Experimental Study for Multi-layer Parameter Configuration of WSN Links

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Abstract—Many applications of wireless sensor networks (WSNs) need to balance multiple yet often conflicting performance requirements such as high energy efficiency, high throughput, low delay and low loss. Finding appropriate WSN parameter configuration to achieve the best trade-off requires in-depth understanding of the joint effect of key parameters residing at different layers on the performance. In this paper, we present an extensive experimental study on the data delivery performance of a WSN link, where 4 major performance metrics, namely energy, throughput, delay and loss, were measured over 6 months under around 50 thousand parameter configurations of 7 key stack parameters. Different from existing work, rich observations are made out of the extensive measurement data, with the focus on the joint effect of these parameters on the performance. Specifically, for each of the four performance metrics, a set of guidelines is derived for parameter optimization. In addition, we propose empirical models for each performance metric to quantify the joint effects, which enable finding optimal settings for parameters such as payload size or retransmissions, in consideration of link quality and other parameter settings, to achieve better performance trade-offs. To demonstrate the potential of this work, the obtained joint parameter optimization results are applied to an example. The outcome is compared with those achieved by following representative single-parameter tuning guidelines from the literature. The comparison reveals that by considering the joint effect of multi-layer parameters together, a WSN application can obtain a much improved performance trade-off.

I. INTRODUCTION

Real-world applications of wireless sensor networks (WSNs) often have performance requirements on the network, such as high energy efficiency, high throughput, low delay and low loss. To meet these requirements, various stack parameters at different layers of the network are the tuning knobs.

However, there exists a large conceptual gap between performance requirements and stack parameter tuning. In most deployments today, the choice of stack parameter setting is simply based on experience and rules of thumb, due to lack of a comprehensive understanding about the (joint) effect of the stack parameters on the performance, particularly on the trade-off between multi-performance objectives. To fill this gap, a number of measurement studies have recently been reported in the literature. They include [1][2][3] on energy consumption, [1][4][5][6] on throughput, [3][4][5][7][8] on delay, and [3][4][7][8][9][10][11][12] on packet loss rate. The considered stack parameters include packet inter-arrival time [4][6][10][13], packet length [1][2][5][14], transmission power [10][11][13], queue size [7], MAC layer parameters such as maximum (re-)transmission times and retry delay [3][6][7][12], and other physical layer parameters including RSSI [9][10][11][13][14], distance [4][5][11] and interference [1][13].

Nevertheless, most of the literature studies focus on the effect of tuning one parameter on the performance. Little is known about the joint effect of multiple parameters on the performance, particularly when multiple performance requirements are to be met simultaneously and there are inherent trade-offs between them. As a result, relying on the parameter-tuning guidelines suggested from the literature may only be able to provide sub-optimal performance trade-offs.

As an example, let’s consider throughput and energy consumption together, which are probably the most fundamental requirements in WSNs. There exists an inherent trade-off: higher transmission power can lead to better throughput but in the sacrifice of higher power consumption. It is intuitive that the optimal parameter setting should lead to maximal throughput with minimal power consumption. Representative prior works aimed to deal with this throughput-energy trade-off include [6][1][11]. In them, tuning guidelines for different single-parameters have been suggested: [6]-tuning retransmission times; [1]-tuning payload size; [11]-tuning output power.

To give a glance on the achieved trade-offs based on the single-parameter tuning guidelines, Fig. 1 is presented. Additionally, Fig. 1 also shows a much improved trade-off achieved by taking into consideration the joint effect of multiple stack parameters on the performance trade-off, which is our work - tuning multiple parameters jointly. (See Sec. VIII for more details about the parameter settings of the example.)

Fundamentally, Fig. 1 reveals the potential gain, which may be achieved by tuning multiple stack parameters together, and hence the necessity of studying their joint effect on the performance. This motivates our work.

![Fig. 1: Comparison of trade-offs: goodput vs. energy](image-url)
The objective of the paper is to investigate the joint effects of multiple stack parameters on the performance and the performance trade-offs, via a parameter space exploration. Specifically, we comprehensively investigate the effects of 7 typical parameters from PHY, MAC and Application Layer on the performance in terms of energy efficiency, throughput, delay and loss. The foundation of our investigation is an extensive experimental study that we conducted, where close to 50 thousand parameter configurations were considered and the metadata of more than 200 million packets were collected over 6 months. The data set is publicly available at [15] [16].

To the best of our knowledge, this is the first measurement study for multi-layer parameter configuration of a WSN link at such an extensive level. Our first contribution is, based on the collected data, to report our empirical experiences and findings about data delivery performance over a WSN link under a wide range of parameter configurations for different link quality levels. Based on these findings, we derive the guidelines for multi-layer parameter optimization for each performance metric. They form the second contribution of this paper. Furthermore, based on measurement data analysis, we make our third contribution by introducing empirical models for energy consumption, maximum goodput, delay and packet loss rate. The empirical models not only quantify the joint effects of the stack parameters but also enable finding optimal settings for parameters such as payload size or retransmissions, in consideration of link quality and other parameter settings, to achieve the best performance and/or performance trade-off.

The rest of the paper is organized as follows. Section II presents the experimental methodology. Section III shows the radio channel characteristics and packet error rate in our experiment environment. The experimental results, empirical models and parameter configuration guidelines are presented for each performance metric: energy consumption in Section IV, goodput in Section V, delay in Section VI and packet loss in Section VII, respectively. Section VIII summarizes the findings for joint parameter tuning to achieve a better performance trade-off. Finally, Section IX concludes our work.

II. THE EXPERIMENT

A. Reasoning of the Setup

The performance of a wireless sensor network (WSN) essentially depends on the performance of each wireless link in the network. In addition, a recent survey indicates that about 25% of current WSN deployments [17] only use one-hop wireless communication. This is indeed not surprising, since WSNs are commonly used in smart home applications [18] and surveillance [19], where one-hop communication is often sufficient. In brief, one-hop wireless communication not only is the foundation of WSN but also is found in popular WSN application scenarios such as smart home. Taking these into consideration, we chose to conduct our experimental study on a WSN link in an indoor environment. Another consideration for this was that the indoor setup allows conducting a more extensive set of experiments for such a study on the joint effect of multiple stack parameters on the performance. Despite the simplicity of the setup, the whole experiment took over 6 months between November 2012 and November 2013, and the fundamental properties of the joint effect of multiple stack parameters are mostly revealed as to be discussed in the paper.

B. The Setup

We employed a sender-receiver pair of TelosB motes, each equipped with a TI CC2420 radio using the IEEE 802.15.4 stack implementation in TinyOS. The IEEE 802.15.4 standard specifies both Physical (PHY) and Medium Access Control (MAC) layer parameters. At the PHY layer, the radio CC2420 achieves a data rate of 250 kb/s using O-QPSK in the ISM band of 2.4 Ghz. At the MAC layer, the beaconless mode with unslotted CSMA-CA was used for channel access.

Specifically, the experiments were conducted in a long hallway of 2 meters by 40 meters. Each mote was fixed on a wooden stand of 0.7-meter high and the positions of the nodes are shown in Fig. 2. For each experiment, we maintained line-of-sight between the two motes. During the experiments, university students and employees may walk in the hallway.

In each experiment, the sender sends packets to the receiver under a particular stack parameter configuration. For each stack parameter configuration, 7 key parameters residing at different layers are considered.

At the PHY layer are the distance (d) between nodes and the transmission power level (Ptx). At the MAC layer are the maximum number of transmissions (NmaxTries), the retry delay time for a new retransmission (Dretry), and the maximum queue size (Qmax) of the queue on top of the MAC layer used to buffer packets when they are waiting for (re-)transmission. At the Application layer are the packet inter-arrival time (Tpkt) and the packet payload size (lD). Table I gives a summary of these parameters and their value ranges as well as the rationales behind the considered values.

C. The Experiment Dataset

For each stack parameter configuration, which is a combination of the 7 parameters summarized in Table I, the sender sent 4500 packets under this configuration. Both the sender and the receiver logged per-packet information that includes RSSI, LQI, time of receiving, actual transmission number, actual queue size, etc.

Specifically, for each distance, all combinations of the remaining 6 parameters were iterated, before the experiments for the next distance were conducted. For each distance, one 8064-parameter-setting trace was collected in days and nights spanning over 4 weeks. For all the distances, the experiments were running over 6 months.
In total, close to 50 thousand parameter configurations were experimented and detailed transmission information of more than 200 million packets was collected, which provides statistical information for understanding the data delivery performance under various parameter configurations.

In the following sections, we conduct analysis on the measurement data and discuss our findings from the aspects of radio channel characteristics, energy efficiency, goodput, delay and loss rate.

### III. Channel Characteristics and Packet Error Rate

In this section, we focus on the experiment results of channel characteristics and Packet Error Rate (PER). While the former is fundamental for understanding the experiment environment, the latter is an important step towards analyzing other performance metrics.

#### A. Radio Channel Characteristics

For radio channel characteristics, we focus on the received signal strength (RSSI) attenuation with distance, RSSI variation and the noise floor distribution. We first plot the average RSSI with increasing distances in Fig. 3. The figure shows the path loss in our hallway matches the well-known log-normal shadowing model [20]. The range of the measured RSSI values indicates that we have measured the performance under a wide range of link qualities.

We show the RSSI deviation for each $P_{tx}$ level at different distances in Fig. 4. We observe that the RSSI is not stable in the indoor environment. Interestingly, there is no consistent correlation between RSSI deviation and the output power. However, the variations at 35m is generally higher than the variations at other distances. A possible cause for this is that 35m link is the weakest link among all distances and it may be influenced by the shadowing effects of human because a kitchen and a meeting room are locating close to the 35-meter position. Note that the RSSI deviation for $P_{tx} = 3$ at 35m is very small because the RSSI values have approached to the sensitivity of CC2420. The results of RSSI deviation suggest the necessity of adapting to dynamic link quality for parameter tuning techniques.

Furthermore, we analyze the noise floor distribution in our environment based on approximately 24 million noise floor samples. We find that the noise floor cannot or should not be influenced by the shadowing effects of human because a kitchen and a meeting room are locating close to the 35-meter distance. A possible cause for this is that variations at other distances. A possible cause for this is that the RSSI deviation for $P_{tx} = 3$ at 35m is very small because the RSSI values have approached to the sensitivity of CC2420. The results of RSSI deviation suggest the necessity of adapting to dynamic link quality for parameter tuning techniques.

#### B. Packet Error Rate

Packet error rate (PER) is the ratio of the number of unacknowledged data packets to the total number of transferred packets. It is calculated as:

\[
PER = \frac{\text{# of non-ACKed transmissions}}{\text{# of total transmissions}}
\]  

As the immediate performance metric of the physical layer, PER is affected by packet payload size $l_D$ and physical layer condition or more specifically SNR.

To show how PER changes with SNR, the scattered PER values are plotted against SNR in Fig. 6(a). The figure shows a strong correlation between SNR and PER and validates the existence of "grey zone" and low-loss zone as observed in previous studies [11] [13].

Interestingly, we observe that the curve of the PER decreases smoother than expected during the transition from the "grey zone" to the low-loss zone. We did not expect this because many prior measurements [11] [13] reported the "sharp cliff" transition of PER. We observe from Fig. 6(b) that the steepness of the slope clearly correlates with payload size. PER decreases more smoothly for larger $l_D$.

We further examine the impacts of $l_D$ on PER at same SNR values. We plot the relation between PER and $l_D$ in Fig. 6(c). The figure clearly shows a positive correlation between payload size and PER. However, the magnitude of the impacts of $l_D$ depends on the SNR value.

To have a complete view of the joint effects of SNR and $l_D$, we plot in Fig. 6(d) the PER with minimum $l_D$, PER with maximum $l_D$ and the average PER of different $l_D$ for the whole SNR region measured in our experiment. Based on the observations from Fig. 6(d), we classify the joint effects of $l_D$ and SNR on PER by 3 different SNR regions. We refer these regions as the 3 joint-effect zones of PER: (1) high-impact zone (SNR 5 dB to 12 dB), where the average PER is the highest among 3 zones and the PER changes dramatically with payload size, (2) medium-impact zone (SNR 12dB to 19dB), where the average PER is relatively low but it still changes significantly with payload size and (3) low-impact zone, where both SNR and payload size have very little influence on PER in this region (SNR ≥ 19 dB).

The different joint effects on PER in these 3 zones have a fundamental impact on other performance metrics, which will be discussed in the following sections.

#### IV. Experiment Results: Energy Efficiency

The focus of this section is on the joint impacts of two configurable parameters, payload size and output power, on the energy consumption. Based on the measurement dataset...
and our analysis, we summarize the rules to find the optimal output power and payload size in different cases. In addition, we introduce an empirical model for the energy metric, which may be utilized to estimate energy consumption for a broad range of parameter configuration and link quality.

A. Observation

Consider the energy spent to transmit data. Adopted from the literature [1], we define the energy consumption for transmitting per information bit $U_{\text{eng}}$ as follows.

$$U_{\text{eng}} = \frac{E_{\text{tx}} \cdot (l_0 + l_D)}{l_D \cdot (1 - \text{PER})} \quad (2)$$

where $l_0$ and $l_D$ are the stack overhead size and packet payload size, respectively. For different output power levels, we estimate $E_{\text{tx}}$ as the energy consumption for transmitting one bit of data for a given output power level according to the data-sheet of CC2420. Accordingly, energy efficiency is defined as $U_{\text{eng}} = 1/U_{\text{eng}}$, which indicates how much information is sent per unit energy consumption.

We first show the impact of $P_{\text{tx}}$ on $U_{\text{eng}}$ at distance 35m with respect to small, medium and large payload size in Fig. 7. The figure shows the output power reaches optimal when the corresponding SNR moves from the “grey zone” to the low-loss zone due to the significant reduction in retransmissions. After that, increasing output power only causes more energy consumption.

As depicted in Fig. 7, it is interesting that the optimal power also depends on payload size. A larger packet seems to require a higher RSSI to achieve the optimal energy consumption. At 35m, the optimal output power is 11 for $l_D$ of 110 bytes while it is 7 for the other two payload sizes. The reason is that for large $l_D$, energy consumption for retransmissions can still be significantly reduced if the link moves from the medium-impact zone into the low-impact zone of PER (Sec. III-B).

Fig. 8 shows a closer look of the impact of $l_D$ on energy consumption. The figure indicates that the optimal payload size depends strongly on SNR. When the link is in the “grey zone” ($P_{\text{tx}} = 3$ in the figure), medium-size packets are preferred to minimize energy consumption due to the reduction in retransmissions for smaller packets. However, when the SNR is above certain threshold (15.8 dB for $P_{\text{tx}} = 7$), the energy-optimal payload size is the largest payload size considered in the experiment (110 bytes).

**Fig. 3:** Log-normal path loss with path loss factor $n = 2.19$ and deviation $\sigma = 3.2$.

**Fig. 4:** RSSI deviation shows no consistent correlation with output power. Large shadowing effects at 35m.

**Fig. 5:** Distribution of real SNR and the SNR by assuming constant noise (-95 dBm is the noise floor average).

**Fig. 6:** The joint effects of SNR and payload size on PER. (a) (b) The PER decreases slowly with SNR for large packet. PER decreases to 0.1 until around 19 dB for maximum $l_D$. (c) PER increases with payload size but the magnitude of increase depends on SNR. (d) Based on the different joint effects of SNR and $l_D$ on PER depicted in (c), the SNR region is divided into 3 joint effect zones.

**Fig. 7:** Optimal transmission power level for $U_{\text{eng}}$ at 35m. Large $l_D$ requires higher $P_{\text{tx}}$ to minimize $U_{\text{eng}}$. 
To summarize both figures, among all the combinations of SNR and payload size, when the output power level is selected such that the minimal necessary SNR for the maximum payload size is just reached, energy consumption decreases to the minimum. This minimal necessary SNR for different payload sizes is up to around 5-7 dB higher than the “grey zone” threshold for the maximum payload size in our radio stack (114 bytes), which is to be explained below.

B. Modeling $U_{\text{eng}}$

In the following, we introduce the empirical model of $U_{\text{eng}}$ by first modeling the PER. The following exponential function fits well with our measurements of PER:

$$PER = \alpha \cdot l_D \cdot \exp(\beta \cdot \text{SNR}),$$

where $\alpha = 0.0128$ and $\beta = -0.15$.

Applying (3) to (2), an empirical model of $U_{\text{eng}}$ is resulted. In Fig. 9, we plot again the relation between $l_D$ and $U_{\text{eng}}$ under transmission power level 3.

Fig. 9 shows that the optimal $l_D$ starts to decrease from maximum size with SNR, when SNR is below a certain threshold (17 dB). It changes from maximum size to less than 40 bytes when SNR decreases from 17 dB to 5 dB. This implies that adapting the payload size to the varying link quality can be an efficient way to minimize energy consumption in dynamic channel conditions. Based on this figure and Fig. 7, we see that when SNR is at 17 dB, the maximum $l_D$ of 114 bytes provides the best energy efficiency among all configurations.

C. Parameter Optimization Guidelines

To reduce energy consumption, joint consideration of optimizing output power and payload size is necessary. If the output power can be set such that the link just moves into the low-impact zone of PER (17 dB according to the empirical model and 19 dB according to observations), then choosing $l_D$ of maximum size (114 bytes) can reduce the energy consumption to the minimum.

If the maximum output power is used and the SNR is still smaller than 17 dB, then choosing a smaller payload size can reduce energy consumption. The exact energy-optimal payload size can be calculated using the empirical model of $U_{\text{eng}}$ for any given link quality.

V. EXPERIMENT RESULTS: GOODPUT

The focus of this section is on the joint impacts of SNR, payload size, maximum number of retransmissions and retry delay on the performance metric goodput - application level throughput. Based on the measurement dataset and our analysis, we show the joint effects of parameters such as payload size and retransmissions on the goodput. In addition, we introduce an empirical model of maximum goodput via modeling the service time and radio loss rate. Based on this model, we further suggest guidelines for choosing the optimal parameter configurations to maximize goodput under different link quality conditions.

A. Observation

Goodput is the application level throughput, i.e., the number of useful information bits received per unit of time. We investigate goodput against SNR for different traffic workloads under four typical MAC configurations: (a) no queue and no retransmission, (b) no queue but with retransmission, (c) with a queue but no retransmission and (d) with a queue and with retransmission. The goodput performance under the four MAC configurations is shown in Fig. 10(a), Fig. 10(b), Fig. 10(c) and Fig. 10(d), respectively.

Among all the impacting parameters, SNR is clearly correlated with goodput. The goodput increases significantly with SNR until around 19 dB. After that, increasing power does not increase goodput much. This SNR value 19 dB is the point where the output power provides the best trade-off between energy consumption and goodput.

Another parameter that has a clear impact on the goodput is the packet inter-arrival time. For the same payload size, a smaller $T_{\text{pmt}}$ seems to have better goodput. This is essentially due to the resulting increased traffic load.

However, the impact of packet size $l_D$ or maximum number of transmissions $N_{\text{maxTries}}$ cannot be easily generalized from these figures due to their complex joint effects on goodput. One well-known trade-off is that shorter packets have smaller latency and are less likely for high retransmissions. However, shorter packets also imply higher overheads. Another trade-off exists between latency and packet loss rate for $N_{\text{maxTries}}$. A small $N_{\text{maxTries}}$ may give shorter delay but possibly higher loss rate on radio transmission.

Therefore, for comprehensive understanding of goodput, we need to first have in-depth understanding of the latency
and radio loss rate under these parameters. In the following, we start from modeling the service time delay and the radio loss rate. Using these models, we provide an empirical model that allows quantifying the maximum goodput. At last, we discuss about the optimal parameter configuration for maximizing goodput.

![Graphs showing goodput under different parameter configurations](image)

**Fig. 10: Goodput under different parameter configurations**

### B. Maximum Goodput and its Modeling

We first introduce the definition of maximum goodput. Adopted from the literature, we define the maximum goodput $\text{maxGoodput}$ as:

$$\text{maxGoodput} = \frac{l_D}{T_{\text{service}}} \cdot (1 - \text{PLR}_{\text{radio}}), \quad (4)$$

Different from the throughput in [1], we use $T_{\text{service}}$ over latency. $T_{\text{service}}$ is the service time defined as the time interval between sending a packet and its arrival. When the packet is sent one after another to maximize the goodput, latency equals to average service time $T_{\text{service}}$. PLR$_{\text{radio}}$ is packet loss rate over radio transmission.

**Modeling average service time $T_{\text{service}}$.** To quantify $T_{\text{service}}$ in the maximum goodput, we propose an empirical model of the service time for any given stack parameter configuration and channel condition. In TinyOS 2.1, the service time depends on (1) $T_{SPI}$ – the one-time hardware SPI bus loading time of a data frame; (2) $T_{\text{frame}}$ – the time to transmit a frame consisting of packet payload and overhead; (3) $T_{\text{MAC}}$ – MAC layer delay consisting of two parts: $T_{\text{TR}}$ and $T_{\text{BO}}$, where $T_{\text{TR}}$ is the turn around time (0.224ms) and $T_{\text{BO}}$ is the average value of initial backoff period (5.28ms); (4) $T_{\text{ACK}}$ – the ACK frame transmission time if ACK frame is received, and based on prior tests $T_{\text{ACK}} \approx 1.96\text{ms}$; (5) $T_{\text{waitACK}}$ – the maximum software ACK waiting period (8.192ms); (6) $N_{\text{tries}}$ – the number of transmissions to deliver the packet successfully; (7) $D_{\text{retry}}$ – the delay between two consecutive retransmissions. Specifically, there are two cases depending on if a packet is successfully transmitted. Accordingly,

- If $N_{\text{tries}} \leq N_{\text{maxTries}}$,
  $$T_{\text{service}} = T_{\text{SPI}} + T_{\text{succ}} + (N_{\text{tries}} - 1) \cdot T_{\text{retry}} \quad (5)$$
- If $N_{\text{tries}} > N_{\text{maxTries}}$,
  $$T_{\text{service}} = T_{\text{SPI}} + T_{\text{fail}} + (N_{\text{maxTries}} - 1) \cdot T_{\text{retry}} \quad (6)$$

where

$$T_{\text{succ}} = T_{\text{MAC}} + T_{\text{frame}} + T_{\text{ACK}}$$
$$T_{\text{fail}} = T_{\text{MAC}} + T_{\text{frame}} + T_{\text{waitACK}}$$
$$T_{\text{retry}} = D_{\text{retry}} + T_{\text{MAC}} + T_{\text{frame}} + T_{\text{waitACK}}$$

In the service time model, the average number of transmissions for a successful delivery $N_{\text{tries}}$ is empirically modeled by the measured average number of transmissions with respect to $l_D$ and SNR, as illustrated in Fig. 11. The following exponential function fits well with our measurements:

$$N_{\text{tries}} = 1 + \alpha \cdot l_D \cdot \exp(\beta \cdot \text{SNR}), \quad (7)$$

where $\alpha = 0.02$ and $\beta = -0.18$ with 95% confidence level.

![Graph showing modeling average number of transmissions](image)

**Fig. 11: Modeling average number of transmissions**

With $N_{\text{tries}}$, the empirical model of average service time, i.e., (5) and (6), can be readily used.

**Modeling radio loss rate.** To quantify $\text{PLR}_{\text{radio}}$ in the maximum goodput, we model the radio loss rate $\text{PLR}_{\text{radio}}$ as a function of payload size, SNR and maximum transmission attempts $N_{\text{maxTries}}$:

$$\text{PLR}_{\text{radio}} = (\alpha \cdot l_D \cdot \exp(\beta \cdot \text{SNR}))^{N_{\text{maxTries}}}, \quad (8)$$

where $\alpha = 0.011$ and $\beta = -0.145$ and its validation with measurement data is depicted in Fig. 12.

**Modeling maxGoodput.** With the modeling of average service time and radio loss rate, the empirical model of maxGoodput is readily obtained by applying them to (4).

With the empirical model, we plot maxGoodput against payload size under different SNR values with and without retransmissions, as depicted in Fig. 13.

We observe from the two sub-plots that the optimal payload size for maximizing goodput depends on both SNR and $N_{\text{maxTries}}$. In general, when the link is the low-loss zone, the optimal payload size is always the maximum $l_D$. 

With $N_{\text{tries}}$, the empirical model of average service time, i.e., (5) and (6), can be readily used.
where packet loss is reduced by retransmission.

The optimal output power that provides the best trade-off between energy and goodput leads to a SNR around 7 dB higher than the “grey zone” threshold (12 dB). If the link is outside the “grey zone”, using the maximum payload size (114 bytes) and large $N_{\text{maxTries}}$ can maximize the goodput.

When the link is in the “grey zone” under the maximum output power, retransmission can still increase goodput. However, the optimal payload size is not the maximum size. It decreases with SNR and also depends on $N_{\text{maxTries}}$. Larger $N_{\text{maxTries}}$ increases the optimal payload size. The exact goodput-optimal payload size for a combination of SNR and $N_{\text{maxTries}}$ can be calculated using our empirical model of maxGoodput.

### VI. Experiment Results: Delay

The delay perceived by a packet consists of two parts: queuing delay and service time delay. The focus of this section is on the joint impacts of $T_{\text{pit}}$, payload size, queue size, $N_{\text{maxTries}}$, and retry delay on the performance delay. Based on our understanding on the service time delay $T_{\text{service}}$ (Cf. Eqs. (5) and (6)), we focus here on the condition of generating queuing delay and how to choose the right parameter configuration to avoid it.

#### A. Observation

To find out how the stack parameters contribute to the delay performance, we investigate the average delay against SNR for different traffic workloads under two typical MAC configurations. The delay performance under the two configurations is shown in Fig. 15(a) and Fig. 15(b), respectively.

We highlight the distinct delay behaviors when the link is in the “grey zone”. It is observed that large $N_{\text{maxTries}}$ and large $Q_{\text{max}}$ are correlated with large delay in the “grey zone”. Specifically, the delays in the “grey zone” with $Q_{\text{max}}$ of 30 are two or three orders of magnitude higher than those with $Q_{\text{max}} = 1$. This difference is due to queuing delay, as to be explained below.

#### C. Parameter Optimization Guidelines

We assume the packet is sent one after another to maximize the goodput. In this case, output power, packet size and $N_{\text{maxTries}}$ are effective for improving the maximum goodput.
where $T_{\text{pit}}$ denotes the packet inter-arrival time and $T_{\text{service}}$ is the average service time. From queuing theory, it is known that while the queuing delay does not change much with $\rho < 1$, it increases extremely quickly when $\rho \to 1$ and will not be bounded if $\rho > 1$ with no dropping mechanism employed.

Using the empirical model of service time introduced in the previous section (Cf. Eqs. (5) and (6)), we can calculate the system utilization for the current link quality and a given parameter configuration. Table II lists a few examples of the system utilization calculated for (part of) the parameter configurations considered in Fig. 15. The results explain the corresponding delay behaviors.

**TABLE II:** Examples of calculating system utilization using the empirical model of service time (Cf. Eqs. (5) and (6))

<table>
<thead>
<tr>
<th>$T_{\text{pit}}$ (ms)</th>
<th>SNR (dB)</th>
<th>$l_D$</th>
<th>$N_{\text{maxTries}}$</th>
<th>$T_{\text{service}}$ (ms)</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>10</td>
<td>110</td>
<td>3</td>
<td>37.08</td>
<td>1.236</td>
</tr>
<tr>
<td>30</td>
<td>20</td>
<td>110</td>
<td>3</td>
<td>21.39</td>
<td>0.713</td>
</tr>
<tr>
<td>30</td>
<td>30</td>
<td>110</td>
<td>3</td>
<td>18.52</td>
<td>0.617</td>
</tr>
</tbody>
</table>

**B. Parameter Optimization Guidelines**

Delay is jointly determined by packet size, packet inter-arrival time, maximum queue length, maximum retransmissions, retry delay and SNR. Choosing appropriate parameter configuration under the current link quality such that the system utilization satisfies $\rho < 1$ to avoid queuing delay, consequently reducing delay possibly by several orders of magnitude. The system utilization can be calculated by the given $T_{\text{pit}}$ and the estimated service time using the empirical model (Cf. Eqs. (5) and (6)).

**VII. EXPERIMENT RESULTS: PACKET LOSS RATE**

Packet loss rate (PLR) consists of two parts: (1) PLR$_{\text{queue}}$ – queuing loss rate, i.e., the ratio of packet loss due to buffer overflow, and (2) PLR$_{\text{radio}}$ – radio loss rate, which refers to the ratio of packets lost on radio transmission.

The focus of this section is on the joint impacts of parameters on the packet loss rate, specifically, queuing loss rate and radio loss rate. Based on our previous quantitative understanding of PLR$_{\text{radio}}$ (Eq. (8)), we focus in this section on the trade-off of the parameter configuration between queuing loss and radio loss.

**A. Observation**

Again, four typical MAC configurations are considered, namely (a) no queue and no retransmission, (b) no queue but with retransmission, (c) with a queue but no retransmission and (d) with a queue and with retransmission. The measured PLR performance under the four MAC configurations is shown in Fig. 16(a), Fig. 16(b), Fig. 16(c) and Fig. 16(d), respectively.

The high SNR resulted from high output power has clearly a positive effect on the packet loss rate. The optimal SNR that provides the best trade-off between energy and PLR is around 19 dB, the same value for best trade-off between energy and goodput or delay.

Interestingly, we observe that retransmissions does not have a clear positive effect on the packet loss rate although retransmission is well known for reducing packet loss. The reason is the trade-off of retransmissions between the queuing loss and radio loss under high traffic arrival rate.

We plot the PLR$_{\text{queue}}$ and PLR$_{\text{radio}}$ for a specific traffic load ($l_D = 110$ bytes and $T_{\text{pit}} = 30$ ms) in Fig. 17. The figure shows the retransmission has a trade-off in the “grey zone”: the decrease in radio loss rate comes with great cost in queuing loss. This is because the system utilization increases quickly to 1 if more retransmissions are allowed. In this case, only large queue size can reduce PLR$_{\text{queue}}$, as illustrated in Fig. 17 (d).

**Fig. 16:** Packet loss rate under different parameter configurations

**Fig. 17:** Queuing loss rate and radio loss rate under different parameter configurations ($l_D = 110$ bytes and $T_{\text{pit}} = 30$ ms)

**B. Parameter Optimization Guidelines**

Large output power, large queue size and small packet size can reduce both radio loss and queuing loss effectively. Under good channel conditions and low traffic arrival rate, retransmissions reduce packet loss.

However, when the link is in the “grey zone” with high traffic load, the choice of the optimal $N_{\text{maxTries}}$ depends on the desired trade-off between the radio loss and queuing loss.

We can use the empirical model of PLR$_{\text{radio}}$ (Eqs. (8)) to find an appropriate $N_{\text{maxTries}}$ such that PLR$_{\text{radio}}$ is minimized and the resulting system utilization $\rho$ is kept under 1, which is estimated by the empirical model of $T_{\text{service}}$ and
the given $T_{pit}$. In case of $\rho \geq 1$, a large queue can be employed to buffer packets and reduce queuing loss.

VIII. PARAMETER OPTIMIZATION FOR PERFORMANCE TRADE-OFFS

So far, we have investigated the joint effects of the stack parameters on energy efficiency, throughput, delay and loss, respectively. Also in these sections, we have suggested various guidelines for multi-parameter tuning to achieve targeted performance in terms of energy efficiency (Sec. IV-C), throughput (Sec. V-C), delay (Sec. VI-B) and loss (Sec. VII-B) separately. However, to achieve multi-performance objectives with (some of) these performance metrics, there are many trade-offs to consider.

In this section, we summarize, based on the observations in Sec. IV – Sec. VII, our findings and empirical models, which can be used for optimizing parameters to achieve the best trade-off in meeting multiple performance requirements together. In addition, we apply these findings and empirical models to the example introduced in Fig. 1, demonstrating that a much improved trade-off can be achieved.

A. Findings Related to Performance Trade-Offs

The optimal output power for the trade-off between energy consumption and QoS metrics. There exists an optimal output power that provides the best trade-offs between energy consumption and QoS metrics including throughput, delay and loss. Due to its impact on PER, a large packet requires a higher SNR than the “grey zone” border to improve both energy efficiency and other performance metrics. Our measurement shows the best trade-off SNR is up to 7 dB higher than the “grey zone” border (12 dB) for the maximum payload size (114 bytes) in our radio stack.

The optimal payload size for the trade-off between energy consumption and goodput. When the SNR is above certain threshold, maximum payload size (114 bytes) can improve both energy efficiency and maximal goodput due to the amortization of the transmission overhead. Our measurement shows the SNR threshold is 17 dB for energy efficiency and 9 dB for maximal goodput. When the SNR is lower than the thresholds, smaller packet size is preferred for both energy consumption and maximal goodput due to resource wastage in retransmissions. However, the optimal $l_D$ for goodput is not the optimal $l_D$ for energy efficiency, therefore an appropriate payload size needs to be selected to meet the desired trade-off between the goodput and energy consumption. The quantitative impacts of $l_D$ on energy consumption or maximal goodput for a given SNR can be calculated using their empirical models.

The optimal number of retransmissions for the trade-off between goodput, delay and loss. When the link is in the “grey zone”, the choice of $N_{maxTries}$ has a great impact on the trade-offs between goodput, delay and loss. On one hand, retransmission is effective for reducing radio loss rate and improving goodput. On the other hand, a higher $N_{maxTries}$ may cause high queuing loss and queuing delay. The empirical models of goodput, delay and radio loss rate quantify the impact of retransmission and provide means to find a reasonable $N_{maxTries}$ that balances the goodput, delay and loss (including both queuing loss and radio loss), particularly when the link is in the “grey zone”.

The optimal queue size for the trade-off between delay and loss. While a large queue is effective to reduce queuing loss, it may increase queuing delay significantly when the link is in the “grey zone” with high traffic load. To balance this delay-loss trade-off, a proper queue size may be chosen and/or we may control packet inter-arrival time and service time to reduce packet queuing.

B. Optimal Parameter Configuration via Empirical Models

The above findings are able to give general parameter configuration guidelines for desired performance trade-offs, however, finding the exact optimal configurations for the best performance trade-offs requires quantitative relations between parameters and performance. Recall that in Sec. IV – Sec. VII, empirical models including energy consumption model $E$, maximum goodput model $G$, service time delay model $D$ and radio loss rate model $L$ have been proposed, which are also summarized in Table III.

For applications where multiple performance metrics among energy consumption, goodput, delay and packet loss rate may be considered together, the multi-parameter optimization problem further becomes a multi-objective optimization problem (MOP):

$$\min(M_1(c_1), M_2(c_2), \ldots M_k(c_k))$$

Where $M_i$ is one metric among $\{E, G, D, L\}$ and $c_i$ is a subset of $\{P_{tx}, N_{maxTries}, D_{retry}, Q_{max}, l_D, T_{pit}\}$. Many MOP solving techniques can be applied to this problem such as the epsilon-constraint method used in [3].

As an example, an indoor sensor needs to transfer bulk data to a base station in a short time slot. The major concern is throughput but application also requires minimized energy consumption. Accordingly, the optimization problem is to minimize $-G$ (i.e., equivalently maximize $G$) while subject to minimum energy consumption $E$. In addition, we may impose a constraint on delay or radio loss rate if real-time or reliable data delivery is relevant.

For all such cases, applying the empirical models to the optimization problem allows us to find the optimal value-setting of the considered stack parameters to meet required performance trade-offs, by solving the optimization problem.

C. Case Study Example

Recall the example shown in Fig. 1 that is taken from the experiments. Table IV shows the resultant parameter values by following the guidelines from the literature [11][6][1] and those from the present study by applying the above-mentioned multi-objective optimization.

Specifically, the guidelines in [11] suggest tuning the transmission power to reduce loss and hence increase throughput. We assume the current SNR increases to 6 dB after the output power level increases from 23 to maximum 31. The guidelines in [6] suggest using retransmission to maximize throughput. In [1], it is suggested to use small payload size for throughput when the interference level is high. In Fig. 1, we seek to use 3 different payload sizes to indicate the effect of payload size.
Table IV also presents their achieved energy-throughput trade-offs. The result shows that adjustment of a single parameter without leveraging other parameters can neither maximize the throughput nor minimize the energy consumption, in comparison with our result that optimizes the performance trade-off through joint consideration of multiple parameters. Note that an inappropriate choice of parameter, e.g., $l_D$ tuning with maximum size as Fig. 1 depicted, can even decrease the performance significantly for a certain link quality.

### TABLE IV: Single-parameter adjustment vs. multi-layer parameter adjustment

<table>
<thead>
<tr>
<th>Methods</th>
<th>$P_{tx}$ (bytes)</th>
<th>$l_D$</th>
<th>$N_{\text{maxTries}}$</th>
<th>Goodput (kbps)</th>
<th>$E_{\text{eng}}$ (μJ/bit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1]-Tuning power</td>
<td>31</td>
<td>114</td>
<td>1</td>
<td>15.39</td>
<td>0.35</td>
</tr>
<tr>
<td>[6]-Tuning times</td>
<td>23</td>
<td>114</td>
<td>1</td>
<td>8.53</td>
<td>1.81</td>
</tr>
<tr>
<td>[1]-Minimal $l_D$</td>
<td>23</td>
<td>5</td>
<td>1</td>
<td>1.49</td>
<td>0.50</td>
</tr>
<tr>
<td>[1]-Maximum $l_D$</td>
<td>25</td>
<td>60</td>
<td>1</td>
<td>11.81</td>
<td>0.28</td>
</tr>
<tr>
<td>Our work</td>
<td>31</td>
<td>68</td>
<td>3</td>
<td>22.28</td>
<td>0.24</td>
</tr>
</tbody>
</table>

### D. Discussions

Our work fills the gap about the joint effects of multiple stack parameters on the major performance metrics and it also proposes a set of empirical models and guidelines for parameter optimization. As with any empirical study, while most of the observations in Sec. III- Sec. VII are conclusive, some are limited to the environment and experiment setup. This limitation will be investigated in our future work.

There are several factors that may lead to even more complex performance behaviors. One is concurrent transmission, which can cause extra packet loss due to packet collisions. Another is that MAC parameters related to periodic wake-ups also have great impact on the performance. Moreover, the environment where the WSN is deployed and the mobility of a node also have a possibly large impact on the performance.

With ongoing experiments, we are evaluating the proposed empirical models considering the aforementioned factors. The purpose of these experiments is to better understand how to adapt our empirical models to these additional factors. With such an investigation, we plan to provide a set of more generic empirical models that can be utilized for multi-parameter optimizations to meet the performance requirements in different application scenarios.

### IX. Conclusion

This paper has presented an extensive experimental study to understand the data delivery performance over a point-to-point 802.15.4 wireless link. The extensive measurement data and analysis enable us to have a comprehensive understanding of the joint effects of key stack parameters on the performance. Specifically, based on observations from the experiments, we have derived the empirical models for energy consumption, delay, maximum goodput and radio loss rate. The models not only quantify the joint effects but also provide guidelines to find the right parameter configuration for a broad range of link quality to achieve the optimization goal of a single or multiple performance metrics in dynamic channel conditions. To demonstrate the potential application of the findings and models, a case study has been presented in the paper as an example. The example shows that tuning multiple parameters jointly may lead to a much improved energy-throughput trade-off than single-parameter tuning. Finally, we are convinced with the necessity of conducting such an extensive experimental study and our results are valuable to the community for a better understanding on the joint effects of stack parameters to fulfill application requirements.

### References