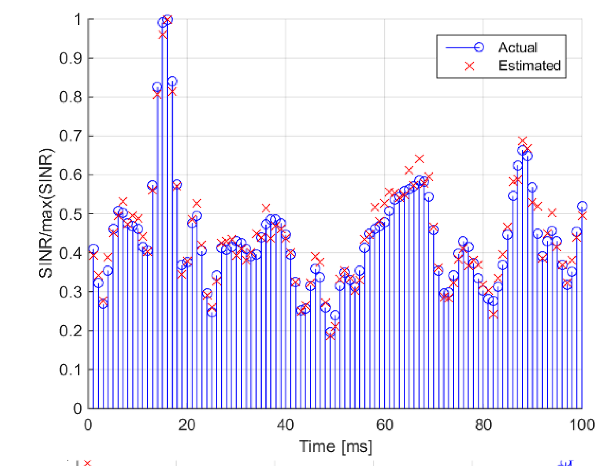
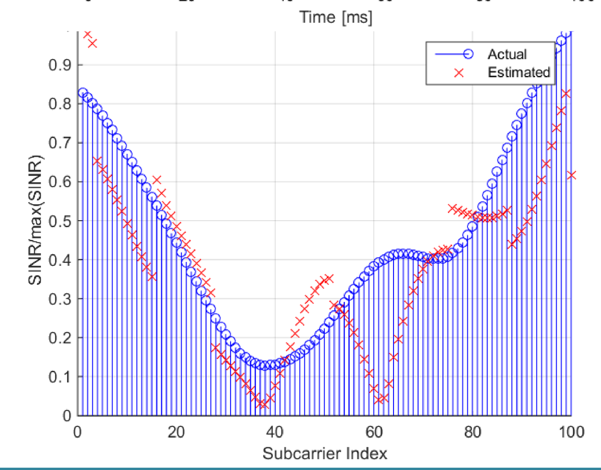
A Supervised Learning Approach to Fast Link Adaptation

Vidit Saxena, Ericsson/KTH

Abstract: LTE networks adapt the transmission parameters for each link according to the instantaneous state of its radio channel. One aspect of this so-called Fast Link Adaptation (Fast LA) is to predict the optimal modulation and coding scheme (MCS) on a per-subframe basis, subject to a desired long-term Packet Error Rate (PER). In this report, we design and study neural networks for predicting the MCS for Fast LA in the LTE uplink. Our simulation results show that the neural network is able to learn the uplink receiver characteristics for a simple single-link scenario, and predict the optimal MCS under the specified PER constraints.

Background & Motivation





In practical radio systems, the radio channel often varies with time on account of the movement of the transmitter, the receiver, or the physical objects that interact with the radio signal. This time-dependent variation is known as "fading", and leads to a time-varying channel response that is illustrated on the images to the left.

The appropriate MCS to be used during data transmission over a time- and frequency-varying channel depends on the instantaneous channel state. The optimal MCS is determined according to one or more constraints such as the expected packet error rate (PER), and signals this MCS to the UE to be used for uplink data transmission.

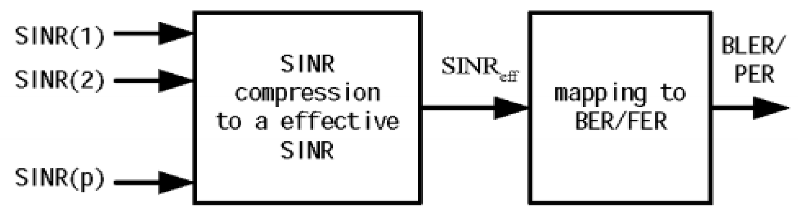
In LTE systems, Fast LA refers to the process of selecting optimal transmission parameters based on the some radio link statistics on a per-subframe basis. In this project, we design and study a neural network based approach for Fast LA in the LTE uplink.

Research Goal & Questions

The most common approach to Fast LA in LTE makes use of the estimated per-subcarrier SINRs to predict the probability of packet error for a given MCS. In general, there are several ways to compress these SINRs to a single metric by using a function such as the Exponential Effective SINR Mapping (EESM) as illustrated in the figure below. However by design, the EESM approach leads to loss in information of the channel state.

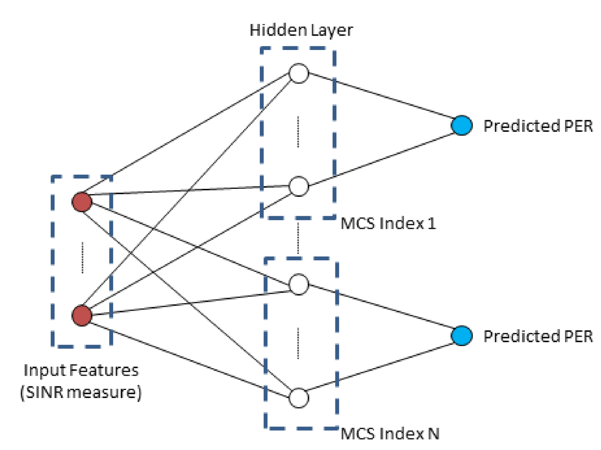
In this project, we ask the question whether neural networks can be used to model the system behavior and select the optimal MCS on a per-subframe basis. The choice of MCS must satisfy some optimality criteria, and must be robust to the channel states observed in practice. Specifically, we wish to find out if neural networks

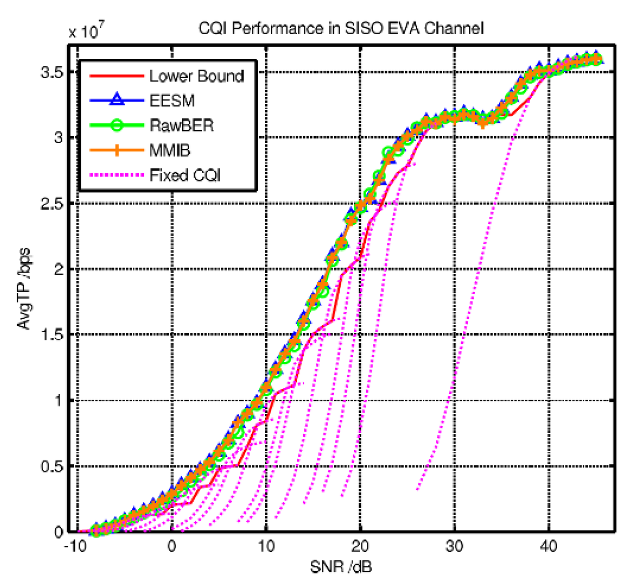
- can be used to model the receiver characteristics sufficiently well for Fast LA
- provide throughput gain compared to a fixed MCS (i.e., no AMC)
- are at least as good as EESM-based fast LA in all scenarios



Effective SINR calculation for EESM-based link adaptation

Methods & Prior Work





In this section, we introduce a neural network design for Fast LA. The goal of the neural network is that given some per-subcarrier SINR measure, the network must provide a probability of successful decoding of a particular MCS. To obtain such probabilities, we construct an array of neural networks spanning all available MCSs. This resulting network diagram is illustrated in the figure to the left.

Our design leads to a two-class classification network for each MCS, where each class denotes successful and unsuccessful decoding respectively. The output activation function is therefore a logistic sigmoid, from the maximum likelihood solution of a two-class classification problem. We choose a logistic sigmoid activation function for the hidden layer as well, to make it functionally similar to the expression for effective SINR in the EESM approach. Again, since we are solving a two-class classification problem, we use cross entropy as a measure of the training performance.

The input feature vector to each neural network contains information derived from the per-subcarrier SINR values before the equalization of the uplink signal. The corresponding output is a single cross-entropy value for each MCS, that we use as the probability of successful decoding of the associated information bits. We then use these probability values to pick the largest MCS such that the probability of successful decoding is less than the PER constraint.

Preliminary Results & Roadmap

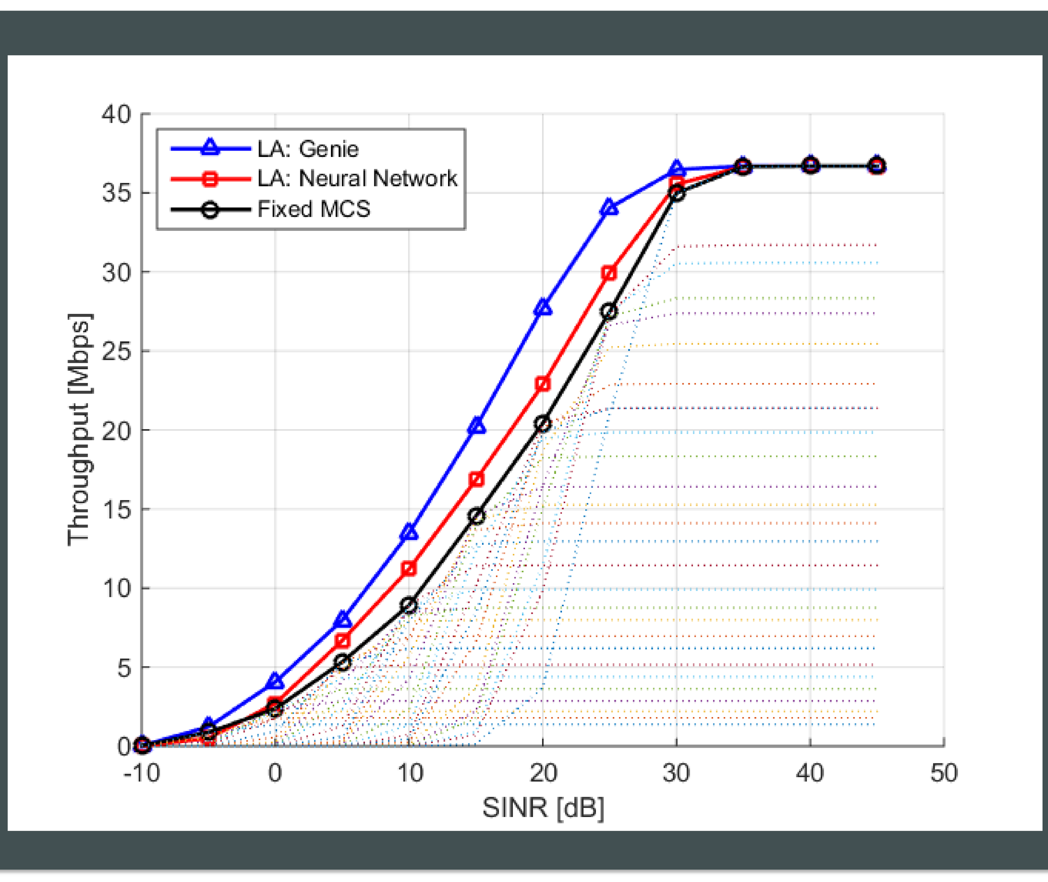
Here we present preliminary evaluation results for the Fast LA performance of the neural network described in the previous sections. The simulation assumptions are listed in the table below, and the results are discussed in the next section. The dataset comprises per-subcarrier SINR values corresponding to 600 subcarriers over 20000 subframes, for each of the 12 long-term average SINR values and each of the available 29 MCS indices. The input for Fast LA (a "sample") comprises per-subcarrier SINR values for a given subframe and long-term average SINR, implying that we have 20000x12 samples for each MCS. We use half of the samples for training the neural network corresponding to each MCS, and the rest for performance evaluation.

Simulation Parameters

Parameter	Value
Carrier Frequency	2 GHz
System Bandwidth	10 MHz
Channel Model	EVA
Doppler Spread	5 Hz, 100 Hz
Transmission Bandwidth	600 subcarriers
MCS Indices	0,1,...,28 [9]
Channel Coding	Turbo code
Channel Estimation	Perfect
Antenna Scheme	SISO 1x1
Target PER	10%
Long-term Average SINR	-10,-5,...,45 dB
Number of Hidden Units	100
Number of Subframes for Training	10000
Number of Subframes for Evaluation	10000

Encouraged by the promising results obtained in this project, we plan to evolve the current solution to encompass more complex wireless communication scenarios, such as those involving multiple antennas, ("MIMO"), a control signaling delay after the MCS prediction, etc. An issue with neural networks is the amount of time and data required to train the network. Therefore, we plan to investigate techniques for efficient neural network training in practical scenarios.

Results

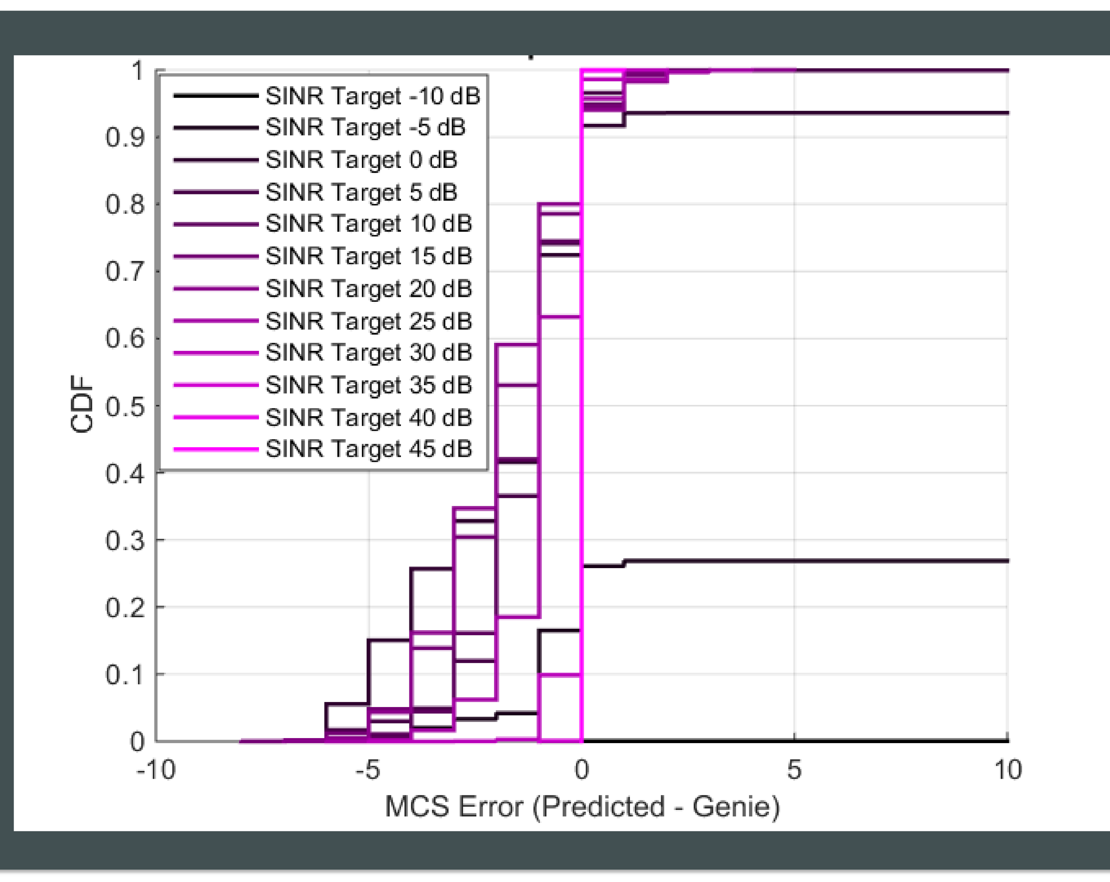


The figure to the left illustrates performance of Fast LA based on algebraic mean of per-subcarrier SINRs over the entire bandwidth. It is assumed that the predicted MCS is immediately available for uplink transmission, implying that there is no control signaling delay. We observe that the neural network based Fast LA improves the throughput up to approximately 15% compared to the maximum non-LA throughput, i.e., achieved by keeping a fixed MCS value over the entire simulation run.

The figure to the right illustrates the prediction error of Fast LA based on algebraic mean of per-subcarrier SINRs over the entire bandwidth, 100 Hz Doppler spread. We observe that barring one curve, the prediction error is always less than or equal to zero for 90% of the samples. From this we observe that the neural network is able to reliably predict the error rate, such that the target PER may be maintained close to or less than a desired value (10% in this case).

From the simulation results, our key observations are:

- Neural networks may be used to model the receiver characteristics sufficiently well for Fast LA.
- For the studied scenarios, the algebraic mean of estimated per-subcarrier SINRs is sufficient to characterize PER performance for a given MCS.
- Neural network based Fast LA can provide up to 15% throughput gains compared to a fixed MCS index.



WALLENBERG AUTONOMOUS SYSTEMS AND SOFTWARE PROGRAM