Scheduling with Predictable Link Reliability for Wireless Networked Control

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***Abstract*— Predictable link reliability is required for wireless networked control, yet co-channel interference remains a major source of uncertainty in wireless link reliability. Integrating the protocol model's locality and the physical model's high fidelity, the physical-ratio-K (PRK) interference model has the potential to enable distributed, predictable control of co-channel interference and thus predictable link reliability. To realize the potential of the PRK model, we design protocol PRKS that addresses the challenge of instantiating the PRK model in the presence of network and environmental uncertainties. Formulating the PRK-model-instantiation problem as a minimum-variance regulation control problem, in particular, PRKS uses a control-theoretic approach to instantiating the PRK model on the fly. Through testbed-based measurement study, we show that, unlike existing scheduling protocols where link reliability is unpredictable and the ratio of links whose reliability meets application requirements can be as low as 0%, PRKS enables predictably high link reliability (e.g., 95%) for all the links in different network and environmental conditions without a priori knowledge of these conditions. Through local, distributed coordination, PRKS also achieves a channel spatial reuse very close to what is enabled by the state-of-the-art centralized scheduler while ensuring the required link reliability. By ensuring the required link reliability in scheduling, PRKS also enables a lower communication delay and a higher network throughput than existing scheduling protocols.**

I. Introduction

Embedded wireless networks are increasingly being explored for real-time control of physical processes [33], [30]. In wireless networked control (WNC), communication across wireless networks is a basic enabler for the coordination among distributed sensors, controllers, and actuators; in supporting mission-critical tasks such as industrial process control, wireless communication is required to be reliable (i.e., having high delivery ratio) [33]. Given the varying impact that the reliability, delay, and throughput of wireless communication have on networked control and the inherent tradeoff between communication reliability, delay, and throughput, the optimal operation of WNC systems requires controlling the tradeoff between the reliability, delay, and throughput in communication, where controlling data communication reliability across wireless links (or *link reliability* for short) in a predictable manner is a basis for such system-level optimization [33], [41], [48]. Causing collisions of concurrent transmissions, co-channel interference is a major source of unpredictability in link reliability [48]. Thus scheduling transmissions for co-channel interference control is a basic element of wireless communication in WNC systems.

Distributed scheduling & interference models. In WNC systems, not only does wireless link dynamics introduce uncertainty as in traditional wireless sensor networks, dynamic control strategies also introduce dynamic network traffic patterns and pose different requirements on communication reliability [34]. For agile adaptation to uncertainties and for avoiding information inconsistency in centralized scheduling, distributed scheduling becomes desirable for interference control in wireless control networks. Despite decades of research on interference-oriented channel access control, most existing literature are either based on the physical interference model or the protocol interference model, neither of which is a good foundation for distributed interference control in the presence of uncertainties [48].

In the *physical model*, a set of concurrent transmissions $(S_i, R_i), i = 1 \dots N$, are regarded as not interfering with one another if the following conditions hold:

$$\frac{P(S_i, R_i)}{N_i + \sum_{j=1 \dots N, j \neq i} P(S_j, R_i)} \geq \gamma, i = 1 \dots N \qquad (1)$$

where $P(S_i, R_i)$ and $P(S_j, R_i)$ is the strength of signals reaching the receiver R_i from the transmitter S_i and S_j respectively, N_i is the background noise power at the receiver R_i, and γ is the signal-to-interference-plus-noise-ratio (SINR) threshold required to ensure a certain link reliability. 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

$$D(C, R) \geq K \times D(S, R) \qquad (2)$$

where $D(C, R)$ is the geographic distance between C and R, $D(S, R)$ is the geographic distance between S and R, and K is a constant number.

The physical model is a high-fidelity interference model in general, but interference relations defined by the physical model are non-local and combinatorial; this is because, as can be seen from (1), whether one transmission interferes with another explicitly depends on all the other transmissions in the network. Thus the physical model is not suitable for distributed protocol design in the presence of dynamics and uncertainties in large-scale networks. The existing physical-model-based scheduling algorithms cannot ensure reliable data delivery in the presence of uncertainties, because they are centralized [9], require network-wide coordination [6], [32], [39], or are based on strong systems assumptions such as the reliable detection of a node's busy-tone signal by the whole network [39], the knowledge of nodes' locations [46], or the negligibility of cumulative interference [49], [43] which are not generically applicable in practice. Many of the physical-model-based MAC protocols are also throughput-oriented, and they do not control multi-hop interference for predictable link reliability [40], [48].

Unlike the physical model, the protocol model defines local, pairwise interference relations; that is, according to (2),

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interference is regarded as existent only between nodes in a local neighborhood, and whether one transmission interferes with another only depends on their own spatial distribution irrespective of other transmissions in the network. Thus the protocol model is suitable for distributed protocol design, *but it is inaccurate and does not ensure reliable data delivery in general* [48]. For instance, Choi et al. have shown that CSMA- and RTS-CTS-based channel access control mechanisms may only enable a data delivery ratio of 16.9% and 36.8% respectively [11].

Besides scheduling based on the physical and protocol interference models, distributed, throughput-optimal scheduling algorithms using general pairwise interference models (e.g., as defined by conflict graphs [22]) have also been proposed [35]. Theoretical in nature, however, these algorithms did not address the important question of how to identify the interference set of each link; their implementation usually assumes a model similar to the protocol model [35] and is unable to ensure predictable link reliability.

Without field-deployable solutions to predictable co-channel interference control, current systems practice, such as the WirelessHART standard for industrial sensing and control [10], avoids co-channel interference by allowing only one node in the whole network to transmit in a wireless channel at any moment in time. Without spatial channel reuse, however, this approach does not fully utilize wireless network capacity, which is undesirable for high data-rate control applications and for new networked control paradigms that involve communications between close-by nodes only [36].

Physical-ratio-K (PRK) interference model. The gap between the existing interference models and the design of distributed, field-deployable scheduling protocols with predictable data delivery reliability calls for an interference model that is both local and of high-fidelity, which are important for the agility and predictability of interference control respectively. Zhang et al. [48] have recently identified the *physical-ratio-K (PRK) interference model that integrates the protocol model's locality with the physical model's high-fidelity*. 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:

$$P(C', R) < \frac{P(S,R)}{K_{S,R,T_{S,R}}} \tag{3}$$

where $P(C', R)$ and $P(S, R)$ is the average strength of signals reaching R from C' and S respectively, and $K_{S,R,T_{S,R}}$ is the minimum real number chosen such that, in the presence of interference from all concurrent transmitters in the network, the probability for R to successfully receive packets from S is no less than the minimum link reliability $T_{S,R}$ required by applications (e.g., control algorithms). As shown in Figure 1, the PRK model defines, for each link (S, R), an exclusion region $\mathbb{E}_{S,R,T_{S,R}}$ around the receiver R such that a node $C \in \mathbb{E}_{S,R,T_{S,R}}$ if and only if $P(C,R) \geq \frac{P(S,R)}{K_{S,R,T_{S,R}}}$. Accordingly, every node $C \in \mathbb{E}_{S,R,T_{S,R}}$ is regarded as interfering with and thus shall not transmit concurrently with the transmission from S to R.

For enabling predictable interference control in the presence of network and environmental uncertainties, the parameter $K_{S,R,T_{S,R}}$ of the PRK model adapts to the specific network and environmental conditions to ensure the application-specific link reliability requirements. By ensuring the required link reliability and by using signal strength instead of geographic distance in model formulation, the PRK model captures the properties of wireless communication (e.g., cumulative interference and anisotropic signal propagation) and thus is *of high-fidelity*. For enabling distributed protocol design and implementation, the PRK model is also *local*: 1) The parameters of the PRK model are either locally measurable (i.e., for the signal strength and link reliability between close-by nodes) or locally controllable (i.e., for $K_{S,R,T_{S,R}}$ of each link (S, R)), thus PRK-based scheduling does not need to rely on parameters such as nodes' locations or channel path loss between far-away nodes which are often used in physical-model-based scheduling [46] but are difficult to obtain precisely, especially in a distributed manner; 2) Only pairwise interference relations between close-by nodes need to be defined in the PRK model, thus PRK-based scheduling does not require explicit global coordination which is often used in physical-model-based scheduling [6], [32]. Through comprehensive analysis, simulation, and measurement, we have observed that PRK-based scheduling can enable a channel spatial reuse very close to (e.g., >95%) what is feasible in physical-model-based scheduling while ensuring application-required reliability [48].

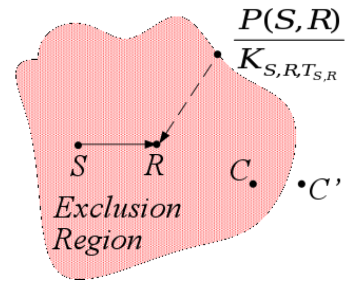

Fig. 1. PRK interference model

Focusing on formulating the PRK interference model and understanding the theoretically achievable performance of PRK-based scheduling, Zhang et al. [48] left the design of distributed protocols for PRK-based scheduling as an open problem. Yet realizing distributed PRK-based scheduling in real-world settings poses the following *major challenge*: the parameter $K_{S,R,T_{S,R}}$ of the PRK model (3) depends on the specific link (S, R), the application requirement on the link reliability (i.e., $T_{S,R}$), as well as the network and environmental conditions such as traffic pattern and wireless path loss which may well be dynamic and unpredictable, thus it is critical to instantiate the PRK model parameter $K_{S,R,T_{S,R}}$ on the fly depending on in-situ application requirements as well as network and environmental conditions; yet the relations between parameter $K_{S,R,T_{S,R}}$ and application requirements as well as network and environmental conditions are complex and difficult to characterize in closed-forms, which makes PRK model instantiation challenging.

Contributions of this paper. To enable predictable link reliability in WNC systems, we address the aforementioned challenge by designing the distributed PRK-based scheduling protocol *PRKS*. In PRKS, we formulate the problem of identifying the PRK model parameter $K_{S,R,T_{S,R}}$ as a minimum-variance regulation control problem, and we design distributed controllers that allow each link to adapt its PRK model parameter for ensuring the desired link reliability through purely local coordination. We have implemented PRKS in TinyOS. Through measurement study in the NetEye [24] and Indriya [1] wireless network testbeds, we demonstrate the following: 1)

The distributed controllers enable network-wide convergence to a state where the desired link reliabilities are ensured; 2) With local, distributed coordination alone, PRKS achieves a channel spatial reuse very close to what is enabled by the state-of-the-art centralized physical-model-based scheduler iOrder [9] while ensuring the required link reliability; 3) Unlike existing scheduling protocols where link reliability is unpredictable and the ratio of links whose reliability meets application requirements can be as low as 0%, PRKS enables predictably high link reliability (e.g., 95%) for all the links in different network and environmental conditions without a priori knowledge of these conditions; 4) By ensuring the required link reliability in scheduling, PRKS also enables a lower communication delay and a higher network throughput than existing scheduling protocols.

Organization of the paper. We present in Section II the network and traffic models as well as the slot-scheduling problem considered in this study. Then we elaborate on our control-theoretic approach to PRK model instantiation in Section III, and we evaluate the performance of PRKS in Section IV. We discuss related work in Section V, and we make concluding remarks in Section VI.

II. Preliminaries

As a first-step towards ensuring predictable link reliability in distributed scheduling, we consider mostly-immobile wireless control networks where nodes are statically deployed and are fixed at specific locations most of the time even though they may be moved around infrequently. In such networks, the average background noise power and the average wireless path loss do not change at short timescales (e.g., a few milliseconds for transmitting a few packets) [8]. Focusing on predictable co-channel interference control, we also only consider the cases when the data transmission power along a link is fixed even though different links may use different transmission powers; mobile networks and data transmission power control are relegated as future research.

Focusing on interference-oriented scheduling of data transmissions at the link layer, our study considers one-hop data transmissions between close-by nodes, but the network itself is multi-hop and with nodes widely distributed in space. Note that predictable reliability in one-hop transmissions is important by itself for new networked control paradigms that involve communications between close-by nodes only [36], and predictably reliable one-hop transmission is also a basis for reliable multi-hop transmission in general as we show in [2].

With the above network and traffic settings, we study the online slot-scheduling problem [9] where, given a set of links in a multi-hop network at any time instant, a maximal subset of the links need to be scheduled in a distributed manner to transmit concurrently while ensuring that the mean packet delivery reliability (PDR) across each of the scheduled links is no less than an application-required PDR across the link. To leverage the locality and high-fidelity of the PRK model, we investigate PRK-based online slot-scheduling.

III. Control-theoretic approach to PRK model instantiation

Minimum-variance regulation control. Given a link (S, R), the task of instantiating the PRK interference model is to identify the parameter $K_{S,R,T_{S,R}}$ such that the resulting scheduling can ensure the required minimum link reliability $T_{S,R}$.[1] It is, however, difficult to characterize the relation between $K_{S,R,T_{S,R}}$ and the packet delivery reliability along (S, R) in closed-form, and the relation is complex and dependent on network and environmental conditions which may well be unpredictable at design time [48]. To address the challenge, we observe that the PRK model instantiation problem can be formulated as an online *regulation control* problem [20], where the "plant" is the link (S, R), the "reference input" is the required link reliability $T_{S,R}$, the "plant output" is the actual link reliability $Y_{S,R}$ from S to R, and the "control input" is the PRK model parameter $K_{S,R,T_{S,R}}$. To address the difficulty in characterizing the "plant model" on the relation between the control input $K_{S,R,T_{S,R}}$ and the plant output $Y_{S,R}$, we observe that changing the PRK model parameter $K_{S,R,T_{S,R}}$ changes the exclusion region around the receiver R and thus the concurrent transmissions along with the transmission from S to R, which in turn leads to the change in the interference power at receiver R. Accordingly, we propose to regard this change in interference power, denoted by ΔI_R, as the actual control input. This way, we can leverage the existing communication theory to derive the plant model on the relation between $Y_{S,R}$ and ΔI_R as follows.

For conciseness, we use $I_R(t)$ to denote, in units of dBm, the sum of the average background noise power and the average power of all interfering signals at the receiver R at time t ($t = 1, 2, \ldots$); we also use $P_{S,R}(t)$ to denote the average received data signal power $P(S, R)$ in units of dBm at time t. Then communication theory gives us the following [48]:

$$Y_{S,R}(t) = f(P_{S,R}(t) - I_R(t)), \tag{4}$$

where $P_{S,R}(t) - I_R(t)$ represents the SINR in dB at time t, and $f(.)$ is an increasing function of $P_{S,R}(t) - I_R(t)$ with $f'(.) > 0$ and the specific function form dependent on the modulation and coding schemes used by the radio.[2] Given that the function f is usually non-linear and to address this challenge of non-linear control, we propose to approximate function f through linearization and use self-tuning regulators [20] to adapt controller behavior depending on the current operating point of the system. Given the SINR $P_{S,R}(t) - I_R(t)$ at time t ($t = 1, 2, \ldots$), more specifically, we linearize function f with the following linear function:

$$\begin{aligned}
&Y_{S,R}(t) = a(t)(P_{S,R}(t) - I_R(t)) + b(t),\\
&\text{where}\\
&a(t) = f'(P_{S,R}(t) - I_R(t)),\\
&b(t) = f(P_{S,R}(t) - I_R(t)) - (P_{S,R}(t) - I_R(t))a(t).
\end{aligned} \tag{5}$$

Assuming a discrete-time model where system properties such as the average background noise power and the average wireless path loss remain constant between time t and $t+1$,[3] $I_R(t+1)$ may differ from $I_R(t)$ for two possible reasons:

- From time t to $t+1$, the PRK model parameter may change from $K_{S,R,T_{S,R}}(t)$ to $K_{S,R,T_{S,R}}(t+1)$.

[1] Focusing on interference-oriented scheduling, we only consider the links whose packet delivery reliabilities are above the required ones in the absence of interference.

[2] Note that feedback control tends to be robust to modeling errors such that it is robust to minor model deviations from the theoretical model (4) in practice [20], [28].

[3] In protocol implementation, the actual time interval between t and $t+1$ can be chosen to be the small interval required for computing a sample of link reliability.

Accordingly, the exclusion region around the receiver R changes from $\mathbb{E}_{S,R,T_{S,R}}(t)$ to $\mathbb{E}_{S,R,T_{S,R}}(t+1)$. If $K_{S,R,T_{S,R}}(t+1) > K_{S,R,T_{S,R}}(t)$, nodes in $\mathbb{E}_{S,R,T_{S,R}}(t+1) \setminus \mathbb{E}_{S,R,T_{S,R}}(t)$ may transmit concurrently with the transmission from S to R and thus introduce interference to R at time t but not at time $t+1$; similarly, if $K_{S,R,T_{S,R}}(t+1) < K_{S,R,T_{S,R}}(t)$, nodes in $\mathbb{E}_{S,R,T_{S,R}}(t) \setminus \mathbb{E}_{S,R,T_{S,R}}(t+1)$ may introduce interference to R at time $t+1$ but not at time t. We use $\Delta I_R(t)$ to denote the average interference change at receiver R due to the change of the PRK model parameter from t to $t+1$. Since the receiver R can control the changes of the PRK model parameter as we will discuss shortly, $\Delta I_R(t)$ can be controlled by the receiver R and is thus treated as the "control input".

- The set of nodes that are not in the exclusion region around the receiver R at t and $t+1$ and are scheduled to transmit concurrently with the link (S, R) may change from time t to $t+1$. Accordingly, the average interference introduced by nodes outside the exclusion region around R changes from t to $t+1$, and we use $\Delta I_U(t)$ to denote this change. Since $\Delta I_U(t)$ is beyond the local control of link (S, R), we treat $\Delta I_U(t)$ as a "disturbance" to the system and denote the mean of $\Delta I_U(t)$ as $\mu_U(t)$.

Therefore,

$$I_R(t+1) = I_R(t) + \Delta I_R(t) + \Delta I_U(t),$$

where $\Delta I_R(t)$ and $\Delta I_U(t)$ are in units of dB. Using the linear approximation of function f as shown by Equation (5) at time t, the predicted link reliability for time $t+1$ calculates as follows:

$$Y_{S,R}(t+1) = a(t)(P_{S,R}(t+1) - I_R(t+1)) + b(t).$$

Therefore, the "plant model" for link (S, R) at time t is

$$\begin{aligned} I_R(t+1) &= I_R(t) + \Delta I_R(t) + \Delta I_U(t) \\ P_{S,R}(t+1) &= P_{S,R}(t) \\ Y_{S,R}(t+1) &= a(t)(P_{S,R}(t+1) - I_R(t+1)) + b(t) \end{aligned} \tag{6}$$

where $(I_R(.), P_{S,R}(.))$ and $Y_{S,R}(.)$ are the "state" and the "output" of the plant respectively. To deal with the noise in measuring $Y_{S,R}(.)$, we use an exponentially-weighted-moving-average (EWMA) filter with a weight factor c ($0 \leq c < 1$) in the feedback loop [20].[4] Thus, the system model is as shown in Figure 2, where

$$y(t) = cy(t-1) + (1-c)Y_{S,R}(t). \tag{7}$$

Given the probabilistic nature of wireless communication, the measured link reliability $y(t)$ is expected to be inherently random. Thus the goal is to minimize the variance of $y(t)$ while making sure that its mean value is the required link reliability. More formally, the objective of the control design at time t is to choose the control input $\Delta I_R(t)$ that minimizes the variance of $y(t+1)$ while ensuring $E[y(t+1)] = T_{S,R}$, where $T_{S,R}$ is the required link reliability.[5] For this minimum-variance regulation control problem, we have

[4] c determines the tradeoff between the stability and agility of the EWMA filter. We let $c = \frac{15}{16}$ in our implementation so that the filter is stable in the presence of noise.

[5] Note that $E[y(t+1)] = E[Y_{S,R}(t+1)]$ at steady state.

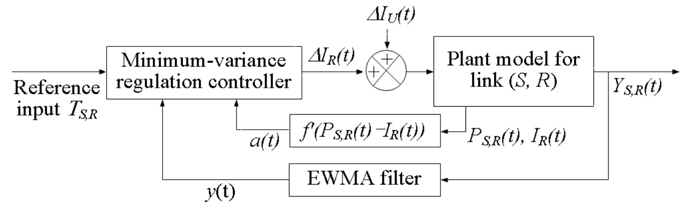

Fig. 2. PRK model instantiation: minimum-variance regulation control diagram

Theorem 1: The control input that minimizes $var[y(t+1)]$ while ensuring $E[y(t+1)] = T_{S,R}$ is

$$\Delta I_R(t) = \frac{(1+c)y(t) - cy(t-1) - T_{S,R}}{(1-c)a(t)} - \mu_U(t). \tag{8}$$

Proof: When $E[y(t+1)] = T_{S,R}$,

$$\begin{aligned} var[y(t+1)] &= E[y(t+1) - E[y(t+1)]]^2 \\ &= E[y(t+1) - E[y(t+1)] - \\ &\quad (1-c)a(t)(\mu_U(t) - \mu_U(t))]^2 \\ &= E[cy(t) + (1-c)[a(t)(P_{S,R}(t+1) - \\ &\quad I_R(t+1)) + b(t)] - T_{S,R} - \\ &\quad (1-c)a(t)(\mu_U(t) - \mu_U(t))]^2 \\ &= E[X - (1-c)a(t)(\Delta I_U(t) - \mu_U(t))]^2 \end{aligned} \tag{9}$$

where

$$\begin{aligned} X \;=\; & cy(t) + (1-c)[a(t)(P_{S,R}(t+1) - I_R(t)) + b(t)] \\ & -T_{S,R} - (1-c)a(t)\mu_U(t) - (1-c)a(t)\Delta I_R(t). \end{aligned}$$

At time t, $a(t)$ is given and $E[\Delta I_U(t) - \mu_U(t)] = 0$. Thus $E[(1-c)a(t)(\Delta I_U(t) - \mu_U(t))] = (1-c)a(t)E[\Delta I_U(t) - \mu_U(t)] = 0$, and we need $X = 0$ to minimize $var[y(t+1)]$. Accordingly, the control input that minimizes $var[y(t+1)]$ at time t is as follows:

$$\Delta I_R(t) = \frac{cy(t) + (1-c)[a(t)[P_{S,R}(t+1) - I_R(t)] + b(t)] - T_{S,R}}{(1-c)a(t)} - \mu_U(t).$$

With a constant data transmission power, we have $P_{S,R}(t+1) = P_{S,R}(t)$. Thus

$$\begin{aligned} \Delta I_R(t) &= \frac{cy(t) + (1-c)[a(t)[P_{S,R}(t) - I_R(t)] + b(t)] - T_{S,R}}{(1-c)a(t)} - \mu_U(t) \\ &= \frac{cy(t) + (1-c)Y_{S,R}(t) - T_{S,R}}{(1-c)a(t)} - \mu_U(t) \\ &= \frac{cy(t) + y(t) - cy(t-1) - T_{S,R}}{(1-c)a(t)} - \mu_U(t) \\ &= \frac{(1+c)y(t) - cy(t-1) - T_{S,R}}{(1-c)a(t)} - \mu_U(t). \end{aligned}$$

Given the above control input $\Delta I_R(t)$,

$$\begin{aligned} y(t+1) &= cy(t) + (1-c)[a(t)(P_{S,R}(t+1) - I_R(t+1)) + b(t)] \\ &= cy(t) + (1-c)[a(t)(P_{S,R}(t+1) - I_R(t) - \Delta I_R(t) - \\ &\quad \Delta I_U(t)) + b(t)] \\ &= cy(t) + (1-c)[a(t)(P_{S,R}(t+1) - I_R(t) - \\ &\quad \frac{cy(t) + (1-c)Y_{S,R}(t) - T_{S,R}}{(1-c)a(t)} + \mu_U(t) - \Delta I_U(t)) + b(t)] \\ &= cy(t) + (1-c)[a(t)(P_{S,R}(t+1) - I_R(t) - \\ &\quad \frac{cy(t) + (1-c)[a(t)[P_{S,R}(t+1) - I_R(t)] + b(t)] - T_{S,R}}{(1-c)a(t)} + \\ &\quad \mu_U(t) - \Delta I_U(t)) + b(t)] \\ &= T_{S,R} + (1-c)a(t)(\mu_U(t) - \Delta I_U(t)) \end{aligned} \tag{10}$$

Since $E[(1-c)a(t)(\mu_U(t) - \Delta I_U(t))] = 0$, $E[y(t+1)] = T_{S,R}$ indeed holds. Thus the control input $\Delta I_R(t)$ defined by (8) is indeed the optimal control input at time t. ■

As a first milestone towards predictable link reliability in interference-oriented scheduling, here we focus on ensuring the expected link reliability. Besides being important for mission-critical control by itself, ensuring the expected link reliability also helps reduce communication delay and improve network throughput as we will show in Section IV, which are important for real-time control too. Instantaneous link reliability at a time instant can also be controlled by integrating PRK-based scheduling with techniques such as power control [27] and rate control [3], but detailed study of this is beyond the scope of this paper.

From $\Delta I_R(t)$ to $K_{S,R,T_{S,R}}(t+1)$. Given that it is convenient for the receiver R to measure link reliability $y(t)$ [47], we propose to execute the minimum-variance controller (8) at R. Through purely local coordination between R and its sender S [2], R can also measure $P_{S,R}(t)$ and $I_R(t)$, thus R can compute $a(t)$ using Equation (5). For each time instant t, R can also derive $\Delta I_U(t-1)$ based on $I_R(t)$, $I_R(t-1)$, $\Delta I_R(t-1)$, and Equation (6); using these derived samples of $I_U(.)$ and an EWMA filter, R can then estimate $\mu_U(.)$. Therefore, R can execute the controller (8) using information that is either locally measured (e.g., for $y(t)$ and $y(t-1)$) or locally derived (e.g., for $a(t)$ and $\mu_U(t)$).

After R computes the control input $\Delta I_R(t)$ at time t, R needs to compute $K_{S,R,T_{S,R}}(t+1)$ so that

$$\begin{cases} K_{S,R,T_{S,R}}(t+1) = K_{S,R,T_{S,R}}(t), & \text{if } \Delta I_R(t) = 0 \\ K_{S,R,T_{S,R}}(t+1) > K_{S,R,T_{S,R}}(t), & \text{if } \Delta I_R(t) < 0 \\ K_{S,R,T_{S,R}}(t+1) < K_{S,R,T_{S,R}}(t), & \text{if } \Delta I_R(t) > 0 \end{cases} \quad (11)$$

and that, when the PRK model parameter is $\min\{K_{S,R,T_{S,R}}(t), K_{S,R,T_{S,R}}(t+1)\}$, the expected interference introduced to R by the nodes in either $\mathbb{E}_{S,R,T_{S,R}}(t)$ or $\mathbb{E}_{S,R,T_{S,R}}(t+1)$ but not in both is as close to $|\Delta I_R(t)|$ as possible while ensuring that the expected link reliability is no less than $T_{S,R}$ when the PRK model parameter is $K_{S,R,T_{S,R}}(t+1)$.[6] To realize this, we define, for each node C that may be included in the exclusion region of R during network operation, the expected interference $I(C,R,t)$ that C introduces to R when C is not in the exclusion region of R. Then $I(C,R,t) = \beta_C(t)P(C,R,t)$, where $\beta_C(t)$ is the probability for C to transmit data packets at time t and $P(C,R,t)$ is the power strength of the data signals reaching R from C.[7] Considering the discrete nature of node distribution in space and the requirement on satisfying the minimum link reliability $T_{S,R}$, we propose the following rule for computing $K_{S,R,T_{S,R}}(t+1)$:

- When $\Delta I_R(t) = 0$, let $K_{S,R,T_{S,R}}(t+1) = K_{S,R,T_{S,R}}(t)$.
- When $\Delta I_R(t) < 0$ (i.e., need to expand the exclusion region), let $\mathbb{E}_{S,R,T_{S,R}}(t+1) = \mathbb{E}_{S,R,T_{S,R}}(t)$, then keep adding nodes not already in $\mathbb{E}_{S,R,T_{S,R}}(t+1)$, in the non-increasing order of their data signal power at R, into $\mathbb{E}_{S,R,T_{S,R}}(t+1)$ until the node B such that adding B into $\mathbb{E}_{S,R,T_{S,R}}(t+1)$ makes $\sum_{C\in\mathbb{E}_{S,R,T_{S,R}}(t+1)\setminus\mathbb{E}_{S,R,T_{S,R}}(t)} I(C,R,t) \geq |\Delta I_R(t)|$ for the first time. Then let $K_{S,R,T_{S,R}}(t+1) = \frac{P(S,R,t)}{P(B,R,t)}$.
- When $\Delta I_R(t) > 0$ (i.e., need to shrink the exclusion region), let $\mathbb{E}_{S,R,T_{S,R}}(t+1) = \mathbb{E}_{S,R,T_{S,R}}(t)$, then keep removing nodes out of $\mathbb{E}_{S,R,T_{S,R}}(t+1)$, in the non-decreasing order of their data signal power at R, until the node B such that removing any more node after removing B makes $\sum_{C\in\mathbb{E}_{S,R,T_{S,R}}(t)\setminus\mathbb{E}_{S,R,T_{S,R}}(t+1)} I(C,R,t) > |\Delta I_R(t)|$ for the first time. Then let $K_{S,R,T_{S,R}}(t+1) = \frac{P(S,R,t)}{P(B,R,t)}$.

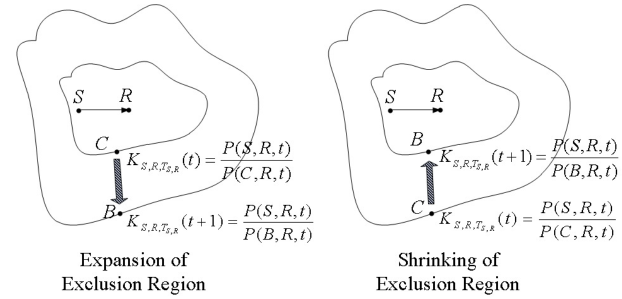

Fig. 3. Computing $K_{S,R,T_{S,R}}(t+1)$

Figure 3 demonstrates the above idea for cases when $\Delta I_R(t) \neq 0$. For convenience, we call the above rule the *PRK-model-adaptation* rule.

In our study, we set the initial value of the PRK model parameter such that the initial exclusion region around R includes every node whose transmission alone, concurrent with the transmission from S to R, can make the link reliability drop below $T_{S,R}$.

Convergence of self-tuning adaptive control. The controller design and analysis based on the linear model (5) tend to be more accurate when $y(t)$ is closer to $T_{S,R}$. When $y(t)$ is far away from $T_{S,R}$, directly using the linear model (5) may lead to significant undershoot or overshoot in feedback control. Assuming the target operating point is A where the link reliability is $T_{S,R}$ in Figure 4, for instance, applying the linear model (5) and the control input (8) when the operating point is B at time t will lead to $E[y(t+1)] = T_{B'}$, which is significantly lower than $T_{S,R}$ and thus leads to significant undershoot; similarly, applying (5) and (8) when the operating point is C at time t will lead to $E[y(t+1)] = T_{C'}$, which is significantly higher than $T_{S,R}$ and thus leads to significant overshoot. Significant undershoot or overshoot is not only undesirable from the perspective of control applications, it may also lead to divergence of feedback control due to the non-linear nature of function $f(.)$.

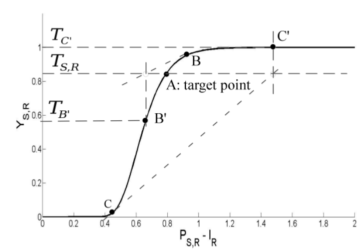

Fig. 4. Convergence of adaptive control (8)

For avoiding significant undershoot and overshoot in control, we propose to replace $a(t)$ with its refined version $a_r(t)$ in the controller implementation:

$$a_r(t) = \begin{cases} a(t), & \text{if } |y(t) - T_{S,R}| \leq e_0 \\ a_0, & \text{if } |y(t) - T_{S,R}| > e_0 \end{cases} \quad (12)$$

[6]Due to the discrete nature of node distribution, the resulting link reliability may be slightly higher than the required reliability $T_{S,R}$ instead of being exactly equal to $T_{S,R}$.

[7]$P(C,R,t)$ and $\beta_C(t)$ can be estimated through purely local coordination between R and C [2].

where e_0 is a threshold value for the linear model (5) to be accurate around the neighborhood of $T_{S,R}$,[8] and $a_0 = \frac{T_{S,R}-y(t)}{f^{-1}(T_{S,R})-f^{-1}(y(t))}$ is the gradient of the line connecting the current operating point $y(t)$ and the target point $T_{S,R}$ on function $f(.)$. Then we have

Theorem 2: With the control input $\Delta I_R(t) = \frac{(1+c)y(t)-cy(t-1)-T_{S,R}}{(1-c)a_r(t)} - \mu_U(t)$ and the PRK-model-adaptation rule, $E[y(t+i)] \geq T_{S,R}$ for $i = 1, 2, \ldots$, that is, the packet delivery reliability along link (S, R) converges to a state where its expected value is no less than the required link reliability $T_{S,R}$.

Proof: When $|y(t) - T_{S,R}| \leq e_0$ and if $\Delta I_R(t)$ can be precisely realized through the PRK model adaptation, $E[y(t+1)] = T_{S,R}$ according to Theorem 1. Due to the discrete nature of node distribution, $E[y(t+1)]$ may not be controlled to be exactly $T_{S,R}$. With the PRK-model-adaptation rule, however, $E[y(t+1)]$ is controlled to be no less than $T_{S,R}$. Thus $E[y(t+1)] \geq T_{S,R}$. Based on the controller design and the PRK-model-adaptation rule, accordingly, $E[y(t+i)] \geq T_{S,R}$ also holds for $i = 2, 3, \ldots$

When $|y(t) - T_{S,R}| > e_0$, $a_r(t) = a_0 = \frac{T_{S,R}-y(t)}{f^{-1}(T_{S,R})-f^{-1}(y(t))}$. Theorem 1 implies that $E[y(t+1)] = T_{S,R}$ if $\Delta I_R(t)$ can be precisely realized through the PRK model adaptation. Due to the discrete nature of node distribution, $E[y(t+1)]$ may not be controlled to be exactly $T_{S,R}$. With the PRK-model-adaptation rule, however, $E[y(t+1)]$ is controlled to be no less than $T_{S,R}$. Thus $E[y(t+1)] \geq T_{S,R}$. Based on the controller design and the PRK-model-adaptation rule, accordingly, $E[y(t+i)] \geq T_{S,R}$ also holds for $i = 2, 3, \ldots$ ∎

From Theorem 2, it takes one control step for the expected link reliability to converge to a state where the minimum required reliability is satisfied. In practice, due to unavoidable errors in modeling function $f(.)$ and imperfection in estimating parameters such as $\mu_U(t)$ and $\beta_C(t)$ (which are used in the $\Delta I_R(t)$ calculation and in the PRK-model-adaption rule respectively), it takes more than one control step for the link reliability to converge. As we will present in our testbed-based measurement study in Section IV, however, link reliability still converges quickly, for instance, with a median convergence time of 22 control steps. Note that, according to Huang et al. [21], the functional form of f in Equation (4) and thus its gradient are much more stable than the specific realization of f (e.g., specific mapping between $Y_{S,R}$ and $P_{S,R} - I_R$) across different network and environmental conditions; hence letting $a_r(t)$ be $a(t)$ instead of a_0 when $|y(t) - T_{S,R}| \leq e_0$ helps ameliorate the inaccuracy of the theoretical model (4) in practice.

IV. Experimental evaluation

Based on the control-theoretic approach to PRK model instantiation presented in Section III, nodes can get to know the set of interfering nodes based on the instantiated PRK model and the average power of wireless signals between close-by nodes.[9] Based on the mutual interference relations between nodes, data transmissions can be scheduled in a TDMA fashion using the Optimal-Node-Activation-Multiple-Access (ONAMA) algorithm [29]. For convenience, we call this overall approach to data transmission scheduling the PRK-based Scheduling (PRKS) protocol. We have implemented PRKS in TinyOS, and we have evaluated PRKS through measurement in the NetEye [24] and Indriya [1] wireless network testbeds. The observations in NetEye and Indriya are similar; due to the limitation of space, here we only present the observations from NetEye, and interested readers can find observations from Indriya in [2].

A. Methodology

Protocols. To understand the design decisions of PRKS, we have comparatively studied PRKS with its variants; due to the limitation of space, however, we relegate the detailed discussions to [2]. Towards understanding the benefits of predictable interference control in PRKS, we also implement in TinyOS the following distributed scheduling protocols and comparatively study their behavior with that of PRKS:

- *CSMA*: a contention-based MAC protocol that uses the basic CSMA/CA mechanism to ameliorate the impact of co-channel interference; this represents the interference control mechanism used by protocols such as B-MAC [38];
- *RTS-CTS*: a contention-based MAC protocol that uses CSMA/CA and RTS-CTS to ameliorate the impact of co-channel interference and hidden terminals; this represents the interference control mechanism used by protocols such as S-MAC [45];
- *RIDB*: a TDMA scheduling protocol that uses a TDMA protocol similar to the one used in PRKS and that uses the physical interference model to derive interference relations between nodes but ignores cumulative interference in networks [49].
- *CMAC*: a contention-based MAC protocol where a node transmits at a time instant only if the SINR of this transmission and the SINRs of other concurrent transmissions overheard by the node are above a certain threshold (e.g., for ensuring a certain link reliability); this represents the interference control mechanism used by protocols such as C-MAC [40];
- *SCREAM*: a TDMA scheduling protocol using the SCREAM primitive [6] to schedule concurrent transmissions according to the physical interference model; this represents the interference control mechanism used by protocols such as FDD [6] and DSS [39].

Among these protocols, CSMA and RTS-CTS represent the protocol-model-based techniques in existing industry standards such as IEEE 802.15.4 and 802.11p; RIDB, CMAC, and SCREAM represent the techniques used in existing physical-model-based scheduling. Focusing on predictable co-channel interference control, we do not compare PRKS with protocols such as WirelessHART [10] that do not consider channel spatial reuse.

Wireless network testbed and application settings. We use a publicly available wireless network testbed NetEye [24] which is deployed in a large lab space at Wayne State University. NetEye deploys 130 TelosB motes in a grid where every two closest neighboring motes are separated by 2 feet and each mote is equipped with a 3dB signal attenuator and a 2.45GHz monopole antenna. The grid deployment enables the study of both grid networks and random networks, where random

[8] In our implementation, we use an e_0 of 5%.

[9] Note that the average power of wireless signals between close-by nodes can be estimated through purely local-coordination between close-by nodes. Interested readers can find more details in [2].

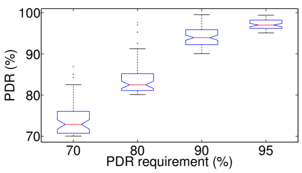

Fig. 5. Packet delivery reliability (PDR) in PRKS

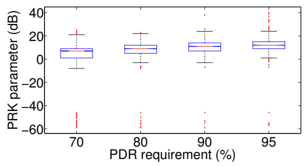

Fig. 6. PRK model parameter in PRKS

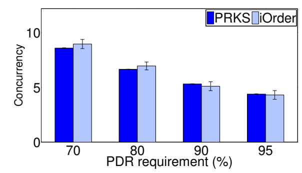

Fig. 7. Mean concurrency in PRKS and iOrder

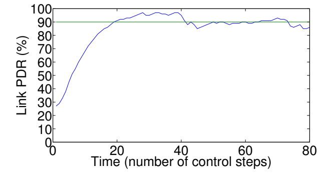

Fig. 8. Temporal link PDR: PDR req. = 90%

networks can be generated using a subset of the 130 motes in experiments (e.g., using each mote with a certain probability). Zhang et al. [48] have shown that, despite its seemingly uniform deployment pattern, NetEye embodies many of the complexities and heterogeneity experienced in outdoor, real-world deployments; for instance, there is a high degree of variability in the background noise power at nodes and in the packet delivery reliabilities for links of equal length, thus reflecting non-uniform network settings as seen in practice.

We use a subset of the 130 TelosB motes in NetEye. The subset of motes form a muli-hop network, and it is generated by using each mote of NetEye with probability 0.8; unless mentioned otherwise, every mote uses a data transmission power of -25dBm (i.e., power level 3 in TinyOS) such that a mote can only reach motes no more than 6 feet away with a packet delivery reliability (PDR) of over 95% in the absence of interference. Focusing on link-layer scheduling for predictable interference control in this study, we mainly consider one-hop data traffic where each mote transmits data packets to one of its neighboring motes to whom the PDR is above 95% in the absence of interference; if there are multiple such neighboring motes, each mote is selected as a receiver with equal probability. For understanding the supportable network throughput while satisfying a certain application PDR requirement, we consider, unless mentioned otherwise, saturated traffic scenario where every mote always has packets to transmit.

For reflecting different application scenarios, we consider the cases when the mean PDR requirement for each link are set to 70%, 80%, 90%, or 95% respectively. To understand the adaptation of PRKS to online dynamics, we run experiments where the mean link-PDR requirement changes over time, for instance, setting the PDR requirement to 70%, 80%, 90%, 95%, 90%, 80%, and 70% over time. To understand the behavior of PRKS in more heterogeneous settings, we also experiment with 1) the "mixed PDR requirement" scenario where the required mean PDR for each link is randomly chosen as 70%, 80%, 90%, or 95% with equal probability, 2) the "mixed traffic pattern" scenario where the inter-packet interval at each mote is randomly chosen as 20ms, 40ms, 100ms, or 200ms with equal probability, and 3) the "mixed transmission power" scenario where different links use different data transmission powers to ensure a SNR of 15dB at receivers in the absence of interference.

We have experimented with other network and traffic conditions including in the Indriya [1] wireless network testbed and with multi-hop traffic, irregular traffic, as well as temporally-varying traffic; we have observed similar phenomena as what we will present in Section IV-B. Interested readers can find the detailed discussions in [2].

B. Measurement results

Behavior of PRKS. For different PDR requirements, Figures 5 and 6 show the boxplots of link packet delivery reliability (PDR) and PRK model parameter in PRKS respectively. We see that PRKS adapts the PRK model parameter according to different PDR requirements, and that the required minimum mean PDR is always guaranteed in PRKS through predictable interference control.[10] In particular, the PRK model parameter increases with the PDR requirement so that more close-by nodes are prevented from transmitting concurrently with a link's transmission.

To understand the spatial reuse in PRKS, Figure 7 shows the mean concurrency (i.e., number of concurrent transmissions at a time instant) and its 95% confidence interval[11] in PRKS as well as in a state-of-the-art, centralized scheduling protocol *iOrder* [9] which maximizes channel spatial reuse in interference-oriented scheduling.[12] We see that, despite its nature of local and distributed control, PRKS enables a concurrency and spatial reuse statistically equal or close to what is enabled by the centralized algorithm iOrder while ensuring the required PDR at the same time.

Despite the distributed nature of the minimum-variance regulation controller in PRKS, the individual controllers converge to a state where the required PDR is satisfied. For a typical link in the network, for instance, Figure 8 shows the temporal behavior of link PDR when the minimum application PDR requirement is 90%. We see that the link PDR converges to its steady state after around 25 control steps, with each control step taking ∼100ms time. As a way of reflecting the network-wide convergence, Figure 9 shows the temporal convergence behavior of the network-wide average deviation of link reliability from the required mean PDR (i.e., $\frac{\sum_{\text{Every link }(S,\,R)} |Y_{S,R}(t)-T_{S,R}|}{\text{Total number of links}}$). In general, link PDRs converge quickly, as shown by Figure 10 where the settling time is defined as the number of control steps taken for a link to reach its steady state PDR distribution. In addition to convergence to a state where the required PDRs are satisfied, the collective behavior of the distributed controllers in PRKS also enables a spatial reuse close to what is feasible with the state-of-the-art, centralized scheduler iOrder as we have shown in Figure 7.

For the adaptation of PRKS to online dynamics, Figure 11 shows, for a typical link in the network, the time series of

[10] Due to the discrete nature of the spatial distribution of concurrent transmitters, the actual PDR tends to be slightly higher than (instead of being strictly equal to) the required mean PDR.

[11] For the figures of this section that present performance statistics (e.g., mean concurrency or PDR), we also show the 95% confidence intervals of the statistics, but some of the confidence intervals may be too narrow to be noticeable in the figures.

[12] In terms of maximizing spatial reuse, iOrder has been shown to outperform well-known existing scheduling protocols such as Longest-Queue-First [26], GreedyPhysical [5], and LengthDiversity [18].

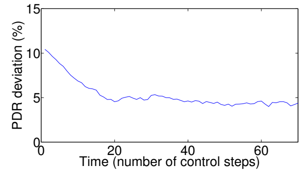

Fig. 9. Network-wide convergence in PRKS

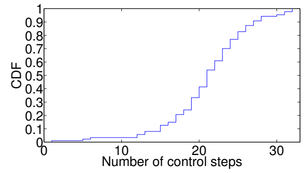

Fig. 10. CDF for the settling time of link PDR

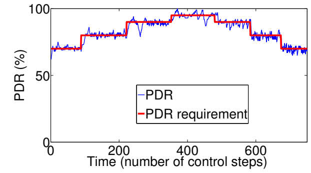

Fig. 11. PDR in PRKS: temporally varying PDR requirements

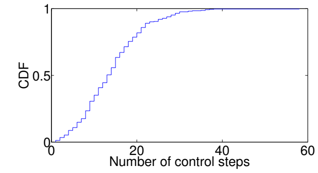

Fig. 12. Settling time: temporally varying PDR requirements

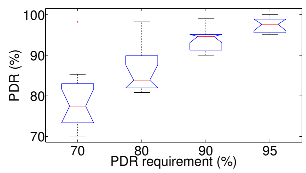

Fig. 13. Packet delivery reliability in PRKS: mixed PDR requirement

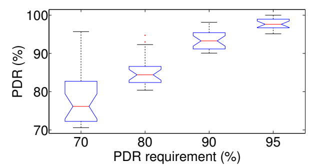

Fig. 14. Packet delivery reliability in PRKS: mixed traffic pattern

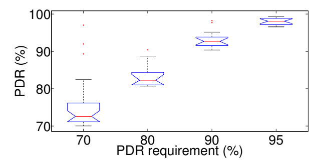

Fig. 15. Packet delivery reliability in PRKS: mixed transmission power

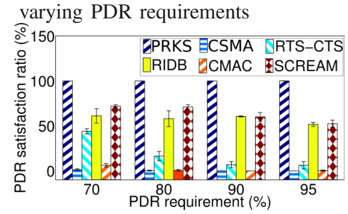

Fig. 16. PDR requirement satisfaction ratios in different protocols

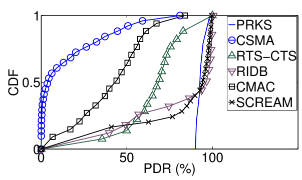

Fig. 17. CDF of link PDRs in different protocols: PDR req. = 90%

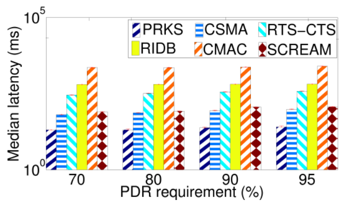

Fig. 18. Median delay: reliability via packet retransmission

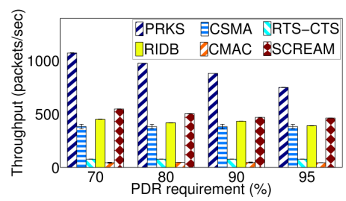

Fig. 19. Mean network spatial throughput

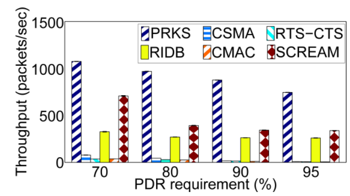

Fig. 20. Mean network throughput: reliability via traffic load reduction

link PDR when the application PDR requirement is set to 70%, 80%, 90%, 95%, 90%, 80%, and 70% over time. We see that, as the application PDR requirement varies, the link PDR adapts to meet the application requirement. In general, link PDRs adapt quickly, as shown by Figure 12 which plots the cumulative distribution function (CDF) of link PDR settling time in the network when application PDR requirements vary.

For the "mixed PDR requirement" scenario where different links of the same network have different PDR requirements, Figure 13 shows the boxplots of link PDR for the links grouped by their PDR requirements. We see that PRKS adaptively ensures the required PDR in a predictable manner even when different links of the same network have different PDR requirements. We have observed similar behavior for the "mixed traffic pattern" scenario and the "mixed transmission power" scenario. For instance, Figures 14 and 15 show that the desired PDRs are ensured when different links use different traffic patterns or different transmission powers respectively.

Comparison with existing protocols. Figure 16 shows the ratio of links whose PDRs are no less than the application required PDRs in PRKS and other existing protocols. As an example, Figure 17 shows the cumulative distribution of PDRs in different protocols when the application PDR requirement is 90%. We see that, unlike PRKS that always ensures application required PDRs for all the links in a predictable manner, existing protocols do not ensure the required PDRs due to co-channel interference that is not well controlled. We also see that the PDR satisfaction ratios in the existing protocols tend to decrease with increasing PDR requirements, thus the existing protocols cannot control link reliability in a predictable manner.

Among the existing protocols, RIDB enables higher PDR satisfaction ratios than RTS-CTS and CSMA do because RIDB considers the physical interference model and application PDR requirements in defining pairwise interference relations between nodes; nonetheless, due to its lack of consideration of cumulative interference from multiple concurrent interferers, RIDB does not ensure predictable interference control and thus does not ensure predictable link reliability. When the application PDR requirement is 95%, for instance, RIDB can only enable a PDR satisfaction ratio 50.72%. RTS-CTS ensures higher PDR satisfaction ratio than CSMA does due to its use of RTS-CTS handshake, but the PDR satisfaction ratios are quite low in both protocols (e.g., as low as 8.5% and 0% in RTS-CTS and CSMA respectively) since neither protocols are based on high-fidelity interference models.

Among the existing protocols that explicitly use the physical interference model, CMAC and SCREAM consider cumulative interference. Nonetheless, the PDR satisfaction ratio is quite low in CMAC, and the PDR satisfaction ratio in SCREAM can also be as low as 50%. CMAC cannot ensure the required PDRs since CMAC cannot ensure predictable interference control when the interference range is greater than the communication range, which is usually the case in practice (especially when the required PDR is high). Since CMAC does not decouple control signaling from data transmissions as in PRKS, interference control in CMAC is also negatively affected by any unreliability in the per-transmission-based control signaling (e.g., observing neighboring nodes' SINRs). In SCREAM, the collision among a set of concurrent transmitters is detected through network-wide coordination. The detection is based on a sample of the status (i.e., success or failure) of concurrent data transmissions and cannot ensure accurate collision detection, thus SCREAM cannot accurately control interference to ensure predictable PDR. Additionally, it takes $\Theta(nk)$ time slots for the network to find the schedule of a single time slot in SCREAM, where n is the number of links in a network and k is the interference diameter of the network (which is approximately the ratio of the geometric diameter of a network to the carrier sensing range) [6]. Thus SCREAM is not suitable for dynamic, large-scale networks where schedules need to adapt to changing network and environmental conditions frequently.

Incapable of ensuring predictable link reliability in scheduling, existing protocols can try to improve link reliability by packet retransmission. Nonetheless, packet retransmission increases data delivery delay; this can be seen from Figure 18 which shows the median packet delivery delay when packets are retransmitted to ensure a certain required PDR. Packet retransmission in existing protocols also reduces network throughput, as shown by Figure 19 which shows the mean number of packets successfully delivered in the network per second. [13]

Existing protocols can also try to improve link reliability by reducing the application traffic load such that interference becomes negligible. Nonetheless, this approach significantly decreases network throughput; this can be seen from Figure 20 which shows the mean network spatial throughput (i.e., number of packets successfully delivered per second in the network) when packet arrival rates are limited from above to ensure a certain required PDR.

V. Related work

Similar to PRKS, existing physical-model-based scheduling algorithms also try to control concurrent transmissions so that link reliabilities or receiver-side SINRs are above a certain threshold. As we have discussed in Sections I and IV, however, due to the non-local, combinatorial nature of the physical interference model, distributed physical-model-based scheduling algorithms have various drawbacks such as requiring network-wide coordination and employing strong systems assumptions which make it difficult to deploy these algorithms in real-world settings.

Learning-based approaches have been taken to discover and concurrently schedule throughput-improving exposed terminals [42], but those approaches did not ensure predictable link reliability since, similar to CMAC as discussed in Section IV, they only try to improve locally-observed throughput without ensuring predictable control of receiver-side cumulative interference. Learning-based approaches have also been taken to generate maximal sets of non-interfering transmitters [14], but they did not address the important question of how to identify the exclusion regions around receivers so that a required link reliability is guaranteed. The concepts of guard-zone or exclusion-region around receivers have also been exercised in distributed scheduling algorithms [7], [19], but these algorithms assumed uniform traffic load or uniform wireless signal power attenuation across the whole network, which are unrealistic in general.

Adaptive physical carrier sensing has been proposed to enhance network throughput [23], [31], but cumulative interference is not considered. We have also observed in [48] that throughput-optimal scheduling usually leads to low link reliability, which is not desirable in wireless networked control. Park et al. [37] considered link reliability when adapting carrier sensing range, but their solution did not guarantee link reliability due to the price function involved. Fu et al. [17] proposed to control carrier sensing range to ensure a certain SINR at receivers, but the derivation of safe-carrier-sensing-range was based on the unrealistic assumption of homogeneous signal power attenuation across the whole network.

Scheduling via local coordination between close-by nodes has also been considered [5], [44], [25], [4]. Not focusing on distributed scheduling for predictable link reliability in real-world settings, however, these work assumed uniform wireless signal power attenuation which does not hold in practice in general [5], [44], [25], they did not consider the important question of how to identify the specific local region for inter-node coordination [4], [25], they focused on centralized scheduling [4], [5], or they focused on maximizing network throughput without considering predictable link reliability [44].

Glossy [16] leverages non-destructive interference between synchronized concurrent transmissions of the same packet to enable efficient flooding of packets across a network, upon which algorithms such as LWB [15], Splash [13], and P^3 [12] have also been developed for many-to-one, one-to-many, and many-to-many communications. These work do not consider spatial reuse of wireless channels to transmit different packets in the same channel at the same time, thus they can lead to capacity loss in large scale networks. Focusing on traditional communication patterns in wireless sensor networks, these work do not consider emerging networked control paradigms that only involve communications between close-by nodes [36] such that the network-wide flooding of the same packet in Glossy and LWB would be a waste of channel resources.

Focusing on addressing the open problem of predictable co-channel interference control in the presence of channel spatial reuse, our study in this paper does not consider frequency hopping for addressing external interference, duty-cycling for energy efficiency, real-time scheduling, other link-reliability control techniques such as rate adaptation and power control, or other interference management techniques such as interference cancellation and multi-channel scheduling. The basic mechanisms of PRKS, however, are synergistic and can be integrated with the aforementioned techniques; due to the limitation of space, we relegate the detailed discussion to [2].

VI. Concluding remarks

To enable predictable reliability in data delivery for wireless networked control, we have proposed a control-theoretic approach to PRK model instantiation, which enables the PRK-based scheduling protocol PRKS for predictable interference control in the presence of network and environmental uncertainties. Extensive experimental analysis shows that PRKS enables predictable link reliability while achieving a high degree of channel spatial reuse in data transmissions. Besides being important by itself, the predictable link reliability enabled by PRKS serves as a basis for predictable real-time data delivery and for predictable tradeoff between the reliability, delay, and throughput in wireless control networks, thus enabling networking and control co-design in wireless networked control systems; the predictable link reliability enabled by PRKS also represents a fundamental departure from the existing link-layer scheduling/MAC protocols which can only provide a best-effort communication service due to the lack of predictable interference control, and this has deep implications to the

[13]The throughput of PRKS is based on memory-unconstrained ONAMA.

design of higher-layer protocols such as routing protocols. These topics of research are interesting future directions worth pursuing.

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