Feed-Forward Neural Networks to Overcome Complex Precoding Matrix Calculation in GEO Broadband Satellite Communication Systems

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***Abstract*—As satellite communication evolves, multi-beam GEO satellite systems have emerged as crucial for delivering high-throughput broadband services across wide geographical expanses. Despite significant strides in this field, these systems are constrained by dependence on traditional precoding techniques, such as Minimum Mean Square Error (MMSE) precoders, known for their high computational complexity and detailed channel matrix knowledge requirement. Accordingly, in this paper, we employ a trained feedforward neural network (FFNN) for precoding based on user locations, eliminating the need for Channel State Information (CSI) or channel matrix estimation. While the proposed FFNN precoder initially necessitates the integration of CSI during the deployment (preliminary offline training) phase, it subsequently develops the capacity in the operational phase to predict the precoding matrix per user position only. Hence, this methodology successfully navigates around the constraints of traditional practices, leading to substantial reductions in computational complexity, overhead, and latency. Correspondingly, in this work, we provide numerical results to illustrate the significant reduction in computational complexity achieved by using a trained feedforward neural network for precoding with a minimal trade-off in the offered capacity performance.**

***Index Terms*—Multi-beam high throughput satellite systems, precoding, Machine learning, deep learning.**

I. Introduction and background

Multibeam geostationary (GEO) satellite communication systems still predominate the business of space-based communication systems. Their main advantage with recent lower-orbit solutions is that GEO orbit appears to be in a fixed position to an earth-based observer, and with a single satellite, one can cover a much wider service area [1].

High throughout GEO satellite systems are characterized by a multi-beam circular footprint of 100-200 km diameter [2]. The available spectrum is strategically distributed across beams to avoid interference between adjacent beams, typically following a 4-color reuse scheme with two orthogonal frequency bands and two orthogonal polarizations. While the 4-color scheme ensures low levels of interference, it fails to provide the necessary capacity in the so-called “hot-spot” areas, where the peaks of demand are extremely high [3].

With the aim to improve spectral efficiency, GEO satellite communication systems can be combined with the so–called linear precoding techniques [4]. Precoding has been shown to improve spectrum usage efficiency and increase satellite communication systems’ capacity by reducing interference and maximizing the signal-to-noise ratio (SNR) [5].

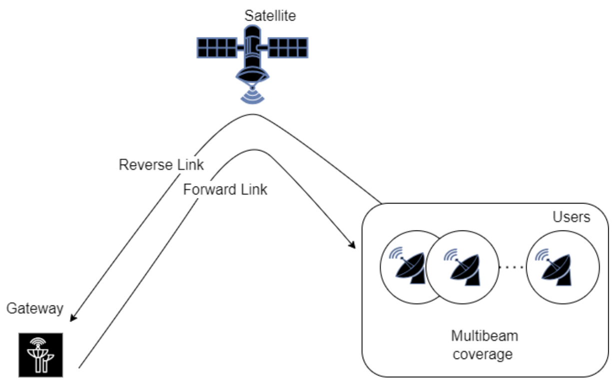

Fig. 1: Multibeam GEO Satellite System Model

Furthermore, it is essential to distinguish between the concepts of beamforming and precoding. In satellite communication systems, beamforming is implemented directly from the antenna array, focusing the created beam pattern towards specific, known terrestrial coordinates. This means that the mere knowledge of a user’s location would be sufficient for its design [6]. Contrarily, precoding is driven by the Channel State Information (CSI) which is an interference mitigation technique. CSI represents the estimated “equivalent channel” complex coefficient that spans from the digital segment of the Gateway (GW) – where the pilots are put together – to the digital facet of the terminal where these pilots are measured [7].

Assuming the absence of adaptive beamforming on the satellite, our study intimates that a mapping can be derived between sets of users (along with their geographical locations) and an apt precoding matrix. Such an approach might exhibit high efficacy for deterministic physical channels, such as Line-of-Sight (LoS) scenarios, especially for the GEO Broadband Satellite Communication Systems, where the CSI can be deduced accurately from the user’s location.

A. Satellite Precoding Challenges

Precoding techniques require the accurate knowledge at the gateway side of the Channel State Information (CSI) of all precoded beams, and a certain additional technical challenges that are summarized in the following:

1) CSI acquisition: Due to the classical frequency division duplexing (FDD) mode of GEO satellite systems as shown in Figure 1, end-user terminals need to perform the measurements and estimation of the downlink channel, and then report it back to the gateway via the return link. CSI estimation is an additional complexity added to the user model, which typically follows a pilot-based correlation algorithm. There is always the presence of estimation errors, which tend to increase when the signal is received in a low carrier-to-noise (C/N) level regime. Furthermore, although the GEO channel is relatively dominated by Line-of-Sight (LoS), the average trip-time of 240 msec (going up to the satellite and down to the gateway) may result in outdated CSI due to potential mobility or different fading/shadowing components [8]. Finally, the CSI feedback is typically quantized, introducing additional noise.

2) Precoding matrix calculation and implementation: Minimum Mean Square Error (MMSE) precoder is the most popular precoding technique due to its proven performance in real GEO systems [5]. However, it involves a channel matrix inversion of complexity $\mathcal{O}(N^3)$ (assuming Cholesky decomposition), where N denotes the number of precoded beams. The precoder matrix is then multiplied by the symbols (i.e. N^2 operations) at the PHY layer frame. Therefore, the calculation and execution has to be performed a frame-level pace, imposing strict timing requirements.

B. Contribution: Data-Driven Precoding Design

The existing literature highlights the potential of machine learning-based precoding techniques to address the limitations of traditional methods, such as the MMSE precoding technique. However, most of these approaches still rely on CSI or channel matrix information, introducing overhead and latency. Using user location information in communication systems has shown promise in various applications, but its integration with machine learning-based precoding remains unexplored.

In this context, machine learning and deep learning techniques, particularly feed-forward neural networks (FFNN), have emerged as promising alternatives to traditional optimization-based precoding methods [9]. FFNNs have demonstrated the ability to model complex, nonlinear relationships and adapt to various channel conditions, making them suitable for precoding applications. This paper presents a novel approach that uses an FFNN to predict the precoding matrix based solely on user locations, circumventing the need for CSI or channel matrix information during operations.

However, a practical challenge arises in how to obtain the training data for the data-driven approach. One option is that the FFNN model is trained with data collected with a relatively small network of operator-owned ancillary receivers distributed across the coverage area, with similar specifications to commercial user terminals but with a CSI acquisition chain.

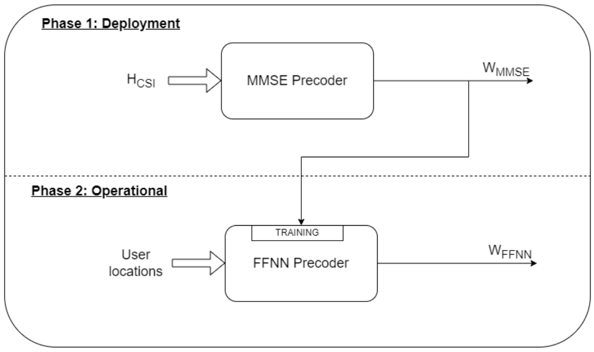

Fig. 2: Functional diagram indicating Deployment and Operational phases

Another approach as shown in Figure 2, is to divide the satellite functional period into deployment and operational phases, where, the data required for the training can be collected during the deployment phase with CSI acquisition chain and use MMSE precoder to mitigate the interference which is then used to train the FFNN. Later, during the operational phase, a trained FFNN precoder can be used for interference mitigation.

II. System and Channel Model

The system model integrates a terrestrial segment featuring an ideal feeder link (a singular gateway) and a complex space segment (a high throughput multi-beam satellite equipped with beamforming capabilities) as depicted in Figure 1. The gateway does unicast random user scheduling for K beams, executes the precoding algorithm, and subsequently carries out the transmission over the feeder link. Upon receiving the signal, the satellite amplifies it, shifts it to a downlink frequency, amplifies it once again, and directs it towards the earthbound users in the user link, utilizing high-gain antennas using full frequency reuse.

The offered capacity performance is obtained using spectral efficiency (ζ) based on DVB-S2X [10] (for specific values of modulation and coding schemes (ACM), DVB-S2X defines a table to map SINR to Spectral Efficiency) and is computed using, $\mathcal{T}_n = B \times \zeta(\gamma_n)$, where B is the bandwidth, γ_n is the Signal-to-Interference-plus-Noise Ratio of any user n and is,

$$\gamma_n = \frac{|h_n^H W s_n|^2}{\sum_{i \neq n} |h_n^H W s_i|^2 + P_n}, \tag{1}$$

where, $|h_n^H W s_n|^2$ is the received signal power at the n-th user, which includes the precoding matrix W and transmitted symbol s_n, $\sum_{i \neq n} |h_n^H W s_i|^2$ is the interference power from all other users (beams), P_n is the noise power at the n-th user. In this formulation, h_n^H represents the conjugate transpose (or Hermitian) of the channel vector from all beams to the n-th user, and s_n and s_i denote the transmitted symbol for the n-th and i-th user, respectively such that the vector of raw symbols that satisfies $\mathbb{E}[ss^H] = I$. We consider unicast user scheduling and hence, the user and the beam are used interchangeably and are denoted using n. Under the benchmark scenario and also for the training data generation, the gateway calculates the precoding matrix employing an MMSE precoder which requires channel knowledge using,

$$W_{RZF} = \eta H^H (HH^H + \alpha_r I)^{-1}, \tag{2}$$

where α_r is a predefined regularisation factor which is equal to the standard deviation of noise and η is the power allocation factor defined as, $\eta = \sqrt{\frac{P_{tot}}{\text{Trace}(WW^\dagger)}}$, with P_{tot} being the total available power.

III. Proposed precoder using Feed-Forward Neural Network

This paper proposes to replace the traditional MMSE precoder with Feedforward Neural Network (FFNN) that predicts the precoding matrix solely based on scheduled user locations. The presented model incorporates a FFNN with an architecture consisting of multiple layers. The initial input layer has 2 × K neurons that correspond to the K user locations within the multi-beam satellite system. This is succeeded by two fully interconnected layers, each with K² neurons. These layers utilize Rectified Linear Unit (ReLU) activation functions to inject non-linearity into the model. Subsequently, a fully connected output layer with 64 neurons (considering K = 16) is set up, correlating to the flattened real part of the MMSE precoding matrix (KxK matrix). A regression layer is employed to handle regression tasks for continuous-valued output, essentially the real values of the MMSE precoding matrix in this context.

The FFNN is trained via the Adam optimization algorithm, utilizing a mini-batch size of 32. To ensure the robustness of the training process, the training data is reshuffled after each epoch, and a validation set is used to monitor progress and prevent overfitting.

IV. Training data and Simulation Parameters

For numerical simulation, we consider 8 beams of a GEO satellite situated at 13 degree east. We then consider a total of 200 users where each beam has 25 users. The users are randomly distributed across the beams. The user and beam positions are as shown in Figure 3. Detailed simulation parameters used to compute the offered capacity for both training data generation and performance analysis are shown in Table I.

We consider a unicast case, and hence from all the 200 users available in the simulation, 8 users are scheduled for $1000,000$ iterations. Out of which, for $800,000$ iterations are used to generate training data and $150,000$ iterations are used for validation. In that case, the precoding matrix computation is computed using Equation (2). Consequently, we consider the remaining $50,000$ iterations to test our proposed FFNN precoder performance. Of course, no-precoding and MMSE precoding performance results are also computed for the testing iterations.

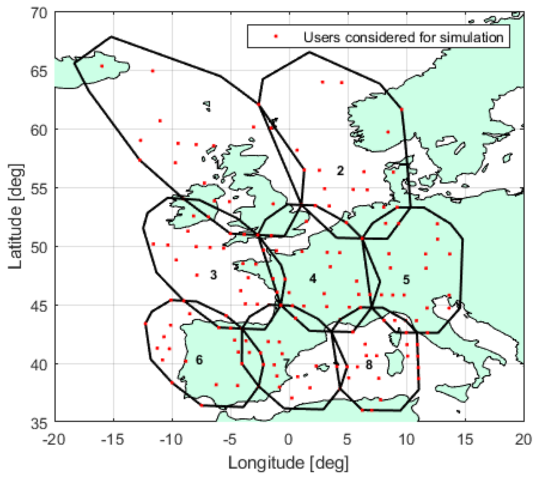

Fig. 3: Beams used for simulation

TABLE I: Simulation Parameters

Satellite longitude	13 degree East (GEO)
Total Number of Beams,	8
Uplink C/N	18.4 dB
Power per beam	13 W
Number of beams per TWTA	1
Number of carriers per TWTA	1
Number of carriers per beam	1
Carrier Frequency	19.96 GHz
Carrier Bandwidth	216 MHz
Useful Bandwidth	216 MHz
Roll off	0.05
Symbol Rate	205 Msps
OBO	3.8 dB
NPR	20 dB
Payload degradations	2 dB
Free space distance	37000 km
Wavelength	0.015182186
Free space path loss	209.7215455 dB
Rain Fade (99.5%)	2 dB
Other losses	2 dB

V. Numerical results

A. Reduced complexity

In general, Run-time analysis is a systematic evaluation of the time taken by algorithms to execute and complete their designated tasks. By measuring this runtime, especially across varied input sizes or conditions, we can derive insights into the algorithm's time complexity. Time complexity, a fundamental concept in computational theory, describes how the runtime of an algorithm changes as the size of the input grows. In our simulation, we measured the elapsed time for specific portions of the code that was used to compute the precoding matrix. This allowed for a granular understanding of which operations or segments of our code contributed most to the total computational time. Through this, not only can we identify potential bottlenecks and optimize code performance, but we can also draw conclusions about the inherent efficiency and scalability of our algorithms.

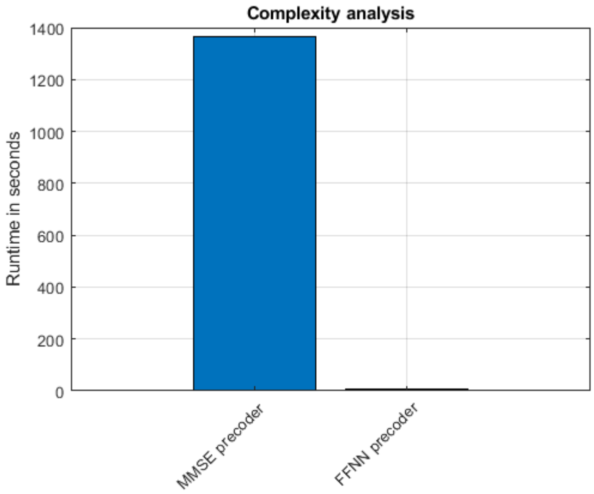

Fig. 4: Beams used for simulation

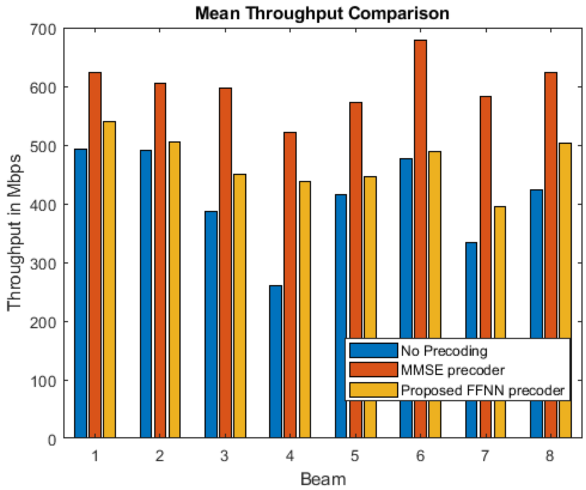

Fig. 5: Beams used for simulation

Accordingly, From Figure 4, for the total testing simulation iterations, the run time has drastically reduced using the proposed FFNN precoder in comparison to the MMSE precoder. This was an expected result as FFNN eliminates the high complexity ($\mathcal{O}(N^3)$) channel matrix inversion of the traditional MMSE precoder.

B. Mean offered Capacity

Mean offered capacity can be defined as an average offered capacity per beam over all the testing iterations of the simulation and can be expressed as,

$$\mathcal{T}_n^{avg} = \frac{\sum_{t=1}^{T} B \times \zeta(\gamma_n^t)}{T}, \tag{3}$$

where B is the bandwidth of transmission.

From the Figure 5, it is evident that the proposed FFNN precoder performance has been better than no-precoding case. However, as the FFNN precoder, which is indeed modeling the MMSE precoder, still fails to match the performance of the MMSE precoder. Nevertheless, considering the significant reduction in complexity, FFNN precoder is still a better replacement for the MMSE precoder, if complexity minimization is the objective function with considerable improvement in the capacity performance in comparison to the no-precoding case.

C. Throughput Deviation

Throughput Deviation (TD) offers a quantitative measure that elucidates the discrepancy in throughput values between two distinct methods: the benchmark MMSE precoder and the proposed FFNN precoder and can be expressed as,

$$TD = \frac{\mathcal{T}_{MMSE}^{\text{avg}} - \mathcal{T}_{NN}^{\text{avg}}}{\mathcal{T}_{MMSE}^{\text{avg}}} \times 100\% \tag{4}$$

The essence of throughput deviation lies in its ability to encapsulate the magnitude of the difference in throughput performances. A higher throughput deviation percentage indicates a larger divergence in throughput values between the MMSE

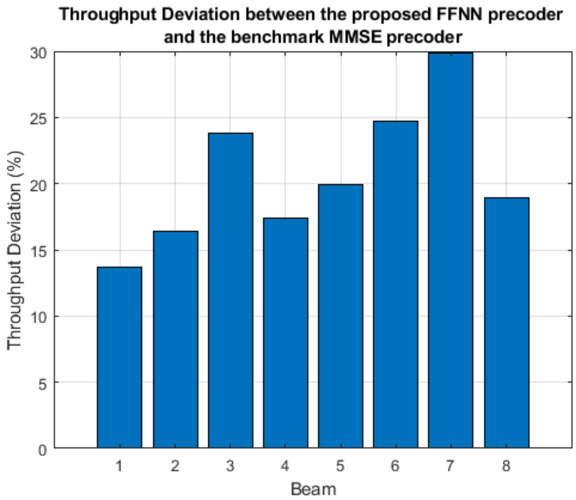

Fig. 6: Beams used for simulation

and FFNN methods. Conversely, a smaller percentage implies that the throughput values of the two methods closely align.

Throughput deviation is especially vital as it offers a normalized perspective, allowing for consistent comparisons across varying scenarios or conditions. Hence, Figure 6 further shows the scope of improvement that can be still achieved by considering better quality training data or better modeling of the FFNN model. Future research should be focused on minimizing this throughput deviation gap.

VI. Conclusion and Future Work

The evolution of precoding techniques in multi-beam GEO satellite systems has revolutionized broadband service delivery over vast territories. Despite their potential, the limitations imposed by conventional precoding techniques, like the MMSE precoders, have been a persistent bottleneck, primarily due to their computational intensity and deep-rooted reliance on channel matrix knowledge. This work heralded a departure from this norm by leveraging a trained feedforward neural network (FFNN) for precoding based solely on user locations. This shift not only sidesteps the need for continuous CSI but also drastically reduces computational overhead and latency. Our numerical results underscore the efficiency of the proposed FFNN precoder, illustrating pronounced reductions in computational complexity, with a small trade-off in capacity performance. Yet, the proposed scheme performs better than the no-precoding case, which is itself a good benchmark success, considering the least complexity involved in the proposed scheme.

While the proposed scheme marks a significant advancement, it also uncovers avenues for further research. Firstly, real-world CSI not only captures the intricacies of the physical channel but also reflects the influences of the entire Radio Frequency (RF) pathway. Furthermore, the methodology's reliability fails in the context of fading channels, which are inherently influenced by the scattering stochastic effect. This effect attenuates the correlation between a user's location and the CSI, urging caution when deriving inferences about user location within these channels. These observations underscore the need for future studies to refine the scheme, particularly by adapting it to non-Line-of-Sight (non-LoS) scenarios. Special emphasis should be directed towards MEO and LEO satellites, where such models become increasingly relevant.

VII. Acknowledgement

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