PRK-Based Scheduling for Predictable Link Reliability in Wireless Networked Sensing and Control

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ABSTRACT
Predictable wireless communication is required for closed-loop sensing and control in many networked cyber-physical systems, yet co-channel interference remains a major source of uncertainty in wireless communication. Integrating the protocol model’s locality and the physical model’s high fidelity, the physical-ratio-K (PRK) interference model is expected to serve as a foundation for distributed, predictable interference control. To realize the potential of the PRK model, we design protocol PRKS that addresses the challenges of model instantiation and protocol signaling in PRK-based scheduling. In particular, PRKS uses a control-theoretic approach to instantiating the PRK model, it uses local signal maps to address the challenges of large interference range and anisotropic, asymmetric wireless communication, and it leverages the different timescales of PRK model adaptation and data transmission to decouple protocol signaling from data transmission. Through testbed-based measurement study, we observe 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. Ensuring the required link reliability in PRKS also reduces communication delay and improves network throughput.

1. INTRODUCTION
Besides deployments for open-loop sensing such as environmental monitoring, embedded wireless networks are increasingly being explored for real-time, closed-loop sensing and control in networked cyber-physical systems [48, 49]. For instance, the wireless networking standard IEEE 802.15.4g has been defined for large scale process control applications such as smart grid sensing and control [4], and wireless networks are expected to serve as major communication infrastructures in neighborhood area networks and home area networks of the smart grid [21, 71, 77]. In addition, wireless networking standards such as the IEEE 802.15.4e, WirelessHART, and ISA SP100.11a have been defined for industrial monitoring and control, wireless sensor networks have been deployed for industrial automation, and the automotive industry has also been exploring the application of wireless networks to inter-vehicle as well as intra-vehicle sensing and control [44]. In wireless networked sensing and control (WSC), message passing across wireless networks (or wireless messaging for short) is a basic enabler for the coordination among distributed sensors, controllers, and actuators; in supporting mission-critical tasks such as industrial process control, wireless messaging is required to be reliable (i.e., having high delivery ratio) [48, 44]. Given the varying impact that the reliability, delay, and throughput of wireless messaging have on networked control and the inherent tradeoff between messaging reliability, delay, and throughput, the optimal operation of WSC systems also requires controlling the tradeoff between reliability, delay, and throughput in messaging, and controlling link reliability in a predictable manner is a basis for such system-level optimization [48, 49, 64, 80]. Causing collisions of concurrent transmissions, co-channel interference is a major source of unpredictability in link reliability [80, 78, 79]. Thus scheduling transmissions for co-channel interference control is a basic element of wireless messaging in WSC systems.

Distributed scheduling & interference models. In WSC 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 messaging reliability [49]. For agile adaptation to uncertainties and for avoiding information inconsistency in centralized scheduling, distributed scheduling becomes desirable for interference control in WSC 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 [80].

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

\[
P(S_i, R_i) \geq \gamma, i = 1 \ldots N
\]

where \(P(S_i, R_i)\) is the strength of signals reaching the receiver \(R_i\) from the transmitter \(S_i\) and \(R_j\) respectively, \(N_i\) is the background noise power at receiver \(R_i\), and \(\gamma\) 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

\[
D(C, R) \geq K \times D(S, R)
\]

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. Even though many centralized TDMA scheduling algorithms have been proposed based on the physical model [10, 23, distributed physical-model-based scheduling still has various drawbacks: it converges slowly due to explicit network-wide coordination [13, 47], it has to employ strong assumptions such as the reliable detection of a node’s busy-tone signal by the whole network [58] or the knowledge of node locations and wireless channel path loss bound [76], it does not control cumulative interference which introduces uncertainties in communication [53, 73], it is not suitable for dynamic network settings due to the need for centrally computing the interference set of each link (i.e., the set of links interfering with the link) [57] or the interference neighborhood of each link (i.e., the set of links causing non-negligible interference to the link) [55], or it does not address the challenge of designing scheduling protocols when interfering links are beyond the communication range of one another [55, 58]. Many of the SINR-based MAC protocols are also throughput-oriented, and they do not control multi-hop interference to ensure predictable link reliability [60].

Unlike the physical model, the protocol model defines local, pairwise interference relations; that is, according to [2], interference is regarded as existent only between nodes in a local neighborhood, and whether one transmission interferes with another only depends their own spatial distribution irrespective of other transmissions in the network. The locality of the protocol model can enable agile protocol adaptation in the presence of uncertainties. However, the protocol model is usually inaccurate [46], thus scheduling based on the protocol model [33, 61, 70] or its variants [36, 39, 65] does not ensure link reliability and also tends to reduce network throughput. Choi et al. [18] recently proposed grant-to-send (GTS) as a new mechanism for collision avoidance. Only focusing on intra-flow interference, GTS does not address inter-flow interference and cannot ensure data delivery reliability; for instance, GTS may only enable a data delivery reliability of 47.4% in event-detection sensor networks [18].

Besides scheduling based on the physical and protocol interference models, distributed scheduling algorithms using general pairwise interference models (e.g., as defined by conflict graphs [30]) have also been proposed [26, 51]. Theoretical in nature, however, these algorithms did not address the important question of how to identify the interference set of each link, and their implementation usually assumes a model similar to the protocol model [51]. These algorithms also did not address important systems issues such as how to design scheduling protocols when interfering nodes are beyond the communication range of one another.

Without field-deployable solutions to predictable co-channel interference control, current systems practice, such as the WirelessHART standard for industrial sensing and control [17], 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 sensing and control applications and for new networked control paradigms that involve communications between close-by nodes only [52].

**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. We have recently identified the physical-ratio-K (PRK) interference model that integrates the protocol model’s locality with the physical model’s high-fidelity [80]. 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:

\[
P(C', R) < \frac{P(S, R)}{K_{S,R,T_S,R}}
\]

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 pack-
ets 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 $E_{S,R,T_{S,R}}$ around the receiver $R$ such that a node $C \in E_{S,R,T_{S,R}}$ if and only if $P(C, R) \geq \frac{P(S, R)}{K_{S,R,T_{S,R}}}$. Accordingly, every node $C \in E_{S,R,T_{S,R}}$ is regarded as interfering with and thus shall not transmit concurrently with the transmission from $S$ to $R$.

Unlike the physical model, the PRK model is local and suitable for distributed protocol design and implementation: 1) The parameters of the PRK model are either locally measurable (i.e., for 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 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. Unlike the protocol model, the PRK model is of high-fidelity because it captures the properties of wireless communication (including cumulative interference, anisotropy, and asymmetry) by ensuring the required link reliability in scheduling and by using signal strength instead of geographic distance in model formulation. 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.

Focusing on formulating the PRK interference model and understanding the theoretically achievable performance of PRK-based scheduling, we 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 challenges:

- The parameter $K_{S,R,T_{S,R}}$ of the PRK model 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. So the challenge is how 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.

- Given a link $(S, R)$ and a specific instantiation of the PRK model, every node in the exclusion region $E_{S,R,T_{S,R}}$ should be prevented from transmitting concurrently with the transmission from $S$ to $R$. As we will discuss in detail in Sections 3.2 and 3.3, however, it is difficult to ensure this property due to large interference range, anisotropy and asymmetry in wireless communication, as well as the delay in protocol signaling.

Contributions of this paper. To enable predictable link reliability in distributed scheduling, we address the aforementioned challenges by designing the 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. For ensuring that nodes interfering with one another do not transmit concurrently, we propose the concept of local signal map that allows close-by nodes to maintain the wireless path loss among themselves; together with the PRK model, local signal maps enable nodes to precisely identify the interference relations among themselves despite large interference range and anisotropic, asymmetric wireless communication. To address the inherent delay in protocol signaling and to avoid interference between protocol signaling and data transmissions, PRKS decouples protocol signaling from data transmissions by leveraging the different timescales of PRK model adaptation and data transmission.

We have implemented PRKS in TinyOS. Through measurement study in the NetEye and Indriya sensor network testbeds, we observe the following: 1) The distributed controllers enable network-wide convergence to a state where the desired link reliabilities are ensured; 2) 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; 3) 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 while ensuring the required link reliability; 4) By ensuring the required link reliability, PRKS also reduces communica-
tion delay and improves network throughput.

**Organization of the paper.** We present the network and traffic models considered in this study as well as the NetEye and the Indriya testbeds in Section 2. We elaborate on the design of PRKS in Section 3 and we evaluate the performance of PRKS in Section 4. We discuss node mobility and related work in Sections 5 and 6 respectively. We make concluding remarks in Section 7.

## 2. PRELIMINARIES

**Network and traffic models.** As a first-step towards ensuring predictable link reliability in distributed scheduling, we consider mostly-immobile wireless sensing and control networks where the average background noise power and the average wireless path loss do not change at very short timescales (e.g., a few milliseconds for transmitting a few packets) [15]. 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 single-hop data transmissions between close-by nodes, but the network itself may be of large scale and with nodes widely distributed in space. Note that predictable reliability in single-hop transmissions is important by itself for new networked control paradigms that involve communications between close-by nodes only [52], and predictably reliable single-hop transmission is also a basis for reliable multi-hop transmission in general [82].

**Sensor network testbeds.** Our study uses a publicly available wireless sensor network testbed NetEye [34] which is deployed in a large lab space at Wayne State University as shown in Figure 2. NetEye deploys 130 TelosB motes in a grid with every two closest neighboring motes separated by 2 feet. The grid deployment enables the study of both grid networks and random networks, where random 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. [80] 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.

Each of these TelosB motes is equipped with a 3dB signal attenuator and a 2.45GHz monopole antenna. In our measurement study, we use a radio transmission power of -25dBm (i.e., power level 3 in TinyOS) for data packets such that the data transmission reliability is over 95% in the absence of interference for links up to 6 feet long. For the transmission power of -25dBm, Figure 3 shows the box-plot of packet delivery ratio (PDR) for links of different length, and Figure 4 shows the histogram of background noise power in NetEye.

![Image](image1.png)

*Figure 2: NetEye wireless sensor network testbed*

![Image](image2.png)

*Figure 3: PDR vs. link length in NetEye when transmission power is -25dBm*

![Image](image3.png)

*Figure 4: Histogram of background noise power in NetEye*
noise power in NetEye. We see that there is a high degree of variability in PDR for links of equal length and in background noise power. Thus the testbed reflects non-uniform network settings as seen in practice. Given the high availability and high fidelity of NetEye, we mainly use NetEye in our measurement study, but we verify key observations using the Indriya testbed too.

3. PRK-BASED SCHEDULING

In what follows, we first present our control-theoretic approach to instantiating the PRK model, then we present the local signal maps for protocol signaling and the protocol PRKS for distributed PRK-based scheduling. For convenience, Table 1 summarizes the major notations used in this section.

| $Y_{S,R}(t)$ | Measured packet delivery rate for link $(S, R)$ at time $t$. |
| $P(S, R, t)$ | Expected power, in units of mW, of data packet signals reaching $R$ from $S$ at time $t$; assumed to be mostly static at short timescales. |
| $P_{S,R}(t)$ | Expected power, in units of dBm, of data packet signals reaching $R$ from $S$ at time $t$. |
| $I_R(t)$ | Sum of background noise power and interference power at receiver $R$ at time $t$, in units of dBm. |
| $f(.)$ | The function modeling the relation between packet delivery rate and SINR. |
| $a(t)$ | $f'(P_{S,R}(t) − I_R(t))$. |
| $b(t)$ | $f(P_{S,R}(t) − I_R(t)) − (P_{S,R}(t) − I_R(t))f'(P_{S,R}(t) − I_R(t))$. |
| $y(t)$ | Smoothed link reliability measurement, i.e., $y(t) = cy(t − 1) + (1 − c)Y_{S,R}(t)$. |
| $\delta$ | Parameter of the EWMA filter in feedback loop. |
| $\Delta I_R(t)$ | Computed control input at time instant $t$. |
| $\Delta I_U(t)$ | Change of interference from outside the exclusion region of $R$ from time $t$ to $t + 1$. |
| $\mu(t)$ | Mean of $\Delta I_U(t)$. |
| $\sigma^2_U(t)$ | Variance of $\Delta I_U(t)$. |
| $K_{S,R,T_S,R}(t)$ | PRK model parameter for link $(S, R)$ at time $t$. |
| $E_{S,R,T_S,R}(t)$ | Exclusion region around receiver $R$ at time $t$; a node $C \in E_{S,R,T_S,R}(t)$ iff. $P_{C,R}(t) ≥ \frac{P_{S,R}(t)}{K_{S,R,T_S,R}(t)}$. |
| $P^*(C', R)$ | Average signal power attenuation from a node $C$ to another node $R$; maintained in nodes’ local signal maps. |

3.1 A 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 $T_{S,R}$. 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 [80]. To address the challenge, we observe that the PRK model instantiation problem can be formulated as an online regulation control problem [28], 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 $\Delta I_R$, 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 $\Delta I_R$ 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 $t$. Given a modulation and coding scheme, communication theory gives us the following [80]:

$$Y_{S,R}(t) = f(P_{S,R}(t) − I_R(t)), $$

(4)

where $f$ is a non-decreasing function, and $P_{S,R}(t) − I_R(t)$ represents the SINR in dB at time $t$. For IEEE 802.15.4-compatible radios such as Chipcon CC2420, for instance,

$$Y_{S,R}(t) = (1 − \frac{8}{15}) \times \frac{1}{16} \times \sum_{k=2}^{16} (-1)^k \left(\frac{16}{k}\right) e^{(20 \times (P_{S,R}(t) − I_R(t)) \times (\frac{1}{k} − 1))} , $$

(5)

where $\ell$ is the packet length in units of bytes [80]. 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 [28] 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:

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

where

$$a(t) = f'(P_{S,R}(t) − I_R(t)), $$

$$b(t) = f(P_{S,R}(t) − I_R(t)) − (P_{S,R}(t) − I_R(t))a(t). $$

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 instants $t$
and \( t+1 \) \( I_R(t+1) \) 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 \( K_{S,R,T_{S,R}}(t+1) \). 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 \( \mathbb{E}_{S,R,T_{S,R}}(t+1) \backslash \mathbb{E}_{S,R,T_{S,R}}(t) \) 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 \( \mathbb{E}_{S,R,T_{S,R}}(t) \backslash \mathbb{E}_{S,R,T_{S,R}}(t+1) \) 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 \( R \) but 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

\[
\begin{align*}
I_R(t+1) &= I_R(t) + \Delta I_R(t) + \Delta I_U(t) \\
P_{S,R}(t+1) &= P_{S,R}(t) \\
Y_{S,R}(t+1) &= a(t)(P_{S,R}(t+1) - I_R(t+1)) + b(t)
\end{align*}
\]

where \((I_R(\cdot), P_{S,R}(\cdot))\) and \(Y_{S,R}(\cdot)\) are the “state” and the “output” of the plant respectively. To deal with the noise in measuring \( Y_{S,R}(\cdot) \), we use an exponentially-weighted-moving-average (EWMA) filter with a weight factor \( c \) (0 ≤ \( c < 1 \)) in the feedback loop \[28\] \[28\]. Thus, the system model is as shown in Figure 5 where

\[
y(t) = cy(t-1) + (1-c)Y_{S,R}(t).
\]

Figure 5: PRK model instantiation: minimum-variance regulation control diagram

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. \[3\] \[3\]. For this minimum-variance regulation control problem, we have

**Theorem 1.** The control input that minimizes \( \text{var}[y(t+1)] \) while ensuring \( E[y(t+1)] = T_{S,R} \)

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

**Proof.** In what follows, we first derive the minimum-variance control input \( \Delta I_R(t) \) by assuming \( E[y(t+1)] = T_{S,R} \), then we show that \( E[y(t+1)] = T_{S,R} \) actually holds with the derived \( \Delta I_R(t) \).

If \( E[y(t+1)] = T_{S,R} \), then

\[
\text{var}[y(t+1)] = E[y(t+1) - E[y(t+1)]]^2 = E[y(t+1) - T_{S,R}]^2 = E[(1 - c)a(t)(\mu_U(t) - \mu_U(t))]^2 = E[(1 - c)a(t)(\mu_U(t) - \mu_U(t))]^2
\]

where

\[
X = \frac{E[(1 - c)a(t)(\Delta I_U(t) - \mu_U(t))]}{E[(1 - c)a(t)(\Delta I_U(t) - \mu_U(t)))]} = 0.
\]

Since \( E[(1 - c)a(t)(\Delta I_U(t) - \mu_U(t)))] = 0 \), we need \( X = 0 \) to minimize \( \text{var}[y(t+1)] \), and the corresponding control input is as follows:

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

\[3\] Note that \( E[y(t+1)] = E[Y_{S,R}(t+1)] \) at steady state.
With a constant data transmission power, we have \( P_{S,R}(t+1) = P_{S,R}(t) \). Thus

\[
\Delta I_R(t) = \frac{c_y(t)+(1-c)\mu(t)P_{S,R}(t)+I_R(t)+c_y(t)-P_{S,R}(t)}{1-\mu(t)} - \mu_U(t).
\]

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

\[
y(t+1) = \frac{c_y(t)+(1-c)\mu(t)P_{S,R}(t+1)+I_R(t+1)+b(t)}{1-\mu(t)}.
\]

Since \( E[y(t+1)] = \frac{c_y(t)+(1-c)\mu(t)P_{S,R}(t)+I_R(t)-\Delta I_R(t)}{1-\mu(t)}\) and \( \mu_U(t) \), then let \( K_{S,R,T_S,R}(t+1) = K_{S,R,T_S,R}(t) \) for the first time. Then let \( K_{S,R,T_S,R}(t+1) = P_{I_R}(S,R,t) \).

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 the link reliability \( y(t) \), we propose to execute the minimum-variance controller \( \delta \) at \( R \). Using similar techniques as what we will discuss in Section 3, \( R \) can also measure \( P_{S,R}(t) \) and \( I_R(t) \), thus \( R \) can compute \( \mu(t) \) using Equation (5). For each time instant \( t \), \( R \) can also derive \( \Delta I_R(t) \) based on \( I_R(t), I_R(t-1), \Delta I_R(t-1) \), and Equation (3); using these derived samples of \( I_R(.) \) and an EWMA filter, \( R \) can then estimate \( \mu_U(.) \). Therefore, \( R \) can execute the controller \( \delta \) using information that is either locally measured (e.g., \( y(t) \) 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

\[
\begin{align*}
K_{S,R,T_S,R}(t+1) &= K_{S,R,T_S,R}(t), & \text{if } \Delta I_R(t) = 0 \\
K_{S,R,T_S,R}(t+1) &= K_{S,R,T_S,R}(t), & \text{if } \Delta I_R(t) < 0 \\
K_{S,R,T_S,R}(t+1) &= K_{S,R,T_S,R}(t), & \text{if } \Delta I_R(t) > 0
\end{align*}
\]

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 \( E_{S,R,T_S,R}(t) \) or \( E_{S,R,T_S,R}(t+1) \) 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 \( K_{S,R,T_S,R}(t+1) \). To realize this, we define, for each node \( C \) in the local region around \( R \), 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 \( C \). 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 rules 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 \( E_{S,R,T_S,R}(t+1) = E_{S,R,T_S,R}(t) \), then keep removing nodes not already in \( E_{S,R,T_S,R}(t+1) \), in the non-increasing order of their data signal power at \( R \), into \( E_{S,R,T_S,R}(t+1) \) until the node \( B \) such that adding \( B \) into \( E_{S,R,T_S,R}(t+1) \) makes \( \sum_{C \in E_{S,R,T_S,R}(t+1) \setminus E_{S,R,T_S,R}(t)} I(C,R,t) \geq l \) for the first time. Then let \( K_{S,R,T_S,R}(t+1) = P_{I_R}(S,R,t) \).
- When \( \Delta I_R(t) > 0 \) (i.e., need to shrink the exclusion region), let \( E_{S,R,T_S,R}(t+1) = E_{S,R,T_S,R}(t) \), then keep removing nodes out of \( E_{S,R,T_S,R}(t+1) \), 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 \( \sum_{C \in E_{S,R,T_S,R}(t) \setminus E_{S,R,T_S,R}(t+1)} I(C,R,t) > l \) for the first time. Then let \( K_{S,R,T_S,R}(t+1) = P_{I_R}(S,R,t) \).

Figure 6 demonstrates the above idea for cases when \( \Delta I_R(t) \neq 0 \). 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 \( T_{S,R} \).

Stability 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 7 for instance, applying the

\footnote{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 \( T_{S,R} \).}

\footnote{\( P(C,R,t) \) and \( \beta_C(t) \) can be estimated through purely local coordination between \( R \) and \( C \) using the protocol signaling mechanism of Section 3.2.}
Note that, according to Huang et al.\[29\], 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 $P_{S,R} - I_0$) across different network and environmental conditions; hence letting $a_t(t) = a(t)$ instead of $a_0$ when $|y(t) - T_{S,R}| \leq e_0$ helps address the inaccuracy of the theoretical model \[4\] in practice. In our implementation, we use an $e_0$ of 5%.

### 3.2 Local signal maps for real-world use of the PRK model

Given a link $(S, R)$ and a specific instantiation of the PRK model, the parameter $K_{S,R,T_{S,R}}(t)$ defines an exclusion region $E_{S,R,T_{S,R}}(t)$ around the receiver $R$ such that a node $C \in E_{S,R,T_{S,R}}(t)$ if and only if $P(C, R, t) \geq K_{S,R,T_{S,R}}(t)$. In PRK-based scheduling, every node $C \in E_{S,R,T_{S,R}}(t)$ should be aware of its existence in $E_{S,R,T_{S,R}}(t)$ and should not transmit concurrently with the reception at $R$; yet it is difficult to ensure this property for the following real-world complexities in wireless communication: 1) node $C$ may be located beyond the communication range of $R$ such that $R$ cannot inform $C$ about its state (e.g., the value of $P(C, R, t)$) with the regular data transmission power; 2) wireless communication may be anisotropic such that it is difficult for $R$ to transmit protocol signaling messages that reaches and only reaches nodes in $E_{S,R,T_{S,R}}(t)$; 3) wireless communication may be asymmetric such that nodes interfering with another may not know another’s state (e.g., $P(C, R, t)$).

**Local signal maps.** To address these challenges, we propose that every node $R$ maintains a local signal map that contains the average signal power attenuation between $R$ and every node $C$ close-by. To measure the signal power attenuation $P'(C, R)$ from a node $C$ to another node $R$, we let $C$ inform $R$ of its transmission power $P_C$ by piggybacking the information onto its packets to $R$, and then $R$ can derive the power attenuation as long as $R$ can estimate the power of the received signals from $C$, denoted by $P(C, R)$\[^5\]. To this end, $R$ samples the RSSI value $P_{total}$ at an instant right before finishing receiving a packet from $C$, and, immediately after receiving the packet, $R$ samples the RSSI value $P_I$ again. As shown in Figure 8, $P_I$ is the sum of the background noise power and the interference power at $R$ right after the packet reception, and $P_{total} = P(C, R) + P_I'$ where $P_I'$ is the sum of the power at $R$ right after the packet reception.\[^6\]

\[^5\]To address the challenge of large interference range, $P_C$ may potentially be higher than the regular data transmission power as we discuss later in this section.

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**Figure 6: Computing $K_{S,R,T_{S,R}}(t + 1)$**

**Figure 7: Stability of adaptive control \[^8\]**

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\[^5\]To address the challenge of large interference range, $P_C$ may potentially be higher than the regular data transmission power as we discuss later in this section.

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**Figure 8: Estimation of signal power attenuation**

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\[^6\]To address the challenge of large interference range, $P_C$ may potentially be higher than the regular data transmission power as we discuss later in this section.
of the background noise power and the interference power at $R$ right before the packet reception. As we will discuss in Section 3.3, signal maps are maintained in the control plane of the protocol PRKS where wireless channel access is based on the traditional random access method CSMA/CA as used in IEEE 802.15.4 and 802.11. Given that $P_{total}$ and $P_I$ can be sampled at very short interval (e.g., less than 0.01 milliseconds for TelosB motes [6]) and that the background noise power as well as the interference power do not change much in such short intervals in CSMA/CA-based wireless networks, the sum of the background noise power and the interference power do not change much immediately before and immediately after a packet reception, i.e., $P'_I \approx P_I$. Thus,

$$P(C, R) = P_{total} - P'_I \approx P_{total} - P_I.$$  

(13)

Once $R$ gets a sample of $P(C, R)$, it can compute a sample of $P'(C, R)$ as

$$P'(C, R) = P_C - P(C, R).$$

(14)

This way, $R$ can get a series of samples of $P'(C, R)$ and then use these samples to derive the average signal power loss from $C$ to itself.

Using the above method of sampling signal power attenuation, nodes close-by can establish their local signal maps through purely local sampling of their packet receptions without any global coordination in the network, and the local signal maps generated in this manner tend to be very accurate as we show next. For mostly-immobile WSC networks which we consider in this study, the local signal maps can be maintained in a passive manner after their initial establishment. That is, signal map maintenance does not introduce extra communication overhead other than having nodes piggyback their transmission powers onto the packets they transmit anyway. Note that the local signal map maintains power attenuation from a node $C$ to $R$ instead of simply the reception power of signals from $C$ to $R$ so that the signal map can be used to estimate the reception power of signals that are transmitted at different powers (e.g., for the control signals of protocol PRKS to be discussed in Section 3.3). For protocol signaling in PRK-based scheduling, the local signal maps also maintain bi-directional power attenuation between a pair of close-by nodes. After estimating $P'(C, R)$, for instance, $R$ informs $C$ of $P'(C, R)$ so that $C$ is aware of the power attenuation from itself to $R$.

To corroborate the effectiveness of the aforementioned method of estimating wireless signal power attenuation, we apply it to estimate power attenuation across links when all the nodes transmit packets using the CSMA/CA-based B-MAC and at an average inter-packet interval of 25 seconds, 2.5 seconds, and 0.1 seconds respectively, which we denote as light traffic, medium traffic, and heavy traffic respectively.

For the NetEye testbed, Figures 9 and 10 show the CDFs of the absolute and relative errors in estimating power attenuation across links in different traffic conditions, where the absolute error for a link is defined as the estimated attenuation minus the ground-truth attenuation for the link and the relative error is defined as the absolute error divided by the ground-truth attenuation. We see that the estimation is quite accurate. For instance, the relative estimation errors are all very close to 0 and almost always within $[-2\%, 2\%]$; in addition, the 95% confidence interval for the median relative error is $[-0.0508\%, 0.0535\%]$, $[-0.0152\%, 0.0280\%]$, and $[-0.0087\%, 0.0245\%]$ for the light, medium, and heavy traffic condition respectively, thus the median estimation error is 0 at the 95% confidence level for all traffic conditions.

For details of the estimation behavior, Figures 11 and 12 show the time series of signal power attenuation for a typical link in NetEye where the power attenuation is estimated in heavy traffic condition and without concurrent transmission (i.e., ground-truth) respectively. We see that the power attenuation has small variation (e.g., mostly less than 1dB); in addition, even though the estimated power attenuation in heavy traffic seems to exhibit greater fluctuation, its mean value is nearly identical to that of the ground-truth data, thus...
Figure 11: Time series for a link’s signal power attenuation in NetEye: heavy traffic

Figure 12: Time series for a link’s signal power attenuation in NetEye: ground-truth

Figure 13: Absolute errors in estimating link signal power attenuation in Indriya

Figure 14: Relative errors in estimating link signal power attenuation in Indriya

Figure 15: Time series for a link’s signal power attenuation in Indriya: heavy traffic

Figure 16: Time series for a link’s signal power attenuation in Indriya: ground-truth

further verifying the validity of the aforementioned method for estimating average signal power attenuation.

For the Indriya testbed, Figures 13 and 14 show the CDFs of the absolute and relative errors in estimating power attenuation across links in different traffic conditions, and Figures 15 and 16 show the time series of the estimated and ground-truth signal power attenuation for a typical link respectively. The observations are similar to those for the NetEye testbed, showing the effectiveness of our method of signal power attenuation estimation in different network and
traffic conditions.

**Protocol signaling based on signal maps.** The local signal map at \( R \) records signal power attenuation between \( R \) and the nodes close-by. Using these information and the transmission power control algorithms proposed by Leung et al. [37], node \( R \) can broadcast signaling packets at an appropriate power level such that these packets with the value of 

\[
\frac{P(S,R,t)}{K_{S,R,T_{S,R}}(t)}
\]

can be received with high probability by all the nodes in the exclusion region \( E_{S,R,T_{S,R}}(t) \) around \( R \); this can be accomplished even if a node \( C \in E_{S,R,T_{S,R}}(t) \) is beyond the regular data communication range of \( R \), in which case the broadcast packets are transmitted at a power higher than the regular data transmission power. Therefore, the local signal map enables addressing the challenge of large interference range through transmission power control. From Inequality 4, we see that the PRK model parameter \( K \) approximately reflects the ratio of the required signaling power to data transmission power; then Figure 20 of Section 2 shows that the required signaling power is usually no more than 22dB over the data transmission power, which makes the power control scheme readily implementable with today’s radio technology [11] 65. To further increase the reliability of protocol signaling, node \( R \) can broadcast each signaling packet multiple times, and nodes in the exclusion region of \( R \) can re-broadcast the signaling packet they hear from \( R \). To reduce the delay in information sharing, signaling packets with fresher information (i.e., information that has been transmitted for fewer number of times) also have higher priorities in channel access by using smaller contention windows in CSMA/CA.

When a node \( C \) receives the signaling packet from \( R \), \( C \) can use its local signal map to decide whether his transmission may interfere with the transmission from \( S \) to \( R \) (i.e., whether \( C \in E_{S,R,T_{S,R}}(t) \)) by checking whether

\[
P(C,R,t) \geq \frac{P(S,R,t)}{K_{S,R,T_{S,R}}(t)}.
\]

Therefore, the signaling packets can reach nodes not in \( E_{S,R,T_{S,R}}(t) \) without falsely including those nodes into \( E_{S,R,T_{S,R}}(t) \), thus addressing the challenge of anisotropic wireless communication. Similarly, using power control algorithms and local signal maps, a pair of nodes \( C \) and \( R \) can inform each other of their respective states (e.g., the PRK model parameter and the data transmission probability) using different transmission powers for signaling packets, thus addressing the challenge of asymmetric wireless communication in protocol signaling.

For the correctness of the above protocol signaling method, the signal map of a node \( R \) should include the set \( E' \) of nodes whose transmission may interfere with the reception at \( R \) or whose reception may be interfered by the transmission by \( R \) (e.g., the transmission of ACK packets by \( R \)). Since the set \( E' \) may well be dynamic and uncertain depending network and environmental conditions, a node \( R \) dynamically adjusts the set of nodes in its local signal map through local coordination with nodes close-by, and \( R \) may also maintain a relative large signal map to include the nodes that may be in \( E' \) over time. Together with the PRK model instantiation method discussed in Section 3.1, the above field-deployable signaling mechanisms enable agile, high-fidelity identification of interference relations among nodes, thus serving as a foundation for predictable interference control.

### 3.3 Protocol PRKS: putting things together

**Decoupling of protocol signaling & data transmissions.** Based on the methods of PRK model instantiation and protocol signaling presented in Sections 3.1 and 3.2, respectively, two basic tasks of interference control are 1) enabling nodes to be accurately aware of the mutual interference relations among themselves and 2) controlling channel access so that no two interfering links use the same wireless channel at the same time. These tasks make the commonly-used single-channel contention-based approach unsuitable for the following reasons:

- In contention-based channel access control, each data transmission is usually preceded by a protocol signaling phase either implicitly through carrier sensing or explicitly through RTS-CTS handshake such as in IEEE 802.11. Due to the probabilistic nature of wireless communication and the potentially large interference range, it is difficult to make such per-transmission protocol signaling perfectly reliable even with the mechanisms discussed in Section 3.2. Accordingly, it is difficult for nodes to be accurately aware of their mutual interference relations, thus it is difficult to control interference in a predictable manner.

- Even if we can make the per-transmission protocol signaling more reliable through mechanisms such as re-transmission of signaling packets, this introduces significant delay and overhead for each data transmis-
sion. Even worse, the signaling packets may well be transmitted at relatively higher power to ensure coverage of the potentially large exclusion regions, and the high-power transmissions of signaling packets introduce significant interference to the data transmissions themselves; in trying to ensure the required data delivery reliability in the presence of strong interference from protocol signaling, nodes will adapt their PRK model parameters to expand their individual exclusion regions, which in turn requires the signaling packets to be transmitted at even higher power and thus leads to system instability (as we have seen in our earlier trials of contention-based approaches).

To address the aforementioned challenges, we propose to decouple protocol signaling from data transmission by leveraging the different timescales of PRK model adaptation and data transmission. Given a link \((S, R)\), highly accurate estimation of its reliability usually requires the knowledge of the transmission status of several (e.g., 20) data transmissions along \((S, R)\) \cite{69}. Accordingly, it takes time to get a new link reliability feedback, and the timescale of PRK model adaptation as well as the resulting change in interference relations between \((S, R)\) and close-by nodes/links is longer than the timescale of individual data transmissions along \((S, R)\). Using the protocol signaling mechanisms discussed in Section 3.2 the receiver \(R\) can inform, after each PRK model adaptation, the relevant nodes of the new value of parameter \(K_{S,R,T_S,R}\) and thus the corresponding change in interference relations; we have observed, in our experimental analysis in Section 4 that each new value of \(K_{S,R,T_S,R}\) can be reliably and quickly signaled within 1.4 transmissions of the signaling packet on average. Therefore, instead of requiring perfectly reliable signaling for each data transmission as in contention-based channel access control, we propose to treat protocol signaling as an independent process which ensures timely awareness of the mutual interference between nodes/links. Based on the latest information on mutual interference relations, data transmissions can be scheduled in a TDMA fashion without being coupled with protocol signaling.

Besides enabling precise awareness of mutual interference relations, the decoupling of protocol signaling and data transmission also enables the transmission of signaling packets and data packets in different wireless channels, thus avoiding the interference between protocol signaling and data transmission as well as the corresponding system instability. For convenience, we regard the wireless channels used for protocol signaling and data transmission as the control channel and the data channel respectively. Using a control channel is necessary for avoiding system instability while addressing the challenges of protocol signaling at the same time; since protocol signaling does not introduce high traffic load, it may well be able to reuse the control channel that has been set aside in industry standards such as IEEE 1609.4 \cite{5} as well as in research proposals \cite{63, 22, 54}.

**Protocol PRKS.** Based on the above design principles, we propose the PRK-based scheduling protocol PRKS that separates the functionalities of PRK-based channel access control into control plane functions and data plane functions as shown in Figure 17. In the control plane, the sender \(S\) and the receiver \(R\) of a given link \((S, R)\) get to know the set of links whose transmissions cannot take place concurrently with the transmission from \(S\) to \(R\) through the protocol signaling mechanisms presented in Section 3.2 and we define this set of links as the conflict set of link \((S, R)\). More specifically, a link \((C, D)\) is in the conflict set of \((S, R)\) and thus conflicting with \((S, R)\) at a time instant \(t\) if links \((C, D)\) and \((S, R)\) share a common end-node, \(C \in \mathbb{E}_{S,R,T_S,R}(t)\), or \(S \in \mathbb{E}_{C,D,T_C,D}(t)\), where \(T_{S,R}\) and \(T_{C,D}\) are the required packet delivery reliability across \((S, R)\) and \((C, D)\) respectively. Based on the conflict sets of links, data transmissions along individual links can be scheduled in a distributed, TDMA manner according to the Optimal-Node-Activation-Multiple-Access (ONAMA) algorithm \cite{53}. With the ONAMA algorithm, a link \((S, R)\) is regarded as active in a time slot if \(S\) transmits to \(R\) in the slot. Given a time slot, the sender \(S\) and the receiver \(R\) of link \((S, R)\) first compute the priorities for \((S, R)\) and the links in the conflict set of \((S, R)\) to be active in the time slot, then \(S\) decides to transmit to \(R\) and \(R\) decides to receive data from \(S\) if and only if, for this time slot, \((S, R)\) has higher priority to be active than every conflicting link. Every node in the network computes link activation priorities in the same manner such that no two conflicting links will be active in the same time slot as long as links are accurately aware of their mutual interference relations. If a link \((S, R)\) is active in a time slot, \(S\) will transmit data packet(s) to \(R\) in this time slot. The status (i.e., successes or failures) of data transmissions in the data plane are fed back into the control plane for estimating the in-situ link reliabilities, which in turn trig-

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\^\text{Note that the periodic sampling of physical processes in WSC networks also makes TDMA an efficient scheduling mechanism as compared with contention-based approaches.}
For a given link, the path losses in the control channel and the data channel are approximately the same given the close proximity of the two channels in spectrum [74].

The length of a time slot is chosen such that the aforementioned actions can be completed in a single time slot whether the node is involved in control plane functions alone or it is also involved in a data transmission/reception.

With the above approach to PRK-based scheduling, the TDMA scheduling of data transmissions happens at the beginning of each time slot based on the PRK model information that is readily available in the control plane, hence there is no need for ensuring perfectly reliable protocol signaling on a per-transmission basis and thus no delay introduced on a per-transmission basis just for protocol signaling either. Given that the timescale of PRK model adaptation at a link (S, R) is longer than the timescale of individual data transmissions along (S, R), in particular, the time instants $t_a$ and $t_b$ for two consecutive PRK model adaptations at (S, R) tend to be well separated such that, within the early part of the time window $[t_a, t_b]$, the PRK model parameter of link (S, R) generated at time $t_a$ can be reliably delivered to the relevant nodes and then be used for the TDMA scheduling of data transmissions.

One premise for the correct operation of PRKS is that, for every link (S, R), the sender S and the receiver R always use the same PRK model parameters of the relevant links when deciding whether (S, R) should be active in a time slot; otherwise, S and R may well derive different conflicting relations between links, and S may think (S, R) shall be active for this time slot and switch to the data channel to transmit, but R thinks (S, R) shall be inactive and stays in the control channel, which makes R unable to receive the transmitted data from S and leads to data packet loss. Since protocol signaling takes time, however, there are transient periods when S and R may have inconsistent information about the PRK model parameters in the network. To avoid the receiver R being in the control channel when the sender S transmits in the data channel, one approach is to have S and R only use the same information about PRK model parameters and delay the use of newly updated PRK model parameters that are not known to both S and R, as in our preliminary study [81]. This approach relies on perfect consistency between S and R in the use of PRK model parameters; due to the probabilistic nature of wireless communication, however, the requirement on perfect consistency introduces non-negligible delay in the use of the latest PRK model parameters, which is undesirable as we will discuss shortly. To allow for the immediate use of the latest PRK model parameters as they become available while ensuring that the receiver R is in the data channel whenever the sender S transmits data packets, we introduce the following sender-receiver coordination mechanism:

- If the link (S, R) shall be active in a time slot $t_0$, the sender S computes the time slot $t_1$ when the link (S, R) will be active again the next time; then S piggybacks the value of $t_1$ onto the data packet, if any, to be transmitted to R at $t_0$ as well as onto every protocol signaling packet that S may transmit during $t_0$ and $t_1$. If the receiver R receives a data or a protocol signaling packet from S showing that S will transmit in a future time slot $t_1$, R will stay in the data channel at $t_1$ even if the local execution of the ONAMA algorithm at R may show link (S, R) as inactive at $t_1$.

- After computing at time $t_0$ the next time slot $t_1$ to transmit to R, S will not transmit to R at any time slot $t'_1 \in (t_0, t_1)$ unless the receiver R tells S to transmit at $t'_1$ as we discuss next. This rule applies even if the local PRK model parameters at S shows at slot $t'_1$ that the link (S, R) shall be active at this time slot; this rule implicitly introduces delay in using the latest information on PRK model parameters, but we have observed that this delay is significantly less than that in the approach based on perfect consistency between S and R as we have discussed.

- After R learns that S will transmit in a future time slot $t_1$, if the execution of the ONAMA algorithm at R at a time slot $t'_0$ shows that the link (S, R) shall be active
at a time slot $t'_1 < t_1$ and if the time window of $[t'_0, t'_1]$ is long enough for $R$ to successfully inform $S$ of the value of $t'_1$ with high probability, $R$ changes its local value of $t_1$ to $t'_1$ and piggybacks the value of $t'_1$ onto packets (e.g., protocol signaling packets) that $R$ may transmit during $[t'_0, t'_1]$. If $S$ receives a packet from $R$ showing that link $(S, R)$ shall be active at a future time slot $t'_1 < t_1$, $S$ changes the value of $t_1$ to $t'_1$. This rule is to ameliorate the implicit delay in using the latest PRK parameter values that the previous rule may introduce.

- If the receiver $R$ does not receive any data packet from $S$ at the time slot $t_1$ (e.g., due to data packet loss), $R$ enters and stays in a “conservative” state until it receives a packet from $S$ again showing that $(S, R)$ shall be active at another future time slot. While in the “conservative” state, the receiver $R$ stays in the data channel for a time slot $t_2$ as long as, at $t_2$, the link $(S, R)$ has higher priority to be active than other links associated with $R$ according to ONAMA [43]; the conservative state ensures that $R$ is in the data channel whenever $S$ transmits a data packet to $R$, and it enables $R$ to be synchronized with $S$ on the data-transmission schedule again.

- In the system boot-up phase, the sender $S$ executes the basic ONAMA algorithm and the receiver $R$ remains in the conservative state when deciding whether to stay in the data or control channel for a time slot, until $S$ transmits for the first time and $R$ receives a first packet from $S$ respectively.

With the above coordination mechanism, the receiver $R$ is guaranteed to be in the data channel whenever the sender $S$ transmits data packets; in the mean time, $R$ stays in the control channel often enough to be updated with the latest PRK model parameters of close-by links.

The aforementioned coordination between a sender and its receiver is the only inter-node coordination needed to address the potential inconsistency on the PRK model parameters during transient periods. In particular, we do not need perfect information consistency that requires the same PRK model parameter of a link $(S, R)$ to be used by link $(S, R)$ and all the links whose transmitters are in the exclusion region around receiver $R$. That is, as long as a receiver is in the data channel when its sender transmits data packets, a node can use the new PRK model parameter of a link the moment the node learns of the parameter. The intuition of this design is that the earliest use of new PRK model parameters helps improve data delivery reliability when the corresponding exclusion regions expand, or it helps improve the channel spatial reuse and the concurrence of data transmissions when the corresponding exclusion regions shrink. As shown in Figure 18 for instance, assuming that node $A$ learns the latest PRK model parameter $K_{S,R,T_{S,R}}(\cdot)$ of link $(S, R)$ earlier than node $C$ does when the exclusion region around $R$ expands or shrinks, then it is desirable for $A$ to use the latest value of $K_{S,R,T_{S,R}}(\cdot)$ without waiting for $C$ to learn it: this prevents $A$ from transmitting concurrently with the transmission along $(S, R)$ when the exclusion region expands, and this allows $A$ to transmit concurrently with the transmission along $(S, R)$ when the exclusion region shrinks.

Our discussions in this paper focus on ensuring data delivery reliability across links, thus we have focused on the exclusion regions around receivers alone. If it is important to ensure ACK reliability at the link layer (e.g., for avoiding unnecessary retransmissions), similar approaches to protecting data receptions can be applied to protect ACK receptions by maintaining an exclusion region around the transmitter of each link. For conciseness of presentation, however, we only focus on ensuring data delivery reliability in this paper.

4. EXPERIMENTAL EVALUATION

We have implemented PRKS in TinyOS [7]. In what follows, we experimentally evaluate PRKS through measurement in the NetEye [44] and Indriya [1] sensor network testbeds.

4.1 Methodology

Protocols. To understand the design decisions of PRKS, we have comparatively studied PRKS with its variants; for clarity of presentation, however, we relegate the detailed discussions to Appendix [A]. Towards understanding the benefits of 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 [50];
- **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 [75].

- **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 [83].

- **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 [60].

- **SCREAM**: a TDMA scheduling protocol using the SCREAM primitive [13] to schedule concurrent transmissions according to the physical interference model; this represents the interference control mechanism used by protocols such as FDD [13] and DSS [58].

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 [17] that do not consider channel spatial reuse.

**Network and environmental settings.** We use a subset of the 130 TelosB motes in NetEye. The subset of motes forms a random network, and it is generated by using each mote of NetEye with probability 0.8; each mote uses a data transmission power of -25dBm (i.e., power level 3 in TinyOS). On average, a node can reach 10 nodes with a data delivery reliability of at least 95% in the absence of interference.

We choose data transmission links such that each mote transmits data packets to a receiver to whom the average SNR is the closest to 15dB in the absence of interference. Unless mentioned otherwise, every node transmits a data packet to its receiver every 20ms. For reflecting different application scenarios, we consider the cases when the required mean data delivery reliability (PDR) is 70%, 80%, 90%, or 95% for all the links and the “mixed PDR requirement” case when the required mean reliability for each link is randomly chosen as 70%, 80%, 90%, or 95% with equal probability.

We have experimented with other network and traffic conditions including in the Indriya I sensor network testbed and with multi-hop data traffic; we have observed similar phenomena as what we will present in Section 4.2. Interested readers can find the detailed discussions in the Appendices B and C.

### 4.2 Measurement results

**Behavior of PRKS.** For different PDR requirements, Figures 19 and 20 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. 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 21 shows the mean concurrency (i.e., number of concurrent transmissions at a time instant) and its 95% confidence intervals in PRKS as well as in a state-of-the-art, centralized scheduling protocol iOrder [16] which maximizes channel spatial reuse in interference-oriented scheduling. 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 22 shows...

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1. 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.
2. 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.
3. In terms of maximizing spatial reuse, iOrder has been shown to outperform well-known existing scheduling protocols such as Longest-Queue-First [55], GreedyPhysical [12], and LengthDiversity [25].
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. As a way of reflecting the network-wide convergence, Figure 23 shows the temporal, convergence behavior of the network-wide average deviation of link reliability from the required mean PDR (i.e., $\left(\frac{1}{\sum_{\text{total number of links}}(S_{\text{R}})}\sum_{\text{every link}}(S_{\text{R}})|Y_{\text{S},S(t)}-Y_{\text{S},R}|\right)$. In general, link PDRs converge quickly, as shown by Figure 24 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 21.

To understand the adaptation of PRKS to online dynamics, we also run experiments where the mean PDR requirements change over time. Figure 25 shows, for a typical link in the network, the time series of 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 26 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 have different PDR requirements, Figures 27 and 28 show the boxplots of link PDR and PRK model parameter 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 also studied the scenario where different links use different transmission powers to ensure a desired SNR of 15dB at receivers in the absence of interference, and have observed similar behavior. For instance, Figure 29 shows that the desired PDRs are ensured when different links use different transmission powers.

**Comparison with existing protocols.** Figure 30 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 31 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 re-
spective) 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 $O(nk)$ 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) \cite{13}. Thus SCREAM is not suitable for dynamic, large-scale networks where schedules need to adapt to changing network and environmental conditions frequently.

Incapped 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 52 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 53 which shows the mean number of packets successfully delivered in the network per time slot.

Existing protocols can also try to improve link reliability by reducing the application traffic load such that interference becomes negligible. Nonetheless, reducing traffic load decreases network throughput; this can be seen from Figure 54 which shows the mean network spatial throughput when packet arrival rates are limited from above to ensure a certain required PDR.

### 5. DISCUSSION

**Mobility.** As a first step in developing field-deployable solutions to distributed, predictable interference control, we have focused on mostly-static WSC networks such as those in smart power grid and industrial automation. In vehicular WSC networks such as those for inter-vehicle active safety control, however, nodes are mostly-mobile as vehicles move. Vehicle mobility introduces dynamics in vehicle spatial distribution and thus dynamics in wireless communication. In particular, dynamics in vehicle spatial distribution increases the dynamics in signal power attenuation between nodes, which challenges the maintenance of local signal maps and the adaptation of the PRK model. While detailed study of PRK-based scheduling in vehicular WSC networks is our future work, we observe that the following facts may well help address the challenges of vehicle mobility: 1) The timescale of non-negligible vehicle movement is in seconds, while the timescale of wireless communication is in milliseconds or microseconds; the significantly longer timescale of the physical movement of vehicles enables vehicles to exchange control signals for PRK-based scheduling adaptation on the fly; 2) There are well-established, microscopic mobility models for vehicle movement \cite{19}; these models can help estimate dynamics in vehicle spatial distribution and thus dynamics in signal power attenuation between vehicles; therefore, these models can help enable predictive adaptation of the signal map and the PRK model. We will explore the above opportunities in our future work.

### 6. 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 1 and 4 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. In addition, many of these algorithms do not address the challenge of designing scheduling protocols when interfering links are beyond the communication range of one another \cite{32, 53}.

The concepts of guard-zone or exclusion-region around receivers have also been exercised in distributed scheduling algorithms \cite{14, 27}, but these algorithms assumed uniform traffic load or uniform wireless signal power attenuation across the whole network, which are unrealistic in general. They did not address the challenge of designing scheduling protocols when interfering links are beyond the communication range of one another either.

Adaptive physical carrier sensing has been proposed to enhance network throughput \cite{32, 53}, but cumulative interference is not considered. We have also observed in \cite{80} that throughput-optimal scheduling usually leads to low link reliability, which is not desirable in wireless sensing and control (WSC) networks. Park et al. \cite{53} 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. [24] 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.

Given that mission-critical WSC applications (e.g., those in transportation [2] and medicine [3]) may well use licensed spectrum, we expect co-channel interference to be a major source of interference in those settings and thus PRKS to be a basic element of those systems. For application domains without licensed spectrum, channel hopping has been leveraged to address external interference [55]. In these settings, PRKS can be integrated with channel hopping to address external interference, for instance, by dynamically changing the wireless channels used for transmitting the signaling packets and data packets in PRKS, but detailed study of this is beyond the scope of this paper. Glossy [23] leverages non-destructive interference between synchronized concurrent transmissions of the same packet to enable efficient flooding of packets across a network, upon which LWB [22] develops algorithms for scheduling many-to-one, one-to-many, and many-to-many communications. Glossy and LWB does not allow for spatial reuse of wireless channels to transmit different packets at the same, thus they can lead to capacity loss in large scale networks. The network-wide flooding of the same packet in Glossy and LWB also leads to waste of channel resources in emerging networked control paradigms that involve only communications between close-by nodes [52].

Focusing on addressing the decades old problem of predictable co-channel interference control, our study in this paper does not consider duty-cycling nodes for energy efficiency. In WSC networks where energy efficiency may be an important issue, the basic design of PRKS can be integrated with duty-cycling mechanisms in ways similar to those in Glossy [23] and LWB [22]; for instance, the communication of data packets and signaling packets in PRKS can be done in the active periods of a network, allowing the network to sleep in its inactive periods. Detailed study of this is, however, beyond the scope of this paper.

Focusing on distributed control of co-channel interference based on the PRK interference model, our study in this paper does not consider other interference management techniques such as interference cancellation and multi-channel scheduling, and we do not consider other link-reliability control techniques such as rate adaptation and power control. Nonetheless, we expect this work to be relevant in the context of these techniques too, since co-channel interference still needs to be managed even with interference cancellation [38], multi-channel scheduling [63], rate control [8], and power control [41]. We will explore this synergy in our future work. Having nodes transmit busy tones in control channels to share their transmission or reception status has also been explored for channel access control [67], but these work did not study the fundamental problem of identifying interference relations between links, thus they could not ensure predictable interference control.

Real-time channel access scheduling algorithms [9, 20, 40, 62] have been proposed for wireless networks, but most were based on the inaccurate protocol interference model [80]. Venkataramanan et al. [68] and Jaramillo et al. [31] also considered delay in distributed scheduling, but they did not address the question of how to identify the interference set of each link. Wang et al. [69] studied delay-constrained link scheduling using the SINR model, but the distributed implementation of their scheduling algorithms requires multiple rounds of network-wide coordination and thus not suitable for dynamic traffic patterns and network conditions. Munir et al. [50] considered using link burst length as the basis of routing and real-time scheduling. But they did not consider cumulative interference in scheduling, and the scheduling algorithm was centralized and not suitable for dynamic, large scale networks either; the algorithm also assumed prior knowledge of traffic patterns and was based on long-term (e.g., 21 days), offline measurement data, thus not suitable for dynamic traffic patterns and network conditions. Sai-fullah et al. [59] considered real-time scheduling for WirelessHART networks; the work assumed application scenarios where the scheduling is centralized and no channel spatial reuse is allowed, thus the scheduling algorithm is not suitable for dynamic, large-scale networks with limited number of channels available. Even though we do not focus on real-time scheduling in this paper, we expect the predictable link reliability enabled by PRKS to serve as a foundation for developing real-time scheduling protocols in the presence of co-channel interference.
7. CONCLUDING REMARKS

To enable predictable reliability in data delivery for wireless networked sensing and control, we have proposed the wireless transmission scheduling protocol PRKS that ensures predictable interference control in the presence of non-local interference as well as network and environmental uncertainties. Extensive experimental analysis of PRKS show that it 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 also serves as a basis for predictable real-time data delivery and for predictable tradeoff between reliability, delay, and throughput in wireless sensing and control networks; we will explore this direction of research in our future work. Building upon the insight from PRKS for mostly-immobile networks, we will also explore mechanisms of extending PRKS to enable predictable link reliability in mobile networks such as vehicular sensing and control networks.

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8. REFERENCES


APPENDIX

A. VARIANTS OF PRKS

To understand the design decisions of PRKS, we comparatively study PRKS with its following variant:

**PRKS-R**: same as PRKS but formulates the PRK model instantiation problem as a deadbeat PID regulation control problem instead of as a minimum-variance regulation control problem.

In PRKS-R, in particular, the control law is as follows:

$$
\Delta I_R(t) = K_P e(t) + K_I \sum_{i=0}^{t} e(i) + K_D (e(t) - e(t-1))
$$

where

$$
K_P = \frac{-1}{\alpha(t)(1-c)},
K_I = \frac{-1}{\alpha(t)(1-c)},
K_D = \frac{-c}{\alpha(t)(1-c)},
$$

$$
e(t) = T_{s,R} + \delta Y - y(t).
$$

Figures 35 and 36 show the mean concurrency and mean deviation of PDR from the PDR requirement as well as their 95% confidence intervals in different variants of PRKS respectively. Even though PRKS-R also meets PDR requirement, its concurrency is significantly lower than that of PRKS. This is because by using the traditional PID regulation control instead of minimum-variance regulation control, PRKS often overshoots above the PDR requirement as Figure 36 shows.

![Figure 35: Mean concurrency in variants of PRKS](image)

![Figure 36: Mean PDR deviation from PDR requirement in variants of PRKS](image)

B. MEASUREMENT RESULTS IN THE INDRiya TESTBED

We have observed similar behavior in the Indriya testbed [1] as those in NetEye. For the Indriya testbed, Figures 37 and 38 show the packet delivery reliability (PDR) and PRK model parameter in PRKS respectively. We see that PRKS ensures required PDRs in an adaptive manner by adjusting the PRK model parameter according to application requirements on PDRs. Figure 39 shows the PDR requirement satisfaction ratios in different protocols. We see that, unlike PRKS, other protocols cannot ensure application required PDR in a predictable manner.

![Figure 37: Packet delivery reliability in PRKS: in Indriya](image)

![Figure 38: PRK model parameter in PRKS: in Indriya](image)

![Figure 39: PDR requirement satisfaction ratios in different protocols: in Indriya](image)

C. MULTI-HOP TRAFFIC

All previous measurements are for single hop traffic. It is not uncommon for packets to traverse multiple hops to reach their destinations in real-world. We also compare PRKS with other protocols in a multi-hop setting. In NetEye, we build a shortest-path routing tree based on the Expected Number of Transmissions (ETX). Each link in the tree has a PDR of at least 95% in the absence of interference. The tree contains 46 nodes and is rooted at node 15. Every node except the root generates a packet every 1.8 second to be delivered to the root. We set the link PDR requirement as 70% for protocols applicable. In each protocol, per-hop retransmission is enabled and up to 8 times.

Figures 40, 41 and 42 show the mean end-to-end PDR, median end-to-end latency including end-to-end retransmission, and mean end-to-end throughput of different protocols as well as their 95% confidence intervals. By ensuring all links’ PDR while maximizing spatial reuse, PRKS outperform all other protocols in end-to-end delivery substantially in terms of reliability, delay, and throughput. Even though
some links in other protocols exhibit high link PDR, others don’t because they cannot ensure predictable reliable links, unlike PRKS. These bottleneck links incur significant queueing delay and queue overflows, thus greatly degrade end-to-end packet delivery. This demonstrates the benefit of ensuring individual link’s PDR through PRKS.

Figure 40: Mean e2e PDR in different protocols

Figure 41: Median e2e latency in different protocols

Figure 42: Mean e2e throughput in different protocols