Spatial Modulation Link Adaptation: a Deep Learning Approach

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***Abstract*—Spatial Modulation (SM) offers a good balance between energy and spectral efficiency of interest for next generation networks. This, together with the need for only one Radio Frequency (RF) chain, makes SM a good proposal for Internet of Things (IoT) devices. In this work, we present a method based on Deep Learning to select the optimum Modulation and Coding Scheme (MCS) in an adaptive SM system. The deep neural network is trained with supervised learning to perform a mapping between the channel conditions and the MCS from a given set. We provide simulations results for a 4×4 SM link which uses several coding rates and three different constellations: QPSK, 8PSK and 16QAM. Results show how the adaptive system has a throughput close to its maximum value and how the outage probability can be reduced easily by applying a back-off margin to the neural network output.**

***Index Terms*—Deep Learning, Link adaptation, MIMO, Neural Network, Spatial Modulation.**

I. Introduction

According to Cisco's Global Mobile Data Traffic Forecast Update [1], a seven-fold increment in the mobile data traffic is expected in the period $2017-2022$. They also forecast that the number of Machine-to-Machine (M2M) connections will see a four-fold increment in the that period, reaching 3.9 billion of connections in 2022. Therefore, future mobile networks are compelled to increase their capacity and serve many more devices, all this in a more energy efficient manner.

In this context, Spatial Modulation (SM) is a multi-antenna technique proposed to enhance the performance of beyond 5G networks since it offers a good trade-off between energy and spectral efficiency [2]. This scheme is specially suited for providing connectivity to Internet of the Things (IoT) devices that require moderate data rates but that have complexity and battery-life constraints [3], since SM transmitters can operate with a unique Radio Frequency (RF) chain.

Modern communication systems incorporate some sort of link adaptation mechanisms to adjust the transmission parameters in order to enhance the performance of the link (throughput and/or reliability) under the time variant channel conditions. The idea behind the link adaptation is the adjustment of the coding rate and the constellation order depending of the channel in order to enhance the spectral efficiency or some other performance metric. For the specific case of SM, works like [4] started to develop the adaptive SM concept, with the constellation order of the symbols sent by each antenna individually tuned. Later works such as [5] consider the use of the same constellation by all the antennas, since this reduces the complexity and avoids the decoding error propagation, problem raised also in [6]. Another recent publication [7] explores the application of Deep Learning (DL) to select a physical layer configuration in adaptive SM systems.

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This paper presents a link adaptation mechanism for adaptive SM systems following a DL approach. Contrary to previous publications, we add a channel encoder whose coding rate is adapted dynamically in conjunction with the constellation order, similarly to more conventional schemes. However, differently from works like [4] or [7], we enforce the use of the same constellation by all the antennas, as proposed also in [5]. The mechanism of selection of the Modulation and Coding Scheme (MCS) in adaptive SM links that we propose is based on a deep neural network, which is trained by means of supervised learning. This works extends our previous results of [8], where we present a coding rate selection mechanism in a simpler setup, with fewer antennas and without adapting the constellation order.

The rest of the article is structured as follows. Firstly, Section II presents the system model and explains the basic concepts behind Spatial Modulation. Then, Section III explains the proposed method for doing the MCS selection. The parameters of the systems employed in the simulations are described in Section IV before the main simulation results are provided in Section V. Lastly, the main conclusions are drawn.

II. System Model

In this work we consider a Spatial Modulation (SM) system which has a single Radio Frequency (RF) chain, so that only one antenna is active during each symbol period. In SM the information is conveyed in two different ways; one, by selecting a modulation symbol s from a constellation $\mathcal{S}$ and, two, by selecting which antenna is employed to transmit that symbol. Therefore, $\log_2(N_t) + \log_2(M)$ bits can be conveyed in each channel use if the transmitter has N_t antennas and the employed constellation has order M.

The general system model of a SM link with N_t transmit antennas and N_r receive antennas is

$$\mathbf{y} = \sqrt{\gamma}\mathbf{H}\mathbf{x} + \mathbf{w}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ is the received signal, γ the average Signal to Noise Ratio (SNR), $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ the channel matrix, $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ the transmitted signal and $\mathbf{w} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{N_r})$ the Additive White Gaussian (AWGN) noise vector. Equation (1) can be further simplified by taking into account that at each time instant $\mathbf{x}$ has only one non-zero component, the l-th component for instance, a complex symbol s taken from the constellation $\mathcal{S}$. Therefore, (1) can be also expressed as

$$\mathbf{y} = \sqrt{\gamma}\mathbf{h}_l s + \mathbf{w} \tag{2}$$

where $\mathbf{h}_l$ denotes the l-th column of $\mathbf{H}$, $l \in \{1, 2, \ldots, N_t\}$. We assume a unit power constraint, i.e., $\mathbb{E}\left[\mathbf{x}^H\mathbf{x}\right] = \mathbb{E}\left[|s|^2\right] = 1$.

Fig. 1 shows the block diagram of an adaptive SM system that, similarly to other communication systems, has two degrees of freedom in the link adaptation. On the one hand, the transmitter can modify the coding rate r of the channel encoder for adapting the level of protection of the information bits. On the other hand, the transmitter can also select the constellation order M of the transmitted symbols. We refer to the combinations of coding rate r and constellation order M which are available for transmission as Modulation and Coding Schemes (MCS).

The SM receiver, depicted also in Fig. 1, is assumed to have perfect Channel State Information (CSI). The estimated SNR γ and channel matrix $\mathbf{H}$ are employed by the Soft Detection block, for computing the log likelihood ratios (LLRs) of each bit required by the channel decoder [9], and by the Adaptation Unit. The CSI is not reported back to the transmitter to reduce the overhead in the return link; this information is rather used by the Adaptation Unit to select the MCS and send the corresponding index to the transmitter to update the parameters of the next frame. This selection is based on a feedforward neural network, which will be detailed in the following section.

In this paper, the link adaptation problem is formulated as the maximization of the spectral efficiency subject to a maximum Bit Error Rate (BER) target value p_0. The set of the K available MCS is represented with $\mathcal{M} = \{m_k = (r_k, M_k),\ k = 1, 2, \ldots, K\}$, with r_k and M_k the coding rate and constellation order of the k-th MCS, respectively. With these considerations, the selection of the MCS can be expressed as the following optimization problem:

$$\arg \max_{m_k=(r_k,M_k)} \quad r_k \log_2(N_t M_k) \tag{3a}$$

$$\text{subject to} \quad m_k \in \mathcal{M}, \tag{3b}$$

$$\text{BER}(\gamma;\ m_k, \mathbf{H}) \leq p_0. \tag{3c}$$

The BER is a function of the SNR γ, the MCS m_k and the channel $\mathbf{H}$. In [8], we have presented a method based on Deep Learning (DL) to perform the coding rate adaptation in a simpler setup, with a fixed QPSK constellation in a 2×2 configuration. Therein, it was shown that the required SNR for guaranteeing a given BER for a specific MCS can change substantially from one channel matrix to another, making the problem (3) more challenging than in conventional adaptive links. In this work, we follow a philosophy very similar to [8], showing how to extend those results to a more general scenario, with more antennas and where, apart from the coding rate, the constellation order can be also adapted.

III. Proposed method

Fig. 2 shows a diagram with the steps required for obtaining a neural network which can be useful to perform the MCS selection in an adaptive SM link. These stages, more elaborated in our previous publication [8], are summarized hereafter.

In the first step, which is the most computationally intensive, system level simulations are executed for obtaining the BER of each MCS for a large number of different channel matrices and values of SNR. The conditions of the simulations, including the channel statistics and receiver algorithms, should match those of the final adaptive system. The output of this step is a collection of performance curves of the MCS for a large number of channel matrices. Mathematically, we denote this as $\text{BER} = f(\gamma;\ \mathbf{H}, \text{MCS})$.

The second step takes the simulation data obtained from the previous phase in order to build a ML dataset $\mathbb{X}$ which can be used later to train and test the neural networks. For each simulated channel state, described by the tuple $(\gamma, \mathbf{H})$, we identify the MCS m_k with the highest spectral efficiency s_k which satisfies the BER constraint p_0, according to the optimization problem formulated in equation (3). With this information, the dataset is built as a collection of L input-output pairs: $\mathbb{X} = \{(\mathsf{x}_i, \mathrm{y}_i), i = 1, \ldots, L\}$. The desired output of the neural network y_i is simply the spectral efficiency s_k of the target MCS (or 0 if no MCS satisfies the BER constraint), with the inputs x_i chosen as some features which are extracted from the SNR γ and the channel matrix $\mathbf{H}$ by means of a transformation $\mathsf{x} = g(\gamma, \mathbf{H})$.

The selection of the neural network input features x is of paramount importance to obtain a good performance. We propose to use the same features as we used in our work [10] to compute the mutual information of a 4×4 SM link. These features consist on the squared norm of the columns of the channel matrix $(\gamma\|\mathbf{h}_l\|^2)$ sorted in ascending order and the Hermitian and Kasner angles [11], Θ_H and φ, between the six possible pair of columns of the 4×4 channel matrix $\mathbf{H}$. This makes a neural network input x vector of size 16.

Once the ML dataset $\mathbb{X}$ is built, an architecture for the neural network must be selected and then, the neural network can be trained with some learning algorithm for obtaining the values of its internal parameters $\boldsymbol{\theta}$. The ultimate goal is that the neural network learn to make good predictions $\hat{\mathrm{y}}$ (the target spectral efficiency) from the input features x (the channel conditions), i.e., $\hat{\mathrm{y}} = h(\mathsf{x}; \boldsymbol{\theta})$. Regarding the design of the architecture of the neural network, this requires the selection

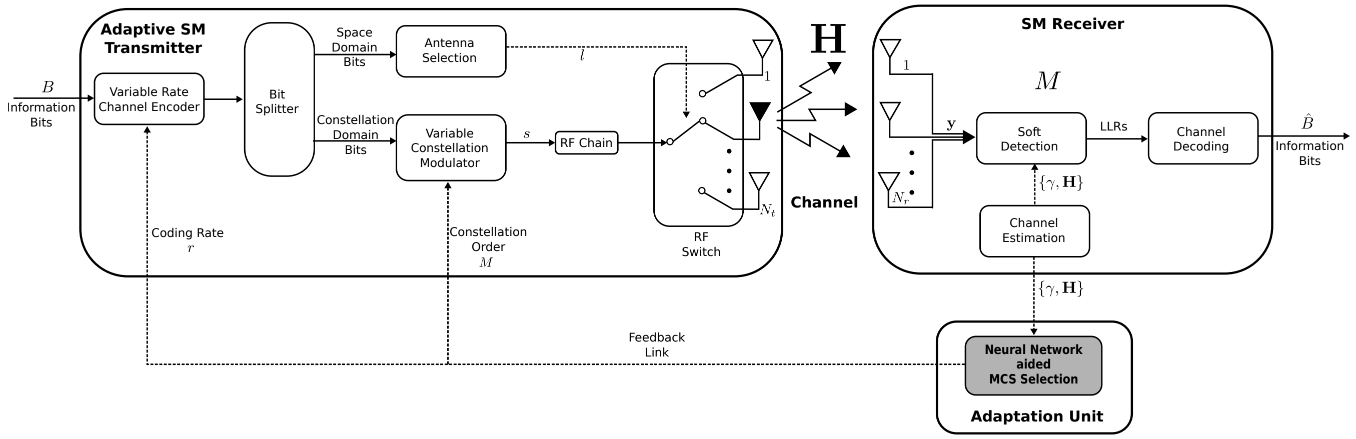


Fig. 1: Block diagram of an adaptive SM system which adapts the coding rate and the constellation order by using a neural network.

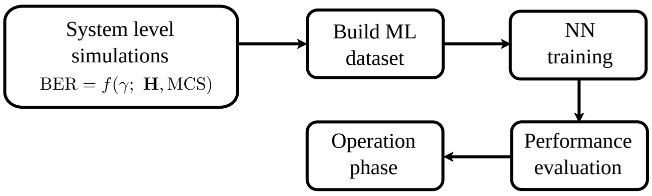


Fig. 2: Diagram showing the steps for obtaining a neural network to perform MCS selection in an adaptive SM system.

of the number of hidden layers (*depth*), the number of neurons per layer (*width*), and the specification of the output units [12]. The neural network computational cost resides on its training phase, which in any case is significantly less demanding than the previous system level simulations, which can take tens of hours.

Lastly, the two final steps shown in Fig. 2 consist on the evaluation of the performance of the neural network with the testing dataset; once a satisfactory performance is achieved, the trained neural network can be employed in the operation phase by the receiver of an adaptive SM system to perform the link adaptation for selecting the optimum MCS.

IV. System simulation setup

The proposed DL-based scheme for SM link adaptation was evaluated in an adaptive 4×4 SM system. The set of MCS $\mathcal{M}$ includes three different constellations (QPSK, 8PSK and 16QAM) as depicted in Table II. Each MCS index k is associated to a constellation, coding rate, and the corresponding spectral efficiency.

For simulation purposes, we have used the channel codes of the DVB-S2 standard [13], which consist on the concatenation of a BCH (Bose-Chaudhuri-Hochquenghem) and a LDPC (Low Density Parity Check) code[1]. The length of the coded frames was fixed to $64,000$ bits like in DVB-S2 standard, yielding then a variable number of information bits per codeword. The LDPC maximum number of iterations was set to 50. The mapping of the coded bits to SM symbols was designed in such a way that two bits are used to select the antenna, whereas the remaining two, three or four bits, depending on the MCS, select a symbol from a QPSK, 8PSK or 16QAM constellation following a Gray bits to symbols mapping.

[1]The most appropriate codes will depend on the specific application setting; the DVB-S2 channel codes are used only for illustration purposes.

The system level simulations to obtain the performance of the codes were run for $N = 1,440$ different 4×4 channel matrices $\mathbf{H}$, generated by following a unit-variance Rayleigh distribution, i.e., $h_{ij} \sim \mathcal{CN}(0, 1)$. For each channel matrix the average BER after the BCH decoding was calculated for 31 values of SNR equispaced between -2.5 and 12.5 dB. The average BER is calculated after simulating the transmission of 25 frames. The target BER for MCS selection was $p_0 = 10^{-4}$. The obtained dataset is divided into three different parts: training (70%), validation (15%) and testing (15%). In Table I, we summarize the main parameters of the system employed in the simulations.

Parameter	Value
System configuration	4×4 SM
Constellations	QPSK, 8PSK, 16QAM
Channel coding	DVB-S2 codes (BCH + LDPC)
Number of MCS	7
Target BER	$p_0 = 10^{-4}$
Channel matrices	1440 Rayleigh distributed
SNR range	-2.5 to 12.5 dB (0.5 dB steps)

TABLE I: Simulated systems parameters.

The MCS selection can be casted as a classification problem, wherein a discrete class $k \in \{0, 1, 2, \ldots, K\}$ is assigned to an input vector $\mathbf{x}$. Traditionally, neural networks for multi-class classification have as many outputs as classes, with the output layers using softmax units [12] to evaluate the probability of each class. Here we would rather use a regression neural network, which outputs an estimate of the achievable spectral

k	1	2	3	4	5	6	7
MCS	QPSK 1/4	QPSK 2/5	QPSK 3/5	8PSK 3/4	16QAM 3/4	16QAM 5/6	16QAM 9/10
Spectral efficiency $\mathbf{s_k}$ (bit/s/Hz)	1	1.6	2.4	3.75	4.5	5	5.4

TABLE II: List of available Modulation and Coding Schemes (MCS).

efficiency y. With this, a simple quantization yields the most efficient MCS, inserting a convenient back-off on the scalar output of the neural network if deemed necessary to guarantee the reliability of the communication. Therefore, the selection of the optimum MCS m^* with spectral efficiency s^* is done in the following way

$$s^* = Q\left(\hat{\mathrm{y}} - \Delta\right) = \arg\min_{s_k} \left|\hat{\mathrm{y}} - \Delta - s_k\right|, \tag{4}$$

where Δ represents a positive back-off margin to be subtracted from the neural network output $\hat{\mathrm{y}}$ in order to reduce the outage probability.

In this work, the hyperbolic tangent is used as the activation function for the hidden layer neurons; the biases and weights are initialized with random values using the Nguyen-Widrow algorithm, and the network training is performed with the Levenberg-Marquardt (LM) backpropagation algorithm [14] to minimize the Mean Squared Error (MSE). Regarding the neural network architecture, the results of the following section were obtained with four hidden layer with 10 neurons per layer. Several architectures were previously tested, with a number of hidden layers ranging from 1 to 6, and a number of neurons between 10 and 40. Each neural network was trained 10 different times with different sets of initial parameters during $1,000$ epochs, with the training halted earlier if the network performance on the validation dataset stopped improving or remained the same for 6 epochs in a row.

V. Simulation results

Firstly, Fig. 3 depicts the relative frequency of each MCS as a function of the SNR obtained for the whole set of data, after using Equation (4) to determine the target MCS. It can be seen that the operation range of each MCS lies between 4 and 6 dB, and that for a given SNR, up to four different MCS can be selected. As expected, when the SNR increases, the target MCS are those with a higher spectral efficiency.

The classification performance of the MCS selection with the proposed neural network without any margin, $\Delta = 0$ in Equation (4), is shown in Table III. The average accuracy on the testing dataset is $87.9\,\%$, ranging the value of the accuracy per target MCS from $74.4\,\%$ (in the case of the QPSK 1/4) to $97.8\,\%$ (in the case of the 16QAM 9/10). Another metric of interest is the rate of underselection, defined as the probability of selecting an MCS with lower spectral efficiency than the target MCS. The value of this probability in the testing dataset is $5.2\,\%$. In terms of the probability of outage, defined as the probability of selecting an MCS with higher efficiency than the target MCS, thus not meeting the target BER, we have that the average outage probability in the testing dataset is $6.9\,\%$.

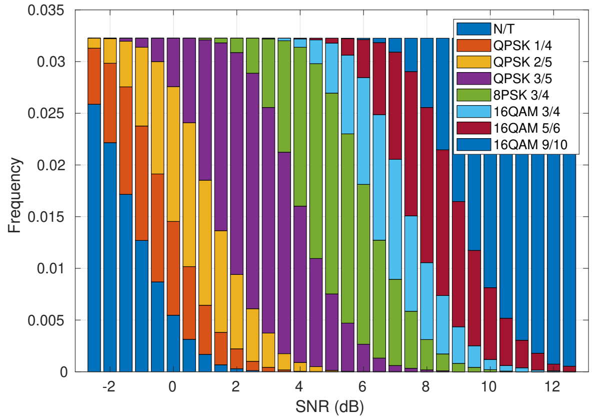


Fig. 3: Relative frequency of each MCS as a function of the the SNR, N/T means No Transmission, i.e., that even the most robust MCS cannot satisfy the BER constraint.

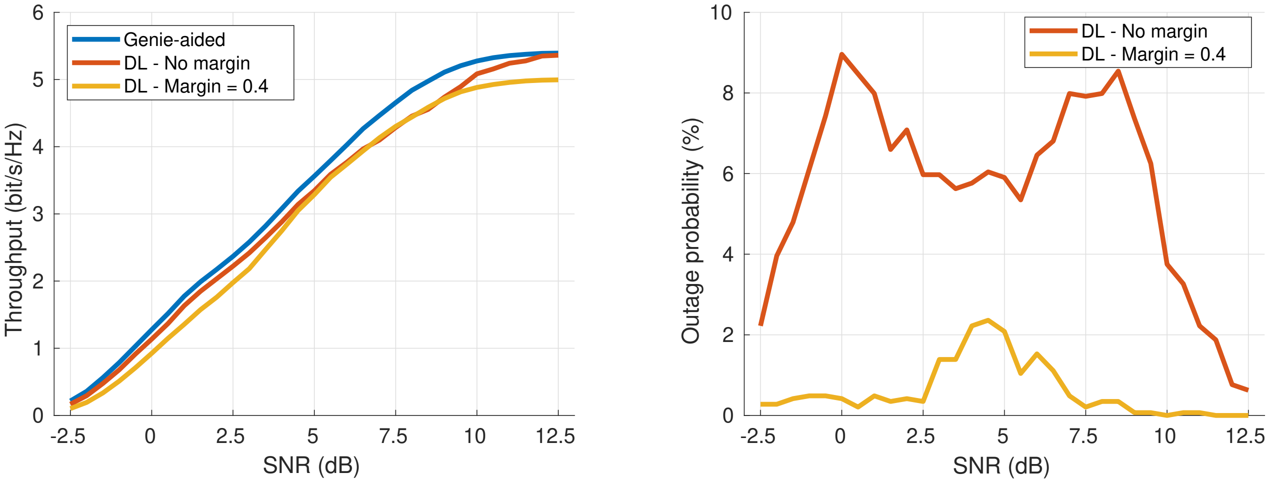
Finally, Fig. 4 provides some results of the performance of an adaptive SM system in terms of the average spectral efficiency and the average outage probability as a function of the SNR. The blue line of Fig. 4a shows the maximum achievable throughput, which corresponds to the perfect genie-aided MCS selection. The orange and yellow lines represent the performance obtained with the proposed DL based MCS selection, for two different cases; one using directly the output of the neural network to select the MCS (orange), and another which applies a margin $\Delta = 0.4$ to the neural network output. The effect of this margin is more noticeable in Fig. 4b, which shows how the application of this margin reduces the outage probability down to approximately $1\,\%$. With regard to the spectral efficiency, Fig. 4a reveals how this link adaptation method based on DL enables the system to achieve a variable throughput in the range of 0 to 5.4 bit/s/Hz depending on how good the channel conditions are.

VI. Conclusions

Link adaptation techniques allow communication systems to make a better use of the channel capacity by means of the adaptation of the transmission bit rate. This adaptation is achieved typically at the physical layer by adjusting the Modulation and Coding Scheme (MCS), i.e., the constellation order and the coding rate of the channel encoder. In this work, a deep neural network trained with supervised learning was proposed to select the MCS in an adaptive Spatial Modulation link. Simulation results show that the adaptation with a neural network allow to achieve a throughput close to the maximum despite some miss-classifications. Moreover,

Minimum accuracy (%)	Average accuracy (%)	Maximum accuracy (%)	Average underselection probability (%)	Average outage probability (%)
74.4	87.9	97.8	5.2	6.9

TABLE III: Performance of the neural network when selecting the MCS based on its zero margin output $\hat{y}$ ($\Delta = 0$) evaluated only in the testing dataset.



(a) Average throughput

(b) Average outage probability

Fig. 4: Average throughput and average outage probability with respect to SNR in a 4×4 adaptive SM system with Rayleigh distributed channel matrices, obtained for the whole dataset.

the proposed method allows to increase the reliability of the communications by means of easily applicable margins.

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