Data-oriented Channel Knowledge Map IoT Transmission under Hardware Impairments

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***Abstract*—Ultra-reliable low-latency IoT communications (URLLC-IoT) has recently gained a growing interest. Here the challenge in reliable low-latency uplink transmission results from the transmission power limitations and lack of multiple antennas. However, in many IoT services the data volumes are small and sensor deployments may include massive number of devices. In this work we consider a coordinated uplink transmission of clustered IoT devices. The focus is on scenarios where location-based channel knowledge map (CKM) can be applied to enable cooperation. We model and analyse the impact of hardware impairments and erroneous CKM information. In the performance evaluation we focus on the recently introduced data-oriented approach that has gathered significant attention in the context of short-packet transmissions. Specifically, it introduces a transient performance metric for small data transmissions, where the amount of data and available bandwidth play crucial roles. Results show that cooperation between clustered IoT devices may provide notable benefits in terms of increased range. Yet, the performance of the coordinated transmission system is heavily depending on the strength of the static channel component in the CKM based cooperation, the level of hardware impairments and the quality of CKM information. Analytic results are verified against simulations, showing only minor differences between analytical and experimental results.**

***Index Terms*—Data-oriented approach, coordinated transmission, channel knowledge map, IoT, hardware impairment, Bussgang decomposition.**

I. Introduction

The Internet of Things (IoT) is a broad concept encompassing various physical devices that connect to the internet, enabling seamless data collection and exchange. Given its critical role in future technologies, numerous surveys have explored different aspects of IoT, including 5G IoT [1] and 6G IoT [2], as well as specialized topics such as ultra-low-power communications [3], machine-type communications [4], and IoT system autonomy [5].

IoT devices can generally be classified into "high-end" and "low-end" categories, each with distinct quality of service (QoS) requirements. For instance, environmental monitoring sensors typically operate with low transmission power and narrow bandwidth, while also being tolerant to delays. In contrast, industrial IoT applications, such as wireless control in large machinery, demand strict latency and reliability constraints. While extensive research has focused on delay-tolerant IoT communications, the emerging paradigm of massive ultra-reliable low-latency IoT communications (URLLC-IoT) has gained significant attention. In the 5G era, URLLC was introduced with select IoT use cases [6], but its role is expected to be even more prominent in 6G [2].

Achieving reliable and low-latency transmission in IoT networks poses several challenges, particularly due to the limited computational resources of IoT devices, which often lack multiple antennas and complex signal processing capabilities. However, two key factors can help facilitate URLLC in IoT: (i) many IoT applications involve small data packets, and (ii) IoT deployments often feature a large number of devices. Unlike massive MIMO systems, where maximizing link capacity is a priority, URLLC-IoT prioritizes link reliability. Furthermore, cooperative transmission among clustered IoT devices can enhance communication reliability with minimal reliance on precise location or channel information. Nonetheless, practical implementations must consider incomplete or erroneous side information in the transmitting cluster.

While joint transmission typically relies on either direction information or channel feedback from the receiver, a novel concept called Channel Knowledge Map (CKM) has recently been introduced [7]. CKM builds on the idea of radio environment awareness and database-assisted communications, as explored in [8], [9], by providing pre-stored channel-related information for specific transmitter-receiver pairs. This approach has the potential to reduce or even eliminate the need for real-time channel state information (CSI) when key channel characteristics—such as the number of significant propagation paths, their power levels, phases, and delays—are known [10].

A particularly favorable scenario for CKM-based communication arises when a strong line-of-sight (LoS) exists between the transmitter and receiver. In such cases, path loss can be accurately estimated if the locations of both nodes are known. However, given that IoT devices are typically power-constrained, path loss information alone may be insufficient for ensuring successful reception, as it merely indicates the power gap that must be overcome. To address this challenge, cooperative transmission strategies can be leveraged, particularly in clustered IoT deployments, where multiple devices can jointly enhance transmission reliability and efficiency.

To evaluate the feasibility of cooperative URLLC-IoT, appropriate performance metrics are essential. The data-oriented

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approach proposed in [11] provides a new perspective on wireless system analysis by considering short-packet transmission within a single channel coherence time. Instead of conventional capacity-based metrics, this approach emphasizes transmission delay outages. The Delay Outage Rate (DOR), introduced in [11], quantifies the probability that a transmission fails to meet a predefined latency threshold, and its application to short-packet transmission over fading channels was further explored in [12]. More recently, [13] analyzed clustered IoT transmission with an information collecting unit (ICU), incorporating channel knowledge maps (CKM) and ICU-assisted side information under imperfect conditions. The study assessed performance in terms of outage probability and DOR, assuming ideal hardware conditions.

However, in beyond 5G (B5G) and 6G networks, hardware impairments become a significant challenge, particularly at higher frequencies, where they can severely degrade communication performance. These impairments arise from unwanted distortions introduced as signals propagate from the transmitter to the receiver [14]. In [15], aggregate statistical models for hardware impairments, including power amplifier nonlinearity and finite-resolution analog-to-digital converters (ADCs), were derived and validated through simulations. Moreover, Bussgang decomposition remains a widely used tool for analyzing systems affected by hardware nonlinearities [16].

In this work, we investigate a URLLC-IoT system where a cluster of IoT devices cooperates to achieve reliable, low-latency uplink transmission to an ICU, which may be either stationary or mobile (e.g., a drone). The analysis focuses on Rician fading scenarios, ensuring a line-of-sight (LoS) link between transmitters and the ICU receiver, while also incorporating nonlinear residual hardware impairments in IoT devices. To the best of our knowledge, this is the first study to integrate hardware nonidealities into a data-driven analysis of cooperative IoT transmission.

II. CKM-based Transmission Mechanism

A. General system model

The general system model is illustrated in Fig.1. Therein IoT devices operate in a cluster, executing a coordinated communication with a transceiver unit that gathers information from the IoT cluster. The transceiver can be either a drone or a stationary radio access point and, in the following, it is referred to as the ICU. The coordinated transmission from IoT cluster towards ICU assumes synchronization within the IoT device cluster and between the cluster and ICU. As depicted in Fig. 1, the coordination of IoT devices within the cluster can be managed, for example, by a cluster head (CH). The CH may also carry out the control information exchange with the ICU, while the IoT devices handle the data transmission. The same data packet is transmitted by all IoT devices. The details regarding the communication procedure is described in [13].

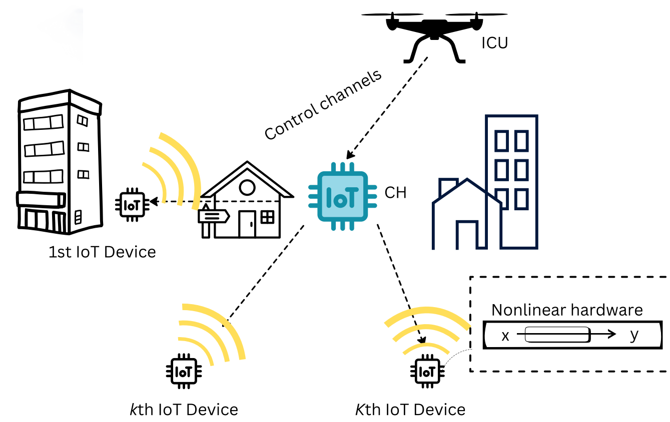

Fig. 1. Illustration of IoT system: IoT devices in a cluster communicate with the ICU, coordinated by a CH.

B. CKM-based coordination

The CKM contains a mapping $(Z_{\text{ICU}}, Z_{\text{IoTD}}) \to \phi$, where Z_{ICU} and Z_{IoTD} include the ICU and IoT device coordinates, respectively, and ϕ is a phase to be used in the IoT transmission. Accordingly, the CKM-based phase weight e^{j} in each active IoT device ensures that ICU receives a coherent sum of signals from cluster of active IoT devices. The CKM can be available either in the CH or in IoT devices. In the first option, CH carries the burden of storing and maintaining the CKM but, on the other hand, it only needs to inform IoT devices before transmission is executed. In the second option, each IoT device stores the CKM of its own. In either of the cases there is no need for uplink channel sounding or channel state information feedback from ICU.

C. Signal and channel models

To model the residual hardware impairments in IoT transmitters, we apply the Bussgang theorem as used in [15]. Thus, the distorted output of the nonlinear hardware is defined as $y = \sqrt{\xi}x + \zeta$, where x is the input signal, $\xi \in [0, 1]$ is the hardware quality factor and ζ is a distortion term modeled as complex zero-mean Gaussian with variance $(1 - \xi)E\{|x|^2\}$. We note that $\xi = 1$ refers to the case of ideal hardware and typically values relatively close to one are applied. Furthermore, the distortion term ζ is independent of the input signal. In the following, we assume that all IoT devices have the same quality factor while the distortion terms of different devices are independent.

Now, if K IoT devices are transmitting symbol s the received sum signal in ICU is modeled as

$$\begin{aligned} r &= \sum_{k=1}^{K} h_k w_k (\sqrt{\xi} s + \zeta_k) + n \\ &= \Big(\sum_{k=1}^{K} h_k w_k \sqrt{\xi} \Big) s + \sum_{k=1}^{K} h_k w_k \zeta_k + n \\ &= \big(\langle \mathbf{h}, \mathbf{w} \rangle \sqrt{\xi} \big) s + N, \end{aligned} \tag{1}$$

where $\mathbf{h} = (h_k)_{k=1}^{K} \in \mathbb{C}^K$ contains complex channel coefficients and n represents a complex AWGN term. Each IoT device admits a fixed transmission power P and $\mathbf{w} = (\sqrt{P}\delta_k e^{j\phi_k})_{k=1}^{K}$, where $\delta_k = 1$ when the k^{th} device is active and $\delta_k = 0$ otherwise. Thus, the total transmission power $\sum_{k=1}^{K} P\delta_k$ applied in the cluster of devices increases with the number of transmitting devices. By ϕ_k we denote the phase applied in the k^{th} device. Finally, we note that noise N contains both AWGN and a noise term due to hardware impairments.

The following assumptions regarding the channels are considered:

- The average propagation loss (including distance dependent loss, shadowing and antenna gains) is the same for all IoT devices belonged by the same cluster such that $\mathbb{E}\left[|h_k|^2\right] = \bar{\gamma}$ where $\mathbb{E}\left[\cdot\right]$ is the expectation operator.
- Rician fading is assumed, so the channel coefficients are of the form $h_k = g_k + \sqrt{\gamma_d} e^{j\varphi_k}$, where g_k represents the scattered and reflected signal part that is a complex zero-mean Gaussian with mean power $\mathbb{E}\left[|g_k|^2\right] = \bar{\gamma}_s$. Furthermore, $\gamma_d \geq 0$ is the power of the static signal part and the amplitudes $|h_k| = \sqrt{\gamma_k}$ are independent and identically distributed (i.i.d.) Rician random variables with the same Rice factor $\nu = \gamma_d/\bar{\gamma}_s$.
- The phase φ_k of the static signal part is a sample from a uniform distribution. Yet, we assume that phase φ_k is fixed or phase drift is so small that it can be neglected.

Based on these assumptions, the IoT devices are organized in clusters, where the mean path loss is uniform for all devices in relation to the ICU. This assumption is particularly valid under LoS conditions, as the distance between the ICU and the IoT device cluster is typically much greater than the size of the cluster. Consequently, the path loss and ICU antenna gain remain nearly constant for all devices within the cluster. The choice of Rice fading is deliberate, as it offers versatility in modeling the fading channel. In environments characterized by rich scattering around the ICU or device cluster, the Rice factor may be small. Conversely, in the presence of a strong LoS component, the Rice factor is large, resulting in an almost static channel.

D. Signal model in presence of CKM-based coordination

It is recalled that the CKM-based side-information is related to the phases $\{\phi_k\}_{k=1}^{K}$. Accordingly, transmitting IoT devices have predefined, location dependent, phase values that they apply once the position of the ICU is known. Since CKM-based phases may contain errors, we assume that CKM is computed or otherwise defined based on pure LoS condition. That is, if the static signal part has the phase φ_k, then the applied phasing is $\phi_k = -\varphi_k + \epsilon_k$, where ϵ_k represents the error emerging from the estimation and possible quantisation of the CKM information. Now we have

$$\begin{aligned} h_k w_k &= \sqrt{P}(g_k + \sqrt{\gamma_d} e^{j\varphi_k}) e^{-j\phi_k} \\ &= \sqrt{P}(g_k + \sqrt{\gamma_d} e^{j\varphi_k}) e^{-j(\varphi_k - \epsilon_k)} \\ &= \sqrt{P}(\tilde{g}_k + \sqrt{\gamma_d} e^{j\epsilon_k}). \end{aligned} \tag{2}$$

Here the complex Gaussian part of the signal $\tilde{g}_k$ admit the same statistical properties as g_k. We emphasize that value of the CKM information depends on the strength of the Rice factor. If it is small, then the value of CKM information is small as well. Phase errors may reflect various non-idealities. Therefore we assume that $\epsilon_k \sim \mathcal{N}(0, \sigma_\epsilon^2)$.

III. Performance Evaluation

A. Outage probability and DOR

For a single data stream transmission, the classical Shannon formula $R = W \cdot \log_2(1+\gamma)$ can be used to define the rate with respect to SNR and transmission bandwidth W. Correspondingly, the outage probability is defined as

$$P_{\text{out}} = P(R < R_{\min}) = F_\gamma(2^{R/R_{\min}} - 1), \tag{3}$$

where $F_\gamma(\cdot)$ is the CDF of SNR. Outage probability is a good measure for the coverage range of a wireless service with a specified rate requirement $R_{\min}$. The analysis of outage requires the distribution of SNR and closed-form expressions for the SNR distribution have been obtained in scenarios with single transmitting devices/antennas. However, if the system model takes into account hardware impairments and erroneous parameters or joint transmissions by multiple devices, then, in general, we need some approximations for the SNR distribution.

In coverage studies, the outage is typically considered in the 5% - 95% range. Classical mobile system coverage estimates focus around 5% outage. More recently, IoT systems like narrow band (NB) IoT [17], [18] has been introduced with extreme re-transmission procedures tolerating even 95% packet losses. However, low-latency applications are not tolerating numerous re-transmissions and DOR is gaining interest as a performance measure. Resulting from this development the extreme left tail of the SNR distribution is in the center of interest and the tail approximation error easily becomes the limiting factor. The DOR is defined as the probability that the required information delivery time for a specific transmission session exceeds the predefined threshold [11]. In presence of optimal rate adaptation, $R = W \cdot \log_2(1+\gamma)$ and if D bits are transmitted, then the data delivery time T_d is given by $T_d = D/R$. As in [13] we can define the DOR as

$$\text{DOR} = P(T_d > T_{th}) = P(R < D/T_{th}) = F_\gamma\big(2^{D/WT_{th}} - 1\big), \tag{4}$$

where T_{th} is time delay threshold for the transmission. Thus, we obtain We note that, as T_{th} increases, the fraction D/WT_{th} becomes small, and DOR decays rapidly. This is clear especially in a logarithmic scale. Resulting curves can be used to find the threshold T_{th} at which reliable transmission, such as a five nine transmission, becomes possible.

B. SNR distribution for CKM scenario

From (1), we find that the receiver signal-to-noise ratio Γ can be written as

$$\Gamma = \frac{|\langle \mathbf{h}, \mathbf{w} \rangle_1|^2}{\mathbb{E}\{|N|^2\}} \xi, \tag{5}$$

where subscript in $\langle \mathbf{h}, \mathbf{w} \rangle_1$, '1', refers to the Scenario 1. As in [13], we use Rice distribution to approximate the distribution of Γ. When compared to the model of [13], the difference is that hardware impairment modeling brings another disruptive factor into the considered mechanism. To consider these changes properly, we first analyze the noise term N and then recall main steps of the SNR approximation method.

We recall from (1) and (2) that the noise term N admits the expression

$$\begin{aligned} N &= \sum_{k=1}^{K} h_k w_k \zeta_k + n \\ &= \sqrt{P}\sum_{k=1}^{K} \tilde{g}_k \delta_k \zeta_k + \sqrt{P}\sum_{k=1}^{K} \sqrt{\gamma_d}\delta_k e^{j\epsilon_k}\zeta_k + n. \end{aligned} \tag{6}$$

In the first sum of the latter formula $\tilde{g}_k$ and ζ_k are both complex zero-mean Gaussian. While the product of two Gaussian variables is not necessarily a Gaussian, the terms of the sum are independent and therefore the first sum of the latter formula of (6) is approximately a complex Gaussian when K is large. Each term in the second sum of the latter formula in (6) are complex Gaussian and thus, the sum is also complex Gaussian. That is, the noise N is a complex Gaussian variable provided that K is large.

We first compute the noise power needed for the distribution of Γ. We have

$$\begin{aligned} \mathbb{E}\{|N|^2\} &= \mathbb{E}\{|\sum_{k=1}^{K} h_k w_k \zeta_k + n|^2\} = \mathbb{E}\{|\sum_{k=1}^{K} h_k w_k \zeta_k|^2\} + 1 \\ &= \sum_{k=1}^{K} \mathbb{E}\{|h_k w_k|^2\}\,\mathbb{E}\{|\zeta_k|^2\} + 1 \\ &= P\sum_{k=1}^{K} \delta_k(\mathbb{E}\{|\tilde{g}_k|^2\} + \gamma_d)(1-\xi) + 1 \\ &= P|\delta|(\bar{\gamma}_s + \gamma_d)(1-\xi) + 1. \end{aligned} \tag{7}$$

Here we have applied (2) and assumptions $\mathbb{E}\{|n|^2\} = 1$, $\mathbb{E}\{|\tilde{g}_k|^2\} = \bar{\gamma}_s$, $\mathbb{E}\{|\zeta_k|^2\} = 1-\xi$. We also used the fact that $\tilde{g}_k, \zeta_k$ are zero-mean, independent from each other, and independent with respect to k.

We follow the approach of [13] when approximating the distribution of $|\langle \mathbf{h}, \mathbf{w}\rangle_1|$. We note that in the CKM-based approach the location of the ICU receiver maps to the transmission phase ϕ_k in each device. While this phase is defined in case of pure LoS, it will adjust only the static channel part. Accordingly, we can write

$$\langle \mathbf{h}, \mathbf{w}\rangle_1 = \sqrt{P}\left(g_s + \sqrt{\gamma_{d,\Sigma}} \cdot e^{j\epsilon_\Sigma}\right), \tag{8}$$

where $g_s = \sum_{k=1}^{K} \delta_k \sqrt{\gamma_{s,k}} e^{j\psi_k}$ contains the reflected/scattered signal part and $\gamma_{d,\Sigma} = \sqrt{\gamma_d}|\sum_{k=1}^{K}\delta_k e^{j\epsilon_k}|$ is the static part of the sum signal after the phasing. Notation ϵ_Σ refers to the phase of the static part. Since g_s is composed by complex zero-mean Gaussian variables, it is also itself a complex zero-mean Gaussian with power $\mathbb{E}\left[|g_s|^2\right] = \bar{\gamma}_s|\delta|$. Thus, $|\langle \mathbf{h}, \mathbf{w}\rangle_1|$ is a Rice variable with Rice factor $\gamma_{d,\Sigma}/\mathbb{E}\left[|g_s|^2\right]$. This factor is depending on the phasing errors $\epsilon = (\epsilon_k)_k$ and following the approach in [13], we approximate it by expectation $\nu_\Sigma = \mathbb{E}\left[\gamma_{d,\Sigma}\right]/\mathbb{E}\left[|g_s|^2\right]$. As shown in [13] there holds

$$\mathbb{E}\left[\gamma_{d,\Sigma}\right] = \gamma_d\Big(\mathbb{E}\left[\langle\delta, \cos\epsilon\rangle^2\right] + \mathbb{E}\left[\langle\delta, \sin\epsilon\rangle^2\right]\Big), \tag{9}$$

where expectations can be computed in closed-form. Resulting expressions are:

$$\begin{aligned} \mathbb{E}\left[\langle\delta, \cos\epsilon\rangle^2\right] &= \tfrac{1}{2}|\delta|\big(1 + e^{-\frac{\sigma_\epsilon^2}{2}}\big) + |\delta|(|\delta|-1)e^{-\sigma_\epsilon^2}, \\ \mathbb{E}\left[\langle\delta, \sin\epsilon\rangle^2\right] &= \tfrac{1}{2}|\delta|\big(1 - e^{-\frac{\sigma_\epsilon^2}{2}}\big). \end{aligned} \tag{10}$$

After combining formulae (9) and (10) we obtain for the Rice factor an approximation:

$$\nu_\Sigma = \nu\big(1 + (|\delta|-1)e^{-\sigma_\epsilon^2}\big). \tag{11}$$

As seen from (11), the CKM-based phasing increases ν_Σ when the number of cooperating devices grow. However, the phase errors in CKM may crucially impact the resulting performance gain.

The approximation for the CDF of Γ is now obtained using the Rice distribution

$$F_\Gamma(\gamma) \approx 1 - Q_1\Big(\sqrt{\tfrac{\mathbb{E}[\Gamma_s]}{\sigma_\Gamma^2}}, \sqrt{\tfrac{\gamma}{\sigma_\Gamma^2}}\Big), \tag{12}$$

where $Q_1(\cdot,\cdot)$ is the Marqum Q-function [19] and

$$\begin{aligned} \mathbb{E}\left[\Gamma_s\right] &= \frac{\gamma_d\xi|\delta|(1 + (|\delta|-1)e^{-\sigma_\epsilon^2})}{1 + P|\delta|(\bar{\gamma}_s + \gamma_d)(1-\xi)}, \\ \sigma_\Gamma^2 &= \frac{\frac{1}{2}\bar{\gamma}_s|\delta|}{1 + P|\delta|(\bar{\gamma}_s + \gamma_d)(1-\xi)}. \end{aligned} \tag{13}$$

Using (12), we obtain approximation for the DOR

$$\mathrm{DOR} \approx 1 - Q_1\Big(\sqrt{\tfrac{\mathbb{E}[\Gamma_s]}{\sigma_\Gamma^2}}, \sqrt{\tfrac{2^{D/WT_{th}}-1}{\sigma_\Gamma^2}}\Big). \tag{14}$$

That is, for a given data volume D and bandwidth W, we can compute the DOR as a function of the delay threshold T_{th}.

IV. Numerical Results

In this section, we present performance results for the outage probability and the delay outage rate. While the same approximation is applied to both outage probability and delay outage rate, the latter focuses on the tail of the distribution, necessitating a highly accurate approximation for the SNR distribution. In contrast, the outage probability is plotted on a linear scale. We have included simulated point values in each figure.

A. Simulation parameters

The mean received SNR from an individual IoT device is expected to be low and, accordingly, set to -15dB. The total transmission power of the cluster is normalized by the number of transmitting IoT devices. This makes it easier to assess the gain from cooperation when power gain from additional IoT devices is ignored. Without normalization the power gain would be notable when the number of IoT devices is large - we have set the number of cooperating devices to 30 in most cases.

Finally, we note that in the DOR performance evaluations we have set $W = 200$kHz and $D = 100$bits. These parameters are compatible with the bNB-IoT system [17]. Even though NB-IoT is typically used for delay tolerant services, it is of

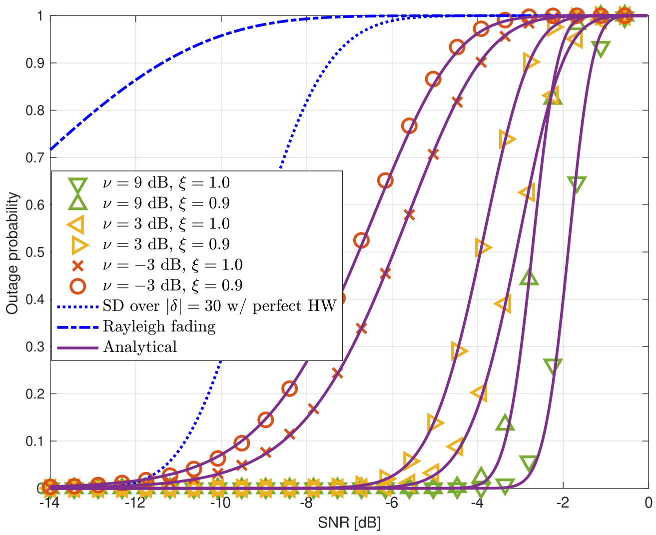

Fig. 2. Outage probability for CKM-based phasing with respect to SNR when $|\delta| = 30$ and Gaussian phase error with standard deviation $\sigma_\epsilon = 30°$ is assumed. The dotted curve refers to the outage probability when SD over 30 devices with perfect hardware is applied and dash-dot curve refers to the Rayleigh fading case.

great interest to understand how to enable low-latency services in similar IoT systems.

B. Outage probability

The outage probability for a clustered cooperative transmission of $K = 30$ IoT devices is given as a function of SNR in Fig. 2. Outages are plotted for two hardware quality factors, namely $\xi = 0.9$ and $\xi = 1.0$, respectively. We also assume that the CKM-based phase information is incomplete and the phase error ϵ follows the Gaussian distribution with standard deviation $\sigma_\epsilon = 30°$.

From Fig. 2 it is found that poor hardware quality of IoT devices reduces the performance but strength of the Rice factor, from $\nu = -3$ dB to $\nu = 9$ dB, has more crucial impact. However, even with erroneous CKM information and poor hardware, the coordinated transmission is superior when compared to uncoordinated transmission (dash-dot curve). Also, coordinated CKM-based transmission provides clear gain over the selection diversity (SD) transmission with ideal hardware. More importantly, the power gain that is obtained from multiple devices transmitting simultaneously cannot be achieved in SD, since transmission power of an individual device cannot be scaled up. It is also worth noticing that cooperative transmission is providing some gain when $\nu = -3$ dB even though difference between $\nu = -3$ dB and $\nu = 9$ dB is large. Since simulated values (ticks) hit the curves well, it is seen that applied approximation works well.

In Fig. 3 the impact of hardware impairments and Gaussian phasing error on the outage performance of cooperative transmission is illustrated. The results indicate that both poor hardware and phasing errors in CKM-based cooperation corrupt notably the performance of cooperative transmission. Interestingly, it seems that $15°$ increase in the standard deviation of the phase error reduces the performance around the

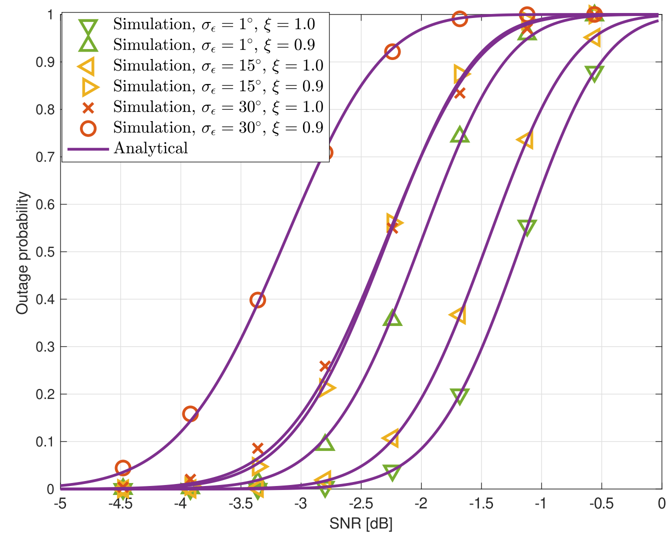

Fig. 3. Outage probability for CKM-based phasing with respect to SNR when $|\delta| = 30$, $\nu = 6$dB and different values of σ_ϵ and ξ, respectively.

same amount as hardware quality factor decrease from 1.0 to 0.9. The match between ticks and curves show that applied approximation works well.

C. DOR

Fig. 4 indicates the impact of hardware quality degradation on the DOR performance. In simulated CKM-based phasing we have 30 devices, the channel Rice factor is 9 dB and standard deviation for the Gaussian phase error is $15°$. The results of this figure show that hardware impairments have clear negative impact on the DOR performance. The decrease of hardware quality factor from 1.0 (ideal hardware) to 0.85 (poor hardware) decreases the delay threshold by 24% on the 10^{-5} delay outage level. Once again, there is a close matching between simulated and analytical results, even though the accuracy of the approximation degrades with the hardware impairment factor.

The applied Rice factor (9dB) in Fig. 4 is favorable for the CKM-based phasing. To assess the losses due to lower Rice factor and higher phase error we have also plotted DOR results in Fig. 5. Clearly, the Rice factor has crucial impact on the DOR performance. We recall that in Fig. 2 the SNR loss with respect to the Rice factor decrease (e.g., from $\nu = 6$ dB to $\nu = 0$ dB) is relatively small, but Fig. 5 shows that in terms of DOR the corresponding loss on low probability levels can be very large. This illustrates the fact that typical outage probability presentations show the performance differences between 10% and 90% probability levels but may hide notable performance changes in tails of the distribution. That is, if the DOR requirement is low, e.g. 10^{-4}, then even small change in the Rice factor or hardware quality factor may seriously degrade the quality of service. Thus, low-latency services are very sensitive for any non-idealities in hardware or changes in the radio environment. Finally, we note that our approximation works quite well in the probability range of Fig. 5. However, if the probability range is extended to very low probabilities, the approximation errors grow.

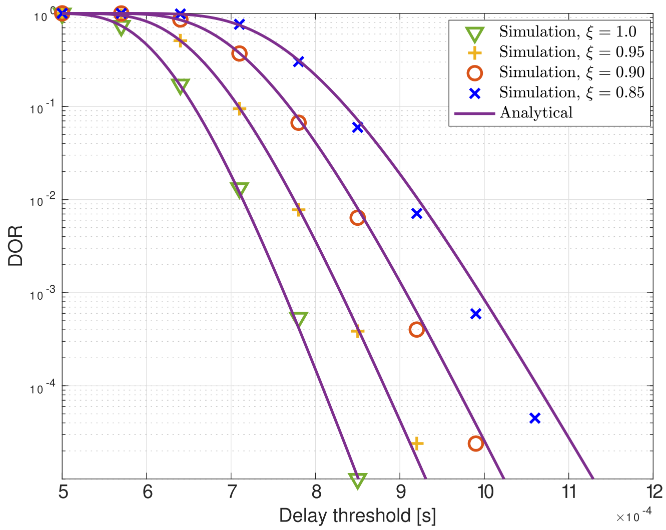

Fig. 4. The DOR performance for CKM-based phasing with respect to delay threshold when $K = 30$, $\nu = 9$dB and Gaussian phase error with standard deviation $\sigma_\epsilon = 15°$ is assumed.

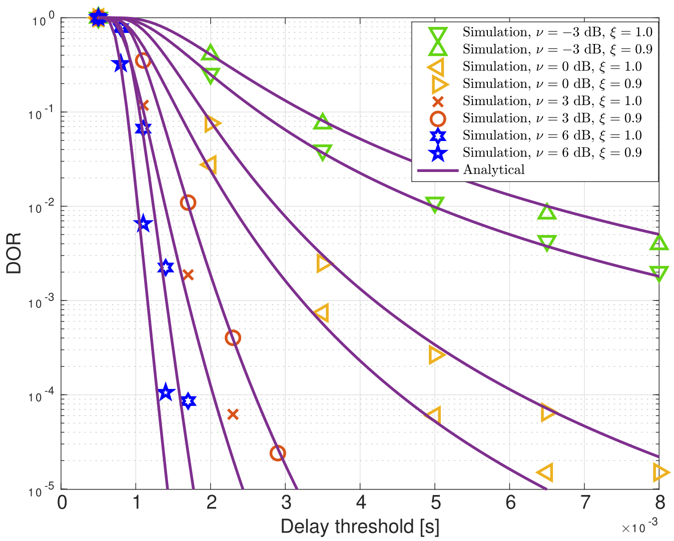

Fig. 5. The DOR performance for CKM-based phasing with respect to delay threshold when $K = 30$ and Gaussian phase error with standard deviation $\sigma_\epsilon = 30°$ is assumed.

V. Conclusions

This work considered Channel Knowledge Map (CKM) - based coordinated transmission by a cluster of IoT devices with hardware impairments. The CKM was used to attach IoT devices with location dependent phasing information. We considered the impact of hardware impairments and errors in the information used for cooperation. Key performance indicators included conventional outage probability and the recently introduced delay outage rate (DOR).

We deduced analytic approximations for the distribution of received SNR, accounting for hardware impairments and errors. Results show that analytic approximation and simulation results demonstrate close agreement. It was demonstrated that significant benefits can be obtained by cooperation of clustered IoT devices even though CKM-based cooperation is sensitive to disruptions in the channel Line of Sight (LoS) component, hardware impairments and errors in the CKM information. We also found that the cluster size required for reliable low-latency transmission may become impractically large.

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