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Predicting Ergodic Data Capacity and BER for MIMO Communication Systems using SVM Model

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***Abstract*—The maximum error-free data rate that a channel can support is known as the data handling capacity of the channel. In today's era of widespread digital communication, all channels inevitably aim to operate at their maximum data rate. Over the years, researchers have extensively explored various technologies and modulation techniques to boost data transmission speeds. Orthogonal frequency division multiplexing followed by a multiple input multiple output system is used for 5G technology to achieve an enhanced data rate. However, as is true for all systems and designs, MIMO systems also have pockets of vulnerability. The two most sensitive parameters are the impairment level at the transmitter end and a variable correlation coefficient at the receiver end. In this paper, we have concentrated on the receiver end distortion because it affects the data rate capacity. In MIMO systems, at the receiver end, the kappa factor, which is a function of the channel impulse response, and α, a factor dependent on the correlation coefficient of the identical antennas, significantly influence the maximum ergodic data rate and the corresponding bit error rate. In this work, we have applied the support vector regression model to simulate the non-linear nature of these issues and established a relation between the SVM-predicted result and data obtained from an open-source data set. The proposed scheme helps the designers and propagation engineers derive realistic data rate values by considering two important factors.**

***Index Terms*— Ergodic capacity, channel impulse response, correlation coefficient, MIMO, and support vector regression.**

I. INTRODUCTION

In the rapidly evolving landscape of digital communications, the efficiency and reliability of data transmission systems are paramount. The advent of technologies like 5G has not only heightened expectations for faster data rates but also underscored the importance of robust communication systems capable of handling the exponential increase in data traffic [1-2]. At the core of these advancements lies the concept of data handling capacity, defined as the maximum error-free data rate that a communication channel can support. This metric is to be considered for the design and optimization of modern communication systems. It is necessary since the goal is to achieve near-perfect data transmission efficiency.
Ergodic capacity describes the maximum reliable communication rate (or capacity) over a channel under the assumption that the transmission time is sufficiently long for the channel to undergo all possible states according to its statistical distribution [3-5].

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In a wireless communication system, the channel characteristics (like path loss, shadowing, and multipath fading) can vary over time. The Ergodic capacity is calculated under the assumption that the channel states change sufficiently over the period considered, allowing the use of statistical averages to predict performance. This calculation often involves averaging the capacity over different states of the channel. Ergodic capacity is an idealized measure and assumes that transmitters and receivers can adapt their coding and modulation schemes perfectly to the instantaneous channel conditions, which is more theoretical but provides a useful benchmark for system performance in variable channels.

Among the various technologies, to be used for the next generation of wireless communications, multiple input multiple output (MIMO) systems [6-7] could be one of the best for their potential to significantly enhance data handling capacity. By utilizing multiple transmitter and receiver antennas, MIMO systems exploit spatial multiplexing to increase throughput without necessitating additional bandwidth or increased transmit power. This capability positions MIMO as a foundational technology for to meet the burgeoning data rate requirements of contemporary data communication networks. However, the practical deployment of MIMO systems reveals a few inherent vulnerabilities that can degrade performance [8]. Two critical factors—non-ideal channel impulse response and variations in the correlation coefficient between antenna pairs [9]—pose significant challenges. The channel impulse response, affected by multipath propagation, introduces distortions that can lead to signal degradation. The correlation coefficient impacts the diversity gain and, consequently, the system's data rate and reliability. These vulnerabilities are particularly problematic in dynamic environments, because the predictability of system performance becomes a big challenge.

This paper examines the complexities at the heart of MIMO communication systems, with a particular focus on receiver end distortions that are pivotal in determining the system's ergodic data capacity and Bit Error Rate (BER). We identify two critical parameters that influence these metrics: the kappa factor, which is a function of the channel impulse response, and α, a factor dependent on the correlation coefficient among identical antenna pairs. These parameters encapsulate the non-idealities that can distort received signals, It, thereby, limits the achievable data rates and reliability of MIMO systems. Traditional analytical methods may fall short in capturing the complex interplay between these factors and their effects on system performance. Therefore, this study suggests a novel approach, which takes use of Support Vector Regression (SVR) to predict the impacts of non-ideal channel impulse response and correlation coefficient variations on MIMO systems. SVR, known for its effectiveness in modeling non-linear relationships, is applied to simulate the intricate dynamics between the kappa factor, correlation coefficient, and the system's performance metrics. By leveraging an open-source dataset, we establish a robust model that predicts the impact of receiver end distortions on the MIMO system's data handling capacity and BER. This methodology not only enhances our understanding of these complex interactions but also provides designers and propagation engineers with a powerful tool to predict realistic data rate values, taking into account critical vulnerabilities. By offering a comprehensive analysis and a novel predictive model, we aim to pave the way for more resilient and efficient MIMO deployments, ensuring that the digital communication landscape continues to thrive in the face of evolving challenges.

II. Proposed Scheme

The data handling capacity of a radio channel is defined by the maximum amount of error-free data it can transmit. Prior to the introduction of MIMO, single input single output (SISO) systems were used, where the focus was solely on the performance of a single channel [1-3]. Of course, in SISO systems, we had to contend with the multi-path phenomenon caused by scattering, diffraction, and other factors. However, with MIMO systems, we can physically transmit multiple channels or sub-carriers simultaneously, say N channels in an N x N system. A common simplifying assumption when calculating the capacity of MIMO channels is that the fading coefficients between the transmit-receive antenna pairs are independent and identically distributed (i.i.d.) according to a Rayleigh distribution [4-6].

In the proposed model, the transfer function of the channel H is taken to be same as H_w. Here, H represents nominal channel matrix and H_w is the channel matrix in the absence of any correlation. However, the ergodic capacity, or the average capacity of a group of channels, is influenced by both the channel state information (CSI) and the fading factor. In a MIMO system, the probability of outage is consequently impacted by these two factors as well [7-10]. Hence, ergodic capacity, defined as the average maximum rate at which information can be transmitted with arbitrarily low error probability in the presence of random variations like fading can be expressed by equation (1).

$$C=E\ [\log_2 \det [I+ (1/\sigma^2)\ HQH^{\dagger})] \quad (1)$$

In equation (1), C represents the ergodic capacity of a MIMO channel system; E [.] denotes the expectation over the channel realizations; H denotes the channel matrix; Q is the input covariance matrix and it depends on CSI; σ^2 is the noise variance; I is the identity matrix; Det (.) represents the determinant of the matrix, formed by the combination of antennas and H† is the Hermitian transpose of H.

As shown in equation (1), the ergodic capacity depends on several factors, with CSI being one of the most critical. The channel matrix, which itself is influenced by the degree of correlation between the antennas, plays a significant role. Additionally, both the channel matrix and its conjugate transpose, or Hermitian transpose, are key factors in determining the ergodic capacity [11-15]. The noise variance also impacts the capacity. When CSI is perfectly known at the transmitter, the matrix Q can be optimized to maximize capacity. In the absence of CSI, Q is usually set to a scaled identity matrix, representing uniform power allocation across all antennas, though this approach is suboptimal. [16-17].

The channel capacity also depends on the distribution of 'H', which can vary depending on the type of fading (e.g., Rayleigh fading, Rician fading).The effect is represented in terms of outage probability. Hence, the outage probability is the probability that the channel ergodic capacity falls below a certain threshold (R).The equation for outage probability in a MIMO system under Rayleigh fading is shown in equation (2) [18-19].

$$P_{outage} = \Pr\{\log_2 \det[\mathbf{I}+(1/\sigma 2)1\mathbf{HQH}\dagger]<R\} \qquad (2)$$

Fading causes the channel parameters to vary, leading to fluctuations in capacity. Deep fades significantly reduce capacity, increasing the outage probability. Diversity techniques in MIMO can combat fading. It in turn, enhances both capacity and reduces outage probability.

Hence, CSI plays a crucial role in maximizing the ergodic capacity of MIMO systems by allowing for optimal power allocation across antennas. Fading impacts both the ergodic capacity and outage probability, with the severity depending on the fading distribution and the MIMO system's ability to exploit diversity.

The relation between the impairment level represented by a kappa factor in MIMO systems [20] and the effect it has on the signal-to-noise ratio (SNR) and, therefore, on the bit error rate (BER) of the system. The simplified relation is expressed in equation 3.

$$BER = f\,(SNR, k, N_t, N_r) \qquad (3)$$

In equation (3), $'k','N_t','N_r'$ represent kappa factor (impairment level in the channel matrix), number of transmit antenna and number of receive antenna in the proposed MIMO system respectively. Equation 4 shows the relationship between k factor and the SNR.

$$SNR_{\_effective} = [SNR/\,(1+k)] \qquad (4)$$

For a given modulation scheme, the effect on the BER can be more explicit. For example, for binary phase-shift keying (BPSK) and in an Additive White Gaussian Noise (AWGN) non-MIMO channel, the BER is expressed in equation (5).

$$BER = Q\,[\sqrt{(2.\,SNR_{\_effective})}] \qquad (5)$$

In equation (5), Q (.) is the Q-function. In MIMO systems, the relationship becomes more complex and is typically derived through extensive system modeling and simulations. Key factors such as spatial multiplexing, space-time block coding, and CSI play crucial roles in determining both the signal-to-noise ratio (SNR) and bit error rate (BER). In our experimental study, we have attempted to establish these relationships using MATLAB and Python code implementations.

These experiments will illustrate the impact of the impairment level (kappa factor, k) on both the SNR and BER, as well as the effect of the correlation coefficient (α factor) on the ergodic data capacity in a MIMO system. The 'α' factor represents the degree of interference between antennas at the receiver end [21-22]. A higher correlation, either at the transmitter or receiver end, leads to a reduction in the MIMO channel's capacity. In contrast, if the antennas are completely uncorrelated, the channel achieves maximum capacity. For this to occur, both the transmission and receive correlation matrices must be identity matrices, as expressed by the following equation. This highlights the critical role that correlation plays in determining MIMO system performance as shown in equation (6).

$$H = R_r^{1/2}\, H_w\, R_t^{1/2} \qquad (6)$$

In equation (6), H_w represents channel matrix when no correlation is present or with i.i.d. complex Gaussian entries and R_r and R_t are the receive and transmit correlation matrices respectively. The 5G communication can work efficiently only with massive MIMO systems. These systems have to be guarded against impairment level and correlation coefficient [23-24]. Fading factors are to be considered to produce a realistic and true ergodic capacity for MIMO channels [25-26].

II. Modeling Using AI

MIMO has become one of the most critical communication systems today, making it essential to accurately predict network data capacity. This is where reliable modeling plays a crucial role. For our study, we chose the Support Vector Regression (SVR) model to demonstrate its effectiveness through the results of our experiments. We decided to compare these results, obtained through simulations, with those from an appropriate AI model. In wireless communication systems, including MIMO, the relationships between various inputs and outputs (such as SNR vs. distance or transmit power vs. range) are inherently non-linear. This non-linearity is primarily due to the behavior of components like mixers and amplifiers that generate the parameters. As a result, many traditional training models are not well-suited for capturing these complex dynamics.

Hence, the support vector machine (SVM) model, using a radial basis function (RBF) kernel, is ideal for such non-linear systems. It excels in predicting values by modeling complex relationships in the data. The RBF kernel is particularly suitable for modeling local, non-linear data sets because it maps input data into an infinite-dimensional space, allowing it to capture intricate patterns that would be missed by simpler models. Additionally, it has fewer hyper parameters compared to polynomial kernels, making it easier to tune for optimal performance. This SVR model offers a narrow deviation from the actual targets while maintaining a flat approximation curve, ensuring that the deviation remains minimal. This balance allows for better and more accurate predictions, making the model a robust choice for approximating complex non-linear relationships in MIMO systems.

We have plotted SVM prediction lines on the relevant graphs to explain the advantage of SVR modeling for predicting SNR and Data Capacity. A binary classification problem can be described with two classes, labeled as $+\varepsilon$ and $-\varepsilon$. Now, let us have a look at the basis of classification. In SVM, we take the output of the linear function and if that output is greater than $+\varepsilon$, we identify it with one class and if the output is $-\varepsilon$, we identify is with another class. Since the threshold values are changed to $+\varepsilon$ and $-\varepsilon$ in SVM, we obtain this reinforcement range of values $[-\varepsilon,+\varepsilon]$ which acts as margin.

A training dataset consisting of input feature vectors X and their corresponding class labels Y is applied.

In linear SVR, the predicted value or output of the model for a given input 'x' is modeled as equation (7)

$$f(x) = w.x + b \qquad (7)$$

In equation (7), 'w','x' and 'b' denote the weight vector, input feature vector, and bias term respectively. The '.' signifies the dot product. The Primary objective is to determine w and b. The SVR also uses a loss function and it is called the 'epsilon-insensitive' loss function as shown in equation (8).

$$L_\varepsilon = (y, f(x)) = \max\,(0, |y - f(x)| - \varepsilon) \qquad (8)$$

Equation (8) shows that errors are assumed to be zero, if they are located within a margin (ε), with respect to the actual values defined for 'y'. SVR focuses on the errors beyond the margin. To ensure the proposed model is as flat as possible, the norm of w, indicated by $||w||$ is minimized. The norm refers to the magnitude of the weights, w. The minimization problem can be formulated as equation (9).

$$\text{Minimize } \tfrac{1}{2}||w||^2 \text{ subject to } |y_i - (w.x_i + b)| <= \varepsilon \text{ for all I} \qquad (9)$$

Linear SVMs use a linear decision boundary to separate the data points of different classes. A hyper-plane that maximizes the margin between the classes is the decision boundary. Non-linear SVM are used to classify data when it cannot be separated into two classes by a straight line. By using kernel functions, nonlinear SVMs can handle nonlinearly separable data. The original input data is transformed by these kernel functions into a feature space, where the number of dimensions increases and then the data points can be linearly separated. A linear SVM is used to locate a nonlinear decision boundary in this modified space.

The SVM kernel is a function that takes low-dimensional input space and transforms it into higher-dimensional space. In other words, it converts non separable problems to separable problems. Therefore, the kernel does some extremely complex data transformations and tries to find out the process to separate the data based on the labels or outputs defined. While using kernels, the function f(x) is expressed as equation (10)

$$f(x) = \Sigma_{i=1 \text{ to } n}\ (\alpha_i K(x_i, x) + b \qquad (10)$$

In equation (10), ‘K (x_i , x)’ is the kernel function and α_i are the coefficients. SVR prediction lines have been plotted on the relevant graphs to show the advantage of SVM modeling for to predict SNR and Data Capacity.

IV. RESULT ANALYSIS

We have shown the plots to prove that-(i) the ergodic capacity in a MIMO system depends on the value of α (Fig. 1); (ii) the dependence of the ergodic capacity on the kappa factor, even when α changes and (iii) the capacity variation with the array of antenna numbers in the absence of any impairments. The plot (Fig. 4) shows that the normal capacity is higher than the ergodic capacity, which is but expected. The final plot (Fig. 5) makes it clear that the effects of α and kappa-factor are rather pronounced on the ergodic capacity. Here, the SVR model outputs, as marked by dotted lines indicate that the predicted values are quite reasonable and the swings of the capacity variations are mostly symmetric about the SVR lines.
Simulation analysis shows a plot of the Ergodic Capacity (measured in bits/s/Hz) against the Signal-to-Noise Ratio (SNR) in decibels (dB) for a Multiple-Input Multiple-Output (MIMO) communication system. It displays three separate curves, each corresponding to a different value of the correlation coefficient α, which can affect the capacity of the communication system. The SNR range was set between 2 dB and 15 dB to cover the range usually available in a MIMO system. The first results were obtained for a fixed k (=0) and different α values.

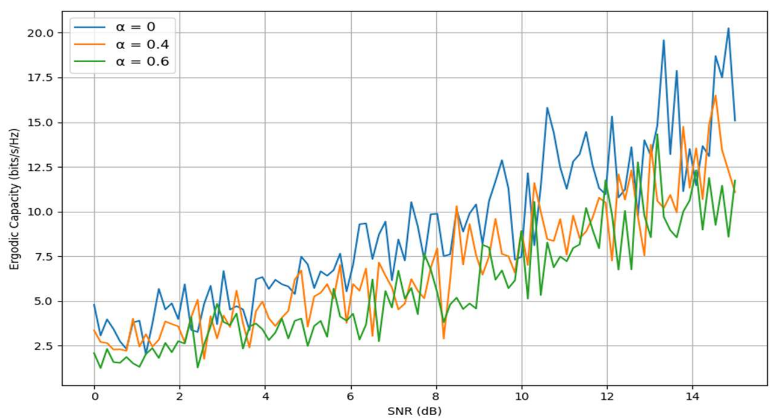

Figure 1: Ergodic Capacity vs. SNR (with K=0 and variable α factor, 0.0, 0.4, 0.6)

Figure 1 shows that as α increases (meaning more correlation), the Ergodic Capacity decreases. It is evident when comparing the blue line (α = 0), which is consistently above the orange (α = 0.4) and green (α = 0.6) lines, especially beyond an SNR of 5 dB. A higher α value leads to a decrease in capacity, which is a result of channel paths becoming more correlated, effectively reducing the MIMO system's ability to send independent streams of data. This simulation indicates that to maximize the Ergodic Capacity of a MIMO system, a lower correlation between transmission paths is preferable, particularly as SNR increases. It also shows that even without channel impairments (κ=0), the system performance can be significantly affected by the correlation between transmission paths.
Let us check the differences at SNR of 12 dB. The Table 1 clearly shows that the capacity changes with α factor- the higher is the value, the lower is the Ergodic capacity and this degradation is expected [equation (1)].

TABLE I: ERGODIC CAPACITY VS A FACTOR

Serial Number	Value of α factor	Ergodic Capacity (in bits/s/Hz)
1	0.0	14.2
2	0.4	11.5
3	0.6	8.0

Figure 2 shows the variation in Ergodic capacity with variation in the kappa factor value along with change in the α factor (0.0, 0.4, 0.6). The blue line represents the scenario with no antenna correlation. As expected, this line shows the highest Ergodic Capacity across the SNR range, indicating that the system performs best when the transmission paths are uncorrelated. The orange line shows reduced capacity compared to the blue line. The performance gap suggests that even moderate correlation (α = 0.4) has a detrimental effect on the system's capacity. The green line indicates an even higher correlation and, accordingly, shows a further reduction in capacity. It reinforces the principle that increased correlation typically degrades MIMO system performance. Table 2 establishes the influence of the kappa factor or the CSI on the data capacity.

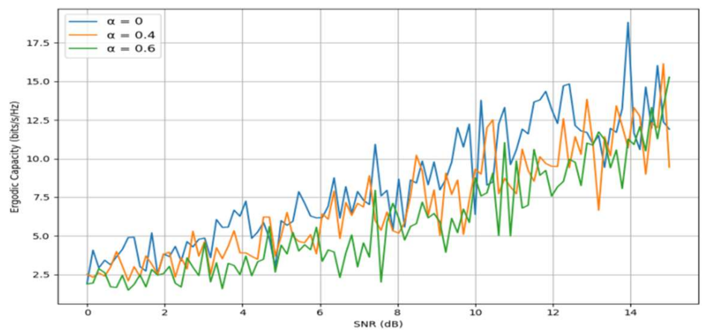

Figure 2: Ergodic Capacity vs SNR (with k= 0.08 and α = 0.0, 0.4, 0.6)

TABLE II: ERGODIC CAPACITY CHANGE WITH K-VALUE

Serial No.	K value	α factor	SNR value (in dB)	Ergodic Capacity (in bits/s/Hz)
1	0.0	0.4	10	10.0
2	0.08	0.4	10	9.0

Figure 3, shows three separate plots, each representing the MIMO capacity for different configurations of transmit (Tx) and receive (Rx) antennas at various Signal-to-Noise Ratio (SNR) levels. The blue lines represent high SNR scenarios, while the red lines represent low SNR scenarios. It states that the capacity is higher when the SNR is low, which is contrary to typical expectations. In a real-world scenario, increasing the number of antennas does not linearly increase capacity due to practical issues such as interference, mutual coupling between antennas, and imperfect channel state information. One has to be very careful about the placements and configuration particularly when the SNR value is high.

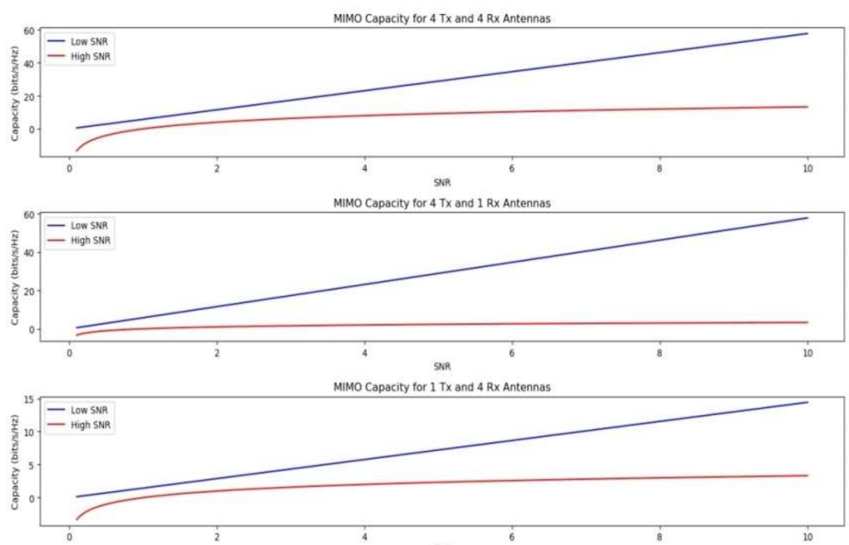

Figure 3: MIMO capacity for variable MIMO antenna configurations (Without any impairment)

Figure 4, illustrates a comparison between the normal channel capacity and the ergodic capacity of a Multiple-Input Multiple-Output (MIMO) system over a range of Signal-to-Noise Ratio (SNR) values in decibels (dB). It conveys the difference in capacity calculations when considering ideal conditions versus realistic conditions that account for channel impairments. Efforts to improve the ergodic capacity are vital for the practical deployment of MIMO systems, ensuring that users experience reliable data rates despite the variability in channel conditions.

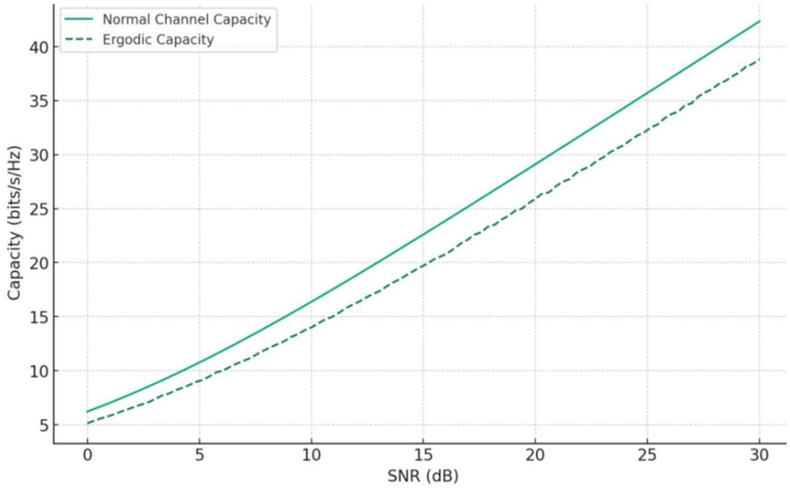

Figure 4: Normal vs. Ergodic Capacity in MIMO systems

Figure 5 presents the ergodic capacity of a MIMO system while considering various values for both the kappa (κ) and alpha (α) factors. The graph also includes Support Vector Regression (SVR) predictions for these combinations. The kappa factor typically represents channel impairments such as fading or shadowing, and the alpha factor represents the correlation coefficient between multiple transmission paths. Figure 5 also emphasizes the need to consider channel impairments and correlation effects when predicting the performance of MIMO systems. Fine-tuning the SVR model or incorporating additional features might improve its predictions, leading to more reliable planning and design of MIMO systems.

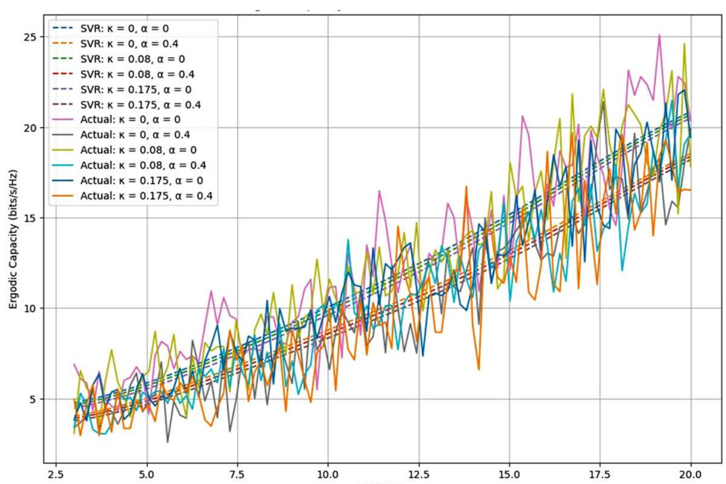

Figure 5: In a single plot, the relative effects of k and α on Ergodic data rate are shown

IV. Discussion

The performance of MIMO systems is significantly influenced by factors such as antenna correlation (α) and channel impairments (κ). As both Tables 1 and 2 suggest, increased α and κ values lead to a reduction in ergodic capacity, since higher α implies stronger correlation, and degrading signal multiplicity, and higher κ reflects more severe channel impairments like fading. Contrary to conventional understanding, Figure 3 indicates an increase in data rate at lower SNR levels across various antenna configurations (4x4, 4x1, 1x4), attributing this to reduced interference at lower signal powers. While this might be true in specific interference-dominated scenarios, generally, higher SNR is associated with better performance. Figure 4 corroborates the expected decrease in data rates with increased impairment for a (4x4) MIMO configuration. Lastly, Figure 5 demonstrates the efficacy of Support Vector Machine (SVM) models in closely predicting ergodic capacity across different values of κ and α, underlining the model's potential in accurately forecasting system performance under varying conditions, which is essential for efficient MIMO system design and capacity planning. We could establish the usefulness of proper modelling even for a highly variable and interference-prone parameter like ergodic data rate. Such AI based regression models will help to improve the quality of wireless communication. However, insufficient availability of real-time data sets is a deficiency so far. The situation is bound to improve because of demand for QoS in wireless communication. We plan to extend our work with new data sets and with new regression models. There is also scope of further improvement of ergodic data rates incorporating different types of multi-rate filters like Kalman filters. We have already planned experiments in this line.

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