most literature has overlooked the feasibility condition for power control.

Gupta et al. [18] investigated the system capacity limitation from co-channel interference and concluded that when identical randomly located nodes, each capable of transmitting at Wbits per second, form a wireless network, the throughput for each node can asymptotically approach 0. This finding indicates that mitigating co-channel interference by optimally utilizing power control and scheduling is required in wireless networks. Elbatt and Ephremides [7] introduced joint scheduling and power control framework to address multiple access issue in wireless ad hoc networks, yet tended to be implemented in a centralized way. Wan et al. [8] further 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. [19] and Wan et al. [8] proposed approximate algorithms in obtaining the maximum set of independent links. Magnús M. Halldórsson conducted extensive research on joint scheduling and power control. Particularly, Magnús M. Halldórsson [20] proposed to divide all links into equal link-length group and allocate transmission power for each group; the algorithm is centralized and does not conisder channel dynamics, thus unsuitable for distributed scheduling and power control in real-world networks of fast-varying channel gains.

Lin et al. [9] has evidenced in field tests that the channel for wireless sensor networks changes over time and adaptive transmission power is required. Their work, however, did not consider joint scheduling and power control to ensure receiver-side SINR all the time. Holliday et al. [21] proposed adaptive power control with channel dynamics to converge to a fixed point. However, their algorithm also did not consider joint scheduling and power control, and it only works for a set of links for which there exist a feasible power assignment. Kandukuri and Boyd [14] proposed optimal power control in interference-limited fading wireless channels with outage-probability specifications. Chiang et al. [22] extended Kandukuri and Boyd's work and proposed distributed power control scheme to converge to the optimal transmission power. Those algorithms, however, only try to ensure avearge packet delivery rate without considering per-packet SINR assurance. Zhang et al. proposed the PRK interference model [11] and a control-theoretic approach to PRK-based scheduling [23] for predictable mean communication reliability. However, their design has only considered scheduling without considering joint scheduling and power control for predictable instantaneous communication reliability.

III. 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

$$\frac{p_i G_{ii}}{\sum_{j \neq i} p_j G_{ij} + n_i} \geq \beta_{th} \tag{1}$$

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 (1), individual link's SINR depends on other links' transmission power. Transform all links$'$ SINR requirements into matrix form. We have

$$P \geq FP + \eta \tag{2}$$

where

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

and

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

Here P is the variant, and F is normalized gain matrix. Inequality (2) can be regarded as a Linear Programming issue [24]. Under constraint $P > 0$, a solution of transmission power exits if and only if (2) is feasible. On the contrary, if $P \geq 0$, the problem can be converted into joint scheduling and transmission power where all infeasible links' transmission power would be 0.

A. Perron-Frobenius theory and feasibility

Theorem 1. *(Perron-Frobenius Theory [25]) 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 $Ax = \lambda x$.*

Lemma 1. *(Feasibility condition [10]) A set of links is feasible if and only $\lambda(F) \leq 1$ when $\eta = 0$ and $\lambda(F) < 1$ when $\eta \neq 0$.*

Lemma 2. *(Optimum power [10]) If a set of links is feasible, the optimum power is $P^* = (F - I)^{-1}\eta$.*

In Lemma 1, $\lambda(F)$ is the the largest eigenvalue of F, called *Perron root*. P^* is called *fixed point*. Lemma 1 can be proved as in [10] when transforming Inequality (2) into $(F-I)P > \eta$. According to the feasibility condition in Lemma 1, two links are infeasible if $\beta_{th}^2 G_{12} G_{21} > G_{11} G_{22}$. It is obvious that two close-by links are easily becoming infeasible under constant path loss law only if the interfering link length is shorter than signal link length. This is consistent with the requirement for scheduling in real systems.

Th Perron-Frobenius theory not only suggests the existence of infeasibility for a set of links but also indicates that a subset of links can be feasible if $\lambda(F_s) < 1$ under thermal noise, where F_s is the matrix corresponding to a subset of links. 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

$$U = \{S_1, S_2, ..., S_m\} \tag{3}$$

and their corresponding optimal power as

$$P_i^* = \{P_1^*, P_2^*, ..., P_m^*\} \tag{4}$$

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 are tended to be distributed. Therefore, we need to figure out a simple way to identify feasible links and remove infeasible links.

B. Pysical-Ratio-K (PRK) model and feasible scheduling K

The physical-ratio-K(PRK) model [11] 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

$$G_{ij} \geq \frac{G_{ii}}{K_{ii}} \tag{5}$$

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 1. *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

$$U_i = \{S_{i1}, S_{i2}, ..., S_{im}\} \tag{6}$$

and corresponding transmission power as

$$P_i = \{P_{i1}, P_{i2}, ..., P_{im}\}. \tag{7}$$

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

$$K_f^i = \min_{j \in N_i} \frac{G_{ii}}{G_{ij}} \tag{8}$$

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 [12] 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

$$p_i^t = \textbf{Rand}(k \oplus t) \oplus t, \ k \in M_i \cup i \tag{9}$$

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.

IV. Distributed Scheduling K and Power Control

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

The core part of this framework 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 1. 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.
- **Case 2**. In case current SINR is smaller than target SINR β_{th}, if $K < K_{rref}$, scheduling K should be increased; otherwise, transmission power should be increased.

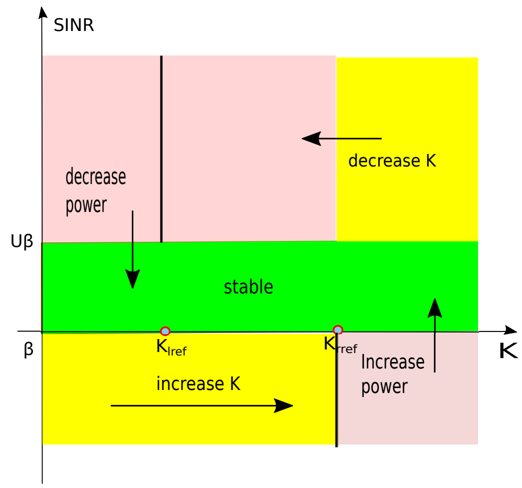

Fig. 1. The plane of scheduling K and SINR. Transmission power and K will be adjusted by their current location in the plane.

The algorithm is as described in Algorithm 2. We 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

$$I_i^t + \Delta I_i^{t+1} = p_i^{t+1} G_{ii}/\beta_{th} \tag{10}$$

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

$$I_i^t/G_{ii} + \sum_{j \in s_i^{t+1}} p_j^{t+1}/k_{ij} = p_i^{t+1}/\beta_{th} \tag{11}$$

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 (11) to

$$I_i^t/G_{ii} + p_i^{t+1}/k_i^{t+1} = p_i^{t+1}/\beta_{th} \tag{12}$$

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

$$I_i^t/G_{ii} - p_i^t/k_i^{t+1} = \frac{p_i^{t+1}}{M\beta_{th}} \tag{13}$$

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

$$p_i^{t+1} = M\frac{K_{rref} - \beta_i^t}{K_{rref}}\frac{\beta_{th}}{\beta_i^t}p_i^t \tag{14}$$

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.

```
Input: k_i^t, β_i^t, p_i^t, β_th
Output: p_i^t, k_i^t
γ_i^t ← β_th / β_i^t
if γ_i^t < 1/U then
    if k_i^t > K_rref then
        k_i^{t+1} ← max( (1/(1−γ_i^t)) β_th, K_lref)
    end
    else
        p(i) ← max(p_i^t/U, sqrt(U γ_i^t p_i^t))
        p(i) = max(p(i), P_min)
        p(i) = min(p(i), P_max)
    end
end
if γ_i^t > 1 then
    if k_i^t < K_rref then
        k_i^{t+1} ← (1/(γ_i^t − 1)) β_th
        if k_i^{t+1} >= K_rref then
            p_i^t ← min(U p_i^t, M ((K_rref − β_i^t)/K_rref) γ_i^t p_i^t)
            k_i^{t+1} ← K_rref
        end
    end
    else
        p_i^t ← min(U p_i^t, sqrt(M γ_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

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 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.

V. 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 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 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 multipath fading are simulated separately. 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 I.

TABLE I
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

A. 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 with constant channel. Fig. 2 shows that scheduling K for each link will be fixed around 50 time slots, and Fig. 3 shows that power control will converge to fixed value around 100 time slots. These results are as expected while our design has limited the adjustment range of transmission power at each time slot to obtain a stable system. As in Fig. 6, all links' SINR is over the target value. This suggests that our design ensures tracking and satisfaction of the required target SINR.

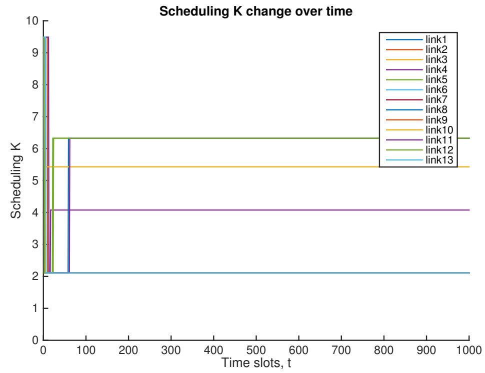

Fig. 2. Scheduling K converges to a fixed point for each link

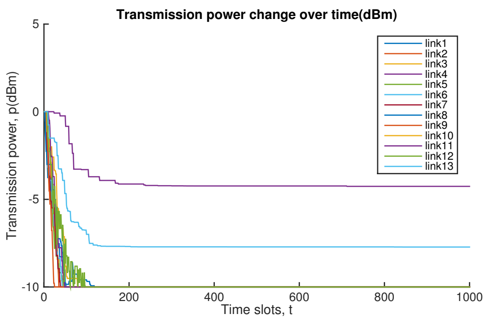

Fig. 3. Transmission power converges to a fixed point for each link

B. 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 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, for some links, transmission power is adjusted due to channel dynamics and then keep stable. Fig. 6 and Fig. 7 are the SINR variation over the 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.

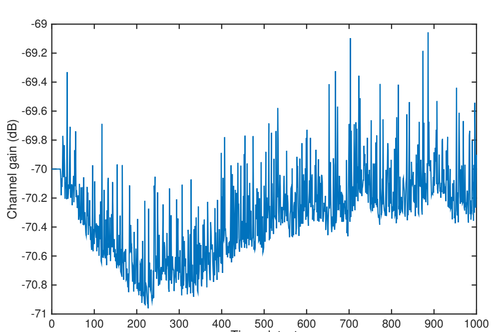

Fig. 4. Instantaneous channel gain over time slots under Rayleigh fading

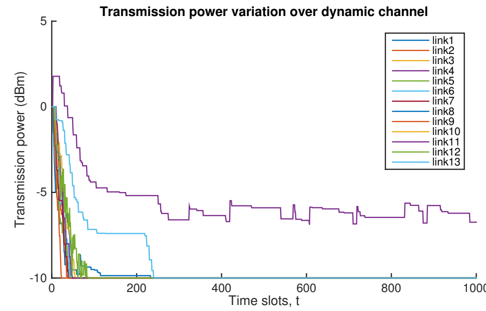

Fig. 5. Power update for each link over Rayleigh fading

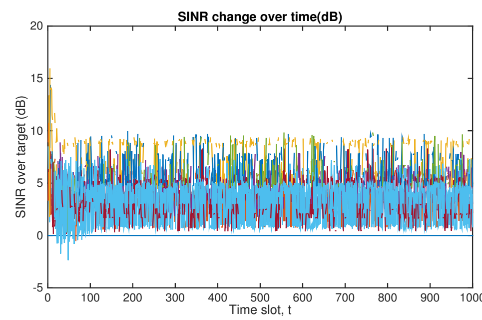

Fig. 6. SINR variation for each link under constant channel

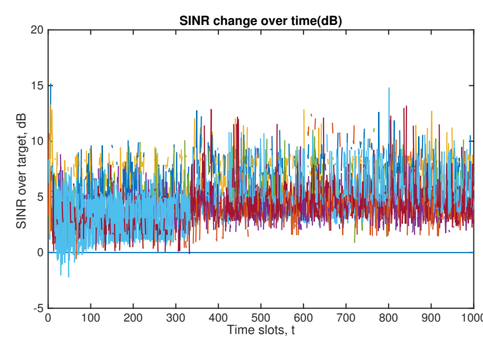

Fig. 7. SINR variation for each link under Rayleigh fading

C. Concurrency

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

- **ALOHA scheduling with Fractional power control**. ALOHA scheduling is random scheduling. Each link has equal chance to transmit or not. For fractional power control [26], 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 [13], $P_{t+1} = \frac{\beta_{th}}{\beta_t} P_t$.
- **Optimal scheduling and transmission power**. CPLEX is an optimization tool. We transform (1) into mixed integer linear programming issue and obtain the maximal number of feasible links and their transmission power given the constant gain matrix of a set of links.

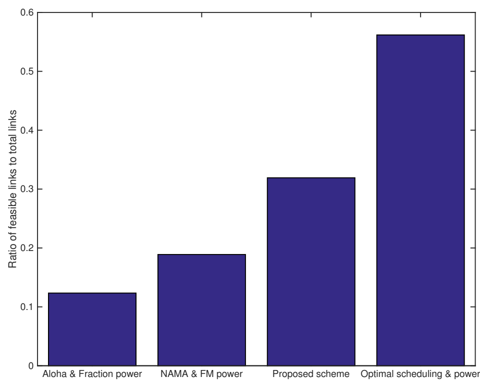

Fig. 8. Comparison of ratio of concurrent links over total links

We run each scheme 50 times and get the average value. Fig. 8 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.

VI. Conclusion

In this paper, 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 verify that this framework 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 framework 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.

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