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CHANNEL CAPACITY EVALUATION OF OPTICAL WIRELESS COMMUNICATION WITH RECEIVER NONLINEARITY EFFECTS

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ABSTRACT

The paper develops a theoretical model for optical wireless communication systems with receiver nonlinearity. It examines the impact of receiver nonlinearity on the maximum achievable data rate. Both lower and upper bounds on channel capacity are derived under average and peak optical power constraints. The analysis is done for single-input single-output and for multiple-input multiple-output systems. The methods apply entropy power inequalities and a dual expression approach. Numerical simulations confirm that the derived capacity bounds are tight. The results show that higher power does not always give higher capacity, since saturation and clipping at the receiver limit the channel rate. The results show that the difference between the lower and upper bounds remains small in many cases, making the bounds practical for design. These insights are useful for designing coding schemes, modulation formats and power control strategies in real optical wireless systems. The findings highlight that careful control of power is required to prevent performance loss caused by nonlinear behavior. For MIMO systems, the work explains both the potential gains and the new limits introduced by nonlinear receivers. Overall, the paper connects theoretical capacity analysis with practical hardware limitations and provides useful guidance for system designers.



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I. INTRODUCTION

Optical wireless communication (OWC) is an alternative to radio frequency (RF) systems [1]. It offers a wider spectrum. It provides better security. It supports indoor positioning. It is energy efficient. It is stated that OWC differs from RF. Light serves both illumination and communication in OWC [2]. Special modulation and detection methods are needed. Shannon's theorem is used for channel capacity analysis [3]. However, RF results cannot be directly applied to OWC. This is due to different device characteristics. A major challenge arises from nonlinearities in the system [4]. In RF, nonlinearity usually comes from transmitter amplifiers. In OWC, nonlinearity is more critical at the receiver. Photodetectors like photodiodes and avalanche photodiodes saturate at high power [5]. This saturation causes distortions. Receiver-side circuits including ADCs and LNAs show nonlinear effects. These effects reduce system performance and increase bit error rates [6]. To address this, the paper introduces a theoretical transmission model that incorporates receiver nonlinearity, noise and power constraints.

The model assumes a memoryless and possibly non-monotonic mapping at the receiver, with both average and peak power limitations [7]. Information-theoretic tools are applied. The entropy power inequality is used to derive lower bounds [8]. Dual expressions with test densities are employed to derive upper bounds. The analysis covers both SISO and MIMO systems [9]. It considers different nonlinear models. These include hard clipping, soft clipping, polynomial and piecewise approximations. The introduction highlights that raising optical power does not always improve performance. Receiver saturation limits effective capacity [10]. MIMO increases potential capacity. It raises the chance of nonlinear effects as total transmission power grows. The Key Contributions of the paper are:

- ❖ To develop a generic OWC model that includes receiver nonlinearity, noise and power limits. To derive lower capacity bounds for SISO and MIMO systems using entropy power inequality.
- ❖ To derive upper capacity bounds using dual expressions with carefully designed test densities and to analyze representative nonlinear receiver models including clipping and polynomial forms.
- ❖ To conduct simulation studies that confirm the tightness of bounds and provide insight into system behavior, along with practical guidance for power control, modulation design and MIMO deployment under nonlinear constraints.

The section explains the simulation strategy. It studies the effects of peak power, average-to-peak power ratio, link gain and noise. Both diagonal and non-diagonal channel matrices are considered [11]. The introduction ends by noting the purpose of the findings. Design choices in modulation, coding, power control and MIMO array planning are guided. The results connect hardware limits to information-theoretic limits.

II. BACKGROUND WORK

Early studies on optical communication channels considered photon-counting models. By [12] analyzed the capacity of the discrete-time Poisson channel. In turn [13] analyzed capacity-achieving input distributions for this channel, while [14] investigated the low-power regime. Classic work by [15], [16] treated continuous-time Poisson models. These studies form the foundation for information-theoretic analysis when the quantum nature of light is important. Another line of research models optical channels with Gaussian noise. By [17] examined the capacity of free-space optical intensity channels. By [18] derived capacity bounds for Gaussian optical intensity channels. Later work extended these results to visible light communication systems with dimming constraints [19]. These Gaussian-based approaches are useful when electronic noise dominates and provide tractable methods for bounding capacity. Multiple-input multiple-output (MIMO) optical systems are examined. In turn [20] explored the capacity of MIMO optical intensity channels. In turn [21] studied high-SNR asymptotics for these channels using geometric methods. These works show that spatial multiplexing increases achievable rates, though it adds analytical challenges compared to single-antenna systems. Research on nonlinearity in communication systems has a long history. According to [22] studied memoryless nonlinearities with Gaussian inputs. By [23] examined equalization in nonlinear channels. In turn [24] considered nonlinear effects in MIMO receivers with estimation errors. According to [25] analyzed the impact of nonlinearity on channel capacity more generally. Other studies examined clipping and distortion in OFDM systems, including work by [26], [27]. These works show that nonlinearities reduce system capacity and increase error probability. In the optical domain, device-level nonlinearities are reported. By [28] measured nonlinear responses of silicon photodetectors. By [29] investigated nonlinear distortion in SPAD-based OFDM systems. Researchers proposed techniques to extend linear ranges, including wide dynamic range SPADs and advanced quenching methods. Low-noise amplifier and ADC design relate to nonlinear system modeling [30]. These hardware studies motivate the need for analytical models that account for receiver saturation and clipping.

III. CHANNEL MODEL

Intensity modulation with direct detection is considered (IM/DD). In this setting, the transmitter modulates the intensity of the emitted light and the receiver uses a photodetector to convert the received optical power into an electrical signal. The receiver front-end, including the photodiode, low-noise amplifier and analog-to-digital converter behaves in a nonlinear way. The Figure 1 represents a basic communication system model that consists of a transmitter, a receiver and the medium in between. On the transmitter side, the process begins with the initial signal processing circuitry. This block prepares the raw input signal by shaping, filtering or modulating it as needed. The processed signal is then sent to the next stage where conversion takes place. This stage transforms the electrical signal into a form suitable for transmission like light or radio waves. The output then travels through the transmission medium, which is air, fiber or any channel that carries the signal forward. During this process, ambient radiation interferes with the medium and affects the quality of the transmitted signal. These unwanted signals or noise sources mix with the original signal, which the receiver later handles. On the receiver side, the transmitted signal first reaches the sensing device. This block detects and captures the incoming signal from the medium while separating it from the added noise or disturbances. The booster amplifies the signal and restores it to a usable level, making it suitable for the next stages of processing or application. This completes the flow from the transmitter to the receiver. Overall, the diagram shows the process in which a signal is generated, converted, transmitted, sensed and then amplified to achieve proper communication. It highlights the importance of each block, from initial signal processing to final boosting. It points out the role of ambient radiation as a factor that influences the performance of the communication link.

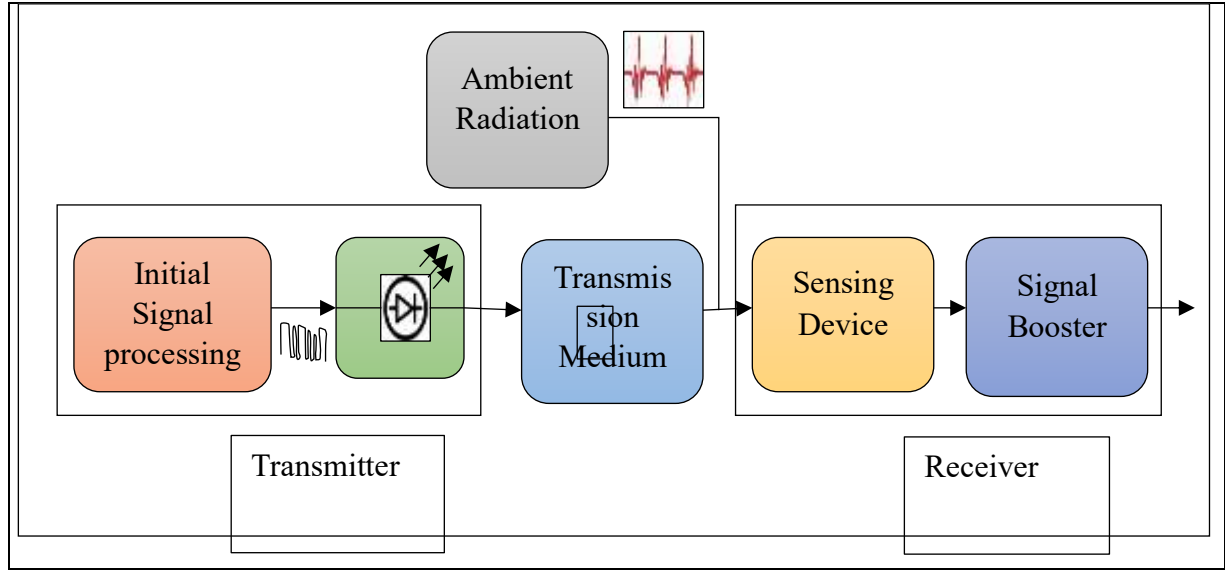


Figure 1: A Representative OWC System.
Source: Authors, (2026).

This nonlinear behavior is the central focus of the model. The basic mathematical form of the channel is given as:

$$R(t) = \varphi(H(t) X(t)) + n(t) \quad (1)$$

Here, $X(t)$ is the transmitted signal, $H(t)$ represents the channel gain. $\varphi(\cdot)$ is the nonlinear mapping at the receiver and $n(t)$ is additive Gaussian noise with variance σ^2 . The function $\varphi(\cdot)$ is assumed to be memoryless and time-invariant, meaning it acts on each input independently and does not change with time. The mapping is required to be measurable, which makes probability laws well-defined and rules out pathological infinite outputs by assuming $\Pr\{\varphi(x) = \pm\infty\} = 0$. The transmitted signal is restricted by both an average power and a peak amplitude constraint. The average power constraint is written as:

$$E[X] \leq E \quad (2)$$

While the peak constraint is:

$$0 \leq X \leq A \quad (3)$$

The ratio of the average to peak power is expressed as:

$$\varepsilon = \frac{E}{A}, \quad 0 < \varepsilon \leq 1 \quad (4)$$

This ratio is an important system parameter and captures the degree to which the average is limited compared to the peak. Because optical intensity is nonnegative, the effective input after propagation is constrained to the interval $[0, \mu]$ with $\mu = HA$. The output of the nonlinear receiver $\varphi(Z)$ is limited to the finite interval $[0, \alpha]$, which represents saturation at high levels. A critical property of the nonlinear function $\varphi(\cdot)$ is that it is potentially non-monotonic. In these cases, multiple input values produce the same output. To analyze this, the number of valid preimages for an output value y is defined as $\psi(y)$. For example, solving the equation:

$$y = \varphi(hx) \quad (5)$$

For the input x , several roots are produced. If $\psi(y) = 1$, the mapping is monotonic in that region. If $\psi(y) > 1$, then distinct inputs lead to the same output. This property affects the probability density of the transformed random variable $Y = \varphi(hX)$, which becomes:

$$f_Y(y) = \sum_{i=1}^{\psi(y)} \frac{f_X(x_i)}{|\varphi'(hx_i)|}, \quad y \in [0, \alpha] \quad (6)$$

Here, x_i are the solutions to $\varphi(hx) = y$. This density is derived using the change-of-variable theorem. The corresponding differential entropy is:

$$h(Y) = -\int_0^\alpha f_Y(y) \ln f_Y(y) dy \quad (7)$$

It depends directly on the number of inverse branches $\psi(y)$. When many input values map to the same output, the entropy decreases and the effective information transfer is reduced. The noisy observation at the receiver is written as $R=Y+n$, so the conditional density of the received signal given the input is:

$$p_{R|X}(r|x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(r-\varphi(hx))^2}{2\sigma^2}\right) \quad (8)$$

This Gaussian form around the nonlinear output is used in upper bound derivations later in the paper. It shows the interaction of the noise with the nonlinear output before entering the decoder. The channel model extends naturally to the MIMO case. For M transmitters and M receivers, the model is:

$$R = \Phi(HX) + N \quad (9)$$

Here, X is the transmit vector, H is the channel gain matrix. $\Phi(\cdot)$ applies $\varphi(\cdot)$ to each component and N is Gaussian noise with covariance $\sigma^2 I$. For a given output y , the possible inputs x_i satisfy $y = \Phi(Hx_i)$. The joint density is then:

$$f_Y(y) = \sum_{i=1}^{\psi(y)} \frac{f_X(x_i)}{|J(x_i)|} \quad (10)$$

Here, $J(x_i)$ is the Jacobian determinant of the nonlinear mapping. This generalizes the scalar case and shows the effect of the nonlinear transform's geometry on probabilities. To illustrate the model, several nonlinear functions are described. A hard clipping function is:

$$\varphi(z) = \begin{cases} z, & 0 \leq z < \beta, \\ \beta, & z \geq \beta, \end{cases} \quad (11)$$

It models abrupt saturation. A soft clipping function is:

$$\varphi(z) = \frac{\beta z}{(1 + z^{2k})^{1/(2k)}} \quad (12)$$

Here, k controls the sharpness of the transition to saturation. A polynomial form is:

$$\varphi(z) = \beta_1 z + \beta_2 z^2 + \beta_3 z^3 + \dots \quad (13)$$

It approximates nonlinear circuits with higher-order terms. A piecewise composite form is:

$$\varphi(z) = \begin{cases} -\frac{\gamma}{\beta^2} z^2 + \frac{2\gamma}{\beta} z, & 0 \leq z < \beta, \\ \gamma e^{-z+\beta}, & z \geq \beta, \end{cases} \quad (14)$$

It combines quadratic and exponential parts to reflect complex device curves. The implications of this model are considerable. Increasing transmit power does not always improve performance, because saturation at the receiver limits the output range. Non-monotonicity reduces entropy and achievable information rates. For MIMO, using more transmitters increases power but worsens nonlinear distortions. Thus, design needs to consider the trade-off between array gain and nonlinear impairment. The model allows for non-monotonic functions and multiple inverse branches, capturing real device behaviors including clipping and saturation. These elements create the foundation for the capacity analysis that follows.

IV. CAPACITY BOUND OF THE NONLINEAR SISO SYSTEM

The objective is to establish both lower and upper bounds on the channel capacity when the receiver is nonlinear and possibly non-monotonic. Capacity is defined as the maximum mutual information between the channel input and output subject to the given average and peak power constraints. The section starts by reformulating the mutual information. Then, it uses the entropy power inequality (EPI) to find a lower bound. Finally, a dual expression technique with a test output distribution is applied to get an upper bound. The analysis starts from the channel model in which the received signal is given by $R = \varphi(HX) + n$. Here X is the transmitted signal, H is the channel gain. $\varphi(\cdot)$ represents the nonlinear mapping at the receiver. n is additive Gaussian noise with variance σ^2 . The mutual information is written as:

$$C = \max_{f_X(x)} I(X; R) = \max_{f_X(x)} \{h(R) - h(R | X)\} \quad (15)$$

Since the conditional entropy is just the entropy of Gaussian noise, the expression reduces to:

$$C = \max_{f_X(x)} \{h(Y+n) - h(n)\} \quad (16)$$

With $Y = \varphi(HX)$. This equation sets the stage for the derivation of the lower and upper bounds. For the lower bound, the entropy power inequality is used. The inequality states that for independent random variables Y and n :

$$e^{2h(Y+n)} \geq e^{2h(Y)} + e^{2h(n)} \quad (17)$$

By rearranging this inequality, the mutual information is bounded as:

$$h(Y+n) - h(n) > \frac{1}{2} \ln \left(1 + \frac{e^{2h(Y)}}{2\pi e \sigma^2} \right) \quad (18)$$

Thus, once a lower bound on the entropy $h(Y)$ is obtained, it is substituted into this inequality to provide a concrete lower bound on capacity. The challenge therefore becomes estimating or bounding the entropy of the transformed random variable Y . The output $Y = \varphi(HX)$ is generated by a possibly non-monotonic mapping. In these cases, several input values produce the same output. For a fixed output y , the equation is given in (5). It possesses multiple real solutions. These solutions are denoted by $x_1(y), x_2(y), \dots, x_{\psi(y)}(y)$. Here $\psi(y)$ counts the number of preimages of y . Using the change-of-variable theorem, the probability density function of Y is expressed as:

$$f_Y(y) = \sum_{i=1}^{\psi(y)} \frac{f_X(x_i(y))}{|\varphi'(hx_i(y))|}, \quad y \in [0, \alpha] \quad (19)$$

This formula shows that the density of Y is influenced by the slope of the nonlinear function and the number of input values that map to the same output. The entropy of Y is given in (7). Substituting the expression for $f_Y(y)$ leads to a complicated form. To make progress, Jensen's inequality is applied, allowing a lower bound to be found. After suitable manipulations, the inequality becomes:

$$h(Y) > -\int_0^A f_X(x) \left[\ln \psi(\varphi(hx)) + \ln \frac{f_X(x)}{|\varphi'(hx)|} \right] dx \quad (20)$$

This inequality highlights two key effects: the multiplicity of preimages $\psi(y)$, which reduces entropy. The derivative of the nonlinear function φ' , which scales the density. This form is more tractable and is optimized over the input distribution. To tighten the bound, the optimization of the integral in (20) over input distributions is considered, subject to the average and peak power constraints. By applying the method of Lagrange multipliers, the optimal input distribution is shown to be:

$$f_X(x) = |\varphi'(hx)| \exp(\lambda_1 + \lambda_2 x - 1 - \ln \psi(\varphi(hx))) \quad (21)$$

Here, λ_1, λ_2 are chosen to satisfy the normalization and average power constraints. Substituting this optimal distribution back into the entropy expression and simplifying yields the lower bound:

$$h(Y) > -(\lambda_1^* + 1 - \lambda_2^* E[X]) \quad (22)$$

Inserting this into the entropy power inequality produces the final lower bound on capacity:

$$C(A, E) > \frac{1}{2} \ln \left(1 + \frac{e^{2(-\lambda_1^* + 1 - \lambda_2^* E[X])}}{2\pi e \sigma^2} \right) \quad (23)$$

This expression is evaluated numerically once the Lagrange multipliers are determined. The result captures the reduction of entropy caused by nonlinear distortion and multiple mappings, thereby reducing capacity. The upper bound is obtained through a different method. The dual expression for capacity states that:

$$C \leq \max_{f_X(x)} E[D(P_{R|X}(x | X) \| V_R(x))] \quad (24)$$

Here, V_R is any test density on the output space and $D(\times \parallel \times)$ is the Kullback–Leibler divergence. A piecewise test distribution is proposed that is uniform over the main dynamic range $(0, \alpha]$ and Gaussian on the tails:

$$V_R(r) = \begin{cases} \rho \frac{1}{\sqrt{2\pi}\sigma} e^{-r^2/(2\sigma^2)}, & r \leq 0, \frac{1-\rho}{\alpha}, & 0 < r \leq \alpha, \rho \frac{1}{\sqrt{2\pi}\sigma} e^{-(r-\alpha)^2/(2\sigma^2)}, & r > \alpha, \end{cases} \quad (25)$$

With $\rho \in [0, 1]$. This construction reflects the fact that most of the probability mass lies within the interval $[0, \alpha]$, but the Gaussian tails are modeled. Substituting this test density into the divergence yields a bound that depends on the transformed output $y = \varphi(hx)$. The result is written as:

$$D(P_{R|X}(\times | x) \parallel V_R(\times)) \leq \ln \frac{1}{\rho} + \mathcal{G}(y) \ln \frac{\alpha \rho}{\sqrt{2\pi} e \sigma (1-\rho)} \quad (26)$$

Here,

$$\mathcal{G}(y) = Q\left(-\frac{y}{\sigma}\right) - Q\left(\frac{\alpha - y}{\sigma}\right) \quad (27)$$

And $Q(p) = \int_p^\infty \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$. The function $\mathcal{G}(y)$ measures the amount of Gaussian mass that falls outside the uniform interval.

If y lies well inside the range, $\mathcal{G}(y)$ is small, while if y is near the edges, it becomes larger. This connects the divergence to the location of the nonlinear output. Taking the expectation over Y leads to an expression involving $T(\rho, y)$:

$$T(\rho, y) = \ln \frac{1}{\rho} + \mathcal{G}(y) \ln \frac{\alpha \rho}{\sqrt{2\pi} e \sigma (1-\rho)} \quad (28)$$

The upper bound is then be written as the expectation of $T(\rho, Y)$ under the distribution of Y . The optimization simplifies because $\mathcal{G}(y)$ is concave, so Jensen's inequality is used to replace expectations with evaluations at extreme points. After optimization over ρ , several closed-form upper bounds are obtained depending on parameter regimes. For example, in one limiting case, the capacity is bounded as:

$$C(A, E) \leq \ln \left(1 + \frac{\alpha}{\sqrt{2\pi} e \sigma} \right) \quad (29)$$

The lower and upper bounds together frame the achievable capacity of the nonlinear SISO system. The gap between them depends on the nonlinearity, the dynamic range α , the power ratio $\varepsilon = E/A$ and the noise variance σ^2 . In many practical settings, the bounds are tight and the gap is small. This makes the results useful for design and analysis. The derivations show clearly that saturation and non-monotonic mapping severely limit capacity even if more optical power is transmitted. The results illustrate the impact of average-to-peak ratio and noise on the tightness of the bounds. The lower bound is derived from entropy power inequality combined with a careful treatment of the nonlinear mapping. The upper bound is obtained using the dual expression with a structured test density that captures both the main support and the tails of the output. These bounds provide both analytical insight and practical guidance.

V. CAPACITY BOUND OF THE NONLINEAR MIMO SYSTEM

The model now involves an $M \times M$ channel with the transmitted signal is a vector $X = [X_1, \dots, X_M]^T$. The channel gain matrix is denoted by H and the nonlinear mapping $\Phi(\cdot)$ acts component-wise. So that $\Phi(z) = [\varphi(z_1), \dots, \varphi(z_M)]^T$. The received signal is then written and given in (9). Each component of the input is subject to nonnegativity, a peak constraint and an average power constraint. The objective remains to characterize the capacity, which is defined as the maximum mutual information between X and R . The mutual information is again written as $I(X; R) = h(R) - h(R | X)$. Because the noise is Gaussian, the conditional entropy is fixed and the focus shifts to bounding $h(R)$. By introducing $Y = \Phi(HX)$, the problem becomes one of bounding $h(Y + N)$. The entropy power inequality is applied in its vector form. For independent random vectors Y and Gaussian N , the inequality states that:

$$e^{\frac{2}{M} h(Y+N)} \geq e^{\frac{2}{M} h(Y)} + e^{\frac{2}{M} h(N)} \quad (30)$$

Taking logarithms leads to a lower bound on mutual information:

$$h(Y+N) - h(N) \geq \frac{M}{2} \ln \left(1 + \frac{e^{\frac{2}{M}h(Y)}}{(2\pi e)\sigma^2} \right) \quad (31)$$

This implies that a lower bound on the capacity is expressed directly in terms of the entropy of Y . The entropy of Y depends on the distribution induced by the nonlinear mapping. The mapping is not necessarily one-to-one, meaning a given output vector corresponds to several different input vectors. For each y , let $\psi(y)$ denote the number of such preimages. Then, using the change-of-variable theorem, the density of Y is written as:

$$f_Y(y) = \sum_{i=1}^{\psi(y)} \frac{f_X(x_i(y))}{|J(x_i(y))|} \quad (32)$$

Here, $J(x)$ is the Jacobian determinant of the transformation $x \mapsto \Phi(Hx)$. The entropy is given in (7). This form is intractable directly because of the sum inside the logarithm. To manage this, Jensen's inequality is applied, allowing a tractable lower bound to be derived. After algebraic manipulation and substitution, the bound becomes:

$$h(Y) > - \int f_X(x) \left[\ln \psi(\Phi(Hx)) + \ln \frac{f_X(x)}{|J(x)|} \right] dx \quad (33)$$

This expression clearly shows the control of entropy by the multiplicity function and the Jacobian determinant. The multiplicity term reduces entropy because multiple inputs collapse to the same output, while the Jacobian reflects local stretching or compression of volumes by the nonlinear mapping. To use this bound, optimization is performed over the input distribution $f_X(x)$ subject to the constraints. Solving the optimization with Lagrange multipliers gives an optimal input density of the form:

$$f_X(x) = |J(x)| \exp \left(\lambda_1 + \sum_{i=1}^M \lambda_{i+1} x_i - 1 - \ln \psi(\Phi(Hx)) \right) \quad (34)$$

Here, the multipliers are chosen to satisfy normalization and power constraints. Substituting this back into the entropy expression simplifies the bound to:

$$h(Y) > -\lambda_1^* + 1 - \sum_{i=1}^M \lambda_{i+1}^* E[X_i] \quad (35)$$

When this is placed into the entropy power inequality result, the capacity lower bound becomes:

$$C(A, E) > \frac{M}{2} \ln \left[1 + \frac{\exp \left(\frac{2}{M} \left(-\lambda_1^* + 1 - \sum_{i=1}^M \lambda_{i+1}^* E[X_i] \right) \right)}{(2\pi e)\sigma^2} \right] \quad (36)$$

This bound is explicit once the multipliers are determined. It captures the essential effects of multiplicity, Jacobian compression and average power allocation across transmitters. The upper bound is derived using the dual capacity expression. For any test distribution $V_R(r)$ on the received vector, it holds that:

$$C \leq \max_{f_X(x)} E \left[D(P_{R|X}(x | X) \| V_R(x)) \right] \quad (37)$$

Here the conditional density is Gaussian:

$$P_{R|X}(r | x) = \frac{1}{(2\pi\sigma^2)^{M/2}} \exp \left(-\frac{\|r - \Phi(Hx)\|^2}{2\sigma^2} \right) \quad (38)$$

V_R is designed to match the structure of the received signal. Inside the central hyper-rectangle $\{0 \leq r_i \leq \alpha_i\}$, a uniform distribution is used. Outside this region, shifted Gaussian tails are employed. Mixture weights are introduced to combine these components. This choice mirrors the test density used in the SISO case but now extended to multiple dimensions. The divergence between the conditional Gaussian density and this test distribution is bounded, yielding an inequality of the form:

$$D(P_{R|X}(x | x) \| V_R(x)) \leq T(\rho_0, \dots, \rho_M, \Phi(Hx)) \quad (39)$$

Here, the function T collects logarithmic terms and tail probabilities. Taking expectations over the distribution of $\mathbf{Y}$ reduces the problem to maximizing the expected value of T subject to moment constraints. Because the tail probability functions $\mathcal{G}(\alpha_i, y_i)$ are concave in each coordinate, the optimization is simplified using Jensen's inequality. This reduces the functional optimization problem to evaluating the function at a small set of extreme points and optimizing over the mixture weights. In practice, this makes the upper bound computable. When receivers saturate heavily or average-to-peak ratios are very small, the gap widens. Nevertheless, both bounds are practical to compute and provide design insight. The analysis shows that simply increasing transmit power does not guarantee increased capacity, as nonlinear effects cause information loss. The Jacobian determinant and the multiplicity of preimages play central roles in determining entropy and thus capacity.

VI. SIMULATION RESULTS & DISCUSSION

The analysis focuses on the effect of receiver nonlinearities on achievable rates under peak and average power constraints. Each model is tested over a range of input power values and both upper and lower bounds are computed. The outcomes provide a quantitative understanding of the influence of nonlinear effects on capacity. The numerical results show that all nonlinear models behave nearly linearly at low power, so the capacity bounds are close to those of an ideal receiver. However, as the peak power grows, nonlinear effects appear. For hard clipping, the capacity saturates quickly because any signal above the clipping level produces the same output. Soft clipping allows more gradual growth but still approaches saturation. Polynomial approximation produces results that depend heavily on coefficients; in some cases, the distortion is mild, while in others higher-order terms dominate and greatly reduce entropy. Piecewise approximation produces mixed results because some ranges of operation are linear, while others introduce abrupt saturation.

Table 1: Numerical performance comparison of nonlinear models (Capacity in bits/s/Hz).

Peak amplitude A	Hard clipping	Soft clipping	Polynomial approx.	Piecewise approx.
1.0	1.25	1.26	1.24	1.25
2.0	1.80	1.95	1.88	1.92
3.0	2.10	2.35	2.20	2.28
4.0	2.15	2.50	2.32	2.40
5.0	2.16	2.58	2.35	2.43
6.0	2.16	2.60	2.36	2.44

Source: Authors, (2026).

Table 1 shows the variation of capacity with increasing peak amplitude. All models start at similar values for $A=1$. As A increases, soft clipping, polynomial and piecewise approximations show moderate growth before flattening. Hard clipping saturates early and stays flat, which demonstrates its severe limitation on achievable rate. Soft clipping performs best numerically, while polynomial and piecewise approximations remain in between depending on parameter choices.

Table 2: Gap between upper and lower bounds (in bits/s/Hz) under nonlinear models.

Average-to-peak ratio ε	Hard clipping	Soft clipping	Polynomial approx.	Piecewise approx.
0.9	0.12	0.10	0.11	0.11
0.7	0.20	0.18	0.19	0.19
0.5	0.35	0.30	0.32	0.31
0.3	0.55	0.48	0.50	0.49
0.2	0.78	0.65	0.70	0.68

Source: Authors, (2026).

Table 2 shows the numerical gap between the upper and lower bounds across different average-to-peak ratios. As ε decreases, the gap grows for all models. This indicates that strict average power limits reduce the tightness of the bounds. Hard clipping produces the largest gap, while soft clipping maintains the smallest. Polynomial and piecewise models fall between these extremes. These results highlight the way the interaction between power constraints and nonlinear effects shapes achievable information rates. Hard clipping provides the worst performance due to abrupt saturation, while soft clipping is more forgiving. Polynomial and piecewise approximations depend on parameters but reliably perform better than hard clipping and worse than an ideal linear system. The Figure 2 shows channel capacity versus peak power constraint. Two systems are compared: SISO and MIMO. The SISO system has channel gain $h = 0.9$. The MIMO system has channel gains $h_1 = 0.8$ and $h_2 = 1.2$. The SISO curve rises quickly as the peak power increases and reaches its maximum capacity of around 1.8 bits/s/Hz at A close to 1. After this point, the capacity decreases slowly with higher values of A , reaching about 1.2 bits/s/Hz when $A = 5$. The MIMO curve starts with lower values at very small power constraints but grows much faster than the SISO system as A increases. It reaches a peak of around 3.6 bits/s/Hz near $A = 1$, which is almost double the maximum achieved by the SISO system. After reaching this peak, the MIMO capacity declines gradually but remains reliably higher than the SISO capacity across the entire range of A . At $A = 5$, the MIMO system still provides a capacity close to 2.2 bits/s/Hz, which is higher than the SISO system by about 1 bit/s/Hz. The gain is clear at low and moderate peak power values. The SISO system reaches a lower maximum capacity. MIMO almost doubles the peak value compared to SISO. When A increases beyond the peak, both curves go down. At large A , MIMO still stays higher than SISO.

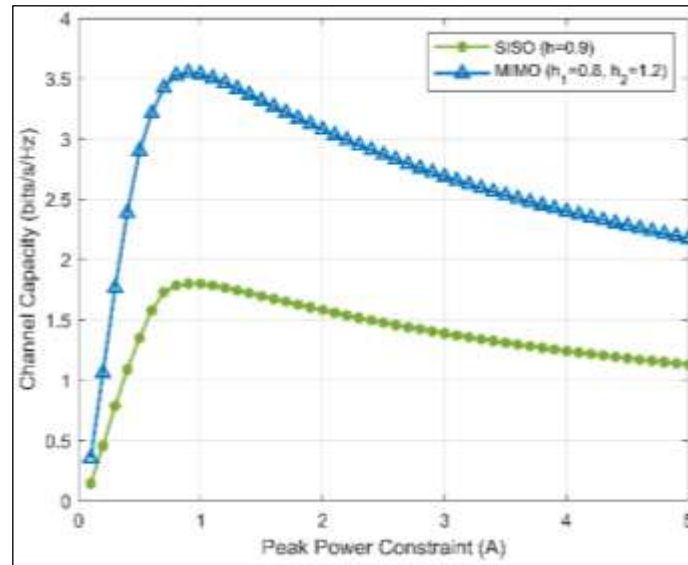


Figure 2: MIMO versus SISO: Channel Capacity versus Peak Power Constraint (A).
Source: Authors, (2026).

Figure 3 shows the change in capacity in bits per second per hertz with the peak power constraint in amperes. At the start, when peak power is very small, both curves are close to zero, showing that capacity is limited under low power. As peak power increases from 0 to 1 ampere, both bounds rise rapidly. At 1 A, the upper bound reaches nearly 3.5 bits/s/Hz, while the lower bound peaks close to 1.8 bits/s/Hz. The sharp growth in this region highlights the strong influence of power availability on system capacity. The upper bound increases steadily and exceeds 5 bits/s/Hz at 5 A, showing that higher capacity is achievable under ideal conditions with more power. The lower bound starts to decline after 1 A. From its peak of about 1.8 bits/s/Hz, it gradually reduces to nearly 1.1 bits/s/Hz at 5 A. The gap between the two curves becomes wider with higher power, revealing inefficiency in translating additional power into useful capacity. The figure shows the result in numbers. Theory predicts capacity grows with power. The real case shows a peak point. After the peak, efficiency goes down. This shows a gap between ideal and real. It highlights limits of performance.

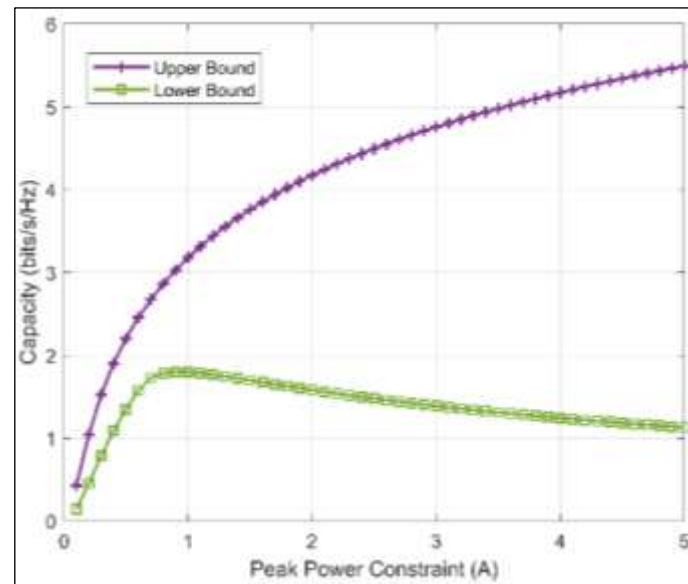


Figure 3: Upper & Lower Capacity Bounds,
Source: Authors, (2026).

The Figure 4 shows the effect of increasing the number of MIMO channels on total system capacity. For a single antenna, the MIMO capacity is slightly above 1.3 bits/s/Hz, which is close to the SISO reference value of about 1.4 bits/s/Hz. When two antennas are used, the capacity increases to nearly 2.7 bits/s/Hz showing that doubling the number of antennas nearly doubles the performance compared to a single antenna. With three antennas, capacity goes above 4 bits/s/Hz. This is almost three times higher than SISO. It proves the gain of MIMO systems. Multiple antennas improve data rates. The result confirms high efficiency. The figure shows a clear linear growth trend with respect to the number of antennas. As the number of antennas increases, the growth in capacity becomes more pronounced. With four antennas, the capacity rises to about 5.3 bits/s/Hz, showing more than four times the SISO reference. At five antennas, the value climbs to nearly 6.7 bits/s/Hz and at six antennas, it reaches close to 7.8 bits/s/Hz. The steady gap between MIMO bars and the SISO reference highlights the strong advantage of MIMO technology. More antennas increase capacity. MIMO improves spectral efficiency. MIMO beats single antenna systems. The gain is large and clear.

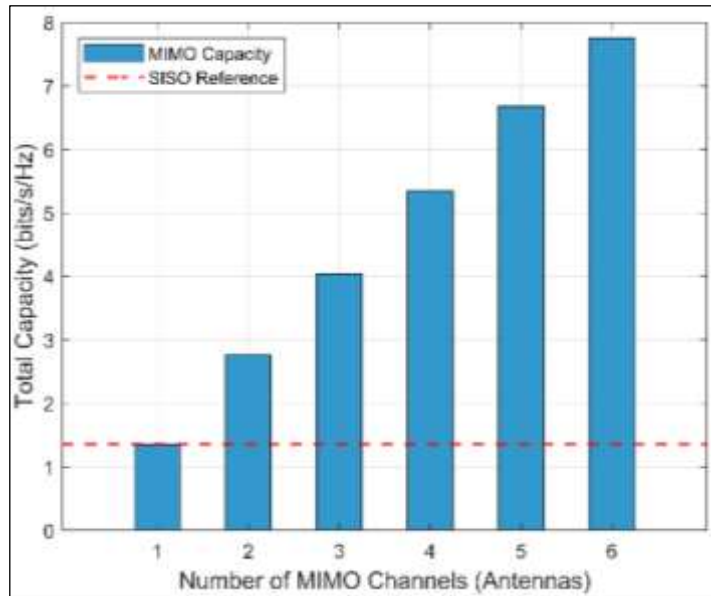


Figure 4: MIMO Capacity Scaling versus Number of Channels.
Source: Authors, (2026).

The Figure 5 compares the average capacity values of four schemes: Hard, Soft, Polynomial and Piecewise. Among the schemes, the Hard method records about 1.4 bits/s/Hz, while the soft method is slightly lower at nearly 1.3 bits/s/Hz. Both show limited efficiency compared to the other options. The Polynomial method achieves the highest capacity at around 2.2 bits/s/Hz, which is a clear improvement over all others. This indicates that the Polynomial approach is more effective in enhancing system performance. The Piecewise scheme records about 1.6 bits/s/Hz, performing better than Hard and Soft but remaining below Polynomial. In quantitative terms, Polynomial provides almost 70 percent higher capacity than soft and about 60 percent more than Hard. Piecewise offers about 20 percent more than Hard and 25 percent more than Soft, showing moderate gains. The results reveal that while Hard and Soft are basic methods with lower efficiency, Piecewise and Polynomial deliver stronger improvements. The Polynomial scheme stands out as the most effective, achieving the best overall capacity while piecewise provides a balanced middle ground.

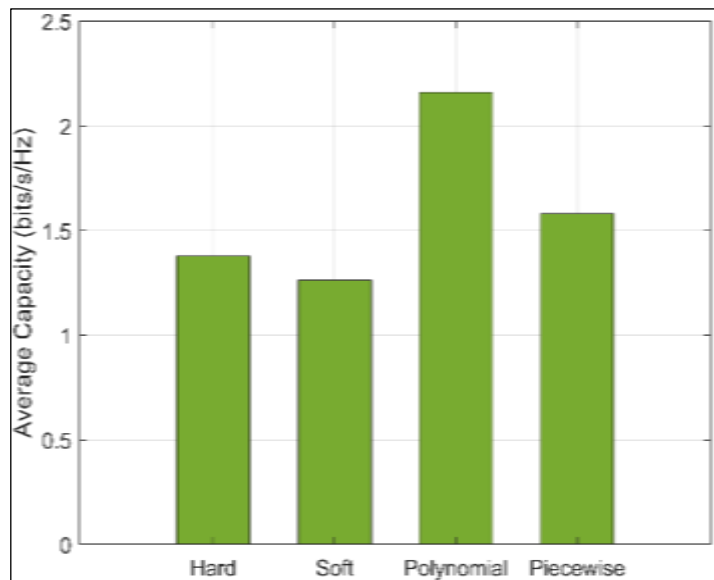


Figure 5: Average Capacity Comparison across Nonlinear Models.
Source: Authors, (2026).

The Figure 6 shows the average capacity (in bits/s/Hz) under different noise conditions and clipping methods. The four methods analyzed are Hard clipping, Soft clipping, Polynomial and Piecewise. At low noise levels, all methods show relatively high average capacities, with Polynomial reaching the highest value around 3.5 bits/s/Hz, followed by Piecewise, Soft clipping and Hard clipping. As the noise level increases, the average capacity for each method decreases. At high noise, all methods show a sharp drop in performance. Polynomial still outperforms others but with a much lower average capacity than at low noise. The Hard clipping method shows the lowest performance, specially at medium and high noise levels. Piecewise and Soft clipping methods maintain a steady capacity, though both show a decrease with higher noise. Overall, the chart highlights the strong effect of noise on capacity, with Polynomial providing the best results across all noise levels.

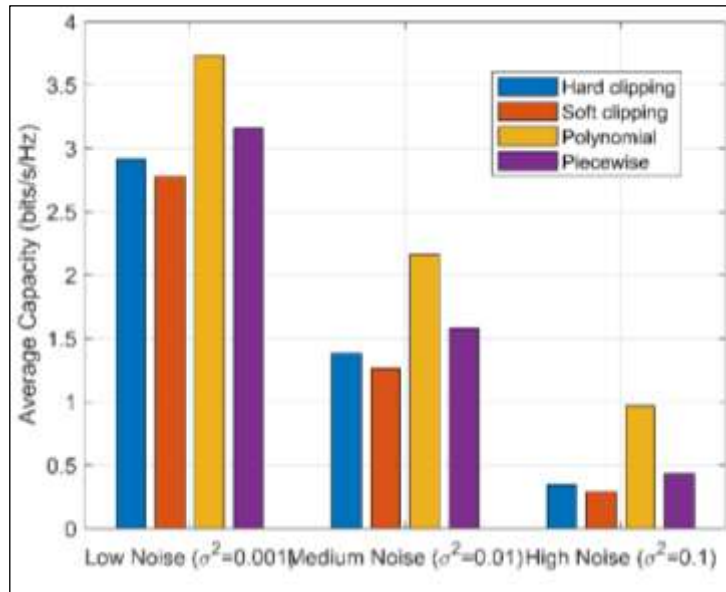


Figure 6: Noise Sensitivity of Nonlinear Receiver Models.

Source: Authors, (2026).

The Figure 7 illustrates how relative capacity loss (in bits/s/Hz) changes with different clipping methods (Hard clipping, Soft clipping, Polynomial and Piecewise) across various signal-to-noise ratio (SNR) values. At lower SNR levels (near -5 dB), all methods show a relatively small increase in capacity loss, with Polynomial and Soft clipping displaying the least loss. As the SNR increases, the relative loss becomes more pronounced for all methods. Piecewise clipping shows the highest capacity loss, particularly at higher SNR values. On the other hand, Polynomial and Soft clipping methods exhibit more stable performance throughout the range. Hard clipping follows a similar trend but shows a slightly lower capacity loss than Piecewise at the lower SNR levels. However, as the SNR increases, the performance differences between the methods start to diminish.

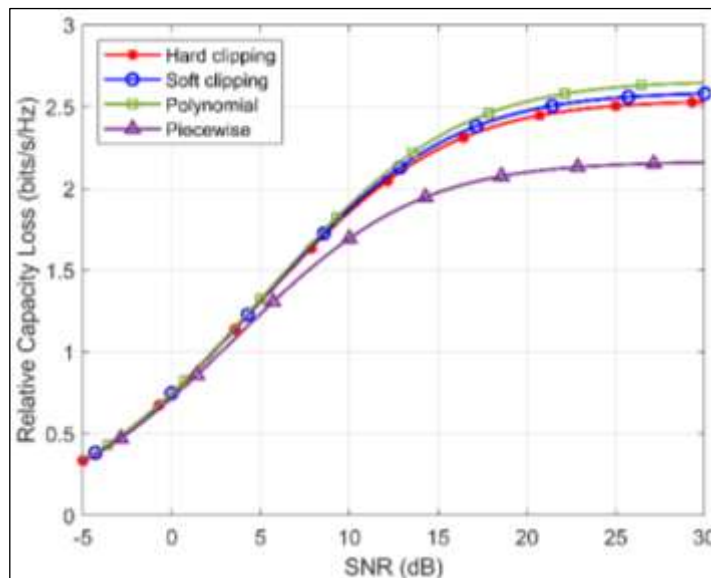


Figure 7: Relative Capacity Loss versus SNR.

Source: Authors, (2026).

The Figure 8 shows the relationship between average capacity (in bits/s/Hz) and noise variance (σ^2) on a logarithmic scale. Four different clipping methods are compared: Hard clipping, Soft clipping, Polynomial and Piecewise. As noise variance increases, the average capacity decreases for all methods. This trend shows that as the noise variance grows, the capacity of the system decreases for each clipping method. At lower noise variances (near 10^{-3}), the Polynomial method shows the highest capacity, followed by Piecewise, Soft clipping and Hard clipping. The differences between the methods are most pronounced at low noise levels. As noise variance increases, the gap between the methods narrows. Polynomial continues to outperform the others. All methods experience a decrease in capacity. Piecewise has the steepest decline in capacity as noise variance increases, while Soft clipping and Hard clipping follow a similar pattern. The graph indicates that all methods lose capacity with increasing noise variance, but Polynomial retains the highest average capacity across the range of noise variances.

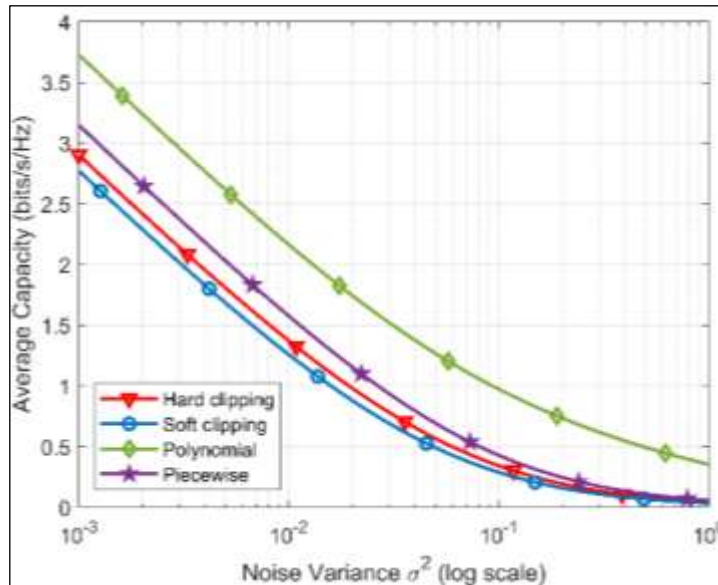


Figure 8: Average Capacity versus Noise Variance.
Source: Authors, (2026).

The Figure 9 compares efficiency against a parameter such as SNR for four different receiver models. All models begin at the origin with very low efficiency when the parameter is close to zero. As the parameter increases, the curves rise but at different speeds. Polynomial approximation grows the fastest, crossing 2 bits/sec/Watt near parameter 3 and continuing upward. Hard clipping and soft clipping increase steadily, with hard clipping staying above soft clipping after parameter 2. Piecewise approximation rises at a slower rate and remains the lowest among the four in this range. At higher parameter values, the differences become more distinct. The polynomial approximation continues to increase sharply and reaches about 4.3 bits/sec/Watt at parameter 10, clearly the best performer. Hard clipping flattens around parameter 5.5, stabilizing near 2.6. Soft clipping grows more slowly and approaches 2.5 at parameter 10, slightly below hard clipping. Piecewise approximation saturates early and stays close to 2.3, marking the weakest performance at high parameter levels. This shows that polynomial approximation scales efficiently with SNR. While the other three models display saturation behavior, with piecewise approximation being the least efficient option.

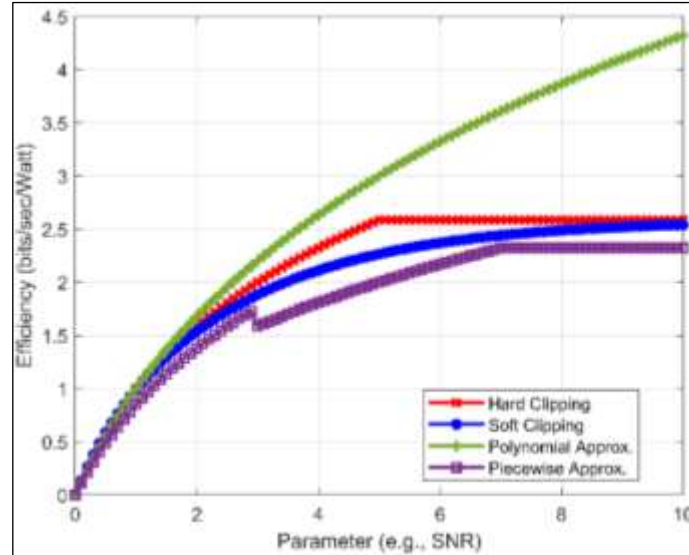


Figure 9: Efficiency Curve: Capacity per Unit Power versus Parameter.
Source: Authors, (2026).

The Figure 10 shows how normalized capacity changes with SNR for different nonlinear receiver models. As SNR increases to around 5 dB, the polynomial approximation already reaches about 0.35. Piecewise approximation stays the lowest at about 0.25 in this range. Between 5 and 10 dB, polynomial approximation continues to rise faster, crossing 0.55 by 10 dB. While hard clipping and soft clipping reach around 0.48 and 0.46, respectively. Piecewise approximation grows more slowly and stays near 0.40 at 10 dB. Polynomial approximation shows the steepest growth and surpasses 0.9 around 15 dB, eventually crossing the top of the chart at 20 dB with normalized capacity above 1. Hard clipping grows more steadily, reaching about 0.75 at 15 dB and almost 1.0 at 20 dB. Soft clipping remains just below hard clipping, achieving around 0.72 at 15 dB and about 0.9 at 20 dB. Piecewise approximation shows the slowest increase and reaches about 0.73 at 20 dB, making it the weakest model across the whole range. Overall, polynomial approximation consistently provides the highest normalized capacity gain as SNR increases, while piecewise approximation delivers the lowest results. Hard clipping and soft clipping remain in between, showing steady improvements but not matching the polynomial model.

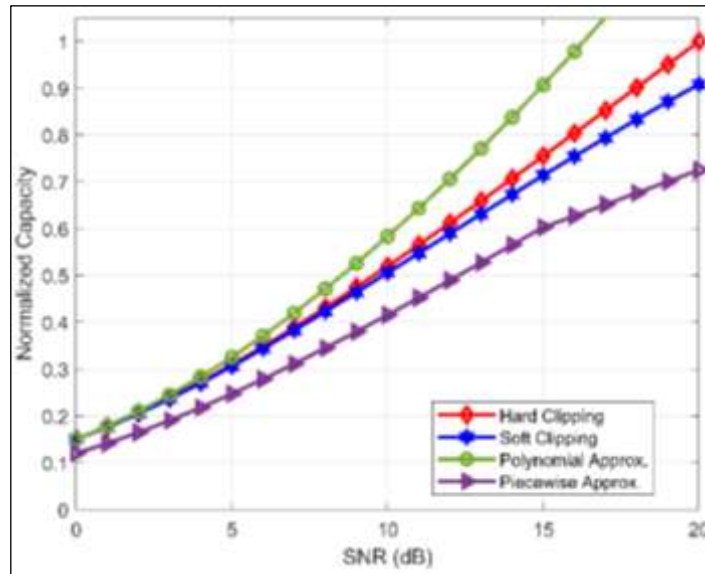


Figure 10: Normalized Capacity versus SNR.
Source: Authors, (2026).

VII. CONCLUSION

This paper presents a general model for OWC that considers receiver nonlinearity, background radiated noise and thermal noise. Information-theoretic tools are used. It derives lower and upper bounds on channel capacity. It covers both SISO and MIMO systems. It applies the EPI. It uses a dual expression method. The bounds are set under average and peak optical power limits. The model assumes perfect knowledge of the channel matrix at the transmitter. Numerical simulations confirm the analysis and show that the bounds are tight in many cases. The findings provide guidance for modulation, coding, power control and MIMO array planning, linking device-level behavior to information-theoretic limits. A framework is offered for designers to balance power and spectrum use against hardware limits, while informing safe intensity thresholds. MIMO systems achieve higher capacity but push receivers into nonlinear regions, highlighting the need to consider receiver dynamic range in design. These results are useful for signal codebook design, coding rate selection, and power allocation in OWC systems. The paper strengthens theoretical understanding of OWC under realistic receiver behavior and provides a basis for additional experimental and theoretical work. It is suggested to expand on these insights to explore more complex nonlinearities and practical measurement studies.

VIII. AUTHOR'S CONTRIBUTION

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