Augmented communications : a solution for overcoming high spatial correlation of the massive-MISO VLC channel

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AUGMENTED COMMUNICATIONS
A SOLUTION FOR OVERCOMING HIGH SPATIAL CORRELATION OF THE MASSIVE-MISO VLC CHANNEL

by

Monette H. Khadr

A Dissertation
Submitted to the University at Albany, State University of New York
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College of Engineering and Applied Sciences
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To my Mom
ABSTRACT

A key challenge for future wireless networks is to come upon a riveting compromise between spectral efficiency, complexity, and energy efficiency. The challenge is also intensified due to the pace at which the Internet-of-Things (IoT) technology is arriving, causing an upheaval to pre-existing network infrastructures in terms of elevating spectrum scarcity. To keep pace with the exploding data demand forecasts, a circumvention is required. One realization is by utilizing the high-band spectrum and the rich body of knowledge on multiple-input multiple-output (MIMO) technologies. One of the prominent high frequency technologies is visible light communications (VLC). VLC provide a large unregulated bandwidth and can be considered an energy efficient technology, as the transmitting elements are serving both their illumination and communication functionalities. Yet, adopting MIMO in VLC imposes challenges, as it lacks the rich scattering nature of radio frequency systems.

This thesis proposes Augmented Communications (ACom). ACom aims to design new modulating waveforms by rethinking and pre-conditioning the in-phase and quadrature (IQ) values of conventional baseband streams. The resulting waveforms attain novel features which can be applied to serve a number of applications. The primary application, which is emphasized in this thesis, is ACom’s approach to overcome high spatial correlation of the massive-MIMO VLC channel. In this realization, ACom’s added features act as address codes or signature sequences for the MIMO system. Results have chosen the immense potential of ACom, as it allows attaining the theoretical limit of spatial modulation based MIMO systems without the need for perfect channel state information or low channel coefficients correlation. Other ACom applications are also presented, namely; ACom as a physical layer (PHY) security technique and ACom as a spectral efficiency enhancing method for single-input single-output systems. As a PHY security technique, unlike other techniques in literature, ACom does not require key exchange over the air. Thus, the keys are protected from being intercepted and network overhead is reduced. Additionally, apart from the PHY layer, this thesis presents medium access control algorithms for spectrum assignment and rate adaption, which are evaluated and conducted using large-scale hardware testbeds. Results have proven the competence of the proposed algorithms in comparison to pre-existing literature.
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CHAPTER 1
Introduction

The unprecedented demand for data traffic has motivated researchers to evolve novel transmission technologies, protocols, and network infrastructure to maximize the attainable throughput and spectral efficiency. Yet, energy consumption has received less devotion. The development of wireless technologies that can satisfy the upsurge in data demand growth while reducing the energy consumption of future networks is a compelling necessity [3]. According to a Cisco conducted survey, 40% of data traffic is spent at home, while 25% occurs at work [3]; the remaining 35% is spent on the move. These statistics are expected to change with the emerging trend of remote work, i.e., working from home, which has been on the rise after the COVID-19 pandemic. Communication services are now expanding from services to humans to services to things [4]. Internet-of-Things (IoT) has become the keyword to describe the connectivity of numerous technologies and devices to the Internet, many of those devices are located in indoor environments. One of the strong contenders for indoor deployments is Visible Light Communications (VLC) technology [5]. Not only does VLC offer a large unregulated amendable bandwidth, the technology is also renowned for its energy efficiency; as the utilized light sources (i.e., VLC transmitters) are already serving as luminaries, which is considered their primary purpose [6]. Hence, VLC technology is offered as a solution to accommodate the demands of emerging technologies, while considering energy [7].

For spectral efficiency enhancement, multiple-input multiple-output (MIMO) communications offer promising techniques that aim to increase the capacity of communication systems. Spatial modulation (SM) has recently established itself as a notable transmission concept that exploits multiple transmitting elements while reducing energy consumption as compared to other MIMO methods. The main concept behind SM-systems is activating only one transmitting element at a time, or multiple elements in the case of generalized SM, and additional information bits are mapped as spatial bits. Those spatial bits are implicitly transmitted by estimating the index of the active transmitting element. Theoretical throughput limits of SM-systems can be achieved given specific propagation conditions including; channel state information (CSI) knowledge at both transmitting and receiving ends, the
transmit-to-receive channel paths are sufficiently independent, and the signal-to-noise-ratio (SNR) is adequately high [8]. Yet, in practice, these conditions are not always satisfied, thus affecting the attainable throughput of SM systems. Firstly, in some conditions, such as in multiple-input single-output (MISO) VLC systems, the channel coefficients are highly correlated. The correlation between the channel coefficients in VLC depends on various system parameters/configurations including; spatial positions of the transmitters and receivers, their spacing and their inter-spacing, the transmitter’s radiation pattern, and the receiver’s field-of-view (FOV), etc [9]. Thus, in some cases, the transmit-to-receive paths in VLC cannot be considered independent. Secondly, CSI errors are difficult to avoid in practical systems [10].

This thesis presents augmented communications (ACom); focusing primarily on its MIMO application known as augmented spatial modulation (ASM). ASM is a technique that adds features to the transmitted signal prior to transmission in order to allow correct transmitter index estimation at the receiver, without low channel correlation or perfect CSI knowledge requirements. It can be observed as intentional fingerprinting or a signature insertion operation that can be decoded using an appropriate receiver. Thus, the theoretical throughput limits of SM can be realized by systems that employ ASM. Details on the design challenges that ASM aims to address are provided in a subsequent section.
1.1 Background

VLC operates in the frequency range between 400 and 800 THz (the visible light range). Figure 1.1 shows the electromagnetic (EM) spectrum, highlighting the seven colours of visible light. In VLC, an optical source, operating in the visible light range, is used to transmit information by modulating its intensity at a rate faster than the response time of the human eye, causing it to be perceived as a steady glow [11]. With the introduction of high luminance light emitting diodes (LEDs), existing fluorescent lamps and light bulbs can be replaced, paving the way for VLC.

1.1.1 History of VLC

The idea of using optical emission to transmit information has been present since ancient times [1]. Back in 1200 BC, according to Homer in the Iliad, optical signals were used to transmit messages regarding the Grecian siege of Troy. By lighting fire beacons placed on mountain tops, they were able to transmit messages over great distances, which was by far the fastest mean to transmit information over long distances at the time. Modern time inventions include the invention of the optical telegraph in early 1790’s by Claude Chappe [12]. It was able to send messages, by changing the orientation of signaling arms on a large tower, over distances of hundreds of kilometers in a matter of minutes. A code book was used to encode the orientations of the signaling arms, forming alphabets, numerals, common words and control signals. Later, in the year of 1880, the photophone was invented by Alexander Graham Bell [13]. The system was designed to transmit a voice signal by modulating reflected light from the sun over a distance of 213 m. But, it was F.R. Gfeller and U. Bapst who suggested the use of diffuse emissions in the infrared (IR) band for indoor communications, and hence the initiation of indoor wireless communications in the year 1979.
The concept of using fast switching LEDs was firstly presented by Pang et al. in 1999, while utilizing White-LED (WLED) for illumination and communication began in the early 2000s in Japan, developed by Tanaka et al. Since that time, an extensive work has been done in modeling indoor channels and optical transmitters and receivers design.

1.1.2 VLC Fundamental Principles

Depending on the environment in which the VLC systems are designed to operate, they can be classified into two main categories: indoor and outdoor systems. In outdoor applications, VLC can be used to create point-to-point links between buildings for instance. The typical transmission distance of free space optical (FSO) links is in the order of some kilometers. Moreover, it can be used for spacecraft communications in outer space. On the other hand, VLC is able to provide efficient and flexible data transmission in indoor environments, over a distance of a few meters. One of the tremendous advantages of VLC is that it can be applied to sensitive environments like hospitals and manufacturing plants which have stringent electromagnetic compatibility restrictions. That is because optical signals do not interfere with the existing electronic systems. In addition, optical signals can easily be contained by opaque boundaries as they do not pass through walls causing the propagation and the transmission range of the optical signals to be restricted to specific spots or areas. This characteristic allows a large spatial reuse of VLC systems, unlike their RF counterparts. Moreover, VLC systems do not require high-frequency circuit designs, compared to RF systems. Due to their vast applications and advantages, VLC became our area of interest, focusing on indoor VLC systems.

Techniques used in VLC have to satisfy the non-negativity constraint, meaning that the transmitted signal has to be non-negative as the emitted optical power cannot be negative. The emitted optical power is also restricted due to eye and skin safety regulations; Fig. 1.2 shows a block diagram of a VLC system. With the increasing number of mobile devices and personal computers and the growing number of broadband applications, the need for developing indoor wireless access networks of wider bandwidth became the interest of many researchers. In indoor applications, for the previously mentioned reasons, light waves are a strong candidate for wireless networks. Previously, the light wave frequency in the IR range was usually chosen due to its low cost. However, in recent years and after the
Table 1.1: Comparison of short-range wireless communication technologies [16].

<table>
<thead>
<tr>
<th></th>
<th>VLC</th>
<th>IR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Rate</td>
<td>&gt; 100 Mb/s possible</td>
<td>4 Mb/s (FIR)</td>
</tr>
<tr>
<td></td>
<td>(LED dependent)</td>
<td>16 Mb/s (VFIR)</td>
</tr>
<tr>
<td>Distance</td>
<td>meters</td>
<td>meters</td>
</tr>
<tr>
<td>Security</td>
<td>Good</td>
<td>Good</td>
</tr>
<tr>
<td>Regulation</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Carrier wavelength</td>
<td>380-780 nm</td>
<td>850 nm</td>
</tr>
<tr>
<td>Services</td>
<td>Communication and illumination</td>
<td>Communication</td>
</tr>
</tbody>
</table>

introduction of LEDs, VLC systems are preferred over IR systems; a comparison between both systems is conducted in Table 1.1. The IR communication is standardized by the Infrared Data Association (IrDA). The data rate for IR communication [16] includes 4 Mb/s for far-IR (FIR) and 16 Mb/s for very-far-IR (VFIR). In VLC, the data rate is dependent on the LED’s modulation bandwidth, which enforces the use of MIMO deployments in VLC.

Visible light communication can be divided into two modes: 1. Infrastructure-to-device communication and 2. Device-to-device communication. An indoor scenario is where LED luminaires are used to illuminate a room; in this case, the luminaires (LEDs) can transmit data to various devices inside the room [17]. Coordination between the LEDs is also made possible to reduce the interference and to even enable multi-point transmission to receiving devices. Currently, the uplink transmission from the devices is still an obstacle facing researchers that is because using LEDs on end-user devices causes noticeable disturbance to users. A solution to this problem is the use of RF or infrared communication for the uplink transmissions. The LEDs can also be used in street lamps and traffic lights to provide internet access to pedestrians and users in cars.

Due to widespread of camera sensors in mobile devices, VLC can also be used for near-field device-to-device communication. Here, the LED pixels on the display of any smartphone can be used to transmit data to the camera sensor of another smartphone. With the design of efficient codes, screen-to-camera streaming can achieve very high throughput. Another form of device-to-device communication, vehicles on the road can communicate with one another to form an ad-hoc network using VLC. Although we discussed the vehicular networking and screen-camera communication, our primary focus in this thesis is towards the design and analysis of indoor infrastructure-to-device networking using visible light.
1.2 Problem Statement

In home and office environments, a typical indoor light fixture should provide illumination levels of about 200 to 1000 lux [2], depending on the performed tasks requirements. The ceiling light installations set up a line of sight (LOS) link to a potential receiver placed within a room. As the name implies, a LOS link means that there is a visual line of sight between the transmitter and the receiver. This configuration has practical bandwidth limitations that are not imposed by the channel but by the modulation bandwidths of the light sources. Moreover, these illumination levels yield high SNRs of more than 60 dB within the room [14]. Power line communications (PLC) transfer the transmitted data to the light fixtures via the existing electrical wiring.

The transmitted data acts as the input to an electronic circuitry that modulates the light source. In other words, the intensity of the emitted light is modulated. Hence, the electrical signal is transferred into an optical signal. In the case of VLC, since the modulation is done by high-frequency pulsed light, it then cannot be perceived by the human eye. As a result, the changes in brightness are imperceptible and the illumination appears to be constant to the human eye. The emitted optical signal is then detected by the receiver and according to the amount of received optical power an equivalent photocurrent is generated. Meaning, the optical signal is reconverted into an electrical signal. Then, the digital signals are decoded using digital signal processing (DSP) techniques.

Intensity Modulation (IM) is defined as the modulation technique in which the transmitted signal is modulated into the LED instantaneous optical power [11]. Direct Detection (DD) uses a photodiode (receiver) to convert the incident (received) optical signal power into a proportional current. Consequently, IM techniques with DD are typically employed in indoor VLC systems. IM/DD can easily be implemented, that is due to the fact that the up/down conversion of the baseband signals to/from the optical transmission frequency can be implemented by the use of low-cost diodes. Unlike the conventional RF modulation/demodulation techniques, there is no need for sophisticated high-frequency circuit designs. However, this simplicity requires new approaches to be developed, as it occurs at the expense of losing the optical carrier’s phase and frequency information. As only the intensity of the optical carrier is detected, conventional RF modulation/demodulation techniques cannot be applied directly to IM/DD based systems. Moreover, given the restricted
bandwidth of commercially available LEDs, spectrally efficient transmission techniques are crucial for indoor VLC systems.

1.2.1 Optical Wireless Channel Model

It is imperative to understand the characteristics of the channel in order to design, implement and operate an efficient optical communication system. Characterization of any communication channel is performed by studying its channel impulse response, which is analyzed to combat the effects of channel distortions. The work that covered both experimental measurement and computer modelling has been published on channel characterization, covering both indoor and outdoor systems [18]. The power losses directly associated with the channel may be broadly separated into two factors, these being optical path loss and multipath dispersion. An IM/DD optical wireless system has an equivalent baseband model, which hides the high-frequency nature of the optical carrier.

Non-LOS links, meaning that there is no visual line of sight between the transmitter and the receiver, especially in indoor applications, are subject to the effects of multipath propagation, just like RF systems. This type of link causes the system to suffer from severe multipath-induced performance penalties. Multipath occurs due to the fact that the power launched from the transmitter may take many reflected paths before arriving at the receiver [1]. This causes the electric field to suffer from severe amplitude fades on the scale of a wavelength. Fading can be defined as the variation of the signal amplitude over time and frequency and can either be due to multipath propagation, known as multi-path (induced) fading, or due to shadowing from obstacles, referred to as shadow fading. The detector would experience multipath fading if the detector size was proportional to one wavelength or less [19]. Fortunately, VLC receivers use detectors having surface areas typically millions of square wavelengths causing indoor VLC links not to suffer from the effects of multipath fading. However, they do suffer from the effects of dispersion, which causes inter-symbol interference (ISI), as some paths are longer than others, not all paths arrive at the same time causing a delay between the different paths. As long as the symbol time is greater than the delay, then the current symbol does not affect the subsequent symbol, implying that ISI is not significant.

A VLC link is represented by its channel, characterized for a given position of transmit-
ter, receiver and other intervening reflecting objects. The characteristics only change when these components are moved by distances of the order of centimeters. The VLC channel can be considered quasi-static, meaning it can be modelled as a static form even if some quantities are allowed to vary slowly with time. This is because the bits are transmitted in high bit rates, and the movement of objects and people within a room is relatively slow. In our study, each transmitter consists of a 2-D rectangular array of low intensity white LEDs, and the transmitters are distributed among the ceiling. The reason for using an array of LEDs is due to technological limitations. A single LED cannot provide the sufficient illumination for an indoor environment [20]. On the other hand, an extremely high-brightness LED luminary can compromise eye safety. Additionally, in order to satisfy high data-rate demands, MIMO realizations are required. Accordingly, having a large number of spatially distributed LEDs is an inevitable solution.

1.2.2 MISO Channel Challenges

An optical MIMO communication system acceding intensity modulation and direct detection can be modeled as [21],

\[
y = Hx + w; \quad (1.1)
\]

where \( w \) represents the noise, \( H \) is the MIMO channel matrix, and \( x \) is the transmitted signal. The noise in VLC is a result of the ambient shot light and thermal noise with a distribution modeled as additive white Gaussian noise (AWGN) with zero mean and a variance of \( \sigma^2 \).
Table 1.2: System parameters for the VLC link.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmitter</td>
<td></td>
</tr>
<tr>
<td>Number of LED grids</td>
<td>4</td>
</tr>
<tr>
<td>Transmitted power per LED</td>
<td>20 mW</td>
</tr>
<tr>
<td>Number of LEDs per array</td>
<td>$60 \times 60 = 3600$</td>
</tr>
<tr>
<td>Receiver</td>
<td></td>
</tr>
<tr>
<td>Active area</td>
<td>1 cm$^2$</td>
</tr>
<tr>
<td>Half-angle FOV</td>
<td>70</td>
</tr>
<tr>
<td>Height w.r.t the floor</td>
<td>0.85 m</td>
</tr>
</tbody>
</table>

The channel in the optical domain is presented as real-valued attenuation coefficients, relying heavily on the transmitter-receiver alignment. The line-of-sight (LOS) channel gain of each propagation link can be calculated by [21]

$$h_{rij} = \begin{cases} \frac{(m+1)A}{2nd_{ij}} \cos^m \phi_{ij} \cos \varphi_{ij} & ; 0 \leq \varphi \leq \varphi_{1/2} \\ 0 & ; \varphi > \varphi_{1/2} \end{cases} \quad (1.2)$$

where the angle of irradiance is $\phi$, $\varphi$ is the angle of incidence, and $d$ is the separating distance between the transmitter $i$ and the receiver $j$. Furthermore, $\varphi_{1/2}$ denotes the FOV semi-angle at the receiver, $m$ is the Lambertian emission, and $A$ is the photodetector area. The channel gain of the first reflection path is [2]

$$h_{rij} = \begin{cases} \frac{(m+1)A}{2\pi d_{ij}d_{2ij}} \cos^m \phi_{ij} Z & ; 0 \leq \varphi \leq \varphi_{1/2} \\ 0 & ; \varphi > \varphi_{1/2} \end{cases} \quad (1.3)$$

where $Z = \cos \varphi_{ij} \cos \alpha_{ij} \cos \beta_{ij}$.

According to [22], there are distinct channel transfer factors between each transmitter and receiver pair, hence, the receiver can track the transmitting source and detect spatial symbols. To verify the practicality of the previous statement, we calculated the channel gains at three random locations shown in Fig. 1.3. A $4 \times 1$ VLC configuration is considered, i.e. 4 transmitters and 1 receiver setup. The room dimensions are $5 \times 5 \times 3$ m$^3$ and the light emitting diodes LEDs are located on the ceiling with a spacing of 2.15 m from the receiving plane. Further used simulation parameters are listed in Table 1.2. Applying Eq. (1.2) into
this scenario, the values of the channel gains are

\[ H_{\text{loc}_1} \approx 10^{-5} \times (0.2211\ 0.2211\ 0.2211\ 0.2211) \]
\[ H_{\text{loc}_2} \approx 10^{-5} \times (0.0933\ 0.0933\ 0.3333\ 0.3333) \]  \hfill (1.4)
\[ H_{\text{loc}_3} \approx 10^{-5} \times (0.1192\ 0.0521\ 0.5667\ 0.1192) \]

Based on (1.4), spatial identification in the center of the room (Location 1) is almost impossible to achieve, as all the channel gains are equal. Moreover, location two and three, shown in Fig. 1.3, also suffer from having equal channel gains. Furthermore, we calculated the channel gains resulting from the first reflected path in the previously given scenarios, the values of the sum of first reflection channel gains from the four walls are

\[ H_{r\text{loc}_1} \approx 10^{-6} \times (0.1489\ 0.1489\ 0.1489\ 0.1489) \]
\[ H_{r\text{loc}_2} \approx 10^{-6} \times (0.1144\ 0.1144\ 0.3420\ 0.3420) \]  \hfill (1.5)
\[ H_{r\text{loc}_3} \approx 10^{-6} \times (0.1988\ 0.0734\ 0.5616\ 0.1470) \]

From (1.5), it is evident that even by considering the first reflection paths, SM remains very sensitive to receiver location and requires perfect CSI. Moreover, we studied other controlling parameters such as changing the transmitter’s half-angle \( \phi_{1/2} \) on the channel gain coefficients, depicted in Fig. 1.4. Yet, the performance of SM remains to be challenging in practical deployments. Approaches such as link blockage and transmitted power imbalance are proposed in [22], however their effect on illumination, which is the primary task of the LEDs, is not studied. As a result, a reliable technique that is capable of identifying the transmitting element without relying on CSI and is independent to transmitter-receiver alignment is needed. In order to achieve spectral efficiency gains while preserving the low complexity requirement, ACom can be applied to SM-based systems, also known as augmented spatial modulation (ASM), to harness the receiver simplicity of SM while overcoming the spatial identification problem for low complexity systems. Based solely on the signal format and receiver design, our approach can identify the transmitting source without relying on CSI, addressing information in the frame or complex digital signal processing (DSP).

Furthermore, applying massive-MISO in RF is facilitated by the rich scattering nature of the RF channel. SM takes advantage of the presence of the large transmitting elements array at the transmitter, while omitting co-channel interference by activating only one antenna
at a time, making it apt for massive-MIMO deployments. Unlike RF, the transmit-to-receive
links in VLC systems vary in independence and the channel impulse responses do not always
represent a unique point/signature \[3\]. Hence, performance of massive-SM in VLC deterio-
rates significantly when the transmit-to-receive links become highly spatially correlated. For
illustration, by reconsidering the \(5 \times 5 \times 3 \) m\(^3\) room model and using Eq. (1.2), the probability
of correctly detecting the spatial information for conventional SM systems is illustrated in
Fig. 1.5. The ceiling of the room is modeled to have 1000 transmitters (emulating a massive
scenario) that are centered in the room with a vertical and horizontal separation distances
of 0.125 m, while the receiver is placed 0.85 m from the floor. As can be observed, the
reliability of the spatial stream varies as the receiver sweeps within the room. Additionally,
the probability of correct detection drops to zero when the receiver is located in the center,
as the channel coefficients from all transmitters are identical and hence spatial identification
becomes unachievable.

1.2.3 Stringent CSI Requirements

In the previous subsection, the MISO case is highlighted as one of the most severe
cases where SM in VLC can be hindered. This subsection shows how channel impairments
can cause MIMO (not solely MISO) based SM system to fail in VLC deployments; the cases
can be listed as the imperfect CSI case and the correlated CSI case that can even occur in
MIMO configurations.
1.2.3.1 Imperfect CSI Case

As previously mentioned, SM detection relies heavily on channel estimation. In practice, facing CSI errors is inevitable. Erroneous CSI can be defined as a relationship between the correct and the estimated channel coefficient at receiver $j$ as

$$
\hat{h}_j = \rho h_j + (1 - \rho)\epsilon^{1 \times N_t} \tag{1.6}
$$

where $\hat{h}_j$ is the estimated channel coefficient at receiver $j$, $h_j$ is the actual channel coefficient at receiver $j$, $\epsilon$ is a normally distributed random variable with zero mean and unit variance, $N_t$ is the number of transmitters in the system, and $\rho$ is a coefficient ranging from 0 to 1 determines the resemblance of the actual CSI to the estimated one. According to (1.6), perfect CSI entails $\rho = 1$. The destructive effect of CSI imperfections on BER performance under AWGN channel for quadrature amplitude modulation (QAM) with an order of 16 is demonstrated in Fig. 1.6. Maximum likelihood detection (MLD) is assumed for the $4 \times 4$ MIMO configuration. Two values of $\rho$ are assumed, namely; 0.7 and 0.85. As expected, the higher the parameter $\rho$ is, the worse the BER performance becomes; as $\rho$ symbolizes channel estimation imperfection.
1.2.3.2 Correlated CSI Case

As previously mentioned, channel correlation is a huge obstacle for MISO and MIMO configurations in VLC systems. Channel correlation, in this context, is the interference of elements of the channel matrix among themselves. It can be presented using a Toeplitz matrix, $\Delta \in \mathbb{R}^{N_t \times N_t}$, with diagonal elements $1 - \delta$ where $\delta$ is a coefficient that accounts for correlation and is bounded between $0 < \delta << 1$. Perfect uncorrelated channel coefficients occur at $\delta = 0$ and an example for an $N_t = 4$ configuration can be given as:

$$\Delta = \begin{bmatrix}
(1 - \delta) & \delta & 0 & 0 \\
\delta & (1 - \delta) & \delta & 0 \\
0 & \delta & (1 - \delta) & \delta \\
0 & 0 & \delta & (1 - \delta)
\end{bmatrix} \quad (1.7)$$

The analysis in the previous section is repeated to evaluate the effect of channel coefficient correlation on BER performance and is provided in Fig. 1.7. Performance is evaluated at two different $\delta$ values; namely at $\delta = 0.3$ and $\delta = 0.15$. As can be observed, the BER performance deteriorates as the value of the correlation coefficient increases.
1.3 Related Work

As previously emphasized, the fundamental essence of SM-MIMO is exploiting the unique fingerprint introduced by the channel for spatial bits retrieval. Then, at the receiver, the channel impulse responses become part of the search space of the demodulation hypothesis-testing. The lack of scattering in the propagation environment leads to higher error probability. SM-MIMO is first explored in [23] for VLC systems. Results in [23] have proven that VLC-MIMO links are highly correlated if the transmitter and receiver locations are not optimized. Transmitter-receiver alignment is one of the solutions proposed for overcoming VLC-MIMO high channel correlation and is also studied in [24]. However, this approach limits application to static-deployments and cannot accommodate cases where the transmitting elements are densely packed. Additionally, any modifications in the transmitting elements (the pre-installed lighting fixtures) can increase the total cost of the system.

Another solution occurs at the transmitter side, which is enforcing power imbalance and was first presented in [22]. However, this approach introduces a trade-off between the accuracy of detecting the spatial domain bits and the signal domain bits. Optimal power allocation in SM for orthogonal frequency division multiplexing (OFDM) based VLC is studied [25], which is considered one of the few efforts that addressed VLC-MISO systems. In [25], the transmitting power of the different transmitters are varied in order to create power surpluses for one-transmitter versus the others while keeping the total transmission
power the same. A power allocation scheme combined with the block Markov superposition transmission (BMST) coding scheme is given in [26]. It is important to note that there has been a number of power allocation approaches, including some for VLC MISO systems, but they are restricted to pulse amplitude modulation (PAM) systems. One of the examples is the power control scheme for PAM-VLC systems proposed in [27]. A more unified approach for power control in PAM-systems is given in [28]. Additionally, the work in [29] demonstrates a modulation precoding scheme that realizes adaptive power control on LEDs for spatial multiplexing PAM-based VLC systems; assuming perfect CSI.

At the receiver side, there are numerous approaches presented in literature to optimally design the receiver grid array. A receiver with an imaging lens and a fixed detector array is presented in [30]. An angular diversity receiver approach that varies the receivers’ normal vectors and in return reduces the correlation of the channel transfer matrix is given in [31]. For spatial multiplexing VLC systems, a receiver model with angular diversity detectors is considered in [32]. The performance of spatial multiplexing (SMP), generalized spatial modulation (GSM), quad-LED complex modulation (QCM), and dual-LED complex modulation (DCM) using convex lens enhanced imaging receivers is compared in [9].

Table 1.3 presents a brief comparison of the aforementioned methods focusing on three primary aspects; their applicability to MISO systems, whether the proposed method requires CSI for spatial identification, and the modulation scheme it was proposed for. As can be observed, all of the aforementioned methods are based on two assumptions; (1) The receiver is equipped with multiple receiving elements, and/or (2) CSI is known at both the transmitter and receiver sides. Additionally, their evaluation is presented for a fixed transmitter-receiver alignment and not for a dynamic geometry. Hence, a different approach is necessary and this is where ACom comes into play. By re-engineering the transmitted signal, ACom adds features that can then be used to differentiate between the transmitting elements.

The concept of signal manipulation is not novel and has been applied on various levels of signal design for several applications. On the bit level, there is code division multiple access (CDMA), which is a multiple access technique that has been used in multiple mobile communications standards such as UMTS, IS-95, and CDMA-2000. On the constellation level, there has been a number of approaches that are mainly proposed to address security concerns. Dirty constellations proposed in [33] pre-distorts the signal to mimic the normal
Table 1.3: Comparison of solutions presented in literature.

<table>
<thead>
<tr>
<th>Reference</th>
<th>MISO</th>
<th>CSI</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhang et al. [25]</td>
<td>✓</td>
<td>×</td>
<td>OFDM</td>
</tr>
<tr>
<td>Fath and Haas [22]</td>
<td>×</td>
<td>✓</td>
<td>PAM</td>
</tr>
<tr>
<td>Chen et al. [26]</td>
<td>×</td>
<td>✓</td>
<td>PAM</td>
</tr>
<tr>
<td>Yesilkaya et al. [27]</td>
<td>✓</td>
<td>✓</td>
<td>PAM</td>
</tr>
<tr>
<td>Ishikawa and Sugiura [28]</td>
<td>✓</td>
<td>×</td>
<td>PAM</td>
</tr>
<tr>
<td>Dambul et al. [30]</td>
<td>×</td>
<td>×</td>
<td>OOK</td>
</tr>
<tr>
<td>Zhuang et al. [31]</td>
<td>×</td>
<td>×</td>
<td>PAM</td>
</tr>
<tr>
<td>Deng and Fan [32]</td>
<td>×</td>
<td>×</td>
<td>OFDM</td>
</tr>
<tr>
<td>Sushanth and Chockalingam [9]</td>
<td>×</td>
<td>×</td>
<td>QAM</td>
</tr>
</tbody>
</table>

imperfection of the hardware and Gaussian distortion arising from the channel. For an illegitimate user, the distortion appears as noise, yet, a receiver aware of the presence of the signal and its encoding technique can decode the noise to reveal the hidden message. Artificial noise insertion is combined with constellation rotation in [34] for ensuring signal confidentiality. At the front ends, fingerprinting techniques are used for authentication [35, 36]. ACom’s perception can be observed as artificial and controlled fingerprinting that are applied on signals prior to transmission. Even though the concept of ACom is versatile, the analysis in this thesis focuses on orthogonal frequency division multiplexing (OFDM) modulation rather than PAM. Due to OFDM’s wide adoption in most wireless standards.

There are a number of research efforts that have manipulated the OFDM signal to achieve certain functionalities. Reverse-polarity optical orthogonal frequency division multiplexing (RPO-OFDM) [37] utilizes a pulse width modulation (PWM) like envelope per OFDM symbol to add dimming support. Hybrid on-off keying and asymmetrically clipped optical OFDM (HOOK-ACO-OFDM) system proposed in [38] simultaneously transmits ACO-OFDM and on-off keying (OOK) signals to add an additional bit per OFDM symbol as a control signal. Mixed-carrier communication (MCC) enables simultaneous wireless services such as broadband access, low-rate IoT connectivity, device-free sensing, and device-based localization [39]. ACom’s inspiration came from the shape of the signal produced in [37], which invigorated attention to the possibility of embedding features within the transmitted waveform. Based solely on the signal format and receiver design, ACom’s approach can be used to serve a multitude of applications, including identifying the transmitting source without relying on channel information, addressing information in the frame nor complex...
digital signal processing (DSP) techniques that involve coding \cite{10} and watermarking \cite{11}.

1.4 Major Contributions

The major contributions of this thesis can be listed as follows:

1. This thesis first introduces augmented spatial modulation (ASM), which utilizes ACom’s perception in order to overcome the aforementioned high spatial correlation of the massive-MISO VLC channel problem. ASM relaxes the uniqueness constraint of conventional SM and replaces it with deterministic signal alterations performed and reversed at the transmitting and receiving ends, respectively. The performance of ASM does not rely on channel uniqueness, thus, does not rely on transmitter-receiver geometry. Additionally, this conception allows ASM’s adoption in massive-MIMO settings, where the transmitting elements are densely placed in close proximity.

2. As the transmitter identification problem can be observed as a classification problem, secondly, machine learning (ML) methods are introduced to enhance the performance of conventional ASM. To achieve performance enhancement, two different ML-based ASM methodologies are used. The first restructures ASM’s receiver and incorporates the use of various ML classifiers, including; naive-Bayesian, support vector machine, logistic regression, and neural network (NN) classifiers. The second proposes ASM transceiver architecture as an end-to-end NN model implementation with an autoencoder structure.

3. Thirdly, other applications to the ACom concept are introduced. ACom is introduced as a physical layer security (PLS) technique that aims to combat eavesdropping attacks and reserve the confidentiality of transmission. Security-aware spatial modulation is presented as a physical layer (PHY) solution for heterogeneous networks adopting radio frequency and optical transmissions simultaneously. Within the analysis, a novel key selection algorithm is introduced aided by the use of a NN to allow periodical PHY rekeying issued by a centralized source to ML-equipped nodes. Another application is increasing the spectral efficiency of single-input single-output (SISO) systems by using ACom’s added features as an additional data stream on top of the explicitly transmitted symbols.
4. Fourthly, this thesis presents medium access control protocols (MAC) orchestrated over large scale hardware testbeds. A number of jamming-aware spectrum assignment algorithms are proposed and evaluated using the Future Internet of Things (FIT-IoT LAB) testbed for various use cases. The algorithms are designed for single users with single channel/transceiver capabilities, single users with multiple channels/transceivers capabilities, and multiple users with multiple channels/transceivers capabilities. Additionally, rate adaptation experimentation on the cloud based hybrid RF-optical network over synchronous links (CHRONOS) testbed is performed.

1.5 List of Publications

The following publications are a direct result of the work presented in this thesis. The work in Chapter Two is submitted in:


The work in Chapter Three is published in:


The work in Chapter Four is published in:


The work in Chapter Five is published in:


Finally, some of my work has been published in the following book chapter:


1.6 Organization

The remaining of the thesis is organized as follows; Chapter two, entitled “Augmented Spatial Modulation” is dedicated to detail ASM providing in depth analysis of it’s perception, transceiver design, design parameters, complexity, and performance evaluation. Chapter three, entitled “Machine Learning Enhanced ASM”, discusses the ML implementation of ASM; describing in detail the utilized ML methods and their performance evaluation. Chapter four, “Other Applications for the Augmented Technology”, presents two of the possible alternative applications for the ACom concept. These applications include a PHY security technique and a technique for spectral efficiency enhancement of SISO based VLC systems.
Chapter five, “Experimentation Testbeds”, depicts rate adaptation and jamming-aware spectrum assignment algorithms evaluated using hardware testbeds. Finally, the thesis concludes in chapter six, which includes future work and potential alternative deployment scenarios.
CHAPTER 2
Augmented Spatial Modulation (ASM)

The simplest form of MIMO is Repetition Coding, which simultaneously sends the same signal over multiple transmitters. It has the advantage of transmit-diversity, making it a technique that is resilient to noise and transmitter-receiver misalignment [22]. However, it does not provide any spectral multiplexing gains, as the same data is transmitted from all transmitters. In spatial multiplexing (SMP), parallel data streams are emitted from the transmitters, enabling high data rates by harnessing spatial multiplexing gains [12]. To provide these gains, low channel correlation is required. Spatial Modulation (SM) comes as a compromise between the two previously techniques, by setting one transmitter ON at a time. Hence, it eradicates inter-channel interference while improving the system’s complexity and spectral efficiency [22]. The concept behind SM is extracting additional bits from the spatial dimension by identifying the transmitting element from which the information was sent. The throughput of an SM system is \( R \leq \log_2(N_t M) \) bits per channel use, where \( M \) denotes the modulation order of the transmitted information and \( N_t \) denote the number of transmitters. Thus, SM allows a maximum throughput increase of \( \log_2(N_t) \) bits over SISO systems. However, as discussed in the problem statement, in order to achieve this increase in throughput, the channel matrix needs to be known at the receiver and its elements have to be unique. Hence, spatial uniqueness plays a fundamental role in recovering the spatial symbol, which is the entire premise of SM.

2.1 Background

A light-emitting diode (LED) and a laser diode (LD) are the two main types of optical sources used in VLC. Most VLC systems are non-coherent, \( i.e. \) the information is conveyed in the intensity of the emitted light. These systems are known as intensity-modulation direct-detection (IM/DD), as the received signal is directly detected, using a photo-detector, \( i.e. \) photodiode (PD), without the need for a local oscillator. OFDM has been widely adopted in VLC due to its frequency domain equalization simplicity and the fact that it is
Figure 2.1: ASM transmitted signals showing the effect of system parameters $\Psi$ and $\eta$. For illustration, a uni-polar real-valued ACO-OFDM signal with $N = 64$ is assumed and $\mu = 1$.

more optical power efficient in comparison to single-sub carrier schemes [43]. Conventional OFDM waveforms used in RF systems cannot be directly applied in IM/DD systems. Since IM/DD systems relies on intensities, the signal has to be real and non-negative. The two most eminent optical OFDM techniques are direct current optical OFDM (DCO-OFDM) and asymetrically clipped optical OFDM (ACO-OFDM). These techniques impose Hermitian symmetry (HS) before performing the inverse fast Fourier transform (IFFT) operation, which results in loss in spectral efficiency. In DCO-OFDM, only half of the OFDM subcarriers are carrying information, while in ACO-OFDM only quarter.

Conceptually, the proposed ACom concept could be applied on any single- or multi-carrier modulation technique. However, in this work, the system model is built on top of OFDM as it is the de facto modulation and multiple access scheme used in most current standards. An OFDM signal comprises of the sum of $N$ independent quadrature amplitude modulation (QAM) subsignals with $N$ representing the number of active subcarriers. A vector of QAM constellation points $X = [X_0, \ldots, X_{N-1}]^T$ is transformed via IFFT into discrete-time vector $x[k] = [x_0, \ldots, x_{N-1}]^T = \text{IFFT}(X)$,

$$x[k] = x = \frac{1}{\sqrt{N}} \sum_{q=0}^{N-1} X_q e^{j \frac{2\pi qk}{N}}$$

(2.1)

where the discrete-time index $[k]$ denotes Nyquist rate samples and superfix $[.]^T$ denotes the
transpose operation. In IM/DD VLC, for $x$ to be real, HS is imposed, i.e. $X_0$ and $X_{N/2}$ must be real and the following constraint must be satisfied [4],

$$X_q = X^{*}_{-q \mod N} = X^{*}_{N - q}$$  \hspace{1cm} (2.2)$$

where $*$ denotes complex conjugate. It is important to highlight that IM does not suffer from destructive fading and light intensities are superimposed constructively.

2.2 ACom in SM-based Systems

ACom in SM-based Systems, i.e. ASM, is built upon ACO-OFDM for its higher power efficiency, making it apt for IoT applications. In order to carry $\log_2 N_t$ bits, representing the different transmitters, along with the conventional data stream $x^N$, $N_t$ codewords are created each consisting of $N$ elements. The superfix $(.)^N$ denotes a vector of length $N \times 1$. The codewords, $b^N$, are binary and divided into $\eta$ groups of identical values. An ASM time-domain transmitted signal, $s^N$ can be given by

$$s^N = p^N \left( \frac{\Psi}{2} - \mu \cdot x^N \right)$$  \hspace{1cm} (2.3)$$

where $p^N$ is related to the transmitter index codeword and is given by $p^N = 2b^N - 1$. $\mu$ is the scaling factor applied to the optical OFDM (O-OFDM) symbols and $\Psi$ is a design parameter limited by the dynamic range of the transmitting light fixture, that parameter also relates the transmitter index identification accuracy with the signal-to-noise-ratio (SNR) penalty associated with the proposed scheme. The effect of the system parameters $\eta$ and $\Psi$ on ASM’s transmitted signal is depicted in Fig. [2.1]. The parameter $\Psi$ controls the amplitude of the transmitted signal chunks, while $\eta$ controls the pattern of the chunks to which the transmitter index codeword is applied to. Figure [2.2] shows the block diagram of an ASM transceiver.

For ACO-OFDM signalling, the average transmitted energy $E[|x^N|^2] = 0.25\sigma^2$, where $\sigma^2$ is the transmitted average electronic energy per QAM symbol. Since $s^N$ is a linear transformation of $x^N$, the probability density function (PDF) of $s^N$ will follow that of $x^N$. Hence, the expected energy of an ASM signal, on the other hand, can be calculated as
Figure 2.2: ASM transceiver with (a) Transmitter showing the codeword generator providing the codeword translating to the transmitter and the data splitter responsible of controlling which transmitting elements are active, and (b) Receiver with the demodulation block entailing SM and QAM demodulation.

\[ E[|s^N|^2] = p^N \left( \left( \frac{\Psi}{2} \right)^2 - 0.25\mu^2\sigma^2 \right) \]. This increase in energy induces the SNR penalty that is proportional to \( \Psi \).

2.3 Maximum Likelihood Detection

2.3.1 Realization

ASM detection consists of maximum likelihood detection (MLD) firstly invoked on the received signal in the time-domain to estimate the transmitter index, followed by frequency-
domain estimation of the bits encoded on the data stream, which is an approach that was also adopted in [45]. The time-domain demodulation process can be modeled as a hypothesis test with nuisance parameters, consisting of $N_t$ hypotheses denoted as $H_i$, with $i = 1, \ldots, N_t$, corresponding to the transmitter codewords conditioned in the form of the vector $p_{H_{i}}^N$. The auxiliary vectors, $u_{H_{i}}^N$, given by $u_{H_{i}}^N = y^N - \frac{\Psi}{2} p_{H_{i}}^N$, are defined, where $y^N$ is the received optical OFDM signal. The MLD returns only the hypothesis that maximizes the likelihood function of the estimated binary sequence, $\hat{b}$, i.e.

$$\hat{b} = \arg \max_i \left[ f_{u_{H_{i}}} (u_0, H_{i}, \ldots, u_{N-1}, H_{i}, | \hat{s}, H_{i}, \hat{H}_{i}) \right]$$

where $f_{u_{H_{i}}}$ is probability density function of $u_{H_{i}}$. Once the codeword is estimated and after simple mathematical alterations based on Eq. (2.3), an estimate of $x_N$ is obtained, i.e. $\hat{x}^N = \frac{1}{T_N} u_{H_{i}}^N$. Then, the output is converted to the frequency-domain to estimate the transmitted symbols.

### 2.3.2 Complexity Analysis

#### 2.3.2.1 Single Carrier Systems

MLD, which is based on the maximum likelihood principle, remains the most popular detection approach due to its optimality. MLD of SM systems involves the joint detection of both the transmitting element index and the transmitted symbol. Under the assumption of perfect CSI knowledge at the receiver, and given that the spatial channels are uncorrelated, MLD can be realized with a search complexity that grows linearly with the number of transmit elements and the modulation order of the transmitted data [46]. The joint MLD is then modelled as

$$\hat{\left( \hat{x}, \hat{i} \right)} = \arg \min_{x, i} \| y - h_i x \|_2^2$$

where $\hat{x}$ and $\hat{i}$ are the estimates of the transmitted symbol and transmitter, respectively, and $\| . \|$ denotes the two norm of a vector operation. Using the definitions introduced in [46], the number of evaluations required for an algorithm to reach a solution can be defined as the order of complexity, while the number of real-valued multiplications involved in solving
the problem is the computational complexity. Accordingly, the order of complexity of joint
MISO-SM using MLD is $MN_t$ and the computational complexity is $6N_tM$ [36]. However, in
practical scenarios, CSI at the receiver is imperfect and requires computationally extensive
channel estimation algorithms. The problem escalates in VLC due to the light propagation
properties which makes channel separation an extremely complexity-intensive task.

### 2.3.2.2 Multi-carrier Systems

OFDM, as previously mentioned, is currently the most predominantly adopted modula-
tion technique in wireless standards; due to its advantage in combining high achievable rates
with the ease in implementation and frequency domain equalization. In OFDM systems,
data is transmitted in symbols, denoted as $X$, which are most commonly QAM symbols.
The symbol undergoes an IFFT operation to produce the time domain symbol $x^N$, where $N$
is the IFFT length. An OFDM received signal in the frequency-domain can be presented by
rewriting Eq. (1.1) as [47]

$$Y = HX + N$$

(2.6)

where $Y$, $H$, $X$, and $N$ are the discrete Fourier transform (DFT) pairs of the received signal,
channel response, transmitted signal and the AWGN, respectively. In a MISO setting, $Y$
has the dimension of $1 \times N$, $H$ has the dimension of $1 \times N_t$, $X$ has the dimension of $N_t \times N$, and
$N$ has the dimension of $1 \times N$. Since the sequence $X$ is deterministic, MLD for OFDM-based
SM systems is performed in the frequency domain and, assuming perfect channel knowledge,
can be observed as

$$(\hat{X}, i) = \arg \min_{X, i} \| Y - H_i X \|_2^2$$

(2.7)

In this case, the order of complexity remains $MN_t$, while the computational complexity
becomes $(2 + 4N)N_tM$. Note that $\| Y - H_i X \|_2^2 = |\Re(Y - H_i X)|^2 + |\Im(Y - H_i X)|^2$ takes 2
real-valued multiplications and $H_i X$ takes $4N$ real valued-multiplications, yielding $(2 + 4N)$
multiplications. $\Re(.)$ and $\Im(.)$ represent the real and imaginary parts of a complex-valued
quantity, respectively.
Table 2.1: Comparison of the conceived detectors.

<table>
<thead>
<tr>
<th></th>
<th>Order of Complexity</th>
<th>Computational Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>SM-MLD</td>
<td>$MN_t$</td>
<td>$6N_tM$</td>
</tr>
<tr>
<td>OFDM-SM-MLD</td>
<td>$MN_t$</td>
<td>$(2 + 4N)N_tM$</td>
</tr>
<tr>
<td>ASM-MLD</td>
<td>$(1 + M)N_t$</td>
<td>$3NN_t + (2 + 4N)N_tM$</td>
</tr>
</tbody>
</table>

2.3.2.3 ASM Complexity Analysis

Compared with conventional transmission, ASM signal generation increases system complexity due to the element-wise multiplication and addition. Focusing primarily on multiplication, based on Eq. 2.3, and as can be observed in Fig. 2.2, two extra multiplications are required to form an ASM sample. Thus, for an OFDM symbol with $N$ samples, the complexity increases by $2N$ multiplication operations. On the other hand, at the receiver side the complexity escalates significantly. Per hypothesis, $N$ multiplications are needed to calculate the auxiliary vectors, $N$ for the binary sequence estimates, and $N$ to obtain $\hat{x}^N$, yielding a total of $3NN_t$ supplementary multiplication operations. The order of complexity is also increased by a factor of $N_t$, as $N_t$ operations are needed to evaluate the transmitter index in addition to the $MN_t$ operations for data stream detection. Table 2.1 lists the detection complexities of the conceived detectors for MISO realizations. As can be observed, in order to adopt the concept of ASM in massive-MISO deployment scenarios, the receiver requires complete restructuring to reduce the entailed complexity.

2.3.3 Codeword Error Correction

Forward error correction (FEC) is one of the fundamental concepts for digital communications and was first introduced in Shannon’s 1948 paper [48], which to this day still serves as the foundations of modern networks [49]. FEC is implemented by adding to the transmitted signal data a parity code that enables the receiver to detect and evaluate the data errors due to noise in the transmission channel. The FEC function comprises of an FEC encoder in the transmitter that accepts information bits and adds computed redundant symbols, producing encoded data at higher bit rate; and an FEC decoder in the receiver that performs the error correction while extracting the redundancy to regenerate the original data.
By analogy, we can observe that there is naturally inherited redundancy in ASM’s
codewords that can be mapped to the FEC concept. In ASM, a signature (i.e. codeword),
b^N, is assigned to each transmitter, being the OFDM symbol of the length N is divided into
η chunks. Within each codeword, N/η samples have the same value. This means that ASM
can be observed to have inherent repetition coding properties. With the aid of a majority
vote decoder, the spatial bits can be corrected based on this inherited redundancy. This
configuration allows ϱ = \frac{N-1}{2} errors to be corrected [50]. The minimum distance between
the codewords is given by d_{min} = 2\varrho + 1 and the probability of error for this configuration
can be obtained through the following relationship

\[ P_{rep} = \sum_{\kappa = \varrho+1}^{N/\eta} C_{\kappa}^{N/\eta} p_c (1 - p_c)^{N/\eta - \kappa} \approx C_{\varrho+1}^{N/\eta} p_c^{\varrho+1} \]  

(2.8)

where \( p_c \) is the probability of error of codeword sample and \( C_n^k = \frac{n!}{k!(n-k)!} \).

2.3.4 Results

To evaluate the efficacy of the proposed system, the configuration discussed in the
chapter 1 is assumed, i.e. a 4 × 1 MISO configuration. The simulation parameters are
16-QAM and the IFFT length is 64 with the presence of AWGN. Figure 2.3 shows the trans-
mitter identification accuracy for various background noise levels vs. the separation distance
between the transmitter and the receiver. The accuracy at distance 2.15 m is highlighted
for clarity. Following Eq. (1.2) and (1.3), the received signal is inversely proportional to
the square of the transmitter-receiver separation, i.e. \( d^2 \). Results provided in Fig. 2.3 show
almost 100% transmitter identification accuracy can be achieved at SNR = 15 dBm, given
the transmitted signal power is 15 dBm and the noise power is equal to 0 dBm at \( d = 2.15 \)
m. Intuitively, as the noise power increase, the identification accuracy decreases. However,
even at SNR = 10 dBm, above 96% identification accuracy is achieved as depicted by the red
curve in Fig. 2.3. These notable findings demonstrate the competence of ASM, as this PHY
identification capability is dependent solely on the design and does not require perfect CSI
conditions. Moreover, it can be simply scaled up as it is independent of channel uniqueness,
providing significant spectral efficiency enhancements.

The effect of the system design parameter \( \Psi \) on the identification accuracy of trans-
Figure 2.3: Identity accuracy vs. transmitter-receiver separation distance for various background noise levels given the transmitted signal power is equal to 15 dBm at $\Psi = 0.2$.

Figure 2.4: Identity accuracy vs. transmitter-receiver separation distance for various values of $\Psi$ given SNR is equal to 5 dBm.

Transmitter indexes is shown in 2.4. The SNR value of the system is assumed to be 5dBm. As depicted, accuracy is proportional to the value of $\Psi$. At the transmitter-receiver separation distance of 2.15m, even at an SNR value of only 5dBm, almost 100% identification accuracy can be achieved for $\Psi = 0.4$ and $\Psi = 0.5$, while $\Psi = 0.3$ has an identification accuracy of about 94%. The reason behind this behaviour can be traced back to Fig 2.1. As previously mentioned, the parameter $\Psi$ controls the distance between the reverse polarity levels; the larger the spacing, the lower the likelihood that transmitter index would be demodulated in error. However, there is a trade-off between transmitter index identification
accuracy and the associated SNR penalty. Figure 2.5 shows this SNR penalty for various \( \Psi \) values using the theoretical performance of 16-QAM transmission (in blue) as a reference curve. The performance of conventional SM-MISO is also included (in grey) for performance evaluation. As depicted, there is a significant improvement, in terms of BER performance, between ASM, for all its \( \Psi \) values, in comparison to conventional SM-MISO transmission. Additionally, as per the discussion, increasing \( \Psi \) comes at a price of an SNR penalty in com-
Figure 2.7: ASM’s BER performance vs. SNR for 16-QAM OFDM transmission with $N = 64$ using various values of $\Psi$ and $\eta = 32$ with reference to correlated CSI cases.

Comparison to the theoretical 16-QAM performance, which is about 3dBm, 6dBm, and 9dBm for $\Psi = 0.2$, 0.4, and 0.6, respectively. The BER performance of ASM is also compared with SM-MIMO’s performance given the imperfect CSI cases and correlated CSI cases discussed in chapter one, which are provided in Fig. 2.6 and 2.7, respectively. From the figures, ASM’s superiority over conventional SM ($4 \times 4$ MIMO configuration) is apparent as transmitter identification does not rely on channel uniqueness and hence is not susceptible to imperfect CSI nor channel correlation. The benefit of this approach is not only to relax the stringent CSI requirements of traditional SM transmission, but also to make the performance uniform and independent of user location or transmitter-receiver alignment/geometry. Moreover, this approach can allow restructuring the distribution of bits among the explicitly sent data stream and those sent implicitly using the spatial domain. In other words, assuming a VLC access-point consisting of a large array/grid of LEDs, a lower modulation order can be chosen for the explicitly transmitted data as more bits can be harvested using the spatial stream as $N_t$ increases.

The capacity of ASM in comparison to SM-MISO and SM-MIMO assuming perfect channel conditions ($\rho = 0$ and $\delta = 1$) for various values of $\Psi$ is shown in Fig. 2.8 assuming an SNR value of 5dBm. Intuitively, capacity increases with $\Psi$, as the error of transmitter index identification decreases. However, as can be observed, $\Psi = 0.5$ is sufficient for ASM’s performance to match that of perfect SM-MIMO transmission. There is minimal improve-
Figure 2.8: Capacity of ASM vs. number of transmitters for various $\Psi$ values in comparison with SM-MISO and SM-MIMO assuming perfect channel conditions.

The gain of using the codeword error correction analysis in Section 2.3.3 is evaluated in Fig. 2.9 for $\Psi = 0.2$. At $\eta = 32$, the number repeated elements in $p^N$ is only equal to 2. Then, spatial error correction cannot be performed (as the redundancy is not sufficient for error correction) and hence, the performance is similar to that presented in Fig. 2.8. Yet, as the value of $\eta$ increases, the number of repeated bits increases and hence spatial error correction can be performed. As previously mentioned, the number of repeated bits is equal to $N/\eta$. It is also important to note that the number of served transmitters is related to the parameter $\eta$, such that the number of served transmitters is equal to $2^\eta$. This explains why capacity at $\eta = 2$ saturates at number of transmitters is equal to 4, as the system can only serve $2^2 = 4$ transmitters.

2.4 An Alternative Approach

2.4.1 Walsh Codes and Bank of Correlators Realization

Walsh codes, which are considered one of the most well-known classes of sequences and are highly adopted in CDMA-based systems [51], are linear codes that map binary strings of length $n$ to binary codewords of length $2^n$. Walsh codes are generated from Hadamard
Figure 2.9: Capacity of ASM vs. number of transmitters after applying spatial error correction at $\Psi = 0.2$ for various $\eta$ values in comparison with SM-MISO and SM-MIMO assuming perfect channel conditions.

matrices that are built recursively in the following form:

$$W_{2n} = \begin{pmatrix} W_n & W_n \\ W_n & W_n^c \end{pmatrix}$$

(2.9)

where $W_1 = (1)$, $W_2 = \begin{pmatrix} 1 & -1 \end{pmatrix}$, and $W_n^c$ denotes the complimentary of $W_n$. As can be observed, the Hadamard matrix $W$ of order $n$ is an $n \times n$ matrix that contains 1s and $-1$s, such that $WW^T = nI_n$ with $I_n$ being the identity matrix of size $n \times n$.

There are three fundamental properties for Walsh codes that have made them a substantial candidate for our realization, namely; their Hamming distance, orthogonality, and the fact that they can be considered complimentary codes. These properties are discussed as follows:

1. **Hamming distance:** The Hamming distance between any two Walsh codes is $2^{n-1}$. Being linear codes, the difference of any two Walsh codes results in another codeword, which implies the distance of $2^{n-1}$.

2. **Orthogonality:** Walsh codes are orthogonal codes by design, meaning that the rows of the generating matrices are mutually orthogonal.
3. **Complimentary Property:** If the all 1s (and in some implementations the all 0s) code is excluded, it can be observed that the number of 1s in any code is equal to the number of −1s within the same code.

By using Walsh codes instead of the randomly generated codes discussed in the previous section, the behaviour of the codes can be better characterized. In other words, the complimentary property allows us to assign codes to transmitters that uniformly affect the SNR penalty discussed previously. The orthogonality property would isolate the cause of incorrect codeword detection from the codewords themselves and the focus would be channel effects and transmitted signal properties. Lastly, the complimentary property would aid in estimating the bounds for incorrect codeword detection, as is discussed in detail in the upcoming subsection. In our case, we want the codewords to be of length \( N \), where \( N \) represents the IFFT length of our OFDM symbol. Hence, \( n \) must equal to \( \log_2 N \) and in return there will be \( N \) codewords of length \( N \) that can be assigned to the different transmitters. Based on this implementation, a limit is enforced on the number of served transmitters given a specific IFFT length.

The alternative transceiver realization using Walsh codes is presented in Fig. 2.10. The transmitter block is similar to Fig. 2.2, with the exception of Walsh codes generation. The receiver on the other hand is realized using a bank of correlators architecture. Unlike the analysis in Section 2.3.3, the introduction of Walsh codes does not allow the analogy to repetition coding. However, given the complimentary property of Walsh codes, the system can be considered capable of detecting errors if there happened to be uneven number of 1s and −1s in the estimated codeword. Hence, in Fig. 2.10, there exists an error detection block responsible to checking the balance property of the predicted codeword.

### 2.4.2 Symbol Error Rate Analysis

Let \( P_e \) be defined as the average symbol error rate (SER) of an ASM-based system and \( P_e^{(i)} \) is the SER assuming that the \( i^{th} \) transmitter is chosen to transmit the information. In this sense, \( P_e \) can be defined as

\[
P_e = \sum_{i=1}^{N_t} P_e^{(i)} = \sum_{i=1}^{N_t} \frac{1}{N_t} P_e^{(i)}
\]  

(2.10)
Figure 2.10: Alternative realization of ASM transceiver with (a) Transmitter showing the codeword generator providing the codeword translating to the transmitter and the data splitter responsible of controlling which transmitting elements are active, and (b) Receiver with the demodulation block entailing SM and QAM demodulation.

given that $P_e^{(i)}$ is the probability of choosing the $i^{th}$ transmitter to transmit the information and the choice between the transmitters is assumed to be equally probable. Intuitively, it can be observed that there are three possible causes for $P_e^{(i)}$: 1) Both the explicitly transmitted symbol and the implicit spatial symbol are received in error, 2) The transmitted symbol is received correctly but the spatial symbol is received in error, or 3) The spatial symbol is demodulated correctly but the transmitted symbol is erroneously received. Hence, $P_e^{(i)}$ can be expressed in the form of the sum of those errors as

$$P_e^{(i)} = P_a^{(i)} P_s^{(i)} + P_a^{(i)} (1 - P_s^{(i)}) + (1 - P_a^{(i)}) P_s^{(i)} = P_a^{(i)} + (1 - P_a^{(i)}) P_s^{(i)}$$  \(2.11\)
where $P_a^{(i)}$ is the probability of error of the spatial symbol transmitted by transmitter $i$ and $P_s^{(i)}$ is the conditional error probability of the transmitted symbol given that it is sent from transmitter $i$. Assuming M-ary QAM transmission, $P_s^{(i)}$ can be expressed as

$$P_s^{(i)} = 1 - \left[1 - \frac{\sqrt{M} - 1}{\sqrt{M}} 2 Q\left(\sqrt{\frac{3\gamma}{M - 1}}\right)\right]^2 \quad (2.12)$$

where $M$ is the modulation order, $\gamma$ represents the SNR, and $Q(.)$ represents the $Q$-function representing the tail distribution of a Gaussian distribution.

In order to analyze $P_a^{(i)}$, let us recall that in this realization the codes applied at the transmitter side, $p^N$, are designed to belong to a set in $N \times N$ Walsh codes generated from Hadamard matrices. For Walsh codes, as previously mentioned, the hamming distance between any two codes is equal to $2^{n-1}$. Based on the aforementioned property and given the orthogonality nature of Walsh codes, assuming an AWGN channel, we can represent the projection of the output of the integrators at the receiver as Fig. 2.11. Assuming transmitter $i$ is chosen to be the active transmitter, out of $N_t$ correlators in the receiver bank only one branch, which corresponds to the code chosen for transmitter $i$, will return the signal back to its original O-OFDM form and after accumulation the value $\sqrt{E_s}$ corresponding to the energy of the transmitted O-OFDM symbol is produced. On the other hand, the output of the other correlators is a distorted version of the original O-OFDM, with $2^{n-1}$ samples having augmented values. Thus, after the accumulation, the result is $\sqrt{E_s}\sqrt{1 + 2^{n-1}\phi/2}$.

Given that transmitter $i$ is active, the probability of error is simply the probability...
where \( a \) is the mid-point between the two signal such that
\[
a = \sqrt{\frac{E_s}{2}} \left[ 1 + \sqrt{1 + 2^{n-1} \Psi / 2} \right] .
\]

\[
P(e|i) = \int_{-\infty}^{a} p(r|i) dr
\]
\[
= \frac{1}{\sqrt{\pi N_o}} \int_{-\infty}^{a} exp \left[ - \frac{(r - \sqrt{E_s})^2}{N_o} \right] dr
\]
\[
= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{2}{N_o} \left[ a - \sqrt{E_s} \right]} e^{-x^2/2} dx
\]
\[
= \frac{1}{\sqrt{2\pi}} \int_{\frac{a}{\sqrt{N_o}} \left[ \sqrt{E_s} - a \right]}^{\infty} e^{-x^2/2} dx
\]
\[
= Q(\sqrt{\frac{2E_s}{N_o}} - a\sqrt{\frac{2}{N_o}}) \tag{2.13}
\]

Similarly, since all the codes have the same hamming distance between them and given the choice of the transmitters is assumed to be equally likely, then average probability of error is
\[
P_a(i) = Q(\sqrt{\frac{2E_s}{N_o}} - a\sqrt{\frac{2}{N_o}}) \tag{2.14}
\]

Substituting (2.12) and (2.14) into (2.11) yields
\[
P_e(i) = Q(\sqrt{\frac{2E_s}{N_o}} - a\sqrt{\frac{2}{N_o}}) + \left( 1 - Q(\sqrt{\frac{2E_s}{N_o}} - a\sqrt{\frac{2}{N_o}}) \right) \left[ 1 - \left( 1 - \frac{\sqrt{M} - 1}{\sqrt{M}} \right) 2Q(\sqrt{\frac{3\gamma}{M - 1}})^2 \right] \tag{2.15}
\]

Based on (2.10), the average SER can then be expressed as
\[
P_e = \sum_{i=1}^{N_t} \frac{1}{N_t} Q(\sqrt{\frac{2E_s}{N_o}} - a\sqrt{\frac{2}{N_o}}) + \left( 1 - Q(\sqrt{\frac{2E_s}{N_o}} - a\sqrt{\frac{2}{N_o}}) \right) \left[ 1 - \left( 1 - \frac{\sqrt{M} - 1}{\sqrt{M}} \right) 2Q(\sqrt{\frac{3\gamma}{M - 1}})^2 \right] \tag{2.16}
\]

### 2.4.3 Parameter Adaptation

In the previous subsections, it was assumed that \( \Psi \) is a predefined design parameter. This implies that the achievable performance is affected by the SNR penalty related to the choice of \( \Psi \). Hence, in this subsection, we further propose a novel parameter adaptation algorithm, in order to circumvent this limitation. More specifically, the algorithm is designed to choose the values of \( \Psi \) and \( M \) (the modulation order) to satisfy certain BER and data-
rate performance for the given SNR conditions. In order to enable the practical adaptive operation, a feedback loop from the receiver to the transmitter is required. Parameter adaptation decisions are chosen based on the metrics that can be inherited from system performance evaluation. Such metrics include the received signal SNR and the packet loss. It is important to note that adaptation for RF links have been well established, the challenge in this case lies in designing a suitable adaptation scheme for VLC. The challenging nature of this task is further aggravated by the fact that, the VLC link has no feedback path and that there are no prior studies on coherent communication in optical links. Hence, alternative technologies such as infrared (IR) or a RF link can feedback the metrics to infer parameter adaptation, which requires careful consideration of the trade-off between performance enhancement and overhead.

1. **SNR:** The coherence of SNR, i.e. how the SNR changes with respect to time and frequency, is a key indicator of the versatility of the SNR metric for the purpose of parameter adaptation. In other words, the coherence of SNR over time, enables the SNR measurements to be used with less frequent updates for the purpose of parameter adaptation, which make the overhead incurred reasonable. Moreover, the coherence of SNR over frequency indicates the possibility of using a single SNR measurement for the entire band, which is especially true at narrower bandwidths, leading to less overhead unlike in [52]. Once the transmitted packets are received at the receiver, they are post-processed and the SNR of the channel is estimated (as in [52]). Then, the measured SNR is sent to the transmitter via an Acknowledgement frame and the transmitter uses the BER-SNR performance to determine the modulation order and value for $\Psi$ for the next transmission.

2. **Packet Loss:** The packet loss is another metric, that can be used to infer the performance of the communication link. The packet loss has the added advantage of capturing the channel quality and the level of congestion. The packet loss metric for rate adaptation can be initially realized by the transmitter transmitting with the highest parameter settings. The receiver evaluates the packet error rate (PER) per every 10 packets received. If the PER exceeds a certain threshold, an Acknowledgement is sent to the transmitter to switch to a lower rate. Note that in both metrics the acknowledgement is only sent when there is a change in the metric detected, and hence both metrics incur reasonable overhead.

The proposed parameter adaptation algorithm can be observed as a sorting problem.
and its objective is to assign an $\Psi$, from set $\Psi^a$ that contains all possible values of $\Psi$, with the least accompanying SNR penalty given certain metrics listed previously. At the beginning of transmission, based on the metrics, there will be the set, $\Psi^a$, listing the possible values of $\Psi$. For clarity, the SNR-based algorithm is executed in three main steps that can be summarized as:

1. The modulation order $M$ is calculated using the knowledge of the required capacity, $(R_{th})$, the number of available transmitters to utilize ($N_t$), and the IFFT length ($N$).

2. The $\Psi$ values that do not satisfy the metric threshold will be excluded from $\Psi^a$ yielding a new feasible set, $\Psi^f$. In other words, the algorithm calculates the SNR performance of the system given the proposed $\Psi$ and the modulation order $M$ and excludes the values of $\Psi$ that do not satisfy the SNR requirement $SNR_{th}$.

3. If the $SNR_{th}$ requirement can be satisfied, then $\Psi$ with the largest value in $\Psi^f$ is chosen. As this is the value that provides the highest identification accuracy given the provided threshold. However, if neither of the values can satisfy the threshold, then $\Psi$ is chosen as the highest value in $\Psi^a$ and the accompanied SNR penalty will cause the $SNR_{th}$ requirement to not be satisfied.

Thus, the pseudocode for the proposed parameter adaptation assignment can be written as Algorithm 1.

**Algorithm 1 SNR-based ASM Parameter Adaptation Algorithm**

**Input:** $SNR_{th}$, $R_{th}$, $N_t$, $N$

**Output:** Chosen modulation order $M$ and $\Psi$

Compute $M$

$M \leftarrow \text{ceil}(2^{\frac{R_{th} - \log_2 N_t}{N}})$

*Initialization*: Let $\Psi^f \leftarrow \Psi^a$

*while* ($SNR_{\Psi}^{(i)} > SNR_{th}$) *do*

$\Psi^f \leftarrow \Psi^f - \{i\}$

$i \leftarrow i + 1$

*end while*

*if* $\Psi^f \neq \emptyset$ *then*

$\Psi \leftarrow \max(\Psi^a)$

*else if* $\Psi^f \neq \emptyset$ *then*

$\Psi \leftarrow \Psi^{(i)}$

*end if*
2.4.4 Results

To verify the accuracy of the theoretical expression of the average SER provided in Eq. (2.16), the theoretical results are compared with the simulation results of the average SER under various \( \Psi \) values in Fig. 2.12. Intuitively, SER decreases with the increase of SNR. Additionally, as can be observed in Fig. 2.12, the derived theoretical values match the simulated SER results. Similar to the previous analysis, the value of \( \Psi \) comes with an
SNR penalty that increases with the value of $\Psi$ in comparison to conventional 16-QAM O-OFDM transmission depicted as blue and red curves, representing theoretical and simulation results, respectively. Identification accuracy versus transmitter-receiver separation distance for different values of $\Psi$ are recalculated based on the new ASM realization and presented in Fig. 2.13. As can be observed, the identification accuracy has improved in comparison to Fig. 2.4, which can be traced back to the orthogonality nature of the Walsh codes that reduced misidentifying the transmitting indices. This improvement in identification accuracy versus $\Psi$ also reflected on the capacity of the system as provided in Fig. 2.14. As depicted, the rate in bit/s/Hz for a given $\Psi$ has improved over the rates provided in Fig. 2.8. Lastly, the parameter adaptation algorithm presented in Section 2.4.3 is evaluated in Fig. 2.15. At $N_t = 10$, meaning there are ten transmitting elements that can be utilized, the system first started by choosing the highest $\Psi$ value, $\Psi = 0.6$, then started to converge to the performance of $\Psi = 0.4$. At $N_t = 100$, given that there are 7 bits that can now be harvested from the spatial domain, the system started adapting both the modulation order and the value of $\Psi$. Same applies for $N_t = 1000$, adaptive ASM (A-ASM) offloads more bits on the spatial domain and uses a lower modulation order, which reduces the SNR penalty significantly.
Figure 2.15: BER performance of adaptive ASM (A-ASM) vs. SNR for a various number of transmitters available to be utilized by the system, given a minimum capacity requirement of 4 bits/s/Hz at an SNR value of 5dB. The performance of non adaptive ASM is also included for comparison.
CHAPTER 3
Machine Learning Enhanced ASM

With the development of cutting-edge hardware architectures, such as tensor processing units (TPUs) and graphical processing units (GPUs), machine intelligence has emerged from laboratory curiosity to practical implementation. In wireless communications, machine intelligence has been used in signal detection [53, 54, 55], channel estimation [56, 57], channel encoding and decoding [58, 59, 60], and CSI sensing [61]. This chapter is dedicated to explore machine learning (ML) approaches to improve the performance of classical ASM.

3.1 Receiver Reconstruction

Since the transmitter identification problem can be observed as a classification problem, ML-based classifiers are evaluated as a replacement for the MLD discussed in the previous chapter. Even though ML algorithms are observed as techniques that entail intensive computational complexity, the truth of the matter is the training phase of the algorithms is the obstacle and not the prediction phase. Unlike applications that are time-varying in nature and require online training, the classification problem in ASM is deterministic and static in nature. Intuitively, since the possible codewords that can be used are fixed, the problem becomes deterministic. Thus, the proposed methods can be trained offline and the training computational complexity can be discarded in system complexity evaluation.

3.1.1 Proposed Machine Learning Techniques

The chosen ML-based classifiers are: naive Bayesian (NB)-classifier, support vector machine (SVM), multi-nominal logistic regression (LR), and a neural network (NN). Well-known multi-class classification approaches are intentionally used because they are readily available off-the-shelf as hardware components that can be employed in practice.
3.1.1.1 Naive Bayesian Classifier

The NB classifier is a supervised learning algorithm based on applying Bayes’ theorem with the naive assumption of conditional independence between every pair of features given the value of the class variable. According to Bayes’ theorem, given class variable $c_z$ and dependent feature (data) vector $d_z$, through $d_{zN}$:

$$
P(c_z|d_z, \ldots, d_{zN}) = \frac{P(c_z)P(d_z, \ldots, d_{zN}|c_z)}{P(d_z, \ldots, d_{zN})}
$$

(3.1)

Using the naive conditional independence assumption, the aforementioned equation can be simplified as

$$
P(c_z|d_z, \ldots, d_{zN}) = \frac{P(c_z) \prod_{i=1}^{N} P(d_z|c_z)}{P(d_z, \ldots, d_{zN})} \propto P(c_z) \prod_{i=1}^{N} P(d_z|c_z)
$$

(3.2)

Then, using Maximum Aposteriori (MAP) estimation, $P(c_z)$ and $P(d_z|c_z)$ can be estimated and the estimated class can be calculated. There are different NB classifiers based on the assumptions they make regarding the distribution of $P(d_z|c_z)$; in this implementation the Gaussian NB classifier is used. The likelihood of the features in Gaussian NB is assumed to be Gaussian, which means that

$$
P(d_z|c_z) = \frac{1}{\sqrt{2\pi\sigma^2_{c_z}}} \exp\left(-\frac{(d_z - \mu_{c_z})^2}{2\sigma^2_{c_z}}\right)
$$

(3.3)

The parameters $\sigma_{c_z}$ and $\mu_{c_z}$ are estimated using maximum likelihood.

3.1.1.2 Support Vector Machines

SVMs are supervised learning methods used for classification, regression and outliers detection. An SVM firstly constructs a hyper-plane or a set of hyper-planes in a high or infinite dimensional space by mapping the training data through a nonlinear feature mapping function $\phi(d)$, where $d$ is the training data [62]. Then, an optimization method is used to maximize the separating margin between the classes in the feature space with the main objective of minimizing the training error $\xi_z$. Given a set of training data $(d_z, c_z)$, $z = 1, \ldots, Z$, where $c_z \in \{-1, 1\}$ denote the labels of the training $d_z$; $-1$ entails not belonging to the class and $1$ entails belonging to the class. The optimization problem can be expressed
as

\[
\text{Minimize: } J_{SVM} = \frac{1}{2} \| \omega \|^2 + D \sum_{z=1}^{Z} \xi_z
\]

\[
\text{Subject to: } c_z (\omega \cdot \phi(d_z) + b) \geq 1 - \xi_z, \quad z = 1, \ldots, Z
\]

\[
\xi_z \geq 0, \quad z = 1, \ldots, Z
\]

(3.4)

where \( D \) is a user-specified parameter and provides a tradeoff between the distance of the separating margin and the training error; in our implementation \( D = 1 \). The parameter \( b \) is a bias parameter and \( \omega \) represents the weights. Another form of the SVM problem can given by

\[
\min_{\omega} \frac{1}{2} \omega^T \omega + D \sum_{z=1}^{Z} \xi(z, d_z, c_z)
\]

(3.5)

where \((.)^T\) denotes the transpose operation. For multiclass classification applications, as in our application, one against all \((i.e. \ \text{one-vs.-all})\) and one against one \((i.e. \ \text{one-vs.-one})\) methods are mainly used for SVM implementation. One-vs.-all consists of an array of SVMs based on the number of classes, which is in our case \( N_t \) classes. All the samples of the \( i \)-th class is trained with positive labels for the \( i \)-th SVM, while the remaining \( N_t - 1 \) classes are trained with negative labels. For one-vs.-one, \( N_t(N_t - 1)/2 \) SVMs are trained with samples from two classes only. In our implementation, the SVM multiclass support is handled according to a one-vs.-one scheme. The implementation is based on the popular SVM library LIBSVM \[63\].

3.1.1.3 Logistic Regression

Logistic regression, despite its name, is a linear model for classification rather than regression. The most commonly used objective function for learning in LR is the cross entropy error function, which is an error function that takes the negative logarithm of the likelihood. The same problem given in (3.5) needs to be solved for LR with the exception of the loss function, \( \xi(z, d_z, c_z) \), which is now \( \log(1 + e^{-c_z(\omega^T d_z + b)}) \) for L2 regularized LR. The aim is also to find the set of weights and biases that reduces (minimizes) this loss function.
Hence, the optimization problem can be formulated as

$$
\min_{\omega,b} \frac{1}{2} \omega^T \omega + D \sum_{z=1}^{Z} \log (1 + e^{-c_z(\omega^T d_z + b)}) \tag{3.6}
$$

One of the solvers for this problem is the lbfgs solver; it is a limited-memory quasi-Newton code for bound-constrained optimization that approximates the Broyden–Fletcher–Goldfarb–Shanno algorithm. Multinomial LR is a simple extension of aforementioned binary LR to allow more than two categories of the dependent or outcome variable. Like binary LR, multinomial LR uses maximum likelihood estimation to evaluate the probability of categorical membership. The training samples are used to train a model that associates the input to a class, which in our case has \( N_t \) possibilities. In our implementation, a multinomial LR with L2 regularization is used and the lbfgs solver is used due to its robustness.

### 3.1.1.4 Neural Network

A NN is a network of small computing units, each of which takes a vector of input values and produces a single output value and learn to induce features as part of the process of learning to classify; NNs share much of the same mathematics as LR. To reduce the complexity of the system, our supervised feed-forward fully-connected NN is limited to a single-hidden-layer. A feed-forward network is a network in which the computing units are connected with no cycles, i.e. the outputs from each layer are passed to the next higher layer, and no outputs are passed back to lower layers. Fully-connected means that each unit in each layer takes as input the outputs from all the units in the previous layer. Our NN comprises of an input layer, one hidden layer, and a dense layer with softmax activation function to perform classification. The network is trained to minimize the sparse categorical cross entropy loss function, which can be defined as

$$
J(\omega) = -\frac{1}{P} \sum_{i=1}^{P} \left[ p_i \log(\hat{p}_i) + (1 - p_i) \log(1 - \hat{p}_i) \right] \tag{3.7}
$$

where \( \omega \) are the weights of the NN, \( p_i \) is the true codeword, and \( \hat{p}_i \) is the predicted codeword. During training, a training sample size of \((250 \times N_t)\) frames, that constitute the data, and are split 80% for training and 20% for testing. The network is trained using a single-SNR
value of 10dBm for 10 epochs with a fixed number of 50 neurons in the hidden layer.

3.1.2 MISO Implementation

The implementation is executed using Google’s colab environment to leverage Google’s hardware architectures that include central processing units (CPUs), GPUs, and TPUs for performance comparison. Firstly, the computation time required for the ML techniques to estimate the utilized transmitter vs. the number of transmitters is calculated and shown in Fig. 3.1(a). As shown, the LR’s performance was the worst by having the highest computation times. On the other hand, both the NB and the NN have considerably constant computation time regardless of number of transmitters, however, with the NB significantly outperforming all the rest due to having the least computation time. Apparently, the NB classifier is faster than the more sophisticated methods, as the decoupling of the class con-
ditional feature distributions means that each distribution can be independently estimated as a one dimensional distribution. This in turn helps to alleviate problems stemming from the curse of dimensionality.

Then, the codewords estimation accuracy of the proposed ML techniques are evaluated. Figure 3.1(b) shows the confidence interval of the various ML-classifiers at $\Psi = 0.2$, $\eta = 32$ and $\mu = 1$. All the ML methods are able to classify up to 4 transmitters with a 100% accuracy, which is the most common number of transmitters utilized in VLC MIMO settings. From Fig. 3.1(b), the NN consistently has the largest interval, i.e. worst performance. On the other hand, the NB-classifier’s accuracy matches that of the LR and SVM. Given its superiority in terms of computation time and classification accuracy, NB-based ASM can be a strong contender in applications with low latency requirements. Finally, any communication system is quantified by its BER performance evaluation. NB-based ASM’s BER performance is compared to theoretical BER performance in Fig. 3.1(c) as a benchmark. As depicted, the BER performance of NB-based ASM is consistent with the theoretical BER under the assumption of an AWGN channel model. The simulation is based on phase-shift-keying (PSK) with a modulation order of 32 optical OFDM-based transmission given $N_t = 10$. The confusion matrices for the various ML techniques are depicted in Fig. 3.2 with $N_t = 10$ at system parameter $\Psi = 0.2$ and $\eta = 16$ and $\mu = 1$. As can be observed, the NB outperformed all the other ML techniques by achieving 100% classification accuracy, while mislabeling occurs at the other ML techniques.

### 3.1.3 Massive MISO Implementation

Even though the performance of the NB classifier is comparable to the three other ML techniques when the number of transmitters is limited, it’s performance significantly degraded (in terms of identification accuracy) as the number of the transmitters increased. Hence, the previous analysis is repeated but this time focusing on the performance of SVM, LR, and NN for the case of massive-MISO implementation. Again, the time needed for the ML techniques to identify the transmitting element using different architectures versus the number of transmitters is evaluated and depicted in Fig. 3.3. As can be observed, the SVM has the worst performance, as it required the most amount of time for computation. Even in the case of 1000 transmitters, both the LR and the NN are able to classify in less than
Secondly, the identification accuracy of the ML techniques are assessed. All the ML techniques are able to accurately identify the transmitting element with an accuracy above 99% even at 1000 transmitters as shown in Fig. 3.4. As can be observed, at $\Psi = 0.4$, LR has the highest identification accuracy, followed by the NN then the SVM. Yet, at $\Psi = 0.6$, the NN has the advantage of remaining relatively constant and independent of the number of transmitters, hence, unlike MLD-ASM, complexity is not a function of the number of transmitters and thus massive-ASM can be facilitated. In our application, the different architectures behaved similarly; however, the TPU has slightly better performance.
the NN has the best identification accuracy, followed by the SVM and then the LR. Even though the identification/classification accuracy improves as the parameter $\Psi$ increases for all techniques, the LR seems to benefit the least from increasing $\Psi$. Consistently, the NN has better performance in our case than SVM, yet the effect of $\Psi$ on LR seems minimal, which is probably due to the fact that LR is based on statistical approaches rather than the geometrical properties of the data like SVM and NN [62]. However, it is important to note that increasing $\Psi$ results in an increase in the SNR penalty, as depicted in Fig. 3.5. As ASM’s perception does not rely on channel uniqueness, the modulation order of the conventional bit stream can be reduced as more information can be conveyed in the spatial stream.
For BER performance evaluation, ASM’s BER performance is compared to SISO systems as a benchmark. Assuming normalized bandwidth, 4-QAM has a spectral efficiency of 2 bps/Hz, while 1024-QAM has 10 bps/Hz. Given the high accuracy in spatial bits detection, we implemented a 4-QAM 1000 transmitter ASM system which is equivalent to the combined transmission of 4-QAM and 1024-QAM SISO links. In such setting, ASM transmits 12-bits per transmission, 2 through the conventional stream and 10 (representing 1000 transmitters) through the spatial stream, resulting in a normalized spectral efficiency of 12 bps/Hz. Figure 3.5 shows that ASM, at $\Psi = 0.4$, only has about 5-dB SNR penalty over single-stream 4-QAM at BER=$10^{-3}$, yet has a gain of 20dB over 1024-QAM even though it supersedes it in terms of spectral efficiency.

3.2 Autoencoder (AE) Architecture

3.2.1 Introduction

Deep learning (DL) techniques are becoming a part of groundbreaking systems in various fields, particularly computer vision and speech recognition. They are applied in various fields to make the systems more efficient. Mostly, they are used in images for applications such as object detection, handwritten digit classification, and face detection. However, there has been a surge of interest in using DL in communication systems. One of the fundamental communication problems is the reliability in the reconstruction of the transmitted messages.
from a noisy environment, i.e. communication reliability between the transmitter and the receiver [64]. In classical communication, a profusion of research has been done in order to improve communication reliability. In a classical approach, all the processing blocks in the communication chain are separately optimized in order to achieve performance close to the theoretical. However, such optimization process is considered sub-optimal. Alternatively, the idea of DL in communication is based on end-to-end performance enhancement through joint optimization of the whole model to map a set of inputs with certain distribution to a finite set of outputs or targets. Consequently, DL has recently become a potential candidate to achieve reliable communication without any prior mathematical modeling to achieve optimal performance through end-to-end training [65].

Communication techniques are developed based on probability and signal processing theory for channel models. Practical imperfections in these models cannot be replicated. These techniques when tested in scenarios, they have some degree of inaccuracy, resulting in false performance evaluation [66]. DL-based systems can detect faults in the systems without using complex equations. DL can perform a wide range of applications in communication systems like channel modeling and prediction, localization, modulation recognition, and spectrum sensing [65]. The problem of modulation recognition can be solved by studying the use of DL techniques on complex IQ samples. One of the technologies where DL can be applied is VLC. The constraints of the optical signals such as, non-negativity for IM, as well as the average and peak intensity restrictions by the LEDs and the targeted illumination profiles, can be met using Deep Neural Networks (DNNs), which are capable of learning more complicated tasks. Open source software libraries like Theano, Keras, and Tensorflow have been useful in building network architectures in different domains. In combination with new hardware systems, new applications are designed for DNNs which has provided a framework for newfangled systems.

AE avoids features which are redundant and include only the pivotal features. It enables capturing the statistical dependencies between different elements of a signal and optimizes a loss function while reconstructing the signal using stochastic gradient descent (SGD) algorithm during backpropagation. Originally, AE was used for data compression due to the limitation of the memory resources. Principal component analysis (PCA) is a technique to find a relation in data points in a dataset to predict future models.
3.2.2 AE Implementation of O-OFDM based VLC Systems

In order to demonstrate the viability of applying DL techniques in VLC, an OFDM based VLC chain using an AE model is developed. The VLC transmitter is fed with one symbol $s$ out of $M$ possible symbols, determined by the modulation order of the M-QAM under investigation. The encoder maps the input $s \in \mathbb{R}^l$ to a reduced dimension $X \in \mathbb{R}^M$, where $M < l$. The decoder reconstructs the original input $s$ through decompression of the reduced input dimension $X$ and thus obtains the estimation of the input denoted by $\hat{s}$. $l$ is the system’s degrees of freedom (time/frequency domain). The system has a communication rate of $R = \frac{k}{c}$ (bits/channel use), where $k = \log_2(M)$. The whole model is trained such that the values of the weights and biases for both encoder and decoder layers are jointly optimized to minimize the cost function. The categorical cross entropy cost function, $L_{\text{cross}}$, is considered and given by:

$$L_{\text{cross}} = H(\hat{s}, s) = H(s) + D_{\text{KL}}(s || \hat{s})$$

(3.8)

where $H(s)$ is the probability mass function (PMF) of the transmitted symbol $s$ and $D_{\text{KL}}(\cdot || \cdot)$ is defined as the Kullback-Leibler divergence between the transmitted and estimated PMF [67]. As shown in Fig. 3.6, the inputs to the transmitter are one-hot encoded symbols $s$. One-hot encoding is when the element corresponding to the transmitted symbol equals to 1 while the others are 0. For illustration, in the case of 4-QAM, symbol one is presented as $(1,0,0,0)$, symbol two is $(0,1,0,0)$, symbol three is $(0,0,1,0)$, and symbol four is $(0,0,0,1)$. The transmitter consists of multiple dense layers followed by a power normalization layer. The output of the normalization layer is mapped to a complex representation. The complex numbers set by the number of sub-carriers $N$, i.e. length of the IFFT block are mapped
Figure 3.7: (a) Constellation diagram for QPSK. (b) Comparison of SER performance of AE model and classical MATLAB simulation model. (c) Plots of accuracy and loss.

and transformed from the frequency-domain to the time-domain. An AWGN channel model is considered, as it is widely used as an accurate channel model for different indoor VLC systems. At the receiver side, the signal is transformed back to the frequency domain using the FFT block then passed to a parallel-to-serial converter. The receiver also consists of multiple dense layers followed by a softmax activation layer and an argmax layer to decode the highest probability received symbol as \( \hat{s} \). Details of the NN architecture are listed in Table 3.1 and the optimized hyperparameters are listed in Table 3.2 with \( E \) as the size of the training dataset. In this implementation, the batch size is equal to the number of sub-carriers. It is important to note that a challenging part in the development of the model is to represent and reshape data in a complex form, because NN-layers only support real values. Accordingly, custom Keras layers are created for this implementation.

The AE model is tested for different modulation orders, \( i.e. M = 4, 8, 16 \) and \( 32 \). The below graphs highlight the performance of \( \pi/2 \) shifted 4-QAM. MATLAB is used to verify and compare the results obtained using the AE model with that of a classical simulation model. Fig. 3.7(a) shows the learned constellation at the transmitter side after the training phase. It can be noticed that it converges to the ideal case to minimize the cost function. The symbol error rate (SER) performance is shown in Fig 3.7(b) for different numbers of sub-carriers/IFFT lengths. Since, the batch size varies with the number of sub-carriers, the case of 8, 16, 32, and 64 sub-carriers are implemented. As depicted in Fig. 3.7(b), the behavior of the obtained curves from the AE model is consistent with the curves obtained using a classical simulation model in MATLAB. Figure 3.7(c) shows the value of the loss function decreasing as the number of epochs increases. A 100% accuracy can be achieved after less than 15 epochs. In summary, even though this OFDM based AE model was trained using a
Table 3.1: AE OFDM-based VLC architecture

<table>
<thead>
<tr>
<th>Encoder Network</th>
<th>Decoder Network</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Layer - Activation</strong></td>
<td><strong>Output dimension</strong></td>
</tr>
<tr>
<td>Input</td>
<td>$(\mathcal{E}, M)$</td>
</tr>
<tr>
<td>Dense - ReLU</td>
<td>$(\mathcal{E}, M)$</td>
</tr>
<tr>
<td>Dense - Linear</td>
<td>$(\mathcal{E}, c)$</td>
</tr>
</tbody>
</table>

Table 3.2: Optimized hyperparameters for AE OFDM-based VLC model.

<table>
<thead>
<tr>
<th>M</th>
<th>SNR (dB)</th>
<th>Epochs</th>
<th>Learning Rate</th>
<th>Training Data</th>
<th>Testing Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>20</td>
<td>50</td>
<td>0.001</td>
<td>8000</td>
<td>2000</td>
</tr>
</tbody>
</table>

single SNR value, its performance was approaching the simulations-based performance which shows the potential of adopting DL in VLC applications.

3.2.3 Autoencoder-Based ASM

3.2.3.1 Network Architecture

As previously mentioned, an AE is a NN architecture that is commonly used for data compression and reconstruction in memory constrained applications. It’s architecture consists of an encoder and a decoder that are jointly trained. This can be used to represent a communication system consisting of a transmitter and a receiver, as one deep feedfoward NN that can be trained as an AE. The communication channel can be emulated as a corruption that is performed on the compressed output vector of the encoder representing the modulated signal, which is then fed to the decoder. In other words, when the AE architecture is adopted in communications, the encoder acts as the transmitter, the decoder as the receiver, and the channel as a corruption to the output of the encoder. The network is trained to minimize a cost function, the categorical cross entropy cost function in our case, by optimizing the values of the weights and biases of the encoder and decoder layers jointly. The categorical cross entropy cost function can be defined as $L_{ce} = -\sum_{i=1}^{M} u_i \log(\hat{u}_i)$, where $u_i$ is the $i^{th}$ target value and $\hat{u}_i$ is the model output [67]. Figure 3.8 shows ASM’s transciever for optical OFDM systems as an AE model. The inputs to the transmitter/encoder are one-hot encoded symbols out of $M$ possible PSK symbols; hence the input layer is $\in \mathbb{R}^{M}$. Two dense layers follows; the first is $\in \mathbb{R}^{M}$ with a ReLU activation function (AF) and the
Figure 3.8: An OFDM-based VLC system over an AWGN channel adopting ASM represented as an AE model with the grey block highlighting the layers specifically designed for ASM at both the encoder (transmitter) and decoder (receiver) ends. The input \( u \) is converted to a one-hot vector, while the output \( \hat{u} \) is chosen as the message with the highest probability over all possible messages.

Second is \( \in \mathbb{R}^n \) with a linear AF, given \( n \) represent the number of channel uses. The encoder also consists of a normalization layer \( \in \mathbb{R}^n \), a dense layer with a linear AF \( \in \mathbb{R}^N \), the IFFT layer \( \in \mathbb{R}^N \), and finally ASM’s unique layer (augmented layer \( \in \mathbb{R}^N \)). The receiver/decoder starts with the de-augmented layer \( \in \mathbb{R}^N \) to reverse the operation of the augmented layer in the encoder and extract the additional augmented data stream. The de-augmented layer is actually composed of two dense layers; the first is \( \in \mathbb{R}^N \) with a ReLU AF and the second is \( \in \mathbb{R}^{2^\eta} \) with a Softmax AF. The remaining layers of the decoder are the FFT layer \( \in \mathbb{R}^N \) and three dense layers. The first has a linear AF \( \in \mathbb{R}^n \), the second has a ReLU AF \( \in \mathbb{R}^M \), and the last has a Softmax AF for classification \( \in \mathbb{R}^M \). The number of trainable parameters is then \( 2(M^2 + M) + (2n + 1)(N + M) + 2n + (N + 1)(N + 2^n) \).

3.2.3.2 Results

The AE model has been tested for different modulation orders; the graphs below highlight its performance at 16-PSK, i.e. \( M = 16 \). Training was done at two fixed SNR values of 10dB and 15dB using Adam optimizer with learning rate equal to 0.001. Adam is considered an extension to the well known stochastic gradient descent (SGD) optimizer and it handles sparse gradients on noisy problems. We used the default Adam optimizer parameters for Keras with Tensorflow backend implementation, \( \beta_1 = 0.9, \beta_2 = 0.999, \) and \( \epsilon = 1 \times 10^{-8} \), where \( \beta_1 \) and \( \beta_2 \) are the exponential decay rate for the first and second moments estimates, respectively. \( \epsilon \) is set to prevent any division by zero in the implementation. The AE seeks to
learn representations \( s \) of the messages \( u \) that are robust to channel noise (mapping \( s \) to \( y \)) to not only recover the transmitted OFDM symbol with small probability of error but also the augmented data stream presented by \( b[n] \) \( \text{i.e.} \) the engineered features added to \( x \) via the augmented layer. We generated 2000 symbols as training data and 1000 symbols were used for testing. Sixteen epochs were needed for the training categorical accuracy to reach 99.5\% with a batch size equal to \( N \).

Figure 3.9(a) shows an example of 5 learned representations of \( s \) for different subcarriers at \( M = 16 \) and \( N = 64 \); the constellation points of each subcarrier are presented by different colors. It can be observed that the learned constellations are not orthogonal, hence, the AE can be considered to perform super-position coding by making the constellations of different subcarriers resemble ellipses with varying focal distances. Figure 3.9(b) shows the block error rate (BLER) performance of ASM using the AE model for various \( \eta \) values. To clarify, ASM’s \( \eta = 6 \) implies 6 additional bits are obtained from the augmented stream per optical OFDM symbol. The performance of uncoded PSK is included in Fig. 3.9(b) as a reference. As can be observed, ASM’s BER curves outperforms the performance of uncoded 16-PSK ACO-OFDM transmission, which shows the potential of ML approaches in comparison to classical communication techniques. This implies that the AE has learned some joint coding and modulation scheme, such that a coding gain is achieved. Our findings are consistent with the AE model in [65], which also outperformed uncoded PSK; the mentioned analysis assumed single-carrier transmission. However, it is important to note that for a truly fair comparison, this result could be compared to a higher-order modulation scheme that uses channel coding. Figure 3.9(c) shows the accuracy of \( b[n] \) estimation at \( N_t = 64 \). As previously mentioned, there are \( 2^\eta \) possible binary sequences. As can be observed from the confusion matrix, an estimation accuracy of 100\% is achieved.

### 3.2.4 Optical Camera Communication (OCC) Implementation

Recently, an optical communication technique known as OCC is proposed [68]. In such systems, an imaging detector is used as a receiver to capture the transmitted signals. In both indoors and outdoors, OCC systems allow implementation of various application scenarios using cameras integrated in mobile devices, without a need for hardware modifications. In OCC, signals are mainly modulated using single-carrier schemes such as OOK. This
subsection is primarily focused on a new design to support multi-carrier OFDM based OCC through DL. The OFDM symbol is translated into OOK signaling, transmitted using a 2D-array of LEDs. The implemented deep NN is different from a classical communication chain, where the processing blocks are separately optimized yielding sub-optimal solutions [65]. In particular, the proposed convolutional autoencoder (C-AE) will enable end-to-end performance enhancement by jointly optimizing the LED array and the camera [69].

3.2.4.1 Network Architecture

The encoder accepts input data $x$ and introduces a corruption process having certain distribution to produce the corrupted information $c(x)$. On the other hand, the decoder performs the denoising process $g(c(x))$ to produce $\hat{x}$ as an estimate of $x$. OFDM is an eminent modulation technique adopted in most current wireless standards [53], while OOK is typically used for its simplicity. In our framework, OFDM transmission in OCC is enabled through the conversion of an OFDM symbol into an $L \times L$ matrix that represents the On and Off states of the pixels of an LED array acting as the transmitting element. Hence, the OFDM symbol is transformed into $L \times L$ OOK signaling. In order to achieve this, the time-domain OFDM symbol is first passed to an $n$-bit quantizer to create a message $x \in M$ discrete levels, with $M = 2^n$. It is then represented as a one-hot vector and passed to the remaining C-AE network layers, as depicted in Fig. 3.10. A rudimentary optical channel
Figure 3.10: Deep learning framework for OFDM-based OCC equipped with an $L \times L$ LED array and a camera with a captured image of dimension $T \times T$.

Table 3.3: Proposed Network Architecture

<table>
<thead>
<tr>
<th>Encoder Network</th>
<th>Decoder Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layer - Activation</td>
<td>Output dimension</td>
</tr>
<tr>
<td>Dense - ReLU</td>
<td>$M \times 1$</td>
</tr>
<tr>
<td>Dense - ReLU</td>
<td>$16 \times L^2 \times 1$</td>
</tr>
<tr>
<td>Conv - ReLU</td>
<td>$4 \times 4 \times L$</td>
</tr>
<tr>
<td>Max Pooling</td>
<td>$2 \times 2 \times L$</td>
</tr>
<tr>
<td>Conv - ReLU</td>
<td>$2 \times 2 \times L$</td>
</tr>
<tr>
<td>Max Pooling</td>
<td>$L \times L$</td>
</tr>
<tr>
<td>Conv - Sigmoid</td>
<td>$L \times L$</td>
</tr>
</tbody>
</table>

is simulated by upscaling the $L \times L$ output from the encoder by 4 with zero-padding of 4 bits. Then, AWGN is applied to the signal with variance $\sigma^2 = (1/R\gamma)$, where $R$ is the communication rate and $\gamma$ is the SNR. At the receiving end, a camera captures the LED array with dimension $T \times T$ such that $T \geq L$. The captured image is then passed to the decoding stage of the C-AE, in order to produce the estimate $\hat{x}$. The detailed structure of the proposed C-AE is given in Table 3.3.

3.2.4.2 Results

In our simulations, we implement a multi-stage training strategy [70]. Keras with Tensorflow backend is used for the proposed C-AE implementation using a GPU backend. Our C-AE is trained with a single SNR value of 20 dB using the Adam optimizer algorithm and a training rate of 0.001. In order to achieve binary signaling, i.e. OOK, a parameterizable sigmoid activation function using the Keras lambda layer with the function $x = \frac{1}{1+e^{-\delta x}}$ is implemented. Due to issues with exploding gradients when $\delta > 4$, the network is trained until it converges for $\delta = 1, 2, 3, 4$ using an iterative process. Then, the trained weights are fitted onto a network with $\delta = 1000$, which is feasible for OOK implementation [70]. The loss function is categorical cross-entropy, the optimum training occurs with batch size $= M$, and
the C-AE is trained for 100 epochs at each $\delta$. Figure 3.11 shows the normalized confusion matrices using $10^6$ time-domain samples of OFDM symbols at $M = 16$ and $M = 64$ for different SNR values during the testing stage. As shown in Fig. 3.11 (a) and (b), when $M = 16$, samples are reconstructed with almost 100% accuracy even at an SNR as low as 5 dB. On the other hand, at $M = 64$, the accuracy is still maintained at SNR = 10 dB, giving about 99% accuracy. However, at an SNR of 5 dB, accuracy drops to 60%.
CHAPTER 4
Other Applications for Augmentation Technology

4.1 Physical Layer Security

Due to the broadcast nature of wireless transmission, the wireless interface is within reach to both legitimate and malicious users. Eavesdropping attacks are the most popular type of threat that affect network confidentiality [71]. To combat eavesdropping, security approaches can be applied at every layer of the network stack, including encryption and authentication protocols in the upper layers as well physical-layer (PHY) mechanisms [72]. Physical-layer security (PLS) is an emerging technology that encompasses approaches proposed for securing wireless communications at the PHY. In PLS, the core idea is to utilize the attributes of wireless channels, such as noise or fading, to model effectively secure transmission schemes. The introduction of new applications, such as IoT with their computational complexity and power limitations, has called attention to the importance of PLS, as the traditional cryptographic methods are normally computationally complex.

4.1.1 Background

In order to enhance system confidentiality, sophisticated signal processing techniques are designed to elevate secrecy capacity. These techniques include security-oriented beamforming [73] [74], artificial-noise-aided security [75] [76], physical-layer secret key generation based methods [77] [78], and security diversity methods [79] [80]. Considering secret key generation techniques, the premise is that the source encrypts the original data with the aid of an encryption algorithm and a secret key, which is exchanged between the source and the legitimate receiver only. Using classic channel estimation methods, legitimate users exploit their estimated CSI for secret key generation and agreement process. The legitimate receiver then decrypts the data using the preshared key. Hence, under the assumption that the eavesdropper lacks information of the secret key, the data reserves its confidentiality. Most PLS techniques exploit the propagation characteristics of the wireless channel. When wireless data is transmitted by a source, multiple replicas of the signal with different delays and
attenuation factors may be received at the destination arriving from different propagation paths caused by signal reflection, diffraction, and scattering.

In a setting that adopts multiple technologies, such as in the case of heterogeneous radio-optical networks, PLS techniques cannot depend on the unpredictability of the multi-path propagation to defend the transmission. As the optical channel is not rich scattering, unlike the RF channel. Hence, the unpredictability criterion is absent in optical transmission. Another approach is PHY-key based techniques that adopt the concept of encryption and authentication based on the presence of a secret key, however, the encryption happens at the PHY. For these techniques, an efficient key management and distribution scheme is fundamental for network confidentiality. As a general scheme, there exists a key management server responsible for generating and managing the keys. The keys are then distributed among the end users; however, the protection of keys in transit must be paramountly considered [81]. Additionally, key distribution results in network over-head due to the exchange to keys over the network. An alternative is key predistribution models, where keys are stored in nodes before deployment, which are popular in a multiple of applications, including wireless sensor networks, due to their low computational complexity and scalability [82].

SM-based PLS can be addressed using various approaches including; precoding, jamming, and subset selection. There are also methods that are considered combinations of the aforementioned PLS approaches, such as the work in [83] that is considered a precoding plus jamming technique. Precoding techniques, such as [84, 85, 86], rely on engineering the precoding matrix coefficients based on CSI of both the legitimate user and eavesdropper to cause the signal to be perceived only by the legitimate user and be hidden from the eavesdropper. The major drawback of precoding approaches is the stringent requirement of CSI. Practically, networks can be oblivious to the presence of an eavesdropper, which makes eavesdropper CSI knowledge un-achievable. Friendly jamming methods create artificial noise in the nullspace of the legitimate user, causing the eavesdropper to undergo destructive effects [87]. Jamming approaches, i.e. artificial noise, can be based on co-operative jamming, where multiple users aid each to mitigate eavesdropping attacks [88, 89]. It can also be based on a MIMO setting, where the legitimate users are equipped with multiple transmitters/receivers [90]. The drawbacks of jamming methods are their power inefficiencies and spectral efficiency losses, as the spatial bits are comprised due to the use of transmitting el-
elements as jamming elements. Lastly, transmitter subset selection methods choose a specific subset of transmitting elements to maximize either the SNR or the Euclidean distance at the legitimate user \cite{91,92}. Similar to jamming approaches, they require CSI of the legitimate users, and they also share the loss in spectral efficiency as the number bits that can be conveyed in the spatial domain are reduced due to the subset selection task.

4.1.2 Security Aware Spatial Modulation (SA-SM)

SA-SM disturbs the time-domain signal prior to transmission (at the PHY) using a key, which reduces the eavesdropper’s channel capacity without influencing the legitimate user channel capacity, which in return increases secrecy capacity. In this sense, SA-SM does not rely on channel characteristics for securing the information, as it’s perception is self-imposed; hence, it can be applied to both RF and optical technologies concurrently, and the security gain in both cases will be the same (as it is not channel reliant). Within the analysis, we introduce a novel key selection algorithm aided by the use of a NN to allow periodical PHY rekeying issued by a centralized source to ML-equipped nodes. Unlike other rekeying methods proposed in literature, SA-SM’s perception does not require keys to be exchanged between the centralized source and the communicating nodes. This perception not only protects keys from being intercepted in transit, but also eliminates rekeying overhead. Instead, SA-SM nodes can intelligently identify which key is chosen by the source, out of a fixed key pool, and decrypt the information accordingly.

4.1.2.1 SA-SM System Model

A heterogeneous radio-optical network is considered that consists of a number of legitimate users \((L)\) and eavesdroppers \((E)\), as shown in Fig. 4.1, a similar model was considered in \cite{93}. The eavesdroppers are located within the coverage area of both radio and optical transmissions. Since both technologies cannot interfere with one another, both technologies are used concurrently and the receivers are equipped with both RF and optical frontends. The source \((S)\) estimates the CSI of the transmission links via pilot signals. Key management is performed by \(S\) which has a pool of size \(P\) keys that it can utilize for its transmission. The choice of the key \(i.e.\) key selection algorithm varies based on whether the eavesdropper is assumed to be active or passive and it is done on a periodical basis. When an \(E\)
is active, it shares its CSI with the centralized source $S$ to receive the information, while when passive its CSI remains unknown, similar to the assumption used in \[93\]. Typically, for channel equalization, the user (whether legitimate or eavesdropper) must be aware of the instantaneous CSI of its receiving link. However, we also consider the case where $E$ remains passive, as it presents a more realistic scenario.

Without the need for $S$ to send the new key to $L$ over the air, SA-SM’s novelty comes in designing a receiver capable of estimating which specific key $S$ chooses out of the pool. In other words, in conventional rekeying techniques either the new key is exchanged over the air between the source and the nodes or the keys are prestored on the nodes themselves. Both those approaches, as previously mentioned, have their downfalls. The former suffers from the vulnerability of the key being intercepted over the air and overhead, and the latter is time exhaustive because the nodes have to search for the correct key from the set of available keys to decrypt the information. It is important to note that link signature keying techniques also do not require the exchange of keys; however, these techniques can only be used when the channel is said to be uncorrelated [94]. In RF transmission, it is normally presumed that links parted by at least half of a wavelength fade independently, yet this statement does not hold in optical transmission. It is important to note that the channel in the optical domain is modeled by real-valued attenuation coefficients. Additionally, the signal incoming via the LOS path dominates those from the reflected paths. In fact, most VLC research focuses mainly on the LOS path and disregard multipath propagation. In this work, channel enforced limitations are not our concentration area, thus our method is investigated in the presence of an AWGN channel for the optical link and a flat fading Rayleigh model for RF.

### 4.1.2.2 Realization of SA-SM’s Approach

The centralized source (based on the key selection algorithm) produces a key which is added to the original time-domain signal; hence, the key can be observed as an extra “disguising” signal. The transmitted signal $s_{R/O}(k)$ can then be observed as a summation of two signals. The first signal, $x_{R/O}(k)$, is the OFDM time-domain signal, whether it is optical or RF, produced by a normalized $M$-QAM constellation whose energy is normalized to 1. The second signal (i.e. the key $p_{R/O}(k)$) is a binary pattern (i.e. with values equal to either 0 or 1). Given that SA-SM does not alter the frame structure of the transmitted symbol,
conventional synchronization and channel estimation methods using preamble symbols can be used, such as the robust timing and frequency synchronization for OFDM systems framework in [95] for the RF link and [96] for the optical link. Training symbol synchronization methods can also be used such as the joint synchronization and channel estimation work presented in [97]. Hence, the transmitted signal, $s_{R/O}$, becomes:

$$s_{R/O}(k) = \beta x_{R/O}(k) + \alpha p_{R/O}(k) \quad (4.1)$$

where $\alpha$ and $\beta$ are design parameters used to satisfy the security requirement and power constraints. The number of possible keys relies on a system parameter we denote as $\eta$, forming $P = 2^\eta$ possible keys; the value of $\eta$ must be a factor of $N$. In other words, the length of the key has to be equal to $N$, which is the IFFT length of the time-domain signal; a key is divided into $\eta$ chunks, each chunk has the same binary value. The block diagram of SA-SM is provided in Fig. 4.2. Given an example of a uni-polar real OFDM for illustration, the effect of the system parameters $\alpha$ and $\eta$ on SA-SM’s transmitted signal is depicted in Fig. 4.3. The parameter $\alpha$ controls the amplitude of the transmitted signal chunks, while $\eta$ controls the pattern of the chunks to which $\alpha$ is applied to.
Figure 4.2: ML-based SA-SM transceiver with (a) Transmitter showing the centralized source providing the key to the transmitter and the data splitter responsible of controlling which transmitting elements are active, and (b) Receiver with the demodulation block entailing SM and QAM demodulation.

Figure 4.3: SA-SM transmitted signals showing the effect of system parameters $\alpha$ and $\eta$. For illustration, a uni-polar real-valued ACO-OFDM signal with $N = 64$ is assumed and $\beta = 1$. 
The information received at the legitimate receiver is indicated as

\[ y_{LR/O}(k) = h_{LR/O}(k) s_{R/O}(k) + n_{LR/O}(k) \]

\[ = h_{LR/O}(k) \left[ \beta x_{R/O}(k) + \alpha p_{R/O}(k) \right] + n_{LR/O}(k) \]  \hspace{1cm} (4.2)

Likewise, the information received by the eavesdropper \( E \) is

\[ y_{ER/O}(k) = h_{ER/O}(k) s_{R/O}(k) + n_{ER/O}(k) \]

\[ = h_{ER/O}(k) \left[ \beta x_{R/O}(k) + \alpha p_{R/O}(k) \right] + n_{ER/O}(k) \]  \hspace{1cm} (4.3)

where \( h_{LR/O} \) and \( h_{ER/O} \) are the channel fading coefficients of the legitimate and eavesdropper links, respectively. The parameters \( n_{LR/O}(k) \) and \( n_{ER/O}(k) \) are the zero mean AWGN random variables. For the eavesdropper, the signal quality is disturbed by the term \( \alpha p_{R/O}(k) \), while the legitimate user (because it has prior knowledge of the key) does not suffer from this disturbance. It is important to note that, the legitimate receiver has the ability to estimate the key \( p_{R/O}(k) \), while the eavesdropper would have to attempt \( 2^N \) possible key combinations for every possible value of system parameter \( \alpha \) per OFDM symbol. In most wireless standards, the number of OFDM subcarriers is at least 64, \( i.e. \ N = 64 \), which means that the eavesdropper would have \( 1.8 \times 10^{19} \) versions of each OFDM symbol, assuming it had knowledge of \( \alpha \), without knowing which of these versions is the transmitted data.

The channel capacities of the legitimate and eavesdropper can be calculated as \( C_{LR/O} = \log_2(1 + \gamma_{LR/O}) \) and \( C_{ER/O} = \log_2(1 + \gamma_{ER/O}) \), respectively. The parameters \( \gamma_{LR/O} \) and \( \gamma_{ER/O} \) are the instantaneous SNR of \( L \) and \( E \) links, respectively. Due to the disturbance factor, mentioned above, the SNR of \( L \) will be significantly higher than that of \( E \). The secrecy capacity \( (C_{SR/O}) \) can then be defined as

\[ C_{SR/O}(k) = \begin{cases} 
[C_{LR/O}(k) - C_{ER/O}(k)]^+, & \text{for } \gamma_{LR/O} > \gamma_{ER/O} \\
0, & \text{otherwise}
\end{cases} \]  \hspace{1cm} (4.4)

where the superfix \([.]^+\) is denoted as a non-negative value, which entails that in order to achieve positive secrecy capacity, \( \gamma_{LR/O} \) must be greater than \( \gamma_{ER/O} \).
4.1.2.3 Secrecy Capacity Proposition

The average secrecy capacity of the RF link, denoted as $C_{sR}$, for a given instantaneous SNR of $L$ and $E$ RF links, i.e. $\gamma_{LR}$ and $\gamma_{ER}$ respectively, can be defined as

$$C_{sR}(\gamma_{LR}, \gamma_{ER}) = \mathbb{E}[C_{sR}(k)] = \int_0^\infty \int_0^\infty C_s(k) f_{\gamma_{LR}}(\gamma_{LR}) f_{\gamma_{ER}}(\gamma_{ER}) d\gamma_{LR} d\gamma_{ER}$$  \hspace{1cm} (4.5)$$

where $\mathbb{E}(.)$ is the expectation operation, and $f_{\gamma_{LR}}$ and $f_{\gamma_{ER}}$ denote the probability density function (PDF) of $\gamma_{LR}$ and $\gamma_{ER}$, respectively. Assuming a Nakagami-$m$ fading distribution, the PDF of the received instantaneous SNR is given as

$$f_{\gamma_z}(\gamma) = \left(\frac{m}{\bar{\gamma}_z}\right)^m \frac{\gamma^{m-1}}{\Gamma(m)} \exp\left(-\frac{m\gamma}{\bar{\gamma}_z}\right), \ \gamma \geq 0$$  \hspace{1cm} (4.6)$$

with $m$ as the Nakagami fading parameter. It is important to note that the Rayleigh channel is considered a special case of the Nakagami-$m$ fading distribution with $m = 1$. Then, the PDF can be simplified into

$$f_{\gamma_z}(\gamma) = \left(\frac{1}{\bar{\gamma}_z}\right) \frac{1}{\Gamma(1)} \exp\left(-\frac{\gamma}{\bar{\gamma}_z}\right), \ \gamma \geq 0$$  \hspace{1cm} (4.7)$$

where $\Gamma(.)$ is denoted as the Gamma function and $\bar{\gamma}_z$ is the average instantaneous SNR defined as

$$\bar{\gamma}_z = \frac{P_s}{N_z} \mathbb{E}(|h_z|^2)$$  \hspace{1cm} (4.8)$$

with $P_s$ is the transmitted power from source $S$ and $N_z$ is the AWGN spectral density. After some algebraic manipulation, (4.5) can be rewritten as

$$C_{sR}(\gamma_{LR}, \gamma_{ER}) = \frac{1}{\ln 2} \left[ \sum_{g=1}^{\infty} (-1)^{g-1} \frac{g}{\Gamma(1)} \left( C_1 - \frac{1}{\Gamma(1)} C_2 \right) \right]$$  \hspace{1cm} (4.9)$$

The terms $C_1$ and $C_2$, using the Meijer-G function denoted as $G(.)$, are given as

$$C_1 = \frac{\Gamma(1+g)\Gamma(-g)}{\Gamma(1-g)}$$  \hspace{1cm} (4.10)$$

$$C_2 = \frac{1}{\bar{\gamma}_{ER}} G_{3,3}^{2,2} \left( \begin{array}{c} \gamma_{ER}, 1, -g, 1/g \\ \gamma_{LR}, 1, -g, 0 \end{array} \right)$$  \hspace{1cm} (4.11)$$
The average secrecy capacity of the optical link can be expressed similarly to the RF link with the variation that the instantaneous SNR is limited to a range controlled by the optical transmitter/receiver alignment. Thus, the optical average secrecy capacity can be expressed as

$$C_{sO}(\gamma_{LO}, \gamma_{EO}) = E[C_{sO}(k)] = \int_{\gamma_{min}}^{\gamma_{max}} \int_{\gamma_{min}}^{\gamma_{max}} C_s(k) f_{\gamma_{LO}}(\gamma_{LO}) f_{\gamma_{EO}}(\gamma_{EO}) d\gamma_{LO} d\gamma_{EO}$$  \hspace{1cm} (4.12)$$

Assuming Lambertian radiation pattern with an order \( l = -\frac{1}{\log_2(\cos(\phi_1/2))} \), with \( \phi_1/2 \) the semiangle of the optical transmitter, (4.12) can be expressed as

$$C_{sO}(\gamma_{LO}, \gamma_{EO}) = \frac{1}{\ln 2} \left[ v(1-v)C_3 + K \left( \frac{2v}{\gamma_{LO}^{-\frac{1}{l+3}}} - \frac{1}{1 - \gamma_{EO}^{-\frac{1}{l+3}}} \right) C_4 - \frac{K^2}{(\gamma_{LO}^{-\frac{1}{l+3}})^\frac{1}{l+3}} C_5 \right]$$  \hspace{1cm} (4.13)$$

where \( v = (1 + \frac{L^2}{r^2}) \) with \( L \) is the vertical distance from the source to the optical receiver and \( r \) is the radius of the optical coverage. The parameters \( C_3, C_4, \) and \( C_5 \) are

$$C_3 = \sum_{g=1}^{\infty} (-1)^{g-1} \left[ \gamma_{max}^g - \gamma_{min}^g \right]$$  \hspace{1cm} (4.14)$$
$$C_4 = \sum_{g=1}^{\infty} (-1)^{g-1} g \left[ \frac{\gamma_{max}^{-\frac{1}{l+3}} - \gamma_{min}^{-\frac{1}{l+3}}} {g - \frac{1}{l+3}} \right]$$  \hspace{1cm} (4.15)$$
$$C_5 = \sum_{g=1}^{\infty} (-1)^{g-1} g \left[ \frac{\gamma_{max}^{-\frac{2}{l+3}} - \gamma_{min}^{-\frac{2}{l+3}}} {g - \frac{2}{l+3}} \right]$$  \hspace{1cm} (4.16)$$

For simplicity, by ignoring the presence of an optical filter and an optical concentrator, \( \gamma_{min} \) and \( \gamma_{max} \) are expressed as

$$\gamma_{min} = \frac{\varepsilon^2 P_s^2}{N_0 B 4\pi^2} \frac{1}{A^2 R^2} \frac{(l + 1) L^{l+1}}{L^2(l+3)}$$  \hspace{1cm} (4.17)$$
$$\gamma_{max} = \frac{\varepsilon^2 P_s^2}{N_0 B 4\pi^2} \frac{1}{A^2 R^2} \frac{(l + 1) L^{l+1}}{(r^2 + L^2)^{l+3}}$$  \hspace{1cm} (4.18)$$

with \( \varepsilon \) being the electrical to optical efficiency, \( B \) is the bandwidth, \( A \) is the detector area, and \( R \) is the responsivity.
4.1.2.4 Key Selection Algorithm

As previously mentioned, in the proposed system model, the radio and optical technologies can be used concurrently. The transmitters remain connected to the legitimate receivers as long as the secrecy rate remains positive. However, when the secrecy rate of any technology (i.e. RF or optical) drops below a certain threshold, \( C_s^{th} \), that entails that the key has been compromised and the source (depicted in Fig. 4.1) chooses another key from the pool and utilizes it. \( C_s^{th} \) is a preset value which has a minimum of 0, and it’s value depends on the security requirements of the system. If \( C_s \) cannot be calculated, because \( \gamma_{E_{R/O}} \) is unavailable, then the algorithm switches to random key selection. Let us consider a binary decision indicator \( I_{p_i} \) for each key \( p_i \in \mathcal{P} \), as follows:

\[
I_{p_i} = \begin{cases} 
1, & \text{if key } p_i \text{ is available} \\
0, & \text{otherwise.}
\end{cases}
\]

Our channel assignment algorithm functions as follows:

1. The keys that are already assigned to other legitimate users and those have been compromised will be eliminated from \( \mathcal{P} \), producing a new set of feasible keys \( \mathcal{P}^f \). Each key has it’s own binary decision indicator, with 1 meaning it is available for use and 0 meaning either it is temporarily unavailable or has been leaked. A set of length \( \mathcal{P} \), \( I_p \), contains the binary indicators for all the keys.

2. Using \( \gamma_{L_{R/O}} \) and \( \gamma_{E_{R/O}} \), the algorithm calculates \( C_s \) using all available keys in \( \mathcal{P}^f \), the calculated \( C_s \) using key \( i \) is denoted as \( C_s^{(i)} \). If \( C_s \) falls below the threshold or cannot be calculated, then the corresponding key is omitted from the feasible key pool obtained in the previous step.

3. If the algorithm fails to find a solution, i.e. \( C_s \) cannot be computed for all available keys, it switches to random key selection out of the keys that are available based on the original \( I_p \) inputted to the algorithm. The random chosen key is denoted as \( p^* \) and it’s corresponding indicator is changed to zero to mark that it has been assigned and \( I_p \) is updated accordingly.

4. If a solution can be found, the algorithm chooses the key with the highest secrecy
capacity. Similar to the previous step, the key’s corresponding indicator is changed to zero to mark that it has been assigned and $I_p$ is updated accordingly.

Algorithm 2 shows the pseudocode of SA-SM key selection algorithm.

**Algorithm 2** SA-SM Key Assignment

**Input:** $P$, $I_p$, $\gamma_{L/R/O}$, $\gamma_{E_R/O}$, $C_s^{th}$

**Output:** An available key $p$

Let $P^f = I_p \times P$

for all $i \in P^f$

Compute $C_s^{(i)}$ using (4.4)

if $C_s^{(i)} < C_s^{th}$ or $C_s^{(i)} = \phi$

$P^f = P^f - \{i\}$

end-of-if

end-of-for

if $P^f = \emptyset$

Random selection of $p^* \in (I_p \times P)$

Adjust the key indicator $I^*_p = 0$

Return $p_i$ and updated $I_p$

else

for all $i \in P^f$

Sort the keys in increasing order of $C_s^{(i)}$

end-of-for

Let $U$ be the sorted key list

Identify the key that is on the top of $U$

Return $p_i$ and updated $I_p$

end-of-if

4.1.2.5 Results

To get a better understanding of the performance of the NN while training, the training accuracy and loss vs. number of epochs is presented in Fig. 4.4. As can be seen in Fig. 4.4(a), only 4 epochs are needed for the NN to reach a 100% accuracy for various values of $P$. As previously mentioned, the size of the dataset used to train the NN is $0.8 \times 250 \times P$, in other words in the case of $P = 1000$ the NN is trained using 200000 frames. Because the training data increases with the number of keys, the NN reaches 100% accuracy and the loss drops to 0 faster as the number of keys increases. The anomaly is the behaviour of the NN at $P = 10$, where the loss approaches (but not reaches) 0 yet the accuracy is 100%. Because of this anomaly, we set the number of epochs to allow the NN to converge. It is important
Figure 4.4: The NN’s accuracy and loss while training vs. number of training epochs for various $P$ values.

Figure 4.5: NN-based SA-SM BER performance vs. SNR, depicting the legitimate user (SA-SM) BER in comparison to that of the eavesdropper (Eve) for 16-QAM OFDM transmission with $N = 64$, $\eta = 32$, $\alpha = 0.2$, and $P = 1000$.

Figure 4.6: Secrecy capacity, $C_s$, for the optical link in (a) and for the RF link in (b) at $\alpha = 0.2$, 16-QAM OFDM transmission, $\eta = 32$, $\beta = 1$, and $P = 1000$. As can be observed, NN-based SA-SM causes $C_s$ to always maintain a positive value.
to note that the perception of SA-SM is scalable, as previously mentioned, the number of keys that can be used is equal to $2^n$, *i.e.* at $\eta = 32$ the system can accommodate over $4 \times 10^9$ different keys. However, in our analysis we set $\mathcal{P} = 1000$ as an example value to show the potential of SA-SM.

To test the security gain of SA-SM, the worst case scenario, which is the case of unknown $C_s$, is evaluated and the algorithm is performed prior to each transmission, *i.e.* the key is changed with each frame. The secrecy bit-error-rate (BER), which can be defined as the BER of the eavesdropper, is firstly tested for the optical link under AWGN channel model in Fig. 4.5(a) and for the RF transmission under flat fading Rayleigh channel model in Fig. 4.5(b) for NN-based SA-SM. In both technologies, the eavesdropper’s BER remains under $10^{-1}$ and for the RF it remains relatively equal 0.5, which is equivalent to random guessing. The eavesdropper BER is annotated as Eve and is depicted in red. It is important to highlight that the reason why the secrecy BER is higher in RF than the optical link is because of channel impairments and not the SA-SM technique. To show the effect of the parameter $\alpha$, the transmitted signal is normalized (has maximum of 1). At $\alpha = 0.2$, the eavesdropper’s BER saturates within the range of $10^{-1}$ with a minimal SNR penalty of about 5dB between the SA-SM signal and conventional OFDM transmission. Increasing $\alpha$ causes an increase in the SNR penalty, however, the higher the $\alpha$ the higher the identification accuracy. Since $\alpha = 0.2$ provides 100% accuracy even at $\mathcal{P} = 1000$, we do not include higher values of $\alpha$ in our analysis. Yet, we anticipate that in applications that require more than 1000 keys, a higher value of $\alpha$ would be needed.

The secrecy capacity of SA-SM is also investigated and provided in Fig. 4.6. The performance of SA-SM is compared with the jamming scheme proposed in [88], multi-user precoding-aided spatial modulation (MU-PSM), and precoding plus jamming scheme proposed in [83], secret precoding-aided spatial modulation (SPSM). In our comparison, the eavesdropper is assumed to have 6 receiving elements. As can be observed, SA-SM’s secrecy capacity outperforms MU-PSM and SPSM, which suffer due to the eavesdropper having multiple receiving elements. SA-SM’s performance, on the other hand, remains positive and is inherently proportional with SNR. SA-SM’s perception allows it’s secrecy capacity to be reserved regardless of the number of receiving elements the eavesdropper has, causing SA-SM’s superiority in terms of secrecy capacity performance. It can be noted that the secrecy
capacity in the optical link is higher than in the RF, however, again, it is due to the severity of channel impairment in RF in comparison to the AWGN model for optical.

4.2 Spectral Efficiency Enhancement for SISO Systems

For spectral efficiency enhancement, higher modulation orders and efficient OFDM are considered [101]. An alternative approach is based on multiple antenna configurations to enable spatial-domain multiplexing and beamforming [102]. However, the performance of these techniques relies heavily on the rich scattering nature of the channel and the accuracy of CSI. Due to the properties of the optical channel, it is extremely challenging to apply MIMO in VLC. The nature of the channel enforces an ill-conditioned (almost singular) channel matrix that prohibits spatial decorrelation. Hence, these schemes are channel dependent and require systems with high complexity. With the uprise of new IoT applications, systems cannot withstand additional complexity. Hence, the focus is reverted to improving the spectral efficiency of pre-existing OFDM techniques.

4.2.1 Realization of ACom’s Approach

In ACom, the transmitted waveform is pre-conditioned by design through augmented modulation (AMod), augmented modulator. Hence, the receiver excerpts two data streams from the received waveform. The modulation stream is associated to reverting conventional IQ-samples to their default form and recovering IQ-symbols using a conventional demodulator. The second stream is the augmented stream and is conveyed with AMod. The augmented stream is recovered through augmented demodulation (ADeMod), augmented demodulator. The transmitted ACom signal, $s$, in its general form is,

$$s = s[k] = g(x[k])$$

(4.19)

where $g(.)$ is the function representing the augmented modulator. Figure 4.7 shows the block diagram of the proposed ACom system, with $w$ denoting the AWGN and $y$ is the received vector. Since the two dominant sources of noise are the shot and thermal noises, an AWGN channel model is an appropriate presentation of a VLC channel. One possible realization, which is the analysis in this section, is the case where $g(x[k])$ is a linear function and can
represented by,

\[ g(x[k]) = \beta x[k] + \alpha b[k] \] (4.20)

where \( \beta \) and \( \alpha \) are design scaling factors, based on the dynamic range of the light source, and \( b[k] \) is a binary sequence with \( b[k] = [b_0, b_1, \ldots, b_{(N-1)}]^T \).

Figure 4.8 illustrates an example of an ACom signal showing the effect of the various parameters on the construction of the transmitted signal \( s[k] \). As depicted in Fig. 4.8, \( x[k] \) is divided into \( \eta \) chunks, with \( N/\eta \) bits in \( b[k] \) taking identical values and the parameter \( \eta \in [1, 2, \ldots, N] \). Values of the scaling factors, \( \beta \) and \( \alpha \), are limited by the characteristics of the transceiver frontends, i.e. light sources, power amplifiers and data converters. Hence, additional information can be transmitted by varying the states of \( b[k] \), giving \( 2^\eta \) possible combinations per OFDM symbol. In our initial design, the set of all possible alterations made by the transmitter through pre-conditioning is assumed known at the receiver, thus the alterations become a deterministic function that can be estimated. In this given system, ACom increases the number of transmitted bits per OFDM symbol, \( \rho \), to become,

\[ \rho = \frac{N}{2} \log_2 M + \eta \] (4.21)

where \( M \) represents the utilized QAM modulation order. The maximum attainable number of bits for this realization is \( \rho_{\text{max}} = N/2 \log_2 M + N \). Hence, the spectral efficiency of ACom using the function specified in (4.20) and the condition when \( \eta = N \), \( \xi_{\text{max}} \), can be calculated as \( \xi_{\text{max}} = \rho_{\text{max}}/N \) [bits/s/Hz]. For illustration, using the equations stated above, assuming a 64-IFFT OFDM-based binary phase-shift keying (BPSK) system with a bandwidth equal to 20 MHz, the throughput of a DCO-OFDM system would be 10 Mbps, while that of ACom-based DCO-OFDM system is 30 Mbps. Table 4.1 compares the spectral efficiency of ACom with eminent HS-based optical OFDM techniques presented in literature.

<table>
<thead>
<tr>
<th>OFDM Technique</th>
<th>Spectral Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACO-OFDM</td>
<td>( N/4 \log_2 M )</td>
</tr>
<tr>
<td>DCO-OFDM</td>
<td>( N/2 \log_2 M )</td>
</tr>
<tr>
<td>eUOFDM</td>
<td>( \leq N/2 \log_2 M )</td>
</tr>
<tr>
<td>SEE-OFDM</td>
<td>( 3N/8 \log_2 M )</td>
</tr>
<tr>
<td>ACom</td>
<td>( \leq N/2 \log_2 M + N )</td>
</tr>
</tbody>
</table>

Table 4.1: Spectral efficiency of optical OFDM techniques
4.2.2 ACom’s Reception

According to the central limit theorem, the subchannel elements $X_q$ can be seen as Gaussian independent and identically distributed (i.i.d) random variables [105], and hence $x[k]$ is an i.i.d. Gaussian random process. Since $g(x[k])$ is a linear transformation of $x[k]$, the probability density function (PDF) of $s[k]$ will follow that of $x[k]$, and hence $s[k]$ is a Gaussian random process. The PDF can be given by

$$p_s(x) = \mathcal{N}(x; 0; \mathbb{E}[|X_q|^2])$$

(4.22)

where

$$\mathcal{N}(x; \mu, \sigma^2) \triangleq \frac{1}{\sqrt{2\pi}\sigma}e^{-(x-\mu)^2/2\sigma^2}$$

(4.23)

with mean $\mu$ and variance $\sigma^2$. Hence, the PDF of the transmitted signal $s$ is

$$p_s(x) = \mathcal{N}(x; \alpha, \beta^2\sigma^2)$$

(4.24)
where $\sigma^2 = \mathbb{E}[|X_q|^2]$ is the average transmitted energy per QAM symbol and the transmit power now becomes

$$\mathbb{E}[s] = \alpha, \quad \mathbb{E}[|s|^2] = \beta^2 \sigma^2 + \alpha^2$$  \hspace{1cm} (4.25)

According to [19], the analytical BER expression for $M$-QAM signaling in AWGN can be approximated as

$$\text{BER} = \frac{2(M - 1)}{M \log_2 M} Q\left(\sqrt{\frac{6 \log_2 M}{M^2 - 1} \text{SNR}}\right)$$  \hspace{1cm} (4.26)

where the $Q$-function is defined as

$$Q(m) \triangleq \int_m^\infty \mathcal{N}(\tau; 0; 1) d\tau \triangleq 1 - \Phi(m)$$  \hspace{1cm} (4.27)

given $\Phi(m)$ is the cumulative distribution function of the normal Gaussian distribution.

The effective SNR, $\text{SNR}_{\text{eff}}$, for the transmitted signal $s[k]$ is

$$\text{SNR}_{\text{eff}} = \text{SNR} \frac{E_s}{E_s + \alpha^2} = \frac{E_s}{N_0} \frac{E_s}{E_s + \alpha^2} = \frac{E_s}{N_0} \frac{1}{1 + \gamma^2}$$  \hspace{1cm} (4.28)

where $E_s$ is the OFDM symbol energy and $\gamma = \alpha/\sqrt{E_s}$. Thus, the term $\frac{1}{1 + \gamma^2}$ represents the SNR penalty cost. At the receiver’s end, firstly, an ACom receiver performs hypothesis testing in order to estimate $b[k]$. There are $2^n$ hypotheses, denoted by $\mathcal{H}_i$, with $i = 1, \ldots, 2^n$, corresponding to the $2^n$ possible binary sequences. Defining $\mathbf{u}^{\mathcal{H}_i}$ as auxiliary vectors given by $\mathbf{u}^{\mathcal{H}_i} = y - \alpha b^{\mathcal{H}_i}$, where $y = y[k] = [y_0, \ldots, y_{N-1}]^T$. Conditioned on $\mathcal{H}_i$ and the corresponding estimates of $x[n]$, $\hat{x}[n]$, the joint PDF of $\mathbf{u}^{\mathcal{H}_i}$ can be indicated as [106]

$$f_{\mathbf{u}^{\mathcal{H}_i}}(u_0^{\mathcal{H}_i}, \ldots, u_{N-1}^{\mathcal{H}_i}|\hat{x}_{\mathcal{H}_i}, \mathcal{H}_i) = \left(\frac{1}{\sqrt{2\pi\sigma_w}}\right)^N \exp\left[-\frac{1}{2\sigma_w^2} \sum_{n=0}^{N-1} (u_n^{\mathcal{H}_i} + b_n^{\mathcal{H}_i} \hat{x}_n, \mathcal{H}_i)^2\right]$$  \hspace{1cm} (4.29)

where $\sigma_w^2$ is the variance of the AWGN $w$. Given the received signal, $y$, the receiver will return the hypothesis that maximizes (4.29), i.e.

$$\hat{b}[k] = \arg\max_i \left[f_{\mathbf{u}^{\mathcal{H}_i}}(u_0^{\mathcal{H}_i}, \ldots, u_{N-1}^{\mathcal{H}_i}|\hat{x}_{\mathcal{H}_i}, \mathcal{H}_i)\right] = \arg\max_i \sum_{n=0}^{N-1} (u_n^{\mathcal{H}_i} + b_n^{\mathcal{H}_i} \hat{x}_n, \mathcal{H}_i)^2$$  \hspace{1cm} (4.30)

Once $\hat{b}[k]$ is known, it is passed to the augmented demodulator to extract the augmented data stream, while the conventional OFDM receiver demodulates $\hat{x}[k]$, which is the received signal $y[k]$ after eliminating $\hat{b}[k]$ (see Fig. 4.7).
Figure 4.9: Relative spectral efficiency gain vs. modulation order ranging from $2^1$ (BPSK) to $2^8$ (256-QAM) at IFFT length of 64. The zero value on the y-axis denotes the spectral efficiency of conventional DCO-OFDM without ACom as a benchmark.

Figure 4.10: Spectral efficiency vs. IFFT length at 64-QAM varying from the smallest length of 64, then 128 for LTE’s 1.4 MHz channels up to 2048 for 20 MHz channels.

4.2.3 Results

Figure 4.9 shows the spectral efficiency gain of utilizing ACom, showing that it provides an enticing spectral efficiency gain as a function of the QAM order. The zero value on the y-axis denotes the spectral efficiency of conventional DCO-OFDM without ACom as a benchmark. From Fig. 4.9, ACom is capable of tripling the spectral efficiency of a BPSK DCO-OFDM based system. In the case of 4-QAM, it is increased by 122%, i.e. more than doubled. This interesting gain can allow transmission at lower modulation orders to suit possible channel degradation while maintaining high data rates. Moreover, the spectral
efficiency can be increased by approximately 25% at modulation orders as high as 256. Additionally, the spectral efficiency gain of ACom also varies with the IFFT length. The analysis adopts the IFFT lengths used in WiFi and LTE standards. Figure 4.10 shows the significant improvement in spectral efficiency especially for higher IFFT lengths at $\eta = N$ when compared to DCO-OFDM transmission without ACom. As shown in Fig. 4.10, the gain is proportional to the IFFT length. Based on these notable findings, ACom is showing its potential as a propitious candidate for meeting future data-rate requirements. Even though the maximum spectral efficiency occurs at $\eta = N$, an analysis on applying smaller values of $\eta$ is given in Fig. 4.11. It can be observed that even by utilizing the simplest realizations, for example at $\eta = 4$, a considerable spectral efficiency gain can still be earned, with a 20% increase for BPSK and a 10% increase for 4-QAM.

The repercussion of varying $\gamma$ on effective SNR is studied and presented in Fig. 4.13 as observed, at $\gamma = 0.2$, the effective SNR penalty is about 0.3 dB. Figure 4.12 shows the effect of varying the parameter $\gamma$ as a function of SNR in the presence of AWGN on the BER performance of the OFDM stream for both the legitimate user and the eavesdropper. The simulation parameters are 64-QAM and an IFFT length of 64. It can be seen that the performance of a user is almost identical to the theoretical model obtained from Eq. (4.26), showing a minimal BER degradation caused by the effective SNR reduction. Increasing $\alpha$ effects the amplitude of the OFDM’s peaks and in return effects the PAPR. The sequence
Figure 4.12: BER vs. SNR performance with the solid orange curve denoting the theoretical performance while the remaining curves show ACom at different $\gamma$ values.

Figure 4.13: Effective SNR reduction vs. $\gamma$ showing that at $\gamma = 0.2$ the effective SNR is reduced only by 0.3 dB.

$b$ follows a uniform distribution with equal probability of either increasing the peak by $\alpha$ or reducing it, i.e. probability of 0.5 to either increase or decrease the peak by the value $\alpha$. Hence, the effect of $\alpha$ on increasing the peak power is averaged over $10^4$ OFDM symbols and depicted in Fig. 4.14. At $\alpha = 0.05$, the peak power is increased only by less than 1% and at $\alpha = 0.15$ by 10%. It is important to note that the analysis focused on peak power, rather than calculating the PAPR, as the peak power is the restricting factor.

ACom is also validated experimentally using a USRP-N210 [107] with integrated LFTX and LFRX daughter-boards, which is connected to an Intel NUC with i7-7567U processor with installed MATLAB 2018b for signal generation and processing as shown in Fig. 4.15. Beside LEDs, LDs have been extensively used in experimental VLC system deployments.
Figure 4.14: The effect of $\alpha$ on the peak power showing that as $\alpha$ increases so does the peak power, hence, there is a trade-off between the eavesdropper’s BER and the system’s PAPR but can be avoided by using $\alpha = 0.05$.

[108], hence, in our demonstration, a LD is used. Our optical frontend is composed of a Thorlabs HL63163DG LD and a PDA10A positive-intrinsic-negative (PIN) PD. The LD is biased to about 70 mA using the TCLDM9 mount and is attached to current and temperature controllers. A fresnel lens with 25 mm focal length is attached to both the LD and the PD to improve signal quality. The signal originates from the NUC and passes to the LFTX daughterboard, which sends the ACom symbols to the transmitter frontend. The PIN PD at the receiver frontend, forwards the received ACom symbols to the LFRX daughterboard and then back to the NUC for processing. The NUC and the USRP are connected via an Ethernet cable. Figure 4.16 shows the experimental OFDM stream BER performance of ACom using 4-QAM at various $\gamma$ values, with a separation distance of 50 cm between the LD and PD. As shown in Fig. 4.16, the SNR penalty is insignificant and consistent with the results obtained via simulations.
Figure 4.15: Experimental setup of ACom using an single USRP-N210 with two integrated daughter-boards showing the optical front-ends and the NUC used for ACom signal processing.

Figure 4.16: Experimental BER vs. SNR performance with the grey curve showing ACom at $\gamma$ equal to zero which is equivalent to DCO-OFDM transmission without ACom, while the remaining curves show ACom at different $\gamma$ values using 4-QAM and an IFFT length of 64.
CHAPTER 5
Experimental Testbeds

5.1 Jamming Mitigation Evaluation using FIT-IoT

Jamming attacks are considered the most common type of attacks in wireless networks [109]. An unavailability threat can be defined as the obstruction of a user/device from sending/receiving its data packets as a result of jamming. Generally, current jamming detection and mitigation methods can be categorized into two groups [110]. One group demands complex network protocols that require additional computing resources or cause delays. The second group requires IoT nodes to have sensing capabilities which limits the applicability of such solutions. On top of the amplified security challenges, mass-scale deployment of IoT devices necessitates a tremendous chunk of bandwidth in order to support their transmissions, however, bandwidth is a scarce commodity. In order to overcome this ordeal, cognitive radio (CR) technology is becoming an emerging trend in IoT system realization by creating an adaptive and intelligent radio that is capable of detecting vacant channels and changing their transmission parameters accordingly. In CR-IoT-based networks, IoT devices share the wireless channel with nodes that act as licensed primary users (PUs). IoT devices, on the other hand, act as unlicensed secondary users (SUs) and are granted access to the spectrum as long as they do not interfere with PUs transmissions.

This section proposes algorithms that considers the security demands of IoT-based CR networks and assigns the channels accordingly, allowing jamming attacks to be mitigated without consuming additional power nor resources [110]. A mathematical model for each CR communicating pair is developed to constitute the packet-invalidity ratio, $r$. It can be described as the probability that the transmission delay of a data packet, $D$, is larger than a preset threshold, $D_{th}$. Invalidity ratio calculations take into account the jammer’s jamming level, the cognitive radio network (CRN) link quality, and PU channel availability duration. The aim is to select the channels that would enhance the CRN throughput for each transmission. To validate the proposed algorithm a testbed is used to bridge the gap between simulation and real device deployment. After an extensive survey on the available
platforms, FIT IoT-LAB is found to be the most fitting for this implementation [111][112].

FIT IoT-LAB is made up of 2728 low-power wireless nodes and 117 mobile robots situated in six different locations across France [113]. It offers a multi-user, open-access, and open-source federated environment for experimentation. The advantage of FIT IoT-LAB is that it provides bare-metal access to its nodes. Their static nodes are divided into three types; WSN430, M3, and A8, differing by their capabilities. The M3 nodes are chosen for this implementation, which feature a 32-bit ARM Cortex-M3 micro-controller and the AT86RF231 radio chip that is IEEE 802.15.4 complaint. The IEEE 802.15.4 standard states both the physical and medium access control (MAC) layers; specifying a typical range of 10-100 meters using 16 orthogonal frequencies around 2.4GHz, i.e. channels 11-26 [114]. Moreover, the standard specifies a maximum frame size of 127 bytes. Additionally, the AT86RF231 radio chip supports a PSDU with data rates of 250 Kbps, 500 Kbps, 1 Mbps, and 2 Mbps [115]. On the software side, five IoT operating systems are maintained including; RIOT, OpenWSN, FreeRTOS, Contiki, and TinyOS. The M3 nodes can only be supported by RIOT, OpenWSN, FreeRTOS, and Contiki. FreeRTOS is chosen for this implementation as it provides fast execution, small memory footprint, and low overhead. It is a micro-kernel that provides semaphores, mutexes, multi-threading, and software timers with a carrier-sense medium access (CSMA) for the MAC layer.

5.1.1 Single User Single Transceiver

5.1.1.1 Optimum Channel Assignment Problem

The set of all available channels for transmissions is denoted as \( \mathcal{M} \), which the CR IoT device can dynamically access. The statuses of the channels are set as either idle or busy, operating a two-state fluctuating renewal activity. The channel is occupied by the PU for the duration \( T_B \), hence the notion \( T_B^{(i)} \) signifies that the channel \( i \) is busy for duration \( T_B \) and can not be used by the CR device. The proposed channel assignment algorithm can be observed as a sorting problem and its objective is to assign an idle channel from set \( \mathcal{M} \) with the least invalidity ratio for the \( j^{th} \) transmission. At the beginning of transmission \( j \), based on PU activity, there will be the set, \( \mathcal{M}_j \), listing the idle channels available for CR devices. Then, the algorithm is executed in three main steps that can be summarized as;
1. The channels that do not satisfy the SNR threshold will be excluded from $\mathcal{M}_j$ yielding a new set of feasible channels $\mathcal{M}_j^f$.

2. The algorithm calculates $r^{(i)}_j$ for the renewed set obtained from step 1.

3. The channel with the least $r^{(i)}_j$ is chosen.

where $r^{(i)}_j$ denotes the invalidity ratio of transmission $j$ over channel $i$. The invalidity ratio for this problem formulation can be defined as

$$r \leq \frac{\left(1 - e^{-\frac{T_I + T_J}{T_{I+J}}}\right)^{N_x} \mathbb{E}[d_k]}{\left(1 - \left(1 - e^{-\frac{T_I + T_J}{T_{I+J}}}\right)^{N_x}\right) (D_{th} - \mathbb{E}[d_k]) + \left(1 - e^{-\frac{T_I + T_J}{T_{I+J}}}\right)^{N_x} \mathbb{E}[d_k]}$$

(5.1)

where $\mathbb{E}[d_k]$ is the statistical mean of the MAC layer delay, $N_x$ is the number of retransmissions allowed by the MAC layer, and $T_I$ and $T_J$ are the mean of the idle times and jamming times, respectively.

5.1.1.2 Results

The throughput performance under different PU activity levels is investigated and presented in Fig. 5.1. The performance of the proposed algorithm, security-aware MAC (SA-MAC), is compared with two reference algorithms: MAX PoS [116, 117] and the greedy approach. The MAX PoS algorithm is a probabilistic-based approach that aims at maximizing network throughput by utilizing the parallel-transmission capability while considering channel quality and availability. However, it is oblivious to jamming. On the other hand, the greedy algorithm aims at selecting the channels with the highest quality in terms of signal-to-noise ratio [118]. In Fig. 5.1(a), $P_B = 0.1$ denotes that the 9 channels out of the available 10 can be occupied for CR transmission. As shown, the proposed technique outperforms random channel assignment significantly, yielding an improvement of about 153%. Almost reaching the non-jamming throughput of about 525 Kbps, which is limited due to the utilized standard and hardware, at $x = 10$. However, as the busy probability increases to reach 0.9, i.e., there is only one available channel to utilize, the performance is equivalent to random selection due to the lack of idle channels, as depicted in Fig. 5.1(c). Similarly, the percentage of dropped packets follow the same trend, showing the best performance at
Figure 5.1: Throughput curves of the proposed security-aware channel assignment algorithm vs. random channel assignment for various busy probabilities, $P_B$, at $N = 10$ and $L = 96$ bytes, (a) Low PU activity with $P_B = 0.1$, (b) Moderate PU activity with $P_B = 0.5$, (c) High PU activity with $P_B = 0.9$.

Figure 5.2: Percentage of dropped packets of the proposed security-aware channel assignment algorithm vs. random channel assignment for various busy probabilities, $P_B$, at $N = 10$ and $L = 96$ bytes, (a) Low PU activity with $P_B = 0.1$, (b) Moderate PU activity with $P_B = 0.5$, (c) High PU activity with $P_B = 0.9$.

$P_B = 0.1$ presented in Fig. 5.2(a). Additionally, as $P_B$ increases as shown in Fig. 5.2(c), the dominant factor becomes the PU activity forcing no improvement over random channel assignment.

5.1.2 Single User Multiple Transceivers/Channels

In this problem formulation, the main objective is to maximize spectrum efficiency by selecting the least number of mostly secured channels for each CR-IoT transmission while satisfying pre-specified quality-of-service (QoS) requirements. Specifically, for a given a CR-IoT transmission, the set of available channels for that transmission and their average availability (and jamming) intervals, the received SNR over each channel, the required QoS
requirements, the communicating pair seek to compute the most secured channel assignment \((\Omega)\) that satisfies the QoS requirements while using the minimum number of channels subject to the following network constraints:

1. **Hardware constraint:** Each CR-IoT device is equipped with \(L\) transceivers (each CR user can utilize up to \(L\) channels at a time).

2. **The QoS constraints:** (1) The invalidity ratio over the selected channels \(r\) (computed based on the delay requirements and jamming behaviours over the selected channels) should be less than a given threshold \(r \leq \gamma\) and (2) the aggregate rate should be greater than a specific rate demands \(R_{th}\) set based on user-demand.

3. **The received signal-to-noise ratio (SNR) constraints:** The received SNR over each assigned channel \(i \in \Omega\) should be greater than a pre-specified threshold \(SNR_{th}\) (\(i.e.\) \(SNR(i) \geq SNR_{th}\)).

Jammers main categories include constant, deceptive, proactive/random, and reactive \[119\]. The constant jammer corrupts all network packets by transmitting random signals continually. However, these types of attacks can be easily detected, as the source of the created interference can be traced \[120\]. A deceptive jammer sends constantly a stream of bytes similar to a legitimate transmission. The consistency of these attacks from a single source again makes them easily traceable. Furthermore, the two aforementioned attacks require a significant amount of power. Hence, in this analysis, the focus is on the two latter types of attacks, the proactive and reactive jammers \[121\]. Proactive jammers alternate between sleeping and jamming phases without any regard to when CR nodes are transmitting. Reactive jammers, on the other hand, are the most energy-efficient type of attacks, as they start their transmissions only when CR transmission is detected. A thorough illustration of these two jamming strategies is provided in the forthcoming subsections. It is important to note that jammers can simply disregard MAC protocols and prevent legitimate users from using the network. Yet, the legitimate users have to abide by IEEE’s MAC protocols, which are normally carrier sense multiple access/collision avoidance (CSMA/CA) based. Such attacks can also introduce packet collisions and force repeated backoffs \[122\]. The behaviour of each type of attack and its impacts on the network performance are described below.
5.1.2.1 Proactive Jammer

The strategy of a proactive jammer can be described by the time interval between two successive jamming signals, \( T_j^{(i)} \), associated with channel \( i \). For successful packet delivery, the packet transmission time, \( t_x \), needs to be less than both the chosen CR channel idle period, \( T_I^{(i)} \), in order not to interfere with PU activity, and the jamming interval across the channel, \( T_J^{(i)} \), to ensure that the packet was not damaged by the jammer. For a given assignment \( \Omega = \{m_1, m_2, \ldots, m_M\} \), the failure probability, as defined in [110], can be expressed as:

\[
p_p = 1 - \Pr\left( \{\min(T_I^{(i)}, T_J^{(i)}) \geq t_x, \forall i \in \Omega \} \right) = 1 - \prod_{i \in \Omega} \Pr\left( \{\min(T_I^{(i)}, T_J^{(i)}) \geq t_x \} \right) \tag{5.2}
\]

Following the memoryless jamming model expressed in [123], where \( T_I^{(i)} \) and \( T_J^{(i)} \) are statistically independent and exponentially distributed random variables (with means of \( T_I^{(i)} \) and \( T_J^{(i)} \), respectively), then, \( p_p \) can be expressed as:

\[
p_p = 1 - \prod_{i \in \Omega} e^{-\frac{t_x}{T_I^{(i)}} - \frac{t_x}{T_J^{(i)}}} = 1 - \prod_{i \in \Omega} e^{-t_x \frac{T_I^{(i)} + T_J^{(i)}}{T_I^{(i)} T_J^{(i)}}} = 1 - \prod_{i \in \Omega} e^{-\lambda_i t_x}, \quad \lambda_i = \frac{T_I^{(i)} + T_J^{(i)}}{T_I^{(i)} T_J^{(i)}} \tag{5.3}
\]

Then, the failure probability after \( N_x \) MAC layer re-transmission attempts is given by:

\[
p_{f_p} = p_p^{N_x} = \left(1 - \prod_{i \in \Omega} e^{-\lambda_i t_x} \right)^{N_x} \tag{5.4}
\]

5.1.2.2 Reactive Jammer

For the case of reactive jamming, the condition for successful packet delivery occurs when the total transmission time of the CR-IoT packet is less than the idle period of the selected channel and no jamming to impact the packet occurs during that time. Since jamming and PU activities are independent random variables, the failure probability, \( p_r \), as
defined in [110], is evaluated as

\[ p_r = 1 - \prod_{i \in \Omega} \Pr(T_i^{(i)} > t_x)(1 - P_j^{(i)}) \]

\[ = 1 - \prod_{i \in \Omega} e^{-\frac{t_x}{T_i^{(i)}}} (1 - P_j^{(i)}) \]  

(5.5)

where \( P_j^{(i)} \) denotes the jamming probability over channel \( i \). Similar to the case of proactive jamming, the failure probability after \( N_x \) retransmissions can be expressed as

\[ p_{fr} = p_r^{N_x} = \left( 1 - \prod_{i \in \Omega} e^{-\frac{t_x}{T_i^{(i)}}} (1 - P_j^{(i)}) \right)^{N_x} \]  

(5.6)

5.1.2.3 Invalidity Ratio Analysis

As previously mentioned, the packet-invalidity ratio, \( r \), can be interpreted as the probability that the transmission delay of a data packet, \( D \), exceeds a preset threshold, \( D_{th} \). Invalidity ratio calculations take into account the jamming interval, the CR network link quality, and PU channel availability duration. A generalized upper bound for \( r \) (denoted as \( r_{up} \)), irrespective of the jammer type, can be calculated as [110]:

\[ r \leq r_{up} = \frac{p_{fr}d_k}{(1 - p_{fr})(D_{th} - d_k) + p_{fr}d_k} \]  

(5.7)

where \( d_k \) is the average MAC-layer delay of transmission \( k \) and \( p_{fr} \) is failure probability after \( N_x \) re-transmissions. The aim is to select the channels that would enhance the CR network throughput for each transmission. In order to achieve this in the presence of a jammer, the algorithm must account for PU activity, link-quality, and jamming behaviour.

Given the upper bound \( r_{up} \), a specific invalidity-rate requirement \( r \leq \gamma \) can be ensured by imposing that \( r_{up} \leq \gamma \). This implies that \( r \leq r_{up} \leq \gamma \), which ensures that \( r \leq \gamma \). For a given \( \gamma \), the upper bound in (5.7) can be equivalently written in terms of \( p_{fr} \) as:
\[
\frac{pf\bar{d}_k}{(1-p_f)(D_{th}-\bar{d}_k) + pf\bar{d}_k} \leq \gamma
\]

\[
p_{f} \bar{d}_k - \gamma(1-p_f)(D_{th}-\bar{d}_k) - \gamma pf\bar{d}_k \leq 0
\]

where \(B_{th}\) is a threshold-dependant delay constant.

By using (5.4) into (5.8), the invalidity requirement can be written in terms of the failure probability, \(p\), for a given assignment \(\Omega\) as:

\[
p^N_x \leq B_{th}^{(D_{th},\gamma,\bar{d}_k)}
\]

\[
p \leq \frac{N_x}{\sqrt{B_{th}}}
\]

Under proactive jamming, using (5.3) into (5.9) and some algebraic manipulation, the invalidity-ratio requirement for a given assignment \(\Omega\) can be written as:

\[
1 - e^{-\sum_{i \in \Omega} \lambda^{(i)}t_x} \leq \frac{N_x}{\sqrt{B_{th}}}
\]

\[
\ln(1 - \frac{N_x}{\sqrt{B_{th}}}) \leq -\sum_{i \in \Omega} \lambda^{(i)}t_x
\]

where \(t_x = \frac{L}{\sum_{i \in \Omega} R^{(i)}}\) with \(L\) representing the packet size and and \(R^{(i)}\) is the rate of transmission in channel \(i\).

Under reactive jamming scenarios, and for a given assignment \(\Omega\), the invalidity-rate
requirement can be written in terms of the jamming behavior by applying (5.6) and (5.9) as:

\[
1 - \prod_{i \in \Omega} \Pr(T_{(i)}^t)(1 - P_{j}^{(i)}) \leq \sqrt[2]{B_{th}}
\]

\[
(1 - \sqrt[2]{B_{th}}) \leq \prod_{i \in \Omega} e^{-\frac{t_x}{T_{(i)}^j}} (1 - P_{j}^{(i)})
\]

\[
\ln(1 - \sqrt[2]{B_{th}}) \leq \ln\left(\prod_{i \in \Omega} e^{-\frac{t_x}{T_{(i)}^j}} (1 - P_{j}^{(i)})\right)
\]

\[
\ln(1 - \sqrt[2]{B_{th}}) \leq \sum_{i \in \Omega} \ln\left(e^{-\frac{t_x}{T_{(i)}^j}} (1 - P_{j}^{(i)})\right)
\]

(5.11)

5.1.2.4 Proposed Solution

The problem formulation for the proposed algorithm is given in detail in Appendix B. From (B.4) and (B.9), the problem can be observed as a binary linear programming (BLP) optimization problems. Generally, the optimal solution to these problems is NP-hard. To solve this problem in polynomial-time, the SFLP procedure [124, 125] is used as a tool to find a near-optimal solution for our BLP problem. The effectiveness of the SFLP procedure in solving BLP problems have been demonstrated in several previous works, where near-optimal solutions were provided in polynomial-time [116, 117, 110, 124, 125]. Thus, the problem in Appendix B, (B.4), can be near-optimally solved in polynomial-time using the SFLP procedure. The proposed channel assignment algorithm operates as follows:

1. Given SNR_{th}, the channels that do not satisfy the SNR threshold will be excluded from \( \mathcal{M} \), yielding a new set of feasible channels \( \mathcal{M}' \). Then, the algorithm arbitrates the per-channel achievable rate, \( \mathcal{R}^{(i)} \), and the required per-channel transmission period accordingly, i.e. \( t_x^{(i)} = L/\mathcal{R}^{(i)} \).

2. Using \( T_{(i)}^t, T_{j}^t, B_{th}, N_x, \) and \( \mathcal{R}^{(i)} \), the algorithm calculates the jammer type dependent variable, \( a^{(i)} \) in the case of the proactive jamming and \( b_i \) and \( c_{ij} \) for reactive jamming, for the renewed set obtained from step 1.

3. The findings are fed to the SFLP procedure and \( \alpha^{(i)} \)'s are computed.
4. If the SFLP fails to find a solution, i.e. a solution such that the throughput constraint is satisfied cannot be found, the algorithm chooses $L_x$ channels with the highest invalidity ratios. In this case, we denote the binary decision variation as $\alpha^*(i)$.

Algorithm 3 shows the pseudocode of PCS-MAC.

Algorithm 3 PCS-MAC Channel Assignment

```
Input: $M$, $B_{th}$, $N_x$, $L_x$, $SNR_{th}$, $SNR^{(i)}$, $T_I^{(i)}$, $T_J^{(i)}$, $R^{(i)}$
Output: A feasible multi-channel assignment $\alpha^{(i)}$

Let $M^f = M$

for all $i \in M$

if $SNR^{(i)} < SNR_{th}$

$M^f = M^f - \{i\}$

else

Compute the invalidity ratio $r^{(i)}$

Compute $a_i$ or $b_i$ and $c_{ij}$ based on the jammer strategy

end-of-if

end-of-for

$\alpha^{(i)} = SFLP$

if $\alpha^{(i)} = \phi$

for all $i \in M^f$

Sort the channels in an increasing order of $r^{(i)}$

end-of-for

Let $U$ be the sorted channel list

Identify the $L_x$ channels that are on the top of $U$

Return $\alpha^*(i)$

else

Return $\alpha^{(i)}$

end-of-if
```

5.1.2.5 Results

In our experiment, there are 10 nodes reserved to act as jammers on the selected channels, which are channels 11 to 21. The positions of the jammers are fixed, however, the channels they jam vary with each run, such that all ten channels are jammed in every iteration. Channel 17, where FIT IoT WiFi access points operate, is excluded to avoid external
interference. Since single-radio multi-channel implementations introduce channel switching delays [126], PCS-MAC is evaluated for the multi-radio case to allow fair evaluation of the proposed scheme. Since the M3 nodes have only one transceiver, virtual nodes are created by combing $L_x$ physical M3 nodes to emulate CR-IoT nodes with parallel transmission capability. There are six reserved virtual nodes, equivalent to 18 M3 nodes in the case of $L_x = 3$ and 12 in the case of $L_x = 2$. Each CR transmission occurs between two randomly selected virtual nodes and is fixed as 1000 packets, each is 96 bytes in length, i.e. $L = 96$ bytes. Considering a time-critical application, a delay threshold of 20 ms is set, i.e. $D_{th} = 20$.

I. Proactive Jammer Results

A memoryless jamming strategy is considered to emulate the proactive jamming attacks. The average availability duration, $T_{I}^{(i)}$, over the ten channels is 5, 100, 30, 5, 45, 50, 100, 5, 45, and 30ms respectively. While, the average jamming interval, $T_{J}^{(i)}$, over the ten channels is 5, 0.2, 10, 2, 20, 5, 0.1, 2.9, 20, and 0.2 $\times$ $x$ ms respectively, where $x$ re-
Figure 5.5: Throughput curves of the proposed PCS-MAC channel assignment algorithm under proactive jamming at $L_x = 2$ and $L_x = 3$ for various QoS requirements.

Figure 5.6: Throughput performance vs. $P_B$ under different jamming activities at $M = 10$ and $L = 96$ bytes under proactive jamming at $L_x = 2$ and $L_x = 3$, i.e. given two and three transceivers.

represents the jamming attack level. Each channel is busy with probability $P_B$. Firstly, the throughput performance under different PU activity levels is investigated and presented in Fig. 5.3 for $L_x = 3$ and $R_{th} = 600$ Kbps, as it is about the highest achievable throughput given 3 transceivers. The reported results are averaged over 1000 runs with the number of allowed MAC re-transmissions fixed as 2 ($N_x = 2$). In Fig. 5.3(a), $P_B = 0.1$ denotes that the 9 channels out of the available 10 can be occupied by CR transmission. As shown, the proposed technique outperforms the greedy approach significantly, yielding about 180% increase in throughput at $x = 20$ ms. PCS-MAC also outperforms MAX-PoS, with a 62% increase in throughput at $x = 20$ ms and $P_B = 0.1$. As $x$ increases, the jamming attacks become less severe, which is intuitive as the period between jamming attacks becomes larger. Throughput, in return, increases with $x$. However, as $x$ increases, PUs activities become the dominant obstacle for throughput performance. For high values of $x$, it can be observed that the performance of MAX-PoS approaches that of PCS-MAC, as the effect of jamming is reduced. Moreover, as the busy probability increases to reach 0.9, i.e. there is only one avail-
able channel to use, the limiting factor becomes channel availability. Thus, the performance of all algorithms is similar due to the lack of idle channels, shown in Fig. 5.3(c).

To evaluate the efficacy of the proposed algorithm in adapting to various delay requirements, Fig. 5.4 shows the effect of varying the delay threshold on the percentage of dropped packets. Intuitively, the larger the $D_{th}$, the more time is allowed for packets to be retransmitted, hence, the number of dropped packets decreases. In Fig. 5.4(a), under low PU activity (i.e. $P_B = 0.1$), it can be observed that PCS-MAC outperforms the other techniques by having the least percentage of dropped packets in both delay requirements. However, similar to the previous results, at high PU activity (i.e. $P_B = 0.9$) all techniques behave similarly ascribed to the lack of available channels. Due to the lack of space and since the performance of PCS-MAC significantly outperforms that of the greedy approach, the remainder of the results focus on comparing PCS-MAC with MAC-PoS. The efficiency of PCS-MAC is also tested for different $R_{th}$ requirements. Figure 5.5 shows the throughput performance at three different data-rate requirements under different PU activity levels at $L_x = 2$ and 3. As can be observed, the algorithm conforms to the specified requirement. In Fig. 5.5(c), since the throughput is already below the required $R_{th}$, the performance is identical to PCS-MAC in Fig. 5.3(c) at $L_x = 3$. Lastly, the effect of varying $P_B$ on the throughput is investigated in Fig. 5.6 for the cases of the nodes equipped with 2 and 3 transceivers. Throughput naturally increases as the number of transceivers increases for MAX-PoS and PCS-MAC. The resilience of PCS-MAC against jamming is highlighted in Fig. 5.6. For high jamming activity, the variance between the throughput performance of PCS-MAC and MAX-PoS is at its peak, as PCS-MAC reduces the number of dropped (invalid) packets which in return increases throughput. As the jamming level decreases, the variance between the throughput enhancement of both techniques declines, yet PCS-MAC is consistently to the fore.

II. Reactive Jammer Results

This section is dedicated to evaluating PCS-MAC under reactive jamming strategy. In this case, the jamming strategy is varied such that each channel $i$ has a jamming probability $p_j^{(i)}$. For the ten channels, the jamming probabilities are 0.06, 0.75, 0.03, 0.15, 0.015, 0.06, 1, 0.105, 0.015, and $0.75 \times p_j^{MAX}$. The jamming probability factor, $p_j^{MAX}$, is bounded such that $0 \leq p_j^{MAX} \leq 1$ forcing the jamming probability of all channels not to exceed 1, which allows us to study throughput performance under different jamming conditions. Firstly, throughput
Figure 5.7: MAX-PoS and PCS-MAC throughput performance vs. $P_B$ under different jamming activities at $M = 10$ and $L = 96$ bytes for reactive jamming at $L_x = 2$ and $L_x = 3$, i.e. given two and three transceivers.

Figure 5.8: Throughput performance vs. $P_{j,MAX}$ under three primary user blocking probabilities at $M = 10$ and $L = 96$ bytes under reactive jamming at $L_x = 2$ and $L_x = 3$, i.e. given two and three transceivers.

is investigated under low, moderate, and high jamming activities vs. $P_B$, depicted in Fig. 5.7). Similar to the case of proactive jamming, the effectiveness of PCS-MAC prevails as the jamming attacks are more severe, i.e. high $p_{j,MAX}$. The throughput improvement is smaller at lower jamming probabilities, as the dominating factors are the channel quality and PUs activities, which are already addressed by MAX-PoS. However, at high $p_{j,MAX}$ and $P_B = 0.1$, about a 100% throughput enhancement over MAX-PoS can be achieved by PCS-MAC using 2 or 3 transceivers, as depicted in Fig. 5.7(c). Figure 5.8 studies the outcome of varying PU activities on throughput vs. $p_{j,MAX}$. It can be noticed that as $P_B = 0.9$, the performance of PCS-MAC gracefully degrades to that of MAX-PoS due to the lack of available idle channels. It can also be observed that throughput is inversely proportional to $p_{j,MAX}$, surrendering to its worst value at $p_{j,MAX} = 0.9$, as the jamming attacks become most vigorous.
5.1.3 Multiple Users Multiple Transceivers/Channels

5.1.3.1 Optimum Channel Assignment Problem

The previously mentioned formulation is extended to account for multiple users. Recall that we seek finding the channel assignment (which channels are assigned to which users) that achieves the design objective of maximizing the number of simultaneously admitted CR-IoT devices with achieved QoS/design constraints. To pursue our formulation, we define a decision 0/1-variable $\alpha_j^{(i)}$ for each CR-IoT transmission $j \in N$ over every channel $i$ as:

$$
\alpha_j^{(i)} = \begin{cases} 
1, & \text{if channel } i \text{ is allocated to CR-IoT } j \\
0, & \text{otherwise.}
\end{cases}
$$

Using the defined decision variables $\alpha$’s, our objective function $O(\alpha_j^{(i)})$ can be written as:

$$
O(\alpha_j^{(i)}) = \sum_{j \in N} 1_{i \in M} \alpha_j^{(i)} + \frac{\sum_{j \in N} \sum_{i \in M} \alpha_j^{(i)} R_j^{(i)}}{\sum_{i \in M} R_j^{(i)}}
$$

(5.12)

where $1[.]$ is the indicator function. Note that the first term of $O(\alpha_j^{(i)})$ represents the number of admitted CR-IoT transmissions while the second term, which is always $< 1$, is used to break the tie between any two assignments with the same number of served CR-IoT devices by selecting the assignment that provides higher total sum-rate. Following the same methodology used in [127], the non-linear term (i.e. the indicator function) in the objective can be linearized by defining the variable $U_j = \sum_{j \in N} 1_{i \in M} \alpha_j^{(i)}$, $\forall j \in N$ and adding the two constraints:

$$
\frac{1}{M} \sum_{i \in M} \alpha_j^{(i)} - U_j \leq 0, \ \forall j \in N
$$

$$
U_j - \sum_{i \in M} \alpha_j^{(i)} \leq 0, \ \forall j \in N.
$$

(5.13)

Therefore, $O(\alpha_j^{(i)})$ becomes:

$$
\max \sum_{j \in N} U_j + \frac{\sum_{j \in N} \sum_{i \in M} \alpha_j^{(i)} R_j^{(i)}}{\sum_{i \in M} R_j^{(i)}}.
$$

(5.14)
Using the introduced binary variables, the rate demand constraints can be written as either/or constraint as:

$$\sum_{i \in M} R_j^{(i)} \alpha_j^{(i)} \geq R_{D_j}, \; \forall j \in N \quad \text{or} \quad \sum_{i \in M} R_j^{(i)} \alpha_j^{(i)} = 0, \; \forall j \in N.$$ 

This constraint can be written in a linear form as:

$$\sum_{i \in M} -R_j^{(i)} \alpha_j^{(i)} - \Psi y_1^{(j)} \leq -R_{D_j}, \; \forall j \in N \quad \sum_{i \in M} R_j^{(i)} \alpha_j^{(i)} - \Psi y_2^{(j)} \leq 0, \; \forall j \in N \quad y_1^{(j)} + y_2^{(j)} = 1, \; \forall j \in N. \quad (5.15)$$

Writing the invalidity-ratio in Eq. (5.11) in terms of $\alpha_j^{(i)}$ variables, the invalidity-ratio constraint can be expressed as:

$$\sum_{i=1}^{M} \left( \ln(1 - \sqrt[B_{th}]{B_{th}} \sum_{j=1}^{M} \sum_{k=1}^{M} \alpha_j^{(i)} \alpha_j^{(k)} R_j^{(i)} R_j^{(k)} \alpha_j^{(i)} \alpha_j^{(k)} \right) \leq \sum_{i=1}^{M} \sum_{k=1}^{M} \ln(1 - P_j^{(i)} R_j^{(k)} \alpha_j^{(i)} \alpha_j^{(k)}) \quad (5.16)$$

After some mathematical steps, (5.16) can be rewritten as:

$$\sum_{i=1}^{M} b_j^{(i)} \alpha_j^{(i)} \leq \sum_{j=1}^{M} \sum_{k=1}^{M} c_j^{(ik)} \alpha_j^{(i)} \alpha_j^{(k)} \quad (5.17)$$

where $b_j^{(i)} = \ln(1 - \sqrt[B_{th}]{B_{th}} R_j^{(i)} + L_j)$, $c_j^{(ik)} = \ln(1 - P_j^{(i)} R_j^{(k)})$, $\forall j \in N, i, k \in M$.

The invalidity-ratio constraint in (5.17) seems to be non-linear, which is hard to optimize. To linearize (5.17), we introduce a new binary parameter $w_j^{(ik)} = \alpha_j^{(i)} \alpha_j^{(k)}$ and we add three auxiliary constraints on $w_j^{(ik)}$ as follows:

$$w_j^{(ik)} \leq \alpha_j^{(i)}, \; \forall j \in N, i, k \in M$$

$$w_j^{(ik)} \leq \alpha_j^{(k)}, \; \forall j \in N, i, k \in M$$

$$w_j^{(ik)} \geq \alpha_j^{(i)} + \alpha_j^{(k)} - 1 \; \forall j \in N, i, k \in M \quad (5.18)$$

The exclusive-channel occupancy and number of utilized channels constraints can be respectively written in terms of $\alpha_i$ as:

$$\sum_{j \in N} \alpha_j^{(i)} \leq 1, \; \forall i \in M \quad (5.19)$$
and

$$\sum_{i \in M} \alpha_j^{(i)} \leq L_{x_j}, \ \forall j \in N \quad (5.20)$$

Given the objective function in (5.14) and the design constraints in (5.13), (5.15), (5.18), (5.19) and (5.20), our optimization problem in terms of the decision variables $\alpha$ can be expressed as:

$$\max \sum_{j \in N} O(\alpha_j^{(i)}) = U_j + \frac{\sum_{j \in N} \sum_{i \in M} \alpha_j^{(i)} R_j^{(i)}}{\sum_{i \in M} R_j^{(i)}}$$

s.t. $U_j - \sum_{i \in M} \alpha_j^{(i)} \leq 0, \ \forall j \in N$

$$\frac{1}{M} \sum_{i \in M} \alpha_j^{(i)} - U_j \leq 0, \ \forall j \in N$$

$$\sum_{i \in M} b_j^{(i)} \alpha_j^{(i)} - \sum_{i \in M} \sum_{k \in M} c_j^{(ik)} w_j^{(ik)} \leq 0, \ \forall j \in N$$

$$\sum_{i \in M} R_j^{(i)} \alpha_j^{(i)} - \Psi y_j^{(i)} \leq -R_{D_j}, \ \forall j \in N$$

$$\sum_{i \in M} R_j^{(i)} \alpha_j^{(i)} - \Psi y_j^{(i)} \leq 0, \ \forall j \in N$$

$$y_1^{(j)} + y_2^{(j)} = 1, \ \forall j \in N$$

$$w_j^{(ik)} \leq \alpha_j^{(i)}, \ \forall j \in N, i, k \in M$$

$$w_j^{(ik)} \leq \alpha_j^{(k)}, \ \forall j \in N, i, k \in M$$

$$w_j^{(ik)} \geq \alpha_j^{(i)} + \alpha_j^{(k)} - 1, \ \forall j \in N, i, k \in M$$

$$\sum_{j \in N} \alpha_j^{(i)} \leq 1, \ \forall i \in M$$

$$\sum_{i \in M} \alpha_j^{(i)} \leq L_{x_j}, \ \forall j \in N.$$
been previously proven to be NP-hard from a graph theory perspective \cite{128}. We note that there are a number of approximate algorithms for solving BLP problems, such as cutting-plane, branch-and-bound, and decomposition methods \cite{129}. However, their worst-case time complexity is still exponential as $N$ and $M$ increase \cite{130}. To obtain sub-optimal solutions for our problem in polynomial-time, the SFLP procedure is adopted. This procedure has been adopted by several existing research efforts to solve similar BLP problems, by which sub-optimal solutions with polynomial-time complexity were demonstrated \cite{131}. The adopted SFLP methodology is executed as follows:

**Step 1.** All unfixed variables are relaxed to real numbers in $[0, 1]$ range, resulting in a relaxed linear programming (LP).

**Step 2.** The relaxed LP problem is solved using the polynomial-time standard LP methods. If the LP is infeasible, then no feasible solution can be found for the original BLP. Otherwise, the CR-IoT communicating pair with the highest summation of $\alpha$’s among the $N$ CR-IoT pairs is identified.

**Step 3.** The decision variable $\alpha$ with the highest value among all unfixed $\alpha$’s of the identified CR-IoT pair is set to 1. The LP is then updated and resolved with the fixed $\alpha$’s. If infeasible, the fixed $\alpha$ is not correct and should be 0.

**Step 4.** The process in Step 3 is repeated until the QoS requirements for the identified CR-IoT pair is either met or all $\alpha$’s of the pair are fixed without meeting its requirements. In the latter case, this pair is blocked and all of its $\alpha$’s are fixed to 0. Otherwise, only the unfixed $\alpha$’s of that pair is set to 0.

**Step 5.** Find the next not yet served CR-IoT pair with the highest summation of unfixed $\alpha$’s. The optimization steps 3-5 are then repeated for the newly identified pair while accounting for all fixed decision variables $\alpha$’s of other pairs.

**Step 6.** The process in Steps 5 is repeated until each of the $N$ CR-IoT pairs is either assigned a set of channels to serve its QoS demands or no feasible assignment can be found.

5.1.3.2 Results

We study the ramifications of reactive jamming attacks and compare our BMRJA-MAC results with that of two MAC protocols, batch-based multi-channel reactive jamming-
Figure 5.9: Testbed throughput performance vs. jamming severity for two $R_D$ at $N = 5$ and $M = 10$ given (a) Low $P_I$ (High PU activity), (b) Moderate $P_I$ (Moderate PU activity), and (c) High $P_I$ (Low PU activity).

Figure 5.10: Testbed throughput vs. $P_I$ for $N = 5$ and $M = 10$ under (a) Severe attacks, (b) Moderate attacks, and (c) Light attacks.

unaware MAC (BMRJU-MAC) and batch-based single-channel reactive jamming-aware MAC (BSRJA-MAC) [127] for low, moderate, and high PU activity. BSRJA-MAC uses only one transceiver ($L_x = 1$), so each CRIoT can be allocated only a single channel. For the other two protocols, we set $L_x = 2$. The transmission power of each device was 1 dBm and the nodes are chosen randomly at the beginning of each experiment. We consider the same average idle and jamming intervals used in the previous analysis. Each CR transmission occurs between two randomly selected M3 nodes sending 1000 packets of length 96 bytes each. The nodes are equipped with various sensors including; pressure and light, as well as a gyrometer and an accelerometer. These sensors are forcefully initialized first prior to each run, causing the throughput to be affected by the software processing overhead.

Figure 5.9 illustrates throughput performance with different jamming severity factor values using $R_D = 0.2, 0.4$ Mbps. The sub-figures show that our BMRJA-MAC protocol outperforms the other two protocols. Intuitively, as the jamming severity factor increases,
network throughput degrades for the three protocols. Yet, our protocol gives the best performance due to awareness of jamming attacks and using the parallel transmission. We conclude from all figures that lower $R_{D}$ requirements gives better throughput, because the probability of finding channels with a lower rates is better than finding a channel with a higher rates. After extensive experimentation, it was discerned that even with no presence of a jammer, network throughput of a single link (i.e. single-channel single-CRIoT pair) fairly exceeded 200 Kbps. The throughput performance for different $P_{I}$ and demand rates is depicted in Fig. 5.10, which also exhibits that our BMRJA-MAC gives an improved performance over BMRJU-MAC at severe and moderate jamming. However, at light jamming, the two protocols give the same performance because the jamming factor becomes less dominant. Also, Fig. 5.10 shows that BMRJA-MAC produces better performance than BSRJA-MAC at moderate and light jamming, as BMRJA-MAC has the advantage of assigning more than one channel, which in return maximizes the transmission rate. Note that under severe jamming attacks, the two protocols show a comparable performance for a small number of idle channels. In general, $P_{I}$ is proportional to throughput, due to the higher number of idle PU channels, which can be utilized for transmission. At severe jamming, throughput performance degrades for all algorithms when the idle channels become limited. Similarly, at severe and moderate jamming, lower rate requirements results have an improved performance over higher demand rates.

5.2 Rate Adaptation Experimentation using CHRONOS

CHRONOS stands for Cloud based Hybrid RF-Optical Network Over Synchronous Links; it is a testbed that aims to virtualize the Radio Access Network (RAN), where the signal processing is separated from the underlying hardware \[132\]. It has three main components: 1) Hybrid Baseband Processor (HBP), 2) Heterogeneous Network Edge (HNE), and 3) Heterogeneous Mobile Terminal (HMT). The HBP is the hybrid cloud platform with multiple processing units, comprised of a combination of Field Programmable Gate Arrays (FPGAs), GPUs, and general purpose CPUs. The baseband (complex I/Q) signals are transported between the HNEs and the HBP over multimode fibers using efficient transport protocols and standardized packet formats. The HNE is the edge node or the wireless transceiver unit, which supports both sub-6GHz, $\mu$-wave, and optical THz bands to dynamically enable
multiple wireless networks. The HNE provides wireless connectivity to the HMT, equipped with similar wireless interfaces as the HNE. HMTs include variety of devices, like evolved smart-phones, low power IoT devices, wearables etc.

The experimentation is implemented in an indoor setup with one HNE node, one HMT, and a HBP. Each HNE and HMT is equipped with a USRP B210, which is connected to an Intel NUC (NUC7i7BNH) with i7-7567U processor and 16GB DDR4 memory for faster processing of the I/O. Figure 5.11 shows one HNE and one HMT with RF and Optical frontends attached to it. Each B210 board has two transmit as well as two receive paths. One RF and one optical link is used at both transmitter and receiver chains for simultaneous communication. B210 is designed to operate as a MIMO transceiver, for which they share
same local oscillator for the two transmit or receive paths. So, they are not tunable to separate frequencies, one for RF and one for the optical link. Hence, 80MHz is chosen as the center frequency for both the paths. The baseband signal is up-converted to 80MHz center frequency from B210 and RF is transmitted as is using a telescopic antenna. As previously mentioned, most indoor OWC systems rely on IM of the light source in baseband to realize inexpensive optical carrier modulation. This is mainly achieved through the elimination of mixers in conventional RF transmission chain [133]. Alternatively, in this experiment, all building blocks of an RF transceiver are reused including I-Q up/down-converters to show the obtained bit-error performance results as a function of modulation order, bandwidth and SNR. The USRPs are synchronized using Octoclock-G and they are connected over Gigabit Ethernet. Octoclock-G provides a 10MHz clock to the USRPs, as well as a Pulse-Per-Second (PPS) signal. Currently, the HBP is an i7 quad-core processor, but there is a direction towards integrating GPUs as well FPGAs into it to make it a hybrid cloud platform capable of meeting latency requirements of fifth generation (5G) wireless networks and beyond.

The optical frontend, in Fig. 5.12, is composed of the HL63163DG LD and the PDA10A P-I-N PD modules from Thorlabs. The LD is biased through the TCLDM9 mount to 70 mA and is attached to current and temperature controllers which protect the LD from damage. An aspheric collimating lens with 40mm focal length is controlling the LD field of view to ensure a parallel light rays beam, and thus obtain the required coverage based on the target distance. On the receiver side a Fresnel lens with 25mm focal length is attached to the PD to collect the incident light onto the PD active area, and thus have high signal quality. One B210 feeds the LD mount with the transmitting signal, whereas on the receiver side another B210 captures the received signal for further processing. The PD module captures the emitted optical signal, converts it into electrical and amplifies the electrical signal using
a transimpedance-amplifier (TIA).

5.2.1 Simultaneous Transmission

Both the transmitter and receiver baseband are implemented to abide by IEEE 802.11 in MATLAB, then pre-processed as well as post-processed to benchmark link capabilities. The MAC frame is generated and a frame check sequence (FCS) is generated to create a physical layer service data unit (PSDU). It is then modulated and encoded, followed by pilot insertion, IFFT and cyclic prefix addition. The baseband signal is stored in a binary file, which is forwarded to the USRP to be transmitted by both RF and Optical paths. At the receiver side, timing and synchronization block provides start of the packet, which is used in other modules. Long preamble is also extracted for channel estimation, which is used in data recovery phase. The SIGNAL Symbol is demodulated to receive the Modulation and Coding Scheme (MCS) as well as length of the packet. This information is used to demodulate rest of the packet after FFT and equalizer blocks. Once the data bits are recovered, cyclic redundancy check (CRC) is performed to determine if the packet was received correctly.

A C wrapper function is implemented for simultaneous transmission from multiple files, which accesses UHD APIs to stream multiple signal streams to the USRP. Similarly, at the receiver end, another code is implemented to receive the two streams and store them in multiple files. The buffer size is increased to transmit/receive two simultaneous 20MHz links. The internal clocks of the HNEs are synchronized using the 10MHz external clock provided by the Octoclock-G, as shown in Fig. 5.11a. However, streaming of data from all USRPs in all the HNEs should start at the same time to ensure that data processing can be done with synchronized set of received or transmitted data set. Hence, a controller is written in the HBP to start the packet transmission or reception from each of the HNEs over a transport control protocol (TCP) connection. However, the pulse per second (PPS) signal is used from the Octoclock-G to reset the clock of all the HNEs and they start transmitting or receiving after a known amount of time (e.g. 2s) such that the streams start transmitting or receiving at the exact clock. Figure 5.13 shows the timing diagram of the synchronization as each HNE starts to execute the code at different times. However, the streaming from USRP starts only after all the HNEs receive a synchronous PPS signal.
5.2.2 Rate Adaptation

The SNR based rate adaptation algorithm for the RF and Optical links are implemented separately as follows: 1. Benchmarking: Initially, the BER performance is benchmarked for the RF and Optical links for varying SNR for the hybrid C-RAN testbed as indicated in figure 5.16. This is used as the guideline to inform the rate adaptation algorithm for each link individually. More specifically, the algorithm is designed to choose the MCS with a BER less than $10^{-2}$, for the given SNR conditions. 2. Rate Adaptation: Once the transmitted packets are received at the receiver, they are post-processed, the SNR of the channel is estimated (as in [52]), the measured SNR is sent to the transmitter via an Acknowledgement frame, and the transmitter uses the BER-SNR performance as in Fig. 5.16 to determine the modulation and coding scheme for the next transmission. This process is similar for both RF and Optical links, except that the Optical link uses the RF link to feedback the SNR information. The packet loss metric for rate adaptation in its current form is such that, the transmitter transmits with the highest rate (or MCS) setting, the receiver evaluates the packet error rate (PER) per every 10 packets received and if the PER exceeds a value of $10^{-1}$, an Acknowledgement is sent to the transmitter to switch to a lower rate. Note that in both metrics the acknowledgement is only sent when there is a change in the
metric detected, and hence both metrics incur reasonable overhead.

5.2.3 Testing & Evaluation

The experiment is divided into benchmarking and evaluating the performance of the setup, then, testing and evaluation of different rate adaptation algorithms on RF and optical links, individually. The goal is to benchmark valid solutions for rate adaptation in order to be able to design a suitable rate adaptation algorithm for joint RF/optical links, which is left as a future work. In order to study the fidelity and analyze the performance of the communication system, metrics including: constellation diagrams, BER, and PER are used. These metrics show the fidelity of both Optical and RF links, their ability to support higher order modulation and their heterogeneity in performance (i.e. which stems from the fact that the channel perceived by the RF and Optical links are very different). The channels perceived by the RF and Optical links are characterized by the SNR of the received signal. Hence, SNR acts as a vital metric for system evaluation due to the impact of thermal noise domination on performance impairments.

The rate adaptation in the context of Cloud-based Hybrid RF-Optical networks have not been addressed in literature. To design an optimal rate adaptation scheme for the proposed system, careful benchmarking of how various rate adaptation metrics and existing schemes perform over the heterogeneous RF and Optical links is required. This can then be used for more informed joint rate adaptation over the RF and Optical links, rather than the naive solution of Multihoming or choosing the lower of the two rates (i.e. between RF & Optical). This can be further extended to infer the joint rate adaptation among several
spatially separated hybrid nodes as in the hybrid C-RAN. Rate adaptation decisions are chosen based on the metrics that can be inherited from system performance evaluation. Such metrics include the received signal SNR and the packet loss. Since rate adaptation for RF links have been well established, the challenge lies in designing a suitable rate adaptation scheme for the Optical link. The challenging nature of this task is further aggravated by the fact that, the Optical link has no feedback path and that there are no prior studies on coherent communication in Optical links. Hence, the RF link can feedback the metrics to infer both the RF and Optical rates, which requires careful consideration of the trade-off between accuracy and overhead.

In addition, the rate adaptation technique is based on a study on throughput analysis. As by definition, the main purpose of any rate adaptation technique is to choose the optimum data transmission rate that is most appropriate for the channel conditions and eventually provides the highest throughput. The intent is to measure throughput at different transmitter and receiver separations (i.e. locations) and at different SNR levels. This both serves as a performance study of the rate adaptation algorithm and as an indicator to more advanced joint-rate adaptation schemes in the future. To evaluate the synchronization between RF and optical links, three tests are performed, where the correlation plots are shown in Fig. 5.14. First, an RF signal is transmitted from one HMT and received with two antennas in HNE, and correlated with a known preamble. Figure 5.14a shows that there is no delay between the transmitted and received signals indicating the two chains are synchronous. Secondly, an RF signal is transmitted by one HMT and received at two separate HNEs, which are synced using a PPS signal. Figure 5.14b shows that there is no delay between both signals. Finally, both RF and Optical signals are transmitted by one HMT and received by another HMT. Figure 5.14c shows there is no delay between the two paths. Although it would be expected that the Optical path might have suffer from optical frontend delays, the evaluation results, surprisingly, show a minimal delay of 50ns.

5.2.4 Results and Discussion

In order to have a better insight on the system performance and testbed evaluation, some experiments are performed. The main goal of these experiments is to present the system capabilities and introduce the available metrics for the single and/or joint RF-optical setup.
Defining these metrics is essential for benchmarking different rate adaptation techniques. The metrics include SNR and packet loss, as previously mentioned. In Figs. 5.15 and 5.16, both RF and optical links are characterized individually, based on packet loss performance. The signals are received at a distance of 1m and post processed on MATLAB. The received signals are correlated with the transmitted packet preambles in time domain to define the frame starting point. The frame is then de-capsulated to do the CRC checks and define faulty and successfully transmitted packets. A single frame consists of at least 100 transmitted packets and a single experiment is performed at least 5 times to obtain average results. A single packet consists of 100 bytes. The USRP gain is varied to obtain different SNR values. Signal and noise levels are measured to calculate SNR values for the x-axis in Figs. 5.15 and 5.16. Based on the CRC checks the total number of failed packets are
calculated and PER is obtained for different modulation orders. As clearly shown in Fig. 5.15, the performance is expected for PER (i.e. y-axis) with respect to SNR (i.e. x-axis). This can be confirmed by the impact of increasing the M-QAM orders on degrading PER performance. For instance, using BPSK for the RF link with SNR less than 5dB results in 100% packet loss (i.e. PER=1). As the SNR increases, the PER is enhanced till reaching zero packet loss (i.e. PER=0) at nearly 8dB. For quadrature phase-shift-keying (QPSK), the performance starts to enhance at nearly 8dB till reaching PER=0 at 10dB. For the 16-QAM and 64-QAM curves there is a gap of 3dB and 7dB, respectively, before the PER provides a reliable performance. There is a noticeable enhanced performance for the optical
link over the RF link. Similarly, the results in Figs. 5.16a & 5.16b give a quick indication of the minimum required SNR for each modulation to pick up the relative modulation order, similar to the concept in [52]. However, this measurement procedure requires huge amount of data for each link to be characterized individually then the same applies for hybrid links. In this case, 100GB of data is generated from the automated measurements process, which is very time consuming in the generation process and the post-processing, as well. Besides, the performance is not very smooth due to the need for even more packets to be transmitted to give a more precise measurement.

Although this approach is acceptable for characterizing both links, it might not be the most convenient for a real time decision. For this purpose, the processing complexity is reduced by replacing the whole procedure of de-capsulation and CRC checks to measure PER and BER by just SNR measurements after the time correlation step. The SNR is justified as a quick measure of the system performance by relating SNR to BER for OFDM systems based on the used M-QAM, as in [135]. Figure 5.17 portrays the 64-QAM constellation diagrams after equalization for both RF and Optical links. Minimum mean square error (MMSE) is chosen for algorithm equalization. The 64-QAM modulated signals were demodulated correctly at 24dB.

Figure 5.18 indicates the effective throughput perceived by the receiver for different SNR values for both the RF and optical links. The effective throughput is evaluated as the achievable maximum throughput given the theoretical throughput at the transmitter and the BER conditions for the given SNR. This serves as a motivation to perform rate adaptation in both the RF and optical links. Figures 5.19 and 5.21 show the rate adaptation based on SNR metric and the packet loss metric for both (a) RF and (b) optical links as the channel conditions vary in a controlled manner emulating a receiver moving away from the transmitter. It is evident that the Optical link is capable of achieving higher rates (MCS) for the under the same SNR conditions as the RF link. Hence, if joint rate adaptation is performed with the link with the least rate determining the overall rate of the heterogeneous links, the RF link would serve as the typical bottleneck under LOS scenarios, with a directed path to the receiver. This is further elaborated in Figs. 5.20 and 5.22 which show the rate adaptation in highly dynamic channel conditions and show that rate adaptation is capable of maintaining a consistently low BER of less than $10^{-3}$ and PER less than $10^{-1}$ respectively.
Figure 5.19: Rate adaptation evaluation based on SNR metric for both (a) RF and (b) optical links. Throughput vs. Time stamps is shown in red, while BER vs. SNR is shown in black (i.e. SNR is varied across the shown time stamps).

Figure 5.20: Rate adaptation evaluation based on random variations of SNR over time for both (a) RF and (b) optical links.
Figure 5.21: Rate adaptation evaluation based on PER threshold of 0.1 for both (a) RF and (b) optical links.

Figure 5.22: Rate adaptation evaluation based on PER threshold of 0.1 at random SNR variations for both (a) RF and (b) optical links.
CHAPTER 6

Conclusion

VLC has been highly recognized as a promising technology to complement traditional RF communications due to the broadly available and unregulated light spectrum \[133\]. The fundamental difference between VLC and legacy RF lies in the propagation properties of light. Unlike VLC, the RF channel is known for its rich scattering characteristics, which enables RF-techniques to exploit these characteristics to harness several benefits, including diversity/multiplexing gains and channel-based PHY security techniques. This thesis proposed ACom, a solution used to bridge the gap between RF-based methods and the non-rich scattering environment of VLC channels. This chapter serves as a summary of the findings of the various ACom applications and discusses the potential trajectory of these applications.

6.1 Augmented Spatial Modulation (ASM)

This thesis firstly presents ASM, which is proposed as a solution to highly correlated channels employing MIMO technology in VLC-based systems. ASM allows transmitting element identification by design and hence the advantages of this approach are: low complexity systems that do not require CSI, the channel no longer restricts the number of transmitters that can be employed, and the performance of the system becomes more reliable and does not vary with users locations, as it does not depend on channel uniqueness. The findings have shown that, using the proper system settings, ASM can match the performance of theoretical SM capacity even under high channel correlation and imperfect CSI cases. ASM’s SNR penalty can be minimized using system parameter adaptation algorithms and performance can be enhanced with the proper choice of associated codewords. The importance of the analysis is its versatility in deployment, as it can be also be adopted in mm-Wave and THz communications. With the trend of operating over higher frequencies, due to the current RF spectrum congestion problem, ASM’s perception can be applied to technologies that share the non-rich scattering environment of VLC. Additionally, other than the proposed indoor realization setting, other applications can be explored, such as optical satellite
communications and drone-to-drone communications.

6.2 Machine-learning Enhanced ASM

ASM’s complexity is investigated to allow its adoption in massive-MIMO settings, which was shown to be dependent on the utilized number of transmitters. This leads to re-envisioning ASM with various ML techniques to decrease its computational complexity. Simulation results showed that SVM, LR, and single-layer NN can be used to identify 1000 transmitters with an accuracy above 99% and without the need of channel knowledge or channel coefficients uniqueness using different hardware architectures. Results show that with the single-layer NN, computation time remain almost constant irrespective to the number of transmitting elements, which show a tremendous potential for ASM’s massive-MIMO deployment while satisfying the low-complexity criterion of various applications including IoT applications. Moreover, ASM is realized using an autoencoder architecture. This realization can be extended to serve multi-objective system performance optimization. The NN architecture is currently used to optimize both the spatial and explicit bits simultaneously. The adoption of ASM under more severe (other than AWGN) channels using autoencoder-based channel equalization approaches can be explored. It can be extended to include PHY security and link adaptation.

6.3 Alternative ACom Applications

Not only is ACom presented as a solution for overcoming the channel uniqueness problem in VLC, it is also proposed as a PHY-security method and as a mean to transmit an additional data stream (that can either be control or data bits) in SISO systems. Results have shown ACom’s efficacy in both approaches. ACom, as a PHY-security technique, is based on PHY rekeying approach that did not require key exchange over the air. It is also proposed as a multi-technology security method that can be adopted by various technologies concurrently and its secrecy capacity is not dependent on the utilized technology. The vision for ACom as a SISO-based spectrum efficiency enhancement method is similar to the PHY-security realization, in terms that it can be considered a multi-technology approach. With the rise of metasurfaces and re-configurable intelligent surfaces (RIS), RF-transmission might
lose its rich scattering nature, opening the door for ACom as a contender for such realizations. Additionally, other ACom applications can include a PHY-authentication method and a user-identification method for cognitive radio applications that require the differentiation between primary and secondary users.

6.4 Testbed Experimentation

Theoretical analysis brings the first proof-of-concept and aids in evolving a prediction of the system’s characteristics and behavior. However, for accurate predictions, highly detailed models must be used which are frequently complex and difficult to comprehend and handle. Simulators are the most adopted methods for system development and verification, as they yield a more realistic evaluation of the system’s performance in comparison to pure theoretical evaluations. Additionally, testing and debugging is allowed on protocols at any design stage. Nevertheless, the reliability of simulators naturally depends on the accuracy of the used models, e.g. channel and energy consumption models, thus the results may not match real world experimentation. Additionally, most simulators do not consider the hardware limitations of the utilized nodes which normally have cogent impacts on the accuracy of the reported results. The stringiest approach is composing real world experiments. Unfortunately, they come at the expense of high software and hardware cost, plus the required manpower for installment and maintenance. Testbeds, contrarily, provide realistic assessment, under factual channel conditions, without the entailed disadvantages of real world experimentation. Chapter 5 highlights the importance of using hardware testbeds for performance evaluation and proposes a number of MAC algorithms orchestrated on large-scale testbeds. The extension of the work would be combining the MAC algorithms presented with the PHY approaches presented in previous chapters. However, the difficulty comes in finding testbeds that have heterogeneous frontends and ML capabilities on their nodes.

6.5 Future Investigation

This thesis studies various possibilities of adopting ACom for communication systems performance enhancement. Yet, there remains a number of ACom’s use cases that require future investigation. A further study could assess the multi-user case and explore its effect
on ACom’s performance. The outcome can pave the wave for commercial use of ACom-based multi-user applications, such as in-flight entertainment where the users are located in close proximity to one another. More research is needed to account for mobility and it’s influence on ACom’s performance. Methods to increase ACom’s scalability can also be investigated through means such as super-symbol transmission and wavelength division multiplexing. Another possible area of future research would be to investigate the use of ACom for uplink communications. Uplink using VLC remains a challenge; however, given the versatility nature of ACom, uplink can be facilitated with the use of IR or other forms of short-range communication technologies. As highlighted in this thesis, SM-MIMO constitutes a promising enabler of reducing the total power consumption of communication networks by deactivating some transmitting elements. Additionally, by adopting VLC, illumination and communication can be combined, thus allowing a significant reduction in power consumption. Further gains can be achieved by adding VLC-based energy harvesting, which constitutes an intriguing area of future work. Considerably more work will need to be done to quantify the energy efficiency of ACom VLC systems in comparison to its radio frequency counterparts. Alternative machine learning architectures are also an interesting direction for extending the current work. Several questions revolving around how ML methods learn and react to the given data still remain to be answered.
APPENDIX A

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APPENDIX B

Problem Formulation for Section 5.1.2

Recall that the channel assignment problem is investigated under proactive and reactive jamming attacks. In this appendix, the channel assignment problem under both types of attacks is formulated. To proceed in the analysis, a binary decision variable, \( \alpha^{(i)} \), for each channel \( i \in \mathcal{M} \) is defined as follows:

\[
\alpha^{(i)} = \begin{cases} 
1, & \text{if channel } i \text{ is chosen to be included in } \Omega \\
0, & \text{otherwise}.
\end{cases}
\]

B.1 Problem Formulation under Proactive Jamming

Under proactive jamming, the invalidity constraint in (5.10) can be rewritten in terms of the decision variable \( \alpha^{(i)} \) as follows:

\[
1 - e^{-\sum_{i=1}^{\lfloor M \rfloor} \lambda^{(i)} t_x \alpha^{(i)}} \leq \sqrt{B_{th}} \\
\ln \left( 1 - \sqrt{B_{th}} \right) \leq -\sum_{i=1}^{\lfloor M \rfloor} \lambda^{(i)} t_x \alpha^{(i)}
\]

Then, \( t_x \) can be re-expressed as \( \frac{L}{\sum_{i=1}^{\lfloor M \rfloor} R^{(i)} \alpha^{(i)}} \).

By writing the design constraints in terms of \( \alpha^{(i)} \), the multi-channel multi-transceiver security-aware channel assignment problem under proactive jamming can be formulated as:

\[
\begin{align*}
\min_{\alpha^{(i)} \in \{0,1\}} & \sum_{i \in \mathcal{M}} \alpha^{(i)} \\
\text{s.t.} & \sum_{i=1}^{\lfloor M \rfloor} \alpha^{(i)} \leq L_x \\
& \ln (1 - \sqrt{B_{th}}) \leq -\sum_{i=1}^{\lfloor M \rfloor} \lambda^{(i)} t_x \alpha^{(i)} \\
& \sum_{i=1}^{\lfloor M \rfloor} R^{(i)} \alpha^{(i)} \geq R_{th} \\
& \text{SNR}^{(i)} - \text{SNR}_{th} \geq \Gamma (\alpha^{(i)} - 1), \forall i \in \mathcal{M}
\end{align*}
\]

where \( \Gamma \) is a very large positive number. Note that the last constraint ensures that \( \text{SNR}^{(i)} \geq \text{SNR}_{th} \).
SNR_{th} for any selected channel \( i \) (i.e., when the SNR^{(i)} < SNR_{th}, the left-hand-side of this constraint is a negative number, and hence the right-hand-side should be a very large negative number, and hence \( \alpha^{(i)} \) should be 0. On the other hand if the SNR^{(i)} ≥ SNR_{th}, then the left-hand-side is always ≥ 0, and hence \( \alpha^{(i)} \) can be either 1 or 0 depending on the optimization problem).

Substituting \( t_x = \frac{L}{\sum_{i=1}^{\vert M \vert} R^{(i)} \alpha^{(i)}} \) into (B.1) and using some algebraic manipulation, the second constraint of (B.2) can be rewritten in a linear form as:

\[
\sum_{i \in M} (R^{(i)} \ln (1 - \sqrt[\vert M \vert]{B_{th}}) + L\lambda^{(i)}) \alpha^{(i)} \leq 0 \quad (B.3)
\]

By letting \( R^{(i)} \ln (1 - \sqrt[\vert M \vert]{B_{th}}) + L\lambda^{(i)} = a_i \), the second constraint in (B.2) becomes \( \sum_{i=1}^{\vert M \vert} a_i \alpha^{(i)} \leq 0 \). The last constraint can be simply guaranteed by setting \( \alpha^{(i)} = 0, \forall i \) with SNR^{(i)} < SNR_{th}. Therefore, the optimization problem in (B.2) becomes:

\[
\min_{\alpha \in \{0,1\}} \sum_{i \in M} \alpha^{(i)} \\
\text{s.t.} \quad \sum_{i=1}^{\vert M \vert} \alpha^{(i)} \leq L_x \\
\quad \sum_{i=1}^{\vert M \vert} a_i \alpha^{(i)} \leq 0 \\
\quad \sum_{i=1}^{\vert M \vert} R^{(i)} \alpha^{(i)} \geq R_{th} \quad (B.4)
\]

B.2 Problem Formulation under Reactive Jamming

Under reactive attacks and after the mathematical steps provided at the top of the next page, the invalidity constraint can be written in terms of \( \alpha^{(i)} \) as:

\[
\sum_{i=1}^{M} b_i \alpha^{(i)} \leq \sum_{j=1}^{M} \sum_{i=1}^{M} c_{ij} \alpha^{(i)} \alpha^{(j)} \\
\]

where \( b_i = \ln(1 - \sqrt[\vert M \vert]{B_{th}}) R^{(i)} + L \) and \( c_{ij} = \ln(1 - P^{(i)}_{j}) R^{(j)} \). Note that the optimization problem is the same as in the case of the proactive jammer but with Eq. (B.6) replacing the 2nd constraint. Up to this point, the formulation is an NLBP problem. In an attempt to linearize the problem, the non-linear constraint in (B.6) can be written in a linear form by replacing the quadratic term \( \alpha^{(i)} \alpha^{(j)} \) with \( w_{ij} \forall i, j \in M \) (i.e., \( w_{ij} = \alpha^{(i)} \alpha^{(j)} \)) and introducing
\[
\ln(1 - \frac{N \sqrt{B_{th}}}{T}) \leq \sum_{i=1}^{M} \left( \ln(1 - P_{j}^{(i)}) \alpha^{(i)} - \frac{t_{x}}{T_{i}^{(i)}} \alpha^{(i)} \right) \\
\leq \sum_{i=1}^{M} \left( \ln(1 - P_{j}^{(i)}) \alpha^{(i)} - \frac{L \alpha^{(i)}}{T_{i}^{(i)} \sum_{j=1}^{M} R_{j}^{(i)} \alpha^{(j)}} \right) \\
\sum_{i=1}^{M} \left( \ln(1 - \frac{N \sqrt{B_{th}}}{T_{i}^{(i)} R_{i}^{(i)}}) \right) \alpha^{(i)} \leq \sum_{j=1}^{M} \sum_{i=1}^{M} \left( \ln(1 - P_{j}^{(i)} T_{i}^{(i)} R_{j}^{(i)} \alpha^{(i)} \alpha^{(j)} - L \alpha^{(i)}) \right) \\
\sum_{i=1}^{M} \left( \ln(1 - \frac{N \sqrt{B_{th}}}{T_{i}^{(i)} R_{i}^{(i)} + L}) \right) \alpha^{(i)} \leq \sum_{j=1}^{M} \sum_{i=1}^{M} \ln(1 - P_{j}^{(i)} T_{i}^{(i)} R_{j}^{(i)} \alpha^{(i)} \alpha^{(j)}) \\
\text{(B.5)}
\]

the following linear set constraints on \(w_{ij}\):

\[
w_{ij} \leq \alpha^{(i)} \\
w_{ij} \leq \alpha^{(j)} \\
w_{ij} \leq \alpha^{(i)} + \alpha^{(j)} - 1. \\
\text{(B.7)}
\]

Note that if either \(\alpha^{(i)}\) or \(\alpha^{(j)} = 0\), then \(w_{ij} = 0\) and if both \(\alpha^{(i)}\) or \(\alpha^{(j)} = 1\), then, \(w_{ij} = 1\). Thus, it is an exact formulation. This will yield \(3 \times M \times M\) constraints to the problem formulation. Thus, the constraint in (B.6) becomes:

\[
\sum_{i=1}^{M} b_{i} \alpha^{(i)} = \sum_{j=1}^{M} \sum_{i=1}^{M} c_{ij} w_{ij} \leq 0 \\
w_{ij} \leq \alpha^{(i)} \quad \forall i \in M, j \in M \\
w_{ij} \leq \alpha^{(j)} \quad \forall i \in M, j \in M \\
w_{ij} \leq \alpha^{(i)} + \alpha^{(j)} - 1 \quad \forall i \in M, j \in M \\
\text{(B.8)}
\]

Now, we have \(M\) \(\alpha^{(i)}\) variables and \(M^2\) \(w_{ij}\) variables. By replacing the non-linear constraint with its equivalent linear form given in (B.8), the problem formulation under
reactive jamming becomes:

\[
\min_{\alpha_i \in \{0,1\}} \sum_{i \in \mathcal{M}} \alpha^{(i)} \\
\text{s.t.} \quad \sum_{i=1}^{\lvert \mathcal{M} \rvert} \alpha^{(i)} \leq \mathcal{L}_x \\
\sum_{i=1}^{\mathcal{M}} b_i \alpha^{(i)} - \sum_{j=1}^{\mathcal{M}} \sum_{i=1}^{\mathcal{M}} c_{ij} w_{ij} \leq 0 \\
\sum_{i=1}^{\lvert \mathcal{M} \rvert} R(i) \alpha^{(i)} \geq R_{th} \\
w_{ij} \leq \alpha^{(i)} \quad \forall i \in \mathcal{M}, j \in \mathcal{M} \\
w_{ij} \leq \alpha^{(j)} \quad \forall i \in \mathcal{M}, j \in \mathcal{M} \\
w_{ij} \geq \alpha^{(i)} + \alpha^{(j)} - 1 \quad \forall i \in \mathcal{M}, j \in \mathcal{M} \quad \text{(B.9)}
\]

As a result, there will be \(3 + 3 \times \mathcal{M}^2\) constraints.
BIBLIOGRAPHY


tional Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), pp. 1–6, 2019.


