VarOLLA: Maximizing Throughput for 5G-RedCap Devices in IIoT Networks

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***Abstract*—In this paper, we propose VarOLLA, a novel approach aimed at maximizing the throughput of 5G-RedCap devices in Industrial Internet of Things (IIoT) environments. VarOLLA addresses the sub-optimal spectral efficiency of Outer Loop Link Adaptation (OLLA) by introducing a 'Throughput Factor' that incentivizes adaptive decision-making based on throughput considerations. Through extensive simulations, we demonstrate significant improvements in throughput, with gains of up to 35% compared to traditional OLLA techniques, particularly in scenarios with high channel outdatedness. Moreover, VarOLLA effectively reduces consecutive transmission failures (rBLER) and achieves substantial reductions in control message overhead, up to 87.5%. Our findings highlight the strong potential of VarOLLA in IIoT networks and its significant contribution to the realization of high-performance applications during the Fourth Industrial Revolution (4IR) in the manufacturing sector.**

***Index Terms*—Industrial IoT, Outer Loop Link Adaptation, 5G-RedCap**

I. Introduction

The Industrial Internet of Things (IIoT) has emerged as a transformative technology that drives the Fourth Industrial Revolution (4IR) by facilitating seamless sensing and real-time data exchange among machines and systems. This integration has significantly impacted the manufacturing sector, revolutionizing traditional manufacturing environments into highly interconnected and intelligent systems. In line with this, our research aims to tackle the challenges associated with optimizing spectral efficiency for high-performance applications in industrial settings.

A fully operational IIoT system in a factory comprises numerous static and mobile nodes that generate a vast amount of data to support various 4IR applications [1]. With these devices wirelessly connected on the factory floor, the communication infrastructure must be capable of accommodating a significant number of devices while ensuring high throughput. Notably, applications like Integrated Worker Health & Safety and Automated Guided Vehicles exemplify the need for high throughput in mobile nodes with limited capacity for real-time control. Additionally, in indoor factory floors, manufacturing industries prioritize devices that require minimal maintenance, such as infrequent battery replacements [1]. Therefore, IIoT networks in such environments must exhibit high throughput, support mobility, scale efficiently, while not increasing the complexity of the nodes.

These requirements fall into a unique category that differs from the traditional 5G use cases of enhanced Mobile BroadBand (eMBB), massive Machine Type Communication (mMTC), and ultra-reliable low latency communication (URLLC). Recognizing this need, the 3rd Generation Partnership Project (3GPP) has introduced 5G-RedCap (Reduced Capability) as a solution in its Release 17 to address these distinct requirements and challenges [2].

One of the characteristic challenges of RedCap-like devices are their inaccurate channel quality sensing [3]. In 5G systems, the Base Station (BS) sends a reference signal measured by the User Equipment (UE). The measured channel quality is discretized into Channel Quality Index (CQI) and sent back to the BS for it to tune its transmission parameters, namely Modulation and Coding Schemes (MCS). Due to the inaccuracies in the channel quality measurements, Link Adaptation (LA) techniques such as Outer Loop Link Adaptation (OLLA) have been utilized at the BS. OLLA intelligently varies the MCS chosen by the BS based on the feedback received from the UE. However, OLLA is known to exhibit sub-optimal throughput, particularly in industrial scenarios [4].

In standard 5G implementations, the limitations of OLLA in terms of spectral efficiency are addressed through the use of 'Type II HARQ' (Hybrid Automatic Repeat Request). HARQ is an error control mechanism that combines error correction and retransmission techniques to optimize the reliability and throughput of wireless communication systems. HARQ can be classified into two types: Type I and Type II. In Type I HARQ systems, if the decoding of a transmission is unsuccessful, the received erroneous block is discarded, and a Negative Acknowledgment (NACK) is sent to request retransmission. On the other hand, Type II HARQ systems retain the erroneous block and utilize it during the decoding of the retransmitted block, thereby increasing the chances of successful decoding. Type II HARQ systems are recognized for their higher spectral

This work is funded in parts by the SUPREME project (project number 15467) under the 'Smart Industries' program; the 'PrimaVera' project (NWO Grant number: NWA.1160.18.238) and the 'InSecTT' project (Grant agreement No 876038). The 'SUPREME' project is financed by The Netherlands Organisation for Scientific Research (NWO), in partnership with Tata Steel, Samiotics, IJssel Technologie, and M2i. The InSecTT project is financed by the ECSEL Joint Undertaking (JU).

efficiency when compared to Type I HARQ systems that employ OLLA [5]. Consequently, concerns have been raised regarding the relevance of OLLA in 5G systems employing Type II HARQ systems [5].

Estimates from [2] suggest that removing the HARQ buffer from UEs can directly reduce their cost and complexity by 10%. Moreover, further reduction up to 8% can be achieved by eliminating its associated entities. Therefore despite the spectral efficiency gains of Type II HARQ, aimed at reducing power consumption and complexity, RedCap UEs are recommended to adopt Type I HARQ [6] and thereby, use OLLA for LA. This necessitates research into improving spectral efficiency of OLLA for 5G-RedCap usecases.

To address these challenges, this paper proposes an enhanced OLLA technique called VarOLLA (Variable Step size OLLA - described in Section III) specifically designed for 5G-RedCap systems in industrial environments. The results demonstrate its superiority over conventional OLLA techniques in terms of throughput performance.

The remainder of the paper is organized as follows: Section II provides a brief overview of OLLA along with techniques that have been proposed in the available literature to enhance OLLA. Section III describes the proposed solution along with the simulation environment and variables analyzed. The simulation results are presented and their implications are discussed in Section IV. Finally, we conclude in Section V, summarizing the contributions of our work and mentioning future works.

II. Background & Related Works

A. Outer Loop Link Adaptation

In the standard operation, each UE periodically reports the observed channel quality to the BS using the CQI. The CQI is a discretized value that represents channel quality based on the Signal-to-Noise Ratio (SNR) measured by the UE. The BS processes the CQI reports from the UE and selects the corresponding MCS to keep the downlink transmission within a known Block Error Rate (BLER) bound. However, the accuracy of the reported CQIs can be compromised due to inherent delays between the SNR measurement by the UE and the selection of the corresponding MCS by the BS [7], [8]. Various other factors also contribute to CQI inaccuracies, including inaccurate UE SNR measurements and unsuccessful transmission of CQI reports. These delays and inaccuracies can lead to inefficient or unsuccessful transmissions.

In scenarios where the chosen MCS exceeds the channel condition, subsequent transmissions are more likely to be unsuccessful. Conversely, choosing a lower MCS can result in successful but inefficient transmissions. To address this issue, the BS relies on additional feedback from the UEs, namely the ACK/NACK messages, to adjust the MCS based on the channel conditions. OLLA combines these two forms of feedback to effectively achieve the desired target BLER ($BLER_{target}$) determined by the specific use case (10^{-1} for eMBB and 10^{-5} for URLLC).

OLLA incorporates an offset (Δ) that is adjusted based on the outcome of each transmission. Following a successful transmission, the offset is increased by a value denoted as Δ_{up}, while an unsuccessful transmission leads to a decrease by Δ_{down}. The resulting offset is then added to the CQI, and the updated value is used for MCS selection. Consequently, in the event of a successful transmission, OLLA increases the offset, prompting the BS to choose a higher MCS and enhance the throughput. Conversely, in the case of an unsuccessful transmission, OLLA decreases the offset, causing the BS to opt for a lower MCS and improve the reliability of retransmission while reducing the throughput.

In this study, the specific values for Δ_{up} and Δ_{down} are determined as $(1 - BLER_{target}) \times \theta$ and $BLER_{target} \times \theta$, respectively, where θ represents the OLLA step size. Consequently, the updated OLLA offset for the $(t+1)$-th transmission is computed as follows:

$$\Delta_{t+1} = \begin{cases} \Delta_t + (BLER_{target} \times \theta), & \text{if ACK} \\ \Delta_t - ((1 - BLER_{target}) \times \theta), & \text{if NACK.} \end{cases}$$

B. Related Works

Several studies have addressed different OLLA challenges and proposed solutions to enhance its performance. One of the primary issues is the fluctuation of OLLA even in near-steady-state conditions. To address this, researchers have proposed using multiple modes of operation with different step sizes based on the BLER value [9], varying the step size depending on the convergence status [7], controlling the step size based on the elapsed time between channel measurements [10], and adjusting the step size based on the mean and standard deviation of the Signal-to-Interference-plus-Noise Ratio (SINR) [11].

Another challenge is the slow convergence of traditional OLLA algorithms. To tackle this, researchers have suggested tuning the initial value of OLLA based on converged OLLA offset from previous connection traces [12]. Furthermore, researchers have identified that the use of a predefined offline model to map CQI values to MCS level has been sub-optimal for different use cases (such as URLLC [13], eXtended Reality [14], IoT) and device types (such as Massive Input Massive Output - MIMO [15] and have proposed specific improvements.

In general, there has been an interest in exploring alternative techniques such as employing a neural network to dynamically select the MCS based on link conditions modeled with mobility speed and average signal strength [16], utilizing Q-Learning to map CQI to MCS instead of relying on a fixed look-up table [17], and applying reinforcement learning and/or Multi-Armed Bandit (MAB) algorithms for transmission parameter tuning [18].

In summary, various studies have addressed the challenges of OLLA and proposed innovative solutions to improve its performance. These solutions encompass a range of approaches, including heuristics-based methods and learning techniques, aimed at fine-tuning the transmission parameters. However, there is still a need to address the poor spectral efficiency of OLLA. In light of these considerations, our proposed VarOLLA technique introduces a 'Throughput Factor' to enhance the MCS adaptation process to improve throughput in 5G-RedCap devices for IIoT applications. The following sections will present the detailed methodology and experimental evaluation of VarOLLA in comparison to the conventional OLLA mechanism

III. Methodology

A. VarOLLA

In Section II-A, we described the OLLA mechanism, which adjusts the MCS level based on changes in channel quality. OLLA aims to optimize the network to meet a specified BLER target by reacting slowly to channel improvements (increasing Δ by 0.1 per ACK) and quickly to channel degradation (decreasing Δ by 0.9 per NACK). However, the mechanism is indifferent to the spectral efficiency of the chosen MCS, as its main objective is to achieve successful transmissions rather than closely track channel variations. It is important to note that the choice of MCS directly impacts both reliability and spectral efficiency. Lower MCS values generally increase reliability but may result in lower spectral efficiency, while higher MCS values offer the opposite trade-off.

To analyze the differences in spectral efficiency among MCS levels, we plotted the ratio of throughput differences for consecutive pairs of MCS in Figure 1. As the figure illustrates, the spectral efficiency of MCS-2 is 2.5 times that of MCS-1, while the spectral efficiency of MCS-12 is only 1.09 times that of MCS-11. Despite these disparities, OLLA consistently requires the same number of successive ACKs to transition to a higher MCS level. If the OLLA step size (θ) is set to 1, OLLA will wait for 10 successive ACKs to move to the next higher MCS level, irrespective of the current MCS in operation. However, it would be more reasonable to wait for a smaller number of successive ACKs when the potential throughput gain is greater, and vice versa. In other words, a throughput-incentivized OLLA approach could take quicker adaptive actions when operating in an MCS with significantly lower spectral efficiency compared to the next successive MCS level. This approach enables a more dynamic and efficient adaptation to channel conditions, thereby maximizing potential throughput gains.

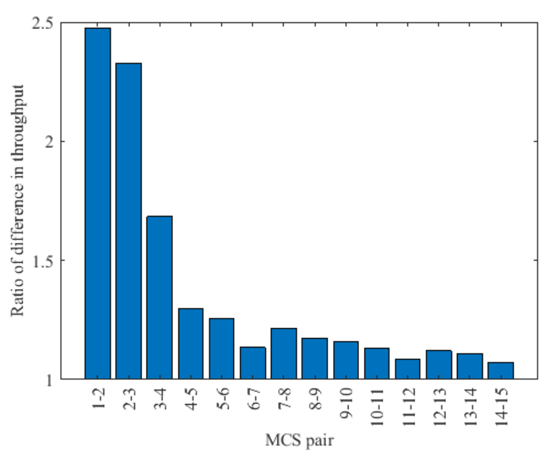


Fig. 1: Ratio of difference in Throughput between the consecutive MCS pairs

To address this limitation, we propose VarOLLA, an enhanced OLLA technique that introduces a '*Throughput Factor*' (γ) into the calculation of the OLLA offset (Δ). The Throughput Factor accounts for the potential throughput gain associated between the current and one level greater MCS used in the BS-UE connection. To determine the number of successive ACKs required to move to a higher MCS level, we consider that each NACK reduces the MCS level by 1. We define $N_{m,m+1}$ as the number of successive ACKs required to move from MCS m to MCS $m+1$. We have to find the value of $N_{m,m+1}$ for which the following inequality holds true:

$$N \times Thr(m+1) \;\geq\; (N+1) \times Thr(m)$$

Here, $Thr(m)$ represents the throughput when MCS m is chosen. If $D_{(m,m+1)}$ denotes the difference in throughput between transmitting with MCS $m+1$ and MCS m, we can then express $N_{(m,m+1)}$ as:

$$N \times (\; Thr(m) + D_{(m,m+1)} \;) \;\geq\; (N+1) \times Thr(m)$$

$$N \;\geq\; \frac{Thr(m)}{D_{(m,m+1)}}$$

To ensure that OLLA waits for $N_{(m,m+1)}$ ACKs before transitioning from MCS m to $m+1$, the throughput factor γ is defined as:

$$\gamma = \frac{1}{N_{(m,m+1)}}$$

Thus, in VarOLLA, the offset, Δ, is updated as follows:

$$\Delta_{t+1} \;= \begin{cases} \Delta_t \;\;+\;\; (\gamma \times \theta), & \text{if ACK} \\ \Delta_t \;\;-\;\; 1, & \text{if NACK.} \end{cases} \tag{1}$$

By incorporating the Throughput Factor, γ, VarOLLA aims to improve the adaptation of the MCS level in response to the channel conditions, considering the varying throughput gains associated with different MCS levels.

B. Simulation Setup

To assess the comparative impact of VarOLLA and OLLA, a simulated factory hall with dimensions 50m x 50m x 6m (length x width x height) is utilized. The BS is fixed at the center of the hall's ceiling. The simulations involve varying positions of the UE to cover every pixel in a 50x50-meter grid, where each pixel represents a 1x1-meter area located 1.5 meters above the floor. The channel model employed in the simulations is generated using the quasi-deterministic radio channel generator (QuaDRiGa) [19], utilizing the propagation parameters specifically designed for industrial indoor scenarios [20]. This setup has been used in our previous research on industrial networks as well [4]. The simulation parameters are summarized in Table I.

TABLE I: Simulation Parameters

Parameter	Value (range)
Carrier frequency	3.5 GHz
Bandwidth	5 MHz
5G numerology	0 (sub-carrier spacing = 15 kHz)
Transmit power	21 dBm
UE speeds	[0.1, 0.3, 1, 3, 10] m/s
CQI periodicity	[2, 5, 10, 20, 40, 80] ms
$BLER_{target}$	10^{-1}
KPI	10^{th} user throughput percentile
CQI levels	Table 5.2.2.1-3 (up to 256QAM) [21]

For the considered network scenario, a full transmit buffer is assumed for the network carrier across all UE positions. Since a single-UE scenario is being investigated, the entire carrier bandwidth is available for the single UE. The Key Performance Indicator (KPI) used in this analysis is the 10th user throughput percentile. Additionally, two BLER metrics are evaluated: the instantaneous BLER (iBLER) and the residual BLER (rBLER). The iBLER represents the count of unsuccessful transmissions, indicating the number of times the initial transmission fails. A higher iBLER value corresponds to a higher number of first transmission failures. On the other hand, the rBLER is determined by assessing the number of instances where retransmitted blocks remain undecodable even after reaching the maximum number of retransmission attempts allowed by the HARQ protocol. A higher rBLER value signifies a poorer ability to adapt to channel variations in a timely manner. The impact of a higher iBLER is an increase in the number of retransmissions, while a higher rBLER indicates a decrease in the reliability of the system.

The step size parameter, denoted as θ, has been widely recognized as a crucial factor impacting the performance of OLLA [7]. The optimal value of θ is the one that maximizes the throughput for a specific UE speed and CQI periodicity, commonly referred to as the 'Optimal θ'. In our study, we conducted simulations using various step sizes, and the behavior of OLLA with the optimal θ for each scenario was chosen as the benchmark (referred to as 'OptOLLA' in the figures). Additionally, we included a genie-based MCS selection method for comparison. This genie-based approach assumes perfect knowledge of the UE's experienced CQI, enabling the BS to accurately select the optimal MCS for transmission. As such, the genie-based mechanism represents the maximum achievable throughput under the given channel conditions experienced by the UE.

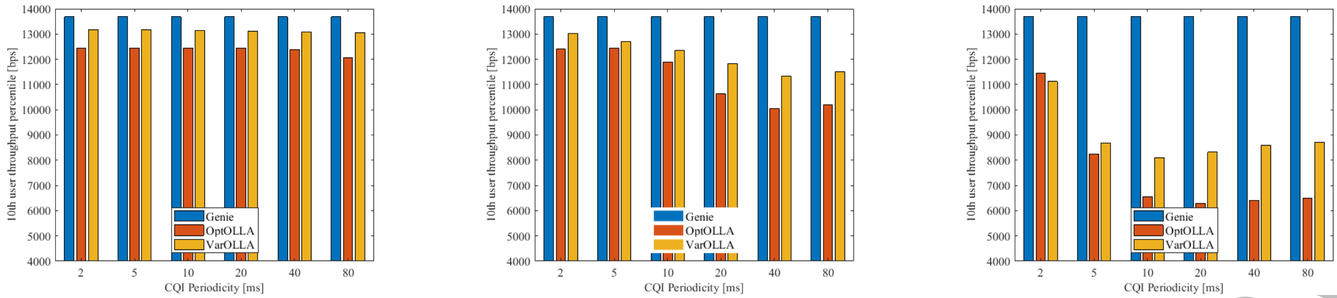
IV. Results & Discussion

This section presents the simulation results of VarOLLA and OptOLLA. Figure 2 illustrates the 10^{th} user throughput percentile for different CQI periodicity, with each sub-figure corresponding to a specific UE speed. Figure 3 depicts the 90^{th} user iBLER percentile, and Figure 4 represents the 90^{th} user rBLER percentile for the same scenarios. We will discuss the performance of VarOLLA based on each KPI scenario-by-scenario in the following paragraphs.

We begin our discussion with the scenario featuring the slowest mobility, which is particularly relevant for indoor IIoT networks: the 0.1 m/s scenario. Figures 2a, 3a, and 4a present the 10^{th} user throughput percentile, 90^{th} user iBLER percentile, and 90^{th} user rBLER percentile, respectively. VarOLLA consistently demonstrates higher throughput than OptOLLA across all CQI periodicity, especially for the least frequent CQI update period of 80 ms, where the throughput gain is even more pronounced. When compared to the genie method, VarOLLA reduces the gap between state-of-the-art and the maximum achievable throughput by a significant 50%. However, it should be noted that VarOLLA exhibits slightly higher iBLER (12.5%) than the $BLER_{target}$ (10%). Nevertheless, in terms of rBLER, which measures long stretches of continuous transmission failures, VarOLLA significantly outperforms OptOLLA. In essence, VarOLLA experiences slightly more initial transmission failures but rapidly adjusts the MCS to avoid long consecutive failures, resulting in better overall throughput and increased reliability compared to OptOLLA.

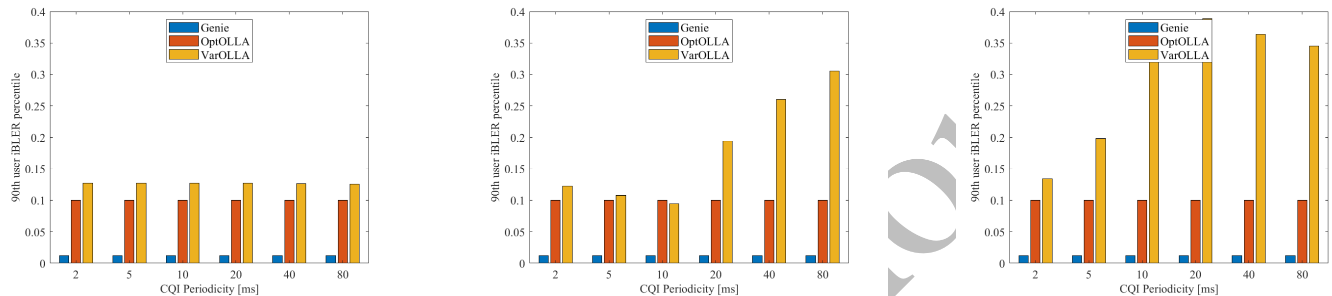
Next, we examine Figures 2b, 3b, and 4b, which display the throughput, iBLER, and rBLER for a UE speed of 1 m/s. The throughput improvements range from 5 to 12% over OptOLLA for different CQI periodicities. Generally, as the period between CQI updates increases, both OptOLLA and VarOLLA experience a decrease in throughput. However, VarOLLA demonstrates a smoother decrease in throughput as channel outdatedness increases, while OptOLLA's throughput is more affected. Regarding iBLER, the situation is reversed. OptOLLA maintains iBLER at the $BLER_{target}$, whereas VarOLLA's iBLER deteriorates with increasing channel outdatedness. On the other hand, VarOLLA consistently achieves very low rBLER for all CQI periodicity. This implies that VarOLLA may encounter slightly more initial transmission errors due to its more frequent use of higher MCS, but it quickly adapts and ensures successful block transmission before reaching the maximum HARQ retransmission limit. OptOLLA's rBLER initially increases as channel outdatedness increases and then drastically decreases (relatively). This behavior can be explained by the fact that OptOLLA maintains iBLER by adopting a more conservative approach in situations of greater channel outdatedness. An interesting observation from a control message perspective is that VarOLLA's throughput at a CQI periodicity of 20 ms is approximately equivalent to OptOLLA's throughput at 10 ms. Therefore, operating VarOLLA with a 20 ms feedback interval would reduce control messages by 50%, creating room for other devices.

We now analyze the results for a UE speed of 10 m/s, as depicted in Figures 2c, 3c, and 4c. OptOLLA's throughput experiences a sharp decline for CQI periods between 2-10 ms, after which it remains relatively stable for periods up to 80 ms. In an attempt to maintain iBLER at the target of 10%, OptOLLA predominantly employs the most reliable MCS for most transmissions, resulting in consistent throughput, iBLER, and rBLER for CQI periodicity beyond 10 ms. On the other hand, VarOLLA outperforms OptOLLA in max-



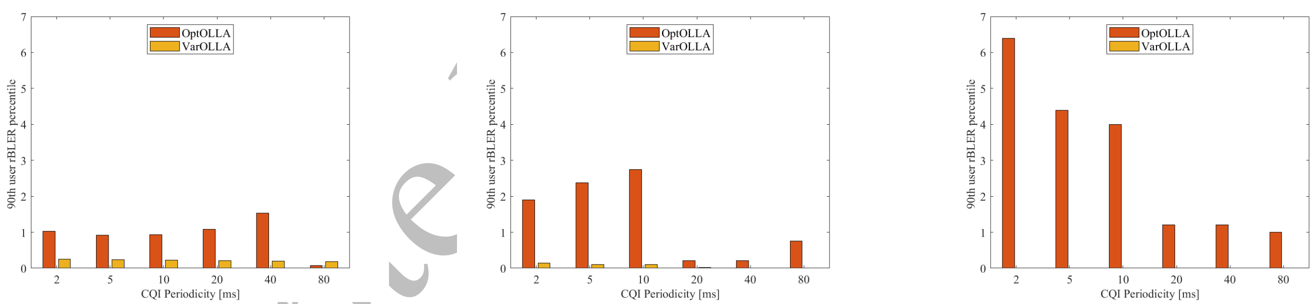
(a) UE Speed = 0.1m/s (0.36Km/hr) (b) UE Speed = 1m/s (3.6Km/hr) (c) UE Speed = 10m/s (36Km/hr)

Fig. 2: The 10th user throughput percentile obtained by using VarOLLA against Opt.OLLA and Genie method for different CQI Periodicity. Each subfigure shows the same for differing UE speeds.



(a) UE Speed = 0.1m/s (0.36Km/hr) (b) UE Speed = 1m/s (3.6Km/hr) (c) UE Speed = 10m/s (36Km/hr)

Fig. 3: The 90th user iBLER percentile obtained by using VarOLLA against OptOLLA and Genie method for different CQI Periodicity. Each subfigure shows the same for differing UE speeds.



(a) UE Speed = 0.1m/s (0.36Km/hr) (b) UE Speed = 1m/s (3.6Km/hr) (c) UE Speed = 10m/s (36Km/hr)

Fig. 4: The 90th user rBLER percentile obtained by using VarOLLA against OptOLLA for different CQI Periodicity. Each subfigure shows the same for differing UE speeds.

imizing throughput under high channel outdatedness while maintaining nearly zero rBLER. As a consequence of this optimization, VarOLLA exhibits an increase in first transmission failures (iBLER). Notably, when the CQI periodicity is 80 ms, VarOLLA achieves a 35% increase in throughput with minimal missed deadlines, comparable to OptOLLA's performance at a CQI periodicity of 10 ms. Consequently, adopting VarOLLA could lead to a reduction of control messages by up to 87.5%.

V. Conclusions & Future Works

In this study, we have addressed the challenges of OLLA in 5G-RedCap systems and proposed VarOLLA, a novel approach to optimize spectral efficiency for high-throughput applications in IIoT systems. Through extensive simulations, we have demonstrated the effectiveness and superiority of VarOLLA over traditional OLLA techniques.

Our findings indicate that VarOLLA achieves significant improvements in throughput (up to 35%) compared to OptOLLA, particularly under conditions of high channel outdatedness. VarOLLA exhibits quick adaptation to channel variations, reducing long consecutive transmission failures (rBLER) and maximizing throughput, while maintaining acceptable initial transmission error rates (iBLER). The near-zero rBLER achieved by VarOLLA showcases its ability to ensure reliability in IIoT networks.

An additional advantage of VarOLLA is its implementation on the BS, enhancing downlink throughput for UEs without increasing the terminal's complexity. Furthermore, VarOLLA demonstrates its potential to significantly reduce control message overhead (up to 87.5%), thereby freeing up network resources for other devices.

While our evaluation focuses on industrial networks, we believe that VarOLLA could also be beneficial in other IoT use cases. Future work includes evaluating VarOLLA in various IoT scenarios and comparing it against machine learning-based LA techniques. Nonetheless, by maximizing throughput and ensuring reliable communication, VarOLLA paves the way for advanced applications in the manufacturing sector, contributing to the realization of the 4IR.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the assistance of ChatGPT, an AI language model developed by OpenAI, in proof-reading.

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