# Adaptive Successive Interference Cancellation using Deep Learning for High Altitude Platform Station in Various K-Rician Channel

Veronica Windha Mahyastuty, Iskandar, Hendrawan, and Mohammad Sigit Arifianto

*Abstract*— **This research proposed the Adaptive-Successive Interference Cancellation (ASIC) method, which enlisted the performance and power efficiency from Successive Interference Cancellation (SIC) conventional. We employed deep learning as new technology for wireless communications. We have simulated for High Altitude Platform System (HAPS) communication using the Power Domain-Non-Orthogonal Multiple Access (PD-NOMA) method for three Ground Stations (GS). We consider three different areas with the various K-Rician channel model on low, medium, and high elevation for analysis. To compare ASIC and SIC performance, we used the Signal-To-Noise Ratio (SNR) and Bit Error Rate (BER) as performance parameters. From the results of extensive research, we prove that ASIC performance is more efficient at the SNR value around 48.21%, 30.27%, and 42.85% in low, medium, and high elevation, respectively.**

*Index Terms*—**Successive Interference Cancellation, Adaptive Communication, Non-Orthogonal Multiple Access, High Altitude Platform System, Signal-to-Noise Ratio**

## I. Introduction

### A. Motivation

IN the 6th generation era, artificial intelligence in communication could not be rejected. This intelligence is needed to resolve communication problems such as limited users, frequencies, time, and space. These limitations open new methods and techniques on communication, one of which is Non-Orthogonal Multiple Access (NOMA), which can communicate plural access to the transmitter in the Power or Code domain. This ability resolves the problem of frequency limitations but causes new problems where the difficulty of power control and the complexity of the code need to be prepared [1].

As one of the multiple access methods that became cellular communication techniques, NOMA has also been used in Unmanned Aerial Vehicle (UAV) communication [2]. UAV, one of the backup strategies in backbone communication, is the High Altitude Platform Station (HAPS), operating in the Stratosphere area. The presence of HAPS and NOMA became the primary key to resolving the problem of coverage blank spots and frequency limitations. However, HAPS is not equipped with a continuous power source to stop before the mission is complete [3]. In addition, low power use for HAPS is a major issue that must be resolved.

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### B. Literature Review

This paper [3] proposes single HAPS and multiple HAPS Long Term Evolution (LTE) cellular capacity analysis. The result also showed that single HAPS capacity is higher for the exact outage probability than multiple HAPS capacity. In the proposed scheme, communication services for long distances requiring very high bandwidth are transmitted optically from the ground station to the HAP station in the stratosphere, where it can cover distances of several hundreds of kilometers on the free-space optical links with multiple serial hops and be transmitted back optically to the distant ground receiver [4]. The HAPs incorporate both satellite communication systems' advantages, and terrestrial Free Space Optic (FSO) links such as high capacity, low transmission delay, and acceptable power consumption. In addition, researchers [5] have analyzed NOMA for access communication using Visible Light Communication (VLC).

This research [6] proposes using a conditional Generative Adversarial Net (GAN) to express channel effects and bridge the transmitter and receiver DNNs so that the transmitter DNN's gradient can be transferred backward from the receiver DNN. According to simulation results, the suggested technique appears to be effective on Additive White Gaussian Noise (AWGN) channels, Rayleigh fading channels, and frequency-selective channels, opening a new avenue for developing data-driven DNNs for end-to-end communication systems. HAPS has a vast coverage area, can service users in Line-of-Sight (LOS), and short propagation time. Cellular communication, which uses LTE technology, is one of the most promising HAPS applications.

As a result, HAPS is actively being investigated as a viable solution for the future of wireless communication networks [7]. With continued disruption in wireless communication designs (e.g., data-driven designs) and developing use cases (e.g., on-demand distributed machine learning platforms and data centers), HAPS systems have grown more tempting in terms of possible benefits. Furthermore, satellites aid the HAPS layer in enhancing hand-off performance.

Paper [8] provides a comprehensive overview of emerging research on DL-based physical layer processing, such as using DL to redesign a module of a conventional communication system (for modulation recognition, channel decoding, and detection) and replace the communication system with a radically new architecture based on an auto-encoder.

Deep Learning (DL) adopts a Deep Neural Network (DNN) to find data representation at each layer, which could be built by using different types of Machine Learning (ML) techniques, including supervised ML, unsupervised ML, and reinforcement learning. Particularly, the following challenges have been identified in the existing physical layer communications: Mathematical model versus practical imperfection: The conventional communication systems rely on the mathematically expressed models for each block. This paper [9] will identify the gains DL can bring to wireless physical layer communications, including the systems with the block structure and the end-to-end structure merging those blocks. The proposed DL-PAS improves the performance in cellular networks with severe pilot contamination by learning the relationship between pilot assignment and the users' location pattern [10]

### C. Proposed Method

In this study, we use an uplink analysis, where every information from Ground Station varies when transmitting to HAPS. In general, multiple access must use time, frequency, or domain code to send information to HAPS. By distinguishing the communication channel from the ground station, interference between signals can be avoided as optimally as possible. Our research considers using Power Domain NOMA (PD-NOMA) simultaneously and frequency domain and takes advantage of interference that occurs using the Super Position Coding (SPC) method to multiplex the signal from the ground station. In addition, we also conduct a decoding process on HAPS; the Successive Interference Cancellation (SIC) method is used to separate the signal between users as before [11].

SIC has become the latest technology in describing interference and restoring the initial signal that has been mixed when transmitting. SIC also has a fatal deficiency, which can harm when many users use this method. If the SIC is assumed perfectly and has no residue, decoding information from the first user to user $n$ gets the same information signal. However, the perfect SIC cannot be applied in the actual communication system, so when one user gets information that is not appropriate (occurs error bits), it will have an impact on the user afterward. For the next user, it is impossible to get complete information and will get more errors than the previous user. We call this effect a domino effect on the SIC disaster.

In this study, we have proposed a smarter SIC system by utilizing Artificial Intelligence (AI). The discovery of AI is not a new thing for technology today, but the application of communication systems is a novelty that can improve the performance of a communication system. This proposal provides the name Adaptive-SIC (ASIC) because the worked algorithm can change the convolution layer model based on bit-bit information from the number of users. We also add deep learning, which can reduce power levels by introducing information signal characters from each user.

This research is divided into four main chapters. The second chapter discusses the methods, block diagrams, and algorithms on the ASIC used in this study. Mathematical models on the Rician channel model, HAPS, and various research parameters were also reported. We analyzed various conditions on the K-Rician, thus getting intact results on ASIC testing written in the third chapter. After all the results were reported, we summarized them in the final chapter.

## II. Research Method

### A. HAPS opportunity for connectivity

Fig. 1 describes the subsystem of HAPS that has an opportunity for 5G and 6G communication [7]. In the taxonomy of HAPS, the telecommunication payload section has been divided into two parts, for Narrowband and Broadband Application. In the subsystem, we analyze the broadband area where Ground Station sends information to support the 5G or 6G platform. Also, the power subsystem is considered for finding the best energy efficiency as thick text.

For three decades, wireless communications designers have researched the inclusion of unmanned aircraft systems into their network architectures "to provide cost-effective wireless connectivity for devices without infrastructure coverage." In addition, compared to terrestrial communications or satellites, HAPS is generally faster to deploy, more flexibly reconfigured, and has better communication channels due to the presence of short-range LOS links [12].

Fig. 2 shows that HAPS has a massive benefit for all communication systems. Communication on HAPS can be done between satellites and HAPS, as a remote in several areas with a closer distance. HAPS can also reach the access section that is directly related to customers. HAPS communicated by Ground Station, capable of continuing communication to other areas connected to optical cables. In addition, HAPS platforms promise to improve existing communications systems both in capacity and coverage.

This study considered the three Ground Stations that communicated uplink to HAPS. Each Ground Station has different information from distinguished through the power allocation. Each Ground Station has a distance transmission and a different estimation value of the channel, so the strategy we consider is the feedback channel from the ground station to determine the large power allocation. In addition, for uplink communication, an immense estimation value of channels will be given a more significant power allocation. The value of a greater allocation for channel estimation is to detect signals when decoding and the SIC process.

### B. HAPS simulation model

Fig. 3 shows the communication model that has been calculated and simulated. We use a simulation model on the moving HAPS by analyzing posting movements. At first, HAPS did not move and had a distance to the ground station with the exact 90-degree elevation angle. In that situation, we do calculations and simulations without using ASIC. After that, HAPS moves and produces a different distance from its original state. We also measure performance after moving HAPS to analyze the performance of the performances that occur. Every change in HAPS, resulting in the value of the elevation angle between HAPS and Ground Station changes, including the value of the K-Rician estimate.

In this study, three elevation models were carried out, (i) low elevation using 27°-30°, (ii) medium elevation using

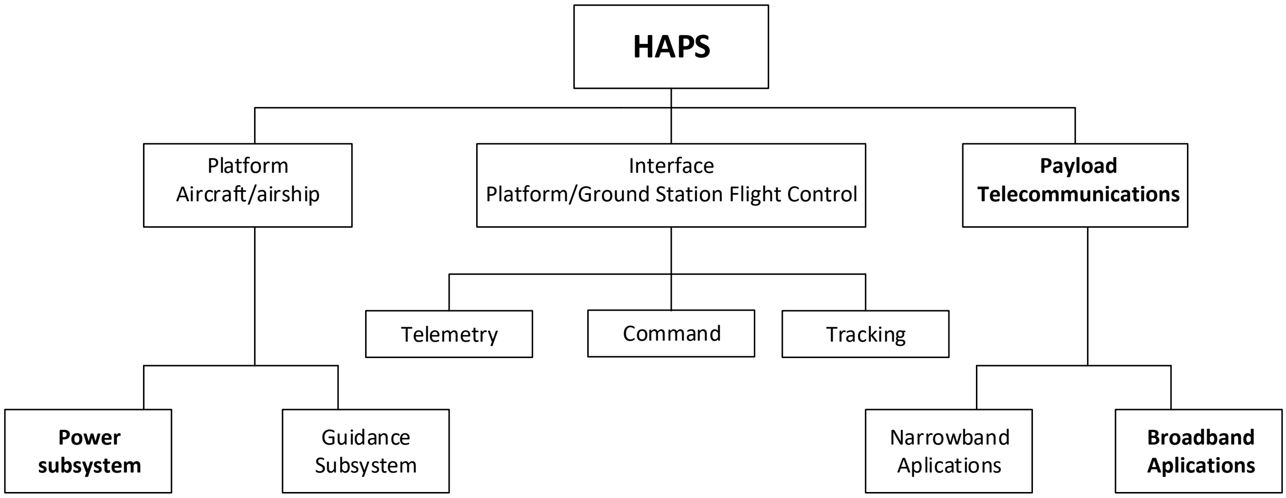


Fig. 1. The segment of HAPS Stratosphere with thickened text.

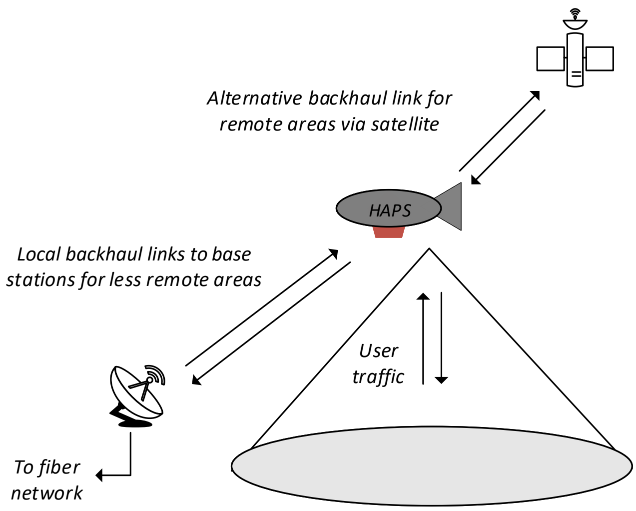


Fig. 2. HAPS connectivity among access and backbone network.

TABLE I
SIMULATION PARAMETERS.

| Parameter | Value |
|---|---|
| Frequency Operation | 48 GHz |
| Transmitted Power | 20 dBW |
| Gain Antenna | 46 dBi |
| Type of deep learning | Convolution 1D |
| Number of bit | 1000 |
| Number of user | 3 |
| Elevation angle range | 27°-90° |
| Transmission distance | 20-40 km |

35°-45° and (iii) high elevation 50°-90°. In addition, we also write down the simulation parameters used in the simulation carried out, as in Table I

This study describes the simulation process of the mathematical model that has been used. First, the information signal is generated randomly as a representation of data in binary. The modulation of the signal used in this simulation is the Binary Phase Shift Keying (BPSK), where if the bit one, then the positive signal is modulated. On the contrary, if the bit is zero, then the signal is negative, as at:

$$m_n = \begin{cases} 1, \ x = 1 \\ 0, \ x = -1 \end{cases} \tag{1}$$

Channel modeling for each user was K-Rician that contains LOS and fading component as shown in

$$H_n = \sqrt{\tfrac{K}{1+K}} \cdot \overline{H} + \sqrt{\tfrac{1}{1+K}} \cdot \overline{H_w}, \tag{2}$$

where $\sqrt{\frac{K}{1+K}} \cdot \overline{H}$ is Line of Sight (LOS) component, $\sqrt{\frac{1}{1+K}} \cdot \overline{H_w}$ is fading component, and $K$ is the Rician K-factor. For $0 \le K \le \infty$, the channel combines a deterministic component (i.e., LOS) and a fading component. The K-factor is the ratio between the energy in the deterministic Line-of-Sight (LOS) component and the energy in the aggregation of the randomly scattered paths (i.e., the fading component); higher K means that the channel is more deterministic.

Using the statistical point of view, the amplitude probability density function in receiver is:

$$f(r) = \frac{r}{\sigma^2} I_0 \left( \frac{r \cdot r_s^2}{\sigma^2} \right) \exp \left( \frac{-r^2 + r_s^2}{2\sigma^2} \right), \tag{3}$$

where $r_s^2$ is amplitude direct ray, $I_0$ is function of Bessel with order zero. The so Rice factor ($K$), is defined as

$$K = 10 \log \left( \frac{r_s^s}{2\sigma^2} \right). \tag{4}$$

However, $K$ can be formulate from a geometrical point of view as [13]

$$K(\theta) = 10 \log \left( \frac{(h/\sin(\theta))}{\sqrt{(\Delta r + r)^2 + h^2 + |\Delta r|}} \right), \tag{5}$$

where $\theta$ is the elevation angle. This angle is determined by the horizontal distance ($r$) and $h$ as the HAPS height to the

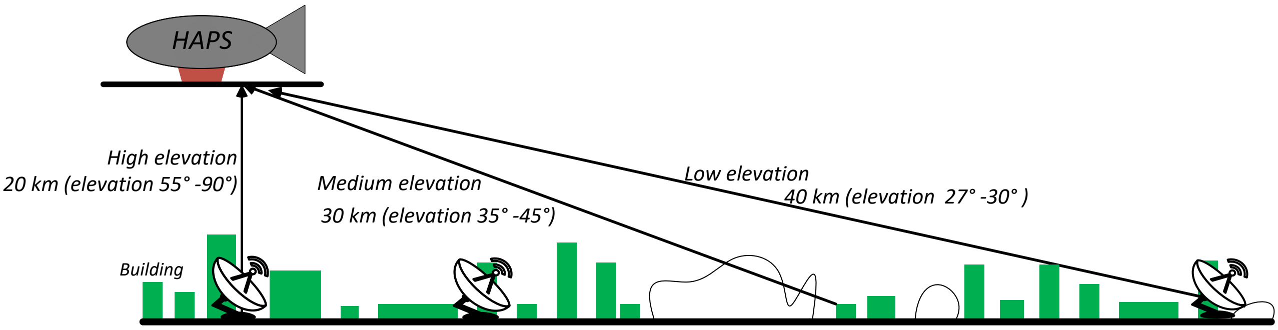


Fig. 3. Uplink communication between ground station and HAPS in various condition.

ground. Then the elevation function on variation of K factor is

$$\begin{aligned} &\theta > 90^\circ \Rightarrow K \to \infty \Rightarrow \text{ Gaussian Channel} \\ &\theta \to [12^\circ < \theta < 90^\circ] \Rightarrow \text{ Rice Channel} \\ &\theta < 12^\circ \Rightarrow K \leq 0 \Rightarrow \text{ Rayleigh Channel} \end{aligned} \tag{6}$$

Each information signal will be given the power allocation based on the transmission distance from the Ground Station to HAPS. We consider calculating distance to angular elevation and produces a K-factor value. The signal that has been given the power allocation and passes the channel shown like

$$x_n = \alpha_n \cdot m_n \cdot H_n, \tag{7}$$

where $\alpha_n$ is user's power allocation. After all the user transmits, the signal is multiplexed using the Super Position Coding (SPC), which mixes all signals and is received by HAPS simultaneously. We consider that this simulation uses coherent time, so no delay is considered during the SPC process. The signals received in HAPS made mathematical models such as:

$$y = \sum_{i=1}^{n} x_i + n. \tag{8}$$

It is assumed that HAPS has information from the feedback channel, so the channel value obtained has been sorted from the largest ($H_1 > H_2 > \cdots > H_N$). To optimize decoding strategies with SIC, we use re-modulation for signals that have been decoded. The first information on demodulation is the first user, with the most significant power allocation and channel value. The signal that comes with a positive value is immediately founded into a bit one (1), while for negative signals is represented with a zero bit (0), as in the formula

$$\bar{x_n} = \begin{cases} y \geq 0, \ \bar{m_n} = 1 \\ y < 0, \ \bar{m_n} = 0 \end{cases} \tag{9}$$

After the first user extracted the bits of information, the bits were remodulated using the power allocation and modulation of BPSK. Finally, the signal that has been programmed is reduced by the results signal from the SPC. Mathematical models that have been used to illustrate the SIC process like in the formula

$$\begin{aligned} \bar{x}_{n-1,n} = & y - [(remod\,(\bar{y_1}\ ) \cdot \sqrt{\alpha_1} \cdot H_1) - \cdots \\ & (remod\,(\bar{x_{n-1}}\ ) \cdot \sqrt{\alpha_{n-1}} \cdot H_{n-1})]. \end{aligned} \tag{10}$$

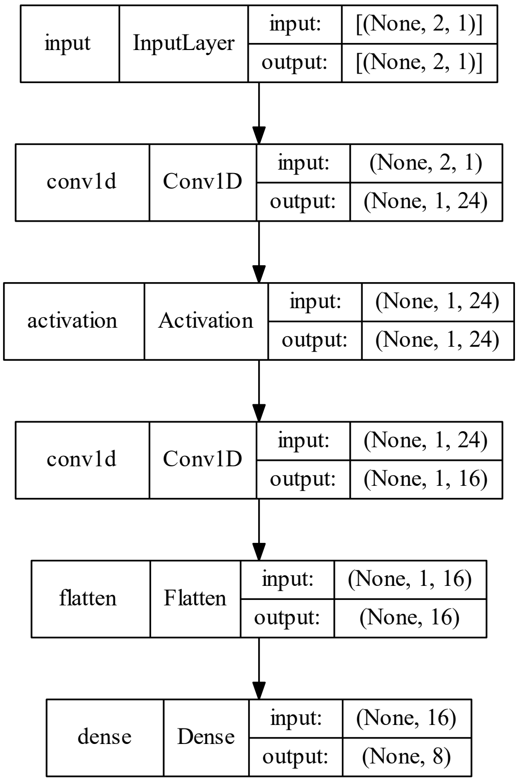


Fig. 4. Adaptive-SIC layers using deep learning process.

After the SIC process and extracting all bit-bits received information, this study uses the Bit Error Rate (BER) parameter to compare the bits received with the bits sent.

### C. ASIC Method

In this study, we added a detection method on the SIC, by utilizing the Deep Learning Method, namely Convolutional Neural Network (CNN). Simply put, we save the SPC signal into the dataset and add the bits to send. CNN studies the SPC signal pattern including power allocation and bits sent. After learning, CNN is added to the SIC method as in the Algorithm 1. For input argument we used $df$ is DataFrame that contains dataset for deep learning from SPC signal, $s$ is transmitted bits, $\alpha$ is the power allocation factor, $h$ is the channel value, $SNR$ is signal to noise ratio value that has been generated, $N$ is the number of bits, $mod$ is modulated signal using BPSK, and $N_{user}$ is number of users.

**Algorithm 1** ASIC Function

import **numpy** as **np**
import **pandas** as **pd**
import **tensorflow**
**function** ASIC(df,$s$,$\alpha$,h,SNR,N,m,mod,$N_{user}$)
    features $\leftarrow$ $[R,\ \theta]$
    $X$ $\leftarrow$ df[features]
    $Y$ $\leftarrow$ df['Bit']
    $x$ $\leftarrow$ array($X$)
    $y$ $\leftarrow$ encode.fit_transform($Y$)
    $y$ $\leftarrow$ array(Y)
    $y_{uni}$ $\leftarrow$ len(unique($y$))
    Sequential()    ▷ Using Sequential model
    model.add(Conv1D($y_{uni}\times$3))
    model.add(MaxPooling1D(pool_size=1))
    model.add(Conv1D($y_{uni}\times$2))
    model.add(Flatten())
    model.add(Dense($y_{uni}$, activation='softmax'))
    model.compile()
    model.fit()
    **for** i in range(len(SNR)) **do**
        **for** k in range($N_{user}$) **do**
            n $\leftarrow$ $s$[i]$\times$ ($\sigma(N)$)
            $\alpha_{user}$ $\leftarrow$ $\sqrt{\alpha}\times\sqrt{m}$
            y[k,:] $\leftarrow$ $\alpha_{user}$[k]*mod[k,:]*h[k]
        **end for**
        $s_{total}$ $\leftarrow$ nsum(y,0)+n
        $\bar{R}$ $\leftarrow$ matrix(abs($s_{total}$)).A1
        $\bar{\theta}$ $\leftarrow$ matrix(angle($s_{total}$)).A1
        $x_t$ $\leftarrow$ matrix([$\bar{R}$,$\bar{\theta}$])'
        $x_t$ $\leftarrow$ $x_t$.A1
        $x_t$ $\leftarrow$ $x_t$.reshape(int(N),2,1)
        $y_t$ $\leftarrow$ model.predict($x_t$)
        $y_t$ $\leftarrow$ argmax($y_t$,1)
        $y_t$ $\leftarrow$ encode.inverse_transform($y_t$)
        $y_{decod}$ $\leftarrow$ matrix(split('guard_code'))
        $y_{decod}$ $\leftarrow$ $y'_{decod}$
        $\bar{y}$[:,:,i] $\leftarrow$ $y_{decod}$
    **end for**
**return** $\bar{y}$
**end function**

Description of the adaptive SIC method, found in the $y_{uni}$ notation at Algorithm 1, which is gradual. This gradual properties increase the Deep Learning model compared to providing manual values on the CNN layers. The number of layers used in ASIC, seen in Fig. 4 where we use 1-dimensional convolution. Convolution of 1 dimension does not burden computing work, so that complexity and delay are very low.

## III. Analysis and Discussion

### A. HAPS using SIC

Fig. 5 explains about changes in the SNR value of performance. We have simulated extensively on elevation of 27-30 °. The K-Rician value obtained by each user varies based on transmission distance to HAPS. First performance evaluation, carried out on low elevation with a wider range of range but the lowest received power. We also observe that the

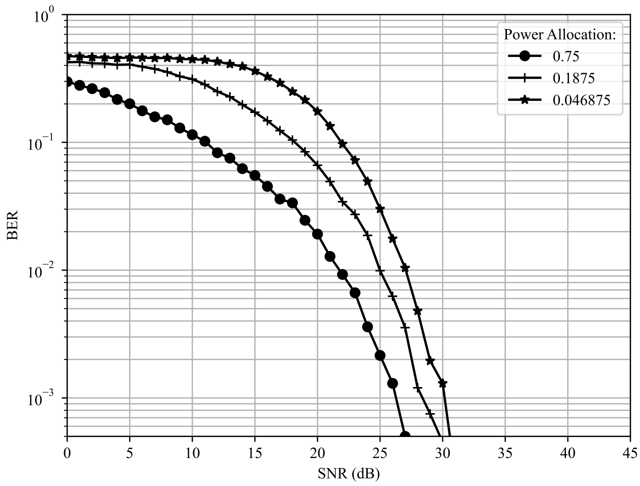


Fig. 5. BER performance in low elevation.

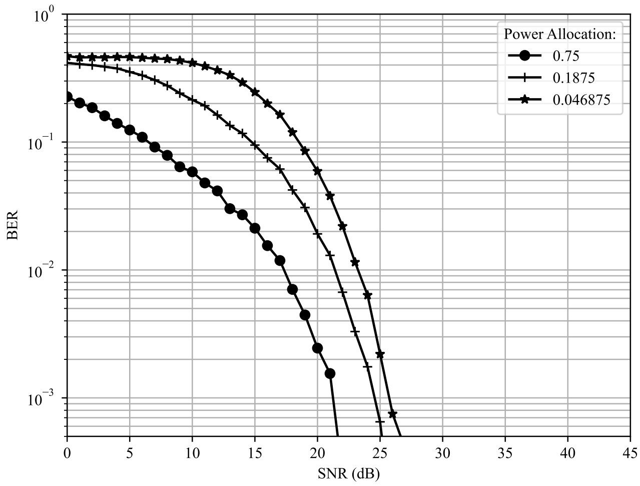


Fig. 6. BER performance in medium elevation.

SPC process affects the performance of the different channel values.

In general, the greater the value of comparison of received power and noise, the better performance. However, the value of the SNR that is too large is difficult to apply because the comparison is too large than the transmitted power that must be prepared. In the curve, the greatest power allocation value obtains the best performance. In addition to the more significant power allocation, the channel value also gets the greatest. We have a target value of $\leq 10^{-3}$, so that if the SNR value is closest to $10^{-3}$ there is around 25-30 dB. We also found that the SIC never received the same SNR value at the target because the decoding process was sequential and dependent. Users with the smallest power allocation value cannot carry out the decoding process before using a more extensive power allocation to solve it.

Changes in the SNR value of performance are explained in Fig. 6. We have done a lot of simulations at elevations of 35-45 °. Depending on the transmission distance to HAPS, each user's K-Rician value fluctuates. The second performance evaluation occurred at a medium elevation, with a narrow range but more significant received power. We also analyzed that the SPC procedure impacts the performance of various channel values.

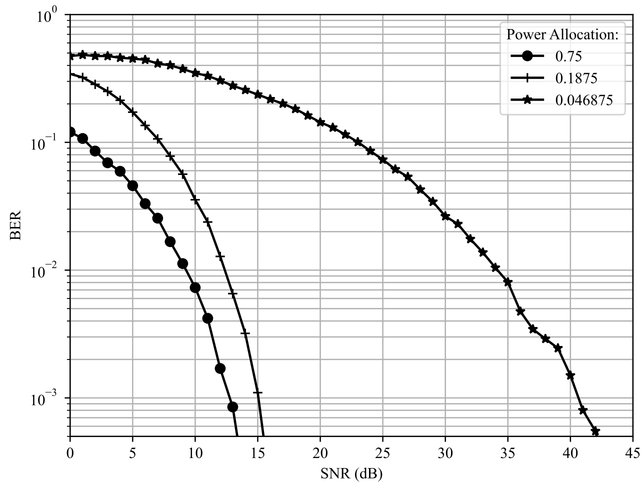


Fig. 7. BER performance in high elevation.

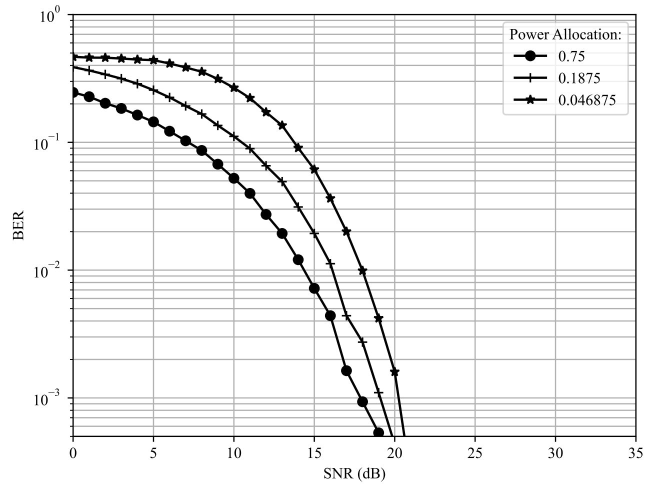


Fig. 8. ASIC performance in low elevation.

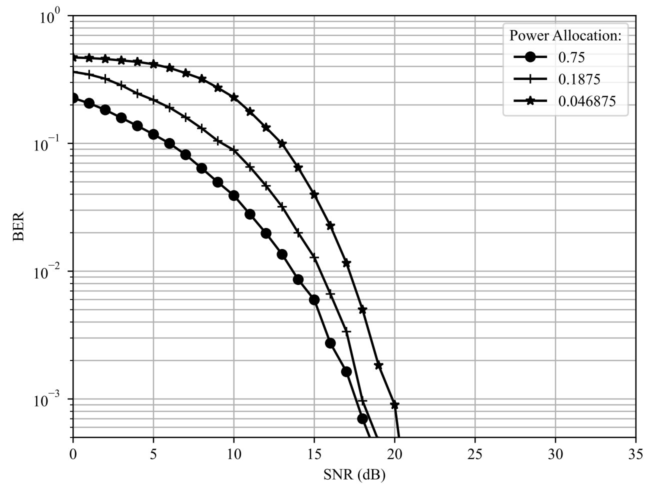


Fig. 9. ASIC performance in medium elevation.

In the simulation results in Medium Elevation, we obtain that the value of the SNR needed is smaller than the low elevation. The user with the greatest power allocation still gets the lowest SNR value with the same power allocation. The SNR obtained from 35-45 ° elevation, or a distance of about 30 km, is 21-26 dB. We found no lines piled in the figure in the second scenario because the SIC process was carried out sequentially.

After simulating and analyzing for low and medium elevation, we conduct a SIC evaluation on high elevation as in Fig. 7. We found that the highest elevation location greatly affected performance on other ground stations. Assuming that the right elevation is 90 degrees, the user with the biggest power allocation requires an SNR value of around 13 dB. However, the user with the smallest allocation power value requires a large SNR (41 dB) to get the same performance results. The transmission distance and K-Rician value are not much different.

Results like this prove that the conventional SIC system is unable to overcome the gap that is too large in the High Elevation area. Conventional SIC requires a longer decoding time for users who use the smallest power allocation. The decoding process must be sequential, and there is a domino effect, making this research contribute to reducing deficiencies in the SIC.

### B. HAPS using ASIC

The PD-Noma that declares the SPC for multiplexing signals and SICs for decoding signals is insufficient to produce appropriate performance. As a result of the power domain, the power needed becomes immense because it is required to use a large SNR to get a targeted value. Therefore, we present the CNN simulation results to form a smarter SIC to recognize the training results' signal character.

Fig. 8 describes the comparison between SNR and after adaptive-SIC use. After a recurring simulation using Monte Carlo, we obtained that the SNR needed to fall significantly compared to conventional SIC. We found that the SNR value was around 18-21 dB for all users in low elevation. This indicates a tiny gap, so each user has almost the same chance as the user with the highest allocation power. We also analyze that the impact resulting from the dataset training makes the decoding process faster with a massive number of datasets before transmitting the real information signal. The SNR gap between the user and the greatest power allocation is only about 3 dB or double the user.

We also simulated in Medium Elevation to see the contribution of ASIC against conventional SIC, as shown in Fig.9. We have observed areas with a transmission distance of 40 km and obtained the results that not too much difference with low elevation.We analyzed that the ASIC has proven the introduction of the SPC signal from the dataset training, the results of the signal detection remain stable. At Medium Elevation, the SNR range to get targeted around 17-21.5 dB. The SNR value is very close to Low Elevation, so the Ground Station in Low Elevation has a performance value similar to Medium Elevation. Also, this proves that power efficiency is significant because the low elevation area does not require great power to obtain a value similar to the medium elevation.

Testing on ASIC, we have also done it in the High Elevation area where the transmission distance is closest to the other elevation area. Fig. 10 holds a smaller gap between the farthest ground station with the closest (90-degree elevation angle). We found that this gap still happened, as produced by conventional SIC. However, using this proposal, the gap between the user and the largest and smallest allocation

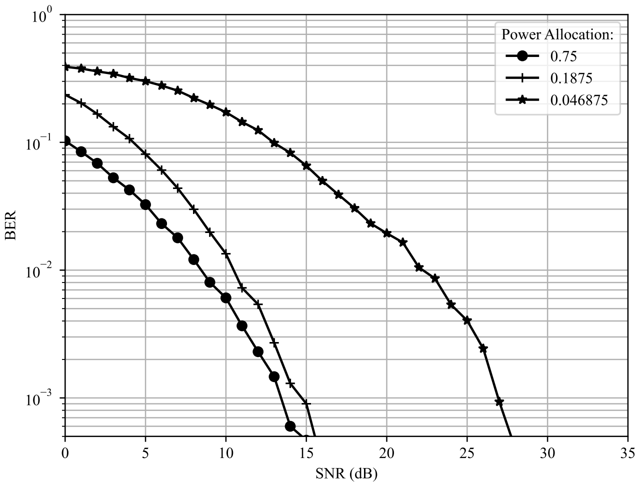


Fig. 10. ASIC performance in high elevation.

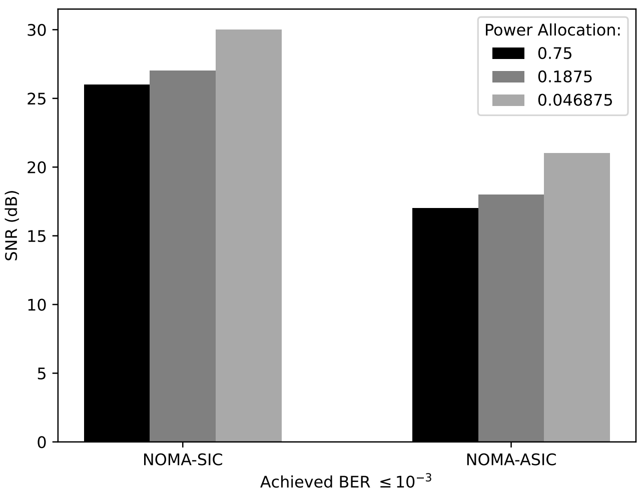


Fig. 11. Comparison of SNR in low elevation.

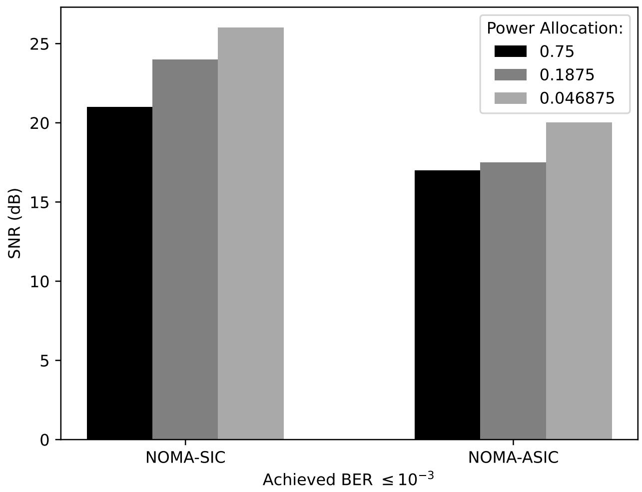


Fig. 12. Comparison of SNR in medium elevation.

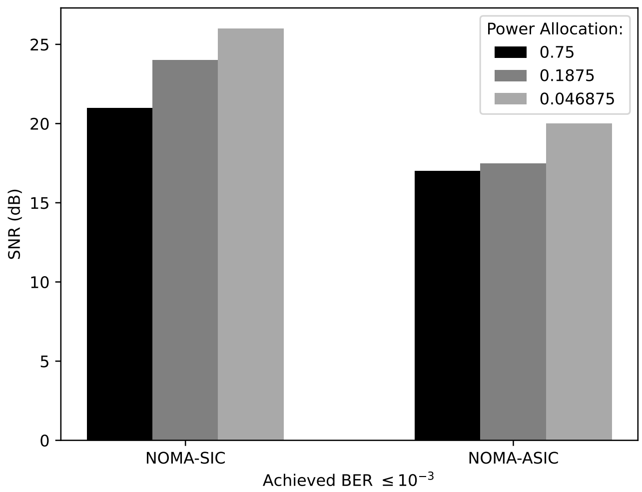


Fig. 13. Comparison of SNR in high elevation.

power is narrower. The first and second users get very close results, where the SNR difference is needed around 2 dB. In comparison, the third user requires an SNR of around 27 dB to get the same results on performance. The value of 27 dB is much smaller when compared to conventional SIC, which requires around 41 dB. We also prove that this proposal is able to reduce power consumption to obtain the results of the target.

### *C. Comparison between SIC and ASIC*

Fig. 11 explains the comparison of the needs of SNR to achieve value in low elevation. We prove that with the same testing parameters, the ASIC method requires a lower SNR when compared to conventional SIC. ASIC makes power efficiency better, and the layer pattern applied to the Adaptive CNN layer has stability in the signal character. If it is not made adaptive, the value of the layer in the CNN raises the possibility of instability due to the clear weight of the signal. In addition, the difference obtained from ASIC and SIC conventional up to 10 dB.

Fig. 12 illustrates the comparison of the SNR value of the ASIC and conventional SIC method in Medium Elevation. We observed further that ASIC in the first and second user had the slightest difference in SNR values on the medium elevation. ASIC proves that the decoding process on both users is almost perfect on two users. Unlike the conventional SIC method, where the gap obtained between SNR is relatively large up to 3 dB. As part of the trade-off, the user who gets the smallest power allocation requires a larger SNR on the ASIC to get targeted. However, on conventional SIC, the value of the difference in the value of the SNR between users is relatively the same as the predetermined allocation power.

The area on High Elevation provides more surprising results compared to Low and Medium Elevation, as shown in Fig. 13. On conventional SIC, the difference between SNR each user is relatively the same, where the user with the biggest power allocation requires the smallest SNR to obtain a target BER. Unlike the ASIC, the first user and both get very small differences, while the third user requires a very large SNR. However, the average SNR value needed by ASIC is smaller than conventional SIC. We also prove that with training datasets, processing on decoding is more manageable and does not require dependence on the previous user. One of the things that make the user get a different SNR to get the same because of the different power allocation in the PD-NOMA scheme.

## IV. Conclusion

After calculating, simulating, and analyzing, we conclude that the proposed adaptive-SIC significantly contributes to increased performance and power efficiency. With the same power allocation for each scenario, using 0.75, 0.1875, and 0.046875 for three users, respectively, we proved that the ASIC method is better than conventional SIC. Deep learning of CNN that we use in the SIC detection also reduces the SNR gap of each user, even though it has a different power allocation. To get BER less than $10^{-3}$, in the low elevation, on average, SIC needs 27 dB SNR, while ASIC is around 18.6 dB SNR. On average, in the medium elevation, SIC needs 23 dB SNR, while ASIC is around 18 dB SNR. Finally, in high elevation, the average SNR needed by SIC is 26 dB, while ASIC is around 18.6 dB. Also, we found that ASIC has proper average SNR around 18 dB for three elevations.

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