INITIAL DESIGN OF A COGNITIVE ENGINE FOR MIMO SYSTEMS[1]

Haris I. Volos, Chris. I. Phelps, and R. Michael Buehrer
Mobile and Portable Radio Research Group (MPRG), Wireless@Virginia Tech
Bradley Department of Electrical and Computer Engineering, Virginia Tech
432 Durham Hall (0350), Blacksburg, VA 24061, USA
{hvolos,chphelp2,buehrer}@vt.edu

Abstract

Multiple-Input-Multiple-Output (MIMO) techniques can provide significant performance enhancements in wireless communication systems. However, MIMO techniques (which include transmit diversity, beamforming, and spatial multiplexing as basic classes) exploit the channel in different ways. Thus, given a specific channel realization, these techniques, combined with modulation and coding, make the selection of an "optimal" solution a difficult task. To address this problem, we, propose the use of a cognitive engine to learn the relationship between the channel observables and the available MIMO/modulation/coding techniques. The overall approach is presented along with results of a partial implementation based on the genetic algorithm. We also provide a discussion of future work.

1. INTRODUCTION

Use of multiple antennas at the transmitter and the receiver has been a focus of both academia and industry, over at the last decade because use of multiple antennas with a suitable Multiple-Input-Multiple-Output (MIMO) technique can provide significant performance enhancements. The performance of individual techniques, such as transmit diversity, beamforming, and spatial multiplexing is already well studied [1], [2], [3]. The performance enhancement of a wireless system using a specific multiple antenna technique depends heavily on the channel conditions and the information available at the transmitter and receiver. Thus, choosing the appropriate MIMO approach to optimize performance is a non-trivial task. Here performance usually refers to maximizing spectral efficiency at specified energy efficiency or maximizing energy efficiency at a specified spectral efficiency.

Most of the MIMO techniques' performance is determined from the received energy per bit (E_b/N_o) and properties of the channel matrix H. When analyzing the performance of a MIMO technique most studies tend to make assumptions for the channel conditions in order to make the analysis manageable. Therefore, one who wants to create rules that cover all possible scenarios has to combine the analysis for all the techniques under different conditions which is not a trivial task. On the other hand, as radios are implemented in software, and the availability of computing resources increases year by year, the idea of designing a radio that is simply given a set of MIMO techniques must determine on its own when to use what is very promising. Motivated by this idea, we lay the foundation for such a radio design. Specifically, we focus on the part of the radio referred to as the Cognitive Engine (CE), which will facilitate the desired abilities.

Selecting the proper MIMO technique is only part of the problem. In addition, the modulation and forward error coding technique used will have a significant impact on the performance and efficiency of the system. The selection of the best MIMO, modulation, and coding technique requires searching a significantly large parameter space. Thus, another part of our goal is the design of a CE which is able to minimize the search time by combining fundamental knowledge of the techniques' performance and its own experiences. In this paper we mainly investigate the search aspect of the problem.

This paper proceeds with a short introduction to the key MIMO techniques: transmit diversity, beamforming and spatial multiplexing. Second, we introduce the cognitive engine with a high level description of it. Third, we present the implementation of the search part of the CE using the Genetic Algorithm (GA). Fourth, results are presented and discussed. Finally, we discuss plans for continuing this work and provide concluding remarks.

1.1. Transmit Diversity

Transmit Diversity techniques improve energy efficiency by transmitting multiple copies of the data over different antennas to exploit diversity in the channel. Space-Time Block Codes are one implementation of transmit diversity schemes which are able to exploit both spatial and temporal diversity and only require channel knowledge (or estimation) at the receiver.

1.2. Beamforming

Beamforming is a method by which a transmitter or receiver spatially filters by weighting a single data stream in accordance with the channel parameters. One use of

[1] This material is based upon work supported by the National Science Foundation under Grant No. 0520418.

beamforming, in the context of MIMO systems, is to improve the energy efficiency by exploiting the strongest mode of the channel. Beamforming can be accomplished at both the transmitter and the receiver, but channel knowledge must be available at the transmitter to perform beamforming at the transmitter.

1.3. Spatial Multiplexing

Spatial Multiplexing theoretically provides a spectral efficiency which increases linearly with the the minimum of the number of transmit or receive antennas used. This increase in spectral efficiency is achieved when the scattering environment is rich enough that transmitted streams are sufficiently decorrelated [3]. Aside from assuring that sub-streams will be sufficiently de-correlated, common implementations of spatial multiplexing, such as V-BLAST, only require that channel knowledge is available at the receiver. Channel knowledge can be exploited at the transmitter however to improve the performance of spatial multiplexing schemes.

2. THE PROPOSED COGNITIVE ENGINE

The objective of this work is to design a CE that will take the current knowledge of the most fundamental MIMO techniques' performance, combine it with observations of their performance in variance scenarios, to generate a set of rules that will provide the MIMO radio with optimal or near optimal performance in a given operating environment (channel).

The proposed CE environment assumes a pair of MIMO radios that either have an internal CE or a CE exists that can interact with them. The definitions and descriptions about the CE's operation will deliberately allow the scenario where we have a network of nodes in future work.

We assume a MIMO radio to be operating based on a set of rules and a CE that will monitor the radio's performance and periodically modify those rules. These statements are illustrated in Figure 1.

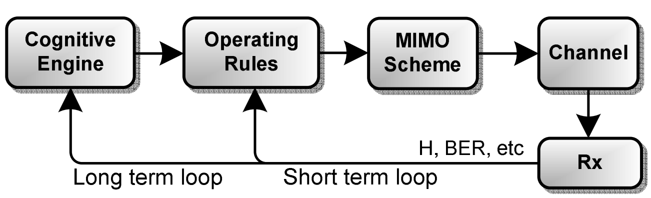

Figure 1 Short and Long Term Operation

2.1. The MIMO Radios

The proposed CE scheme assumes that each MIMO radio has three main blocks (Figure 2 (a)):

First, the "Operating Rules" block is a set of rules defining the radio's short term operation. These rules are updated periodically by the CE.

Second, the "Short Term Local Observations Memory" block keeps a record of the actual performance under various conditions as observed by each individual radio. These observations are periodically sent to the CE to be added to its "Observations Database" and subsequently to update the rules.

Finally, the "Cognitive Engine" block monitors the radio(s) performance and optimizes the performance, as is defined by its objective(s), by updating the operating rules. It may reside physically on the radio and/or in other radio(s)/devices of the same network.

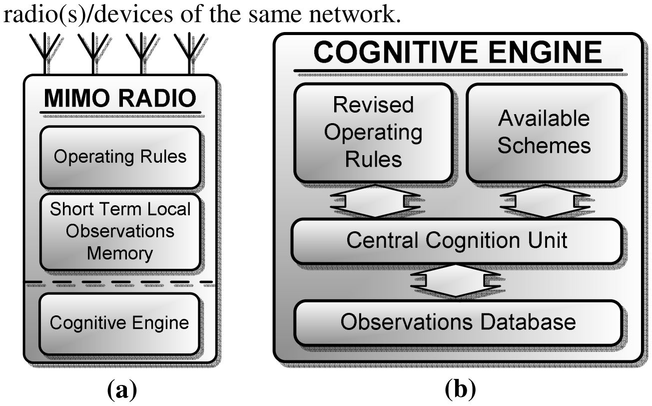

Figure 2 MIMO Radio and CE Diagrams

2.2. The Cognitive Engine

The CE has four main blocks (Figure 2 (b)):

First, the "Revised Operating Rules" block is the set of rules that is being updated by the Central Cognition Unit.

Second, the "Available Schemes" block defines the set of actions of the CE, such as which techniques are available to use, ordered by how they serve the radio's objectives.

Third, the "Central Cognition Unit (CCU)" block uses the information in the observations database and the available schemes to revise the operating rules. When the revision is over, the updated operating rules are forwarded to the radio(s).

Finally, the "Observation Database" block stores the observed performance of the radio(s) under various conditions. This is used by the CCU for updating its rules.

The cognition cycle (Figure 3) begins with the radio recording observations about the performance of a used MIMO/modulation/coding scheme and the channel conditions that preceded it. Once a specified number of such observations are recorded, the observation are passed to the CE. Then, the observations are used to update the observations database by creating new entries and/or modifying existing ones. Furthermore, the CCU runs its reasoning process with consideration of the rules that are affected by the new data. The CCU will do any number of the following operations: Update a rule, delete a rule, and create a new rule. Then any completed independent rule modifications (which don't affect any other rules) are forwarded to the radio(s).

The processed CE scheme does not suggest specific implementation methods; rather, these are to be determined in future research. Topics for research are suitable data structures for the rule specifications, the memory storage, and learning techniques. The CCU can use any Artificial Intelligence (AI) technique (e.g., neural networks) and any search technique (e.g., genetic algorithms). Furthermore, this overall approach is influenced by the description of a Case Based Reasoning (CBR) System as described in [4]. In a CBR system a case consists of the problem (what is the best scheme for these conditions) and its solution (the scheme). The CBR solves a new problem by retrieving cases for similar problems, reusing or adapting previous solutions, testing and saving the solution once it's confirmed. A CBR point of view is an intuitive way of dividing the cognition process into independent parts.

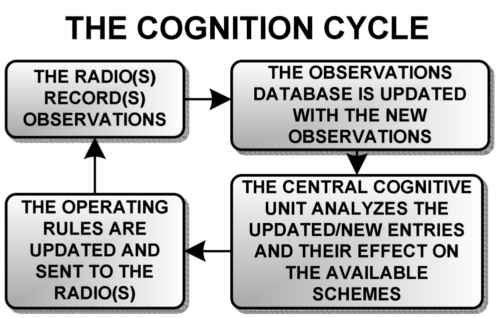

Figure 3 The Cognition Cycle

3. INITIAL IMPLEMENTATION

In our initial implementation we focus on the CCU. The CCU is given partial channel information, a number of techniques, and is called to find the best possible scheme given the channel conditions.

The complete system is much more complicated in that it must learn in real situations. This imposes several challenges because the system must learn and try new things while it is doing normal business like sending data across the network all while meeting quality of service requirements. Furthermore, the system has to deal with imperfect information about the channel conditions and the effects of noise and other interfering signals. Updating the rules is a time consuming task because the CE must wait for certain observations to occur and it can only investigate new schemes at a fraction of the system's operating time.

In the current implementation, the CE is only observing the average E_b/N_0 and the maximum pairwise correlation between any two transmit or receive antennas of a 4x4 MIMO system. Using this information the CE has to determine what is the best possible MIMO, modulation, and coding rate combination. This combination will be referred to as a "scheme". In this work, the best scheme is the one that maximizes its spectral efficiency while maintaining a BER at or below a threshold.

For this work, the CE's available MIMO techniques are transmit diversity (STBC) and spatial multiplexing (VBLAST) both of which do not require channel knowledge at the transmitter. The available modulation techniques are QPSK, 16, 64, 128, and 256QAM. And the coding rate options are 1 (uncoded), ¾, and ½ convolutional FEC.

We make the assumptions that the CE can observe the measurement pair (E_b/N_0, [Max] Correlation) and is able to react by employing one of the 30 possible schemes. This formulation makes each new measurement pair a search problem that can be solved by employing the genetic algorithm (GA). The GA was selected because it has the ability to search parameter spaces despite having little or no information. The GA is used as follows: First, the channel conditions are observed; second, those schemes that were used in similar conditions are retrieved from the database; third, those schemes are added to the GA's initial population; and fourth the GA returnsthe best scheme based on its search. The new scheme (along with its performance) is stored in the observations database. Finally, the CCU updates the operating rules.

The GA works by trying to maximize a fitness function by employing evolutionary principles (e.g., modifying 'genes') to a population of schemes. In our case each scheme has three genes: the MIMO technique, the modulation technique, and the coding rate. The GA continuously evolves its population until certain stopping criteria are met. The discussion on the implementation of the GA begins by describing the fitness function F :

$$F(a,b)=\begin{cases}a+0.5-b & b\le MaxBER\\ 0.5-b & \text{otherwise}\end{cases} \quad (1)$$

where a is the spectral efficiency, and b is the BER observed using a certain scheme under some channel conditions. MaxBER is the maximum allowable BER, which is set in this work to 1×10^{-3}. One can observe that when the BER requirements are not met, the GA maximizes the energy efficiency, and as soon as the BER requirements are met, it maximizes the spectral efficiency.

The GA works as follows:

1. Starts with either a random population of three schemes or a population consisting of two schemes that were found to work for similar conditions and a random scheme.
2. Evaluates the fitness function, and assigns to each scheme a probability proportional to its fitness evaluation. Then, randomly selects 2 schemes based on their probabilities.

3. Generates a child scheme by selecting a random number of genes from parent scheme A and the rest of the genes from parent scheme B (crossover).
4. With a probability of 25%, the child scheme undergos a mutation (i.e., a gene is set to a random value).
5. The child is added to the population and the process is repeated from 2 until the population has a total of eight schemes.

The GA stopping condition implies that the GA evaluates approximately 27% of all the available schemes. Ideally we would like have a stopping criterion based on the fitness function.

4. RESULTS

The performance of the GA in our current CCU implementation was evaluated by varying the E_b/N_0 over the range 0 to 39 dB and the neighboring antenna correlation over the range of 0.1 to 0.9 in steps of 1 and 0.1 respectively. The performance under those channel conditions was evaluated by means of simulation. For each channel conditions set, several channel realizations were considered until at least 1000 errors occurred or a timeout occurred (meaning the BER at those conditions was well below the target BER of $1x10^{-3}$.)

The results are shown in Figure 4. Compared to the optimal case shown Figure 5, the GA did not always find the optimal case, but it was extremely close, especially taking into account that it searches a fraction of the search space. This is because the GA exploits the knowledge of the performance of schemes at neighboring measurement pairs.

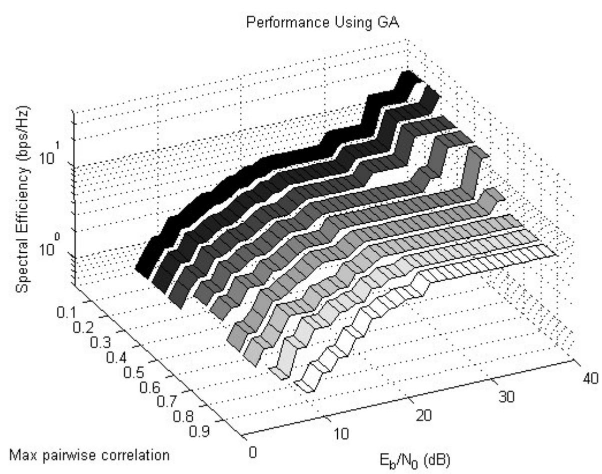

Figure 4 GA Performance Vs E_b/N_0 and Max Pairwise Correlation

Using this knowledge improves the possibility of finding an optimal or near optimal solution.

In Figure 6, the correlation is set to 0.1 in order to get a closer look at the selection of schemes. On the plot the reader can directly observe the optimal spectral efficiency for the available MIMO, modulation and coding schemes. The FEC code rate used can be inferred from the spectral efficiency, the MIMO technique, and the modulation technique. The reader is reminded that 4x4 STBC has a spectral efficiency factor of ¾ and 4x4 VBLAST has a spectral efficiency increase of 4 as compared to the single antenna case. For example, looking at E_b/N_0=25dB, the spectral efficiency is 6. From the symbol at that E_b/N_0 we can infer that the gray color means (STBC), the upwards arrow means 256QAM, and the coding rate that will make ¾ times 8 ($\log_2(256)$) equal to 6, is 1 (uncoded). Furthermore, it can be observed that spatial multiplexing (VBLAST) can only be used at high values of E_b/N_0, as compared to transmit diversity. This, of course, is to be expected.

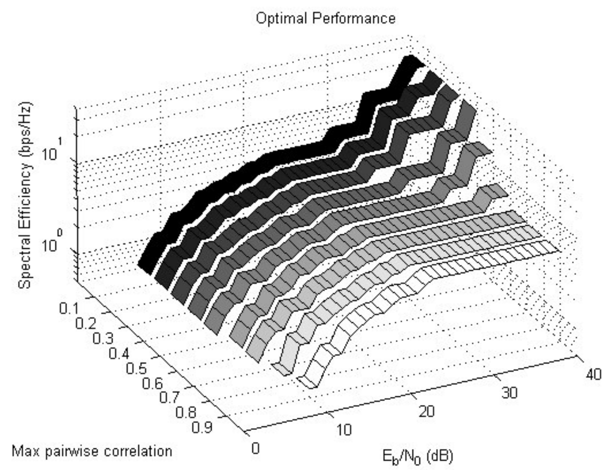

Figure 5 Optimal Performance Vs E_b/N_0 and Max Pairwise Correlation

The previous results demonstrate that the GA can determine a near-optimal relationship between correlation/EbNo and spectral efficiency. We also wanted to examine how this near-optimal set of rules benefits the system in a time-varying channel. Figure 7 shows the examined E_b/N_0 variation in a time-varying fading channel, Figure 8 plots the spectral efficiency versus time, while Figure 9 shows the BER versus time. Also plotted in the two figures are the spectral efficiency and BER performance of an adaptive modulation scheme employing a fixed MIMO scheme (STBC). It can be seen from the graphs that being able to optimize the MIMO technique in addition to modulation/coding provides a benefit in terms of performance.

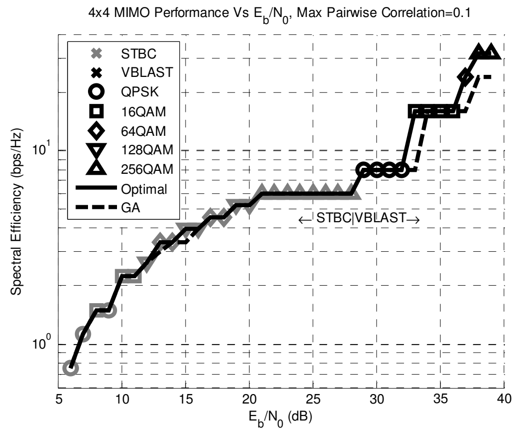

Figure 6 Performance Vs E_b/N_o for Max. Pairwise Correlation=0.1

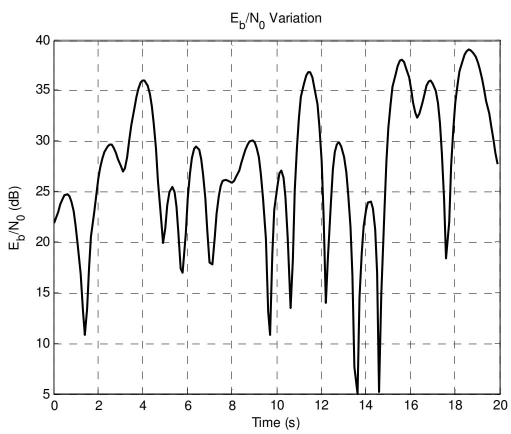

Figure 7 E_b/N_0 Variation

In addition to varying the E_b/N_0, the case of varying the maximum pair wise antenna correlation was also investigated (Figure 10). Correlation has a more profound effect on high E_b/N_0's, and for this reason, the E_b/N_0 was fixed to 35dB. The effect of varying the correlation is shown in Figure 11. For reference purposes, the performance of using just STBC is also included. Finally, the observed BER is shown in Figure 12. It can be seen that high correlation reduces the energy efficiency of the selected MIMO technique (VBLAST). When the correlation is high, the CE is operating using STBC. At correlation levels less than 0.5 the CE is able to use VBLAST.

5. FUTURE WORK

At the moment, this work has some shortcomings. First, the GA's searching abilities could be improved by providing a better solution for the initial population based on current knowledge, increasing the probability that the GA will find the highest performing scheme. Currently, the stopping condition is the number of schemes in the population. Other stopping conditions are desired in order to reduce search time. If spectral efficiency were considered, the stopping condition could be reaching a certain percentage of the Shannon capacity bound.

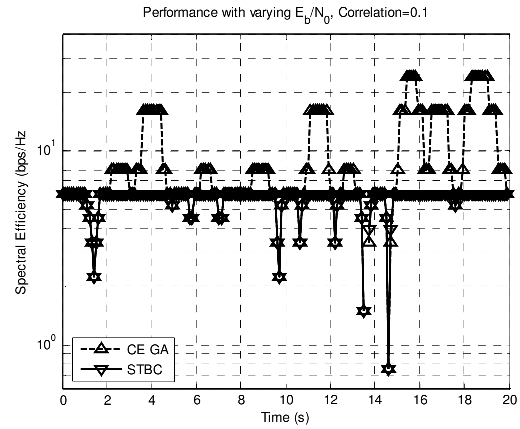

Figure 8 Performance over time with varying E_b/N_0

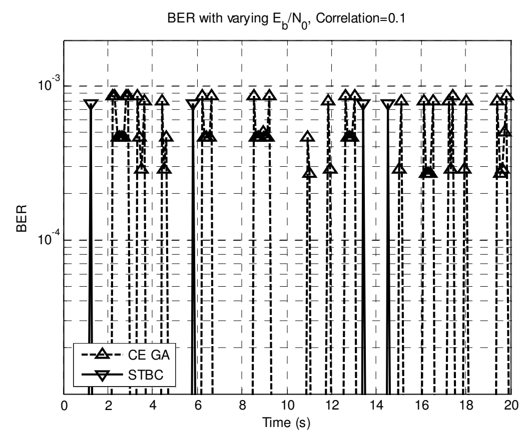

Figure 9 BER over time with varying E_b/N_0

In order to meet the objectives above, and to add additional capabilities to the CE, exploration of learning methods that determine which observable parameters (metrics) of the channel best predict its performance. Parameter examples are the E_b/N_0, various channel matrix statistics, and time dispersion parameters. Such knowledge would allow the CE to be more efficient by estimating, processing, and storing only useful metrics. If a metric is not found to be a significant predictor of performance or if it can be replaced by a simpler metric, then that metric should be ignored. This ability would also help when channel estimation is not perfect.

The CE should be able to derive conclusions about the system's performance that will be comparable to the established analytical models, when such models exist.

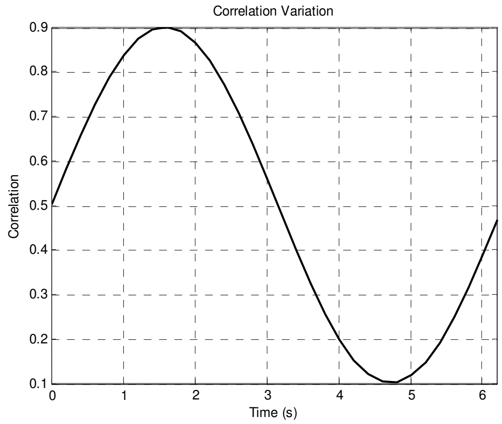

Figure 10 Varying Correlation over time

The next step in this work will be the investigation of how a parameter can be tested to determine its ability to predict performance. This investigation can be done by evaluating the applicability of techniques such as inductive learning. This technique, given a collection of examples of *f*, should return a function *h* hypothesis that approximates *f*. Learning can also be done in other ways such as using Bayesian networks or neural networks [5].

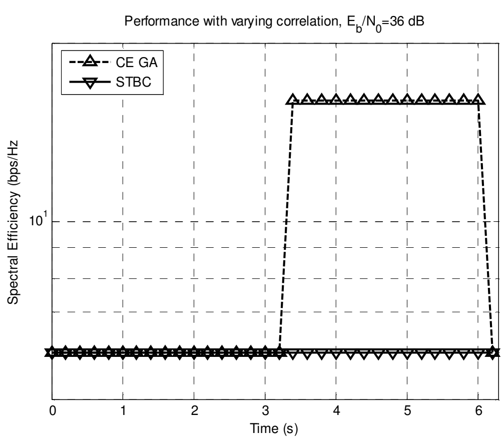

Figure 11 Performance over time with varying correlation

A balance must be defined between the information learned and the search for other possible options by means of the GA. Learning and searching are both considered to be very important tasks because they complement each other. Searching explores options that wouldn't be considered by relying on learning techniques alone, thus increasing the possibility of finding relationships that are not easy to observe. Furthermore, as was already mentioned, learning can help the search algorithm to explore faster possible solutions. Researchers occasionally discover key findings by accidentally coming across them; it is desired for the CE to have this ability.

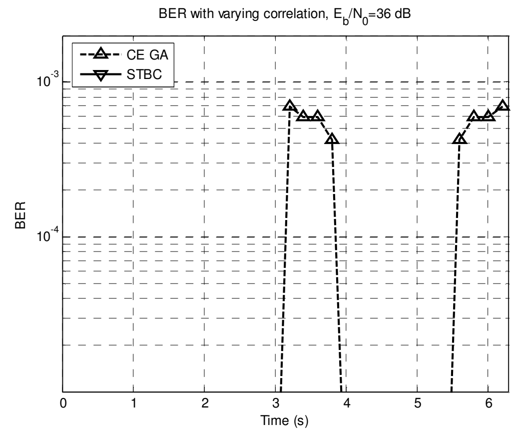

Figure 12 BER over time with varying correlation

6. CONCLUSIONS

This paper proposed a CE for MIMO systems. MIMO systems can exploit multiple antennas using a variety of techniques. The selection of which technique to use under certain conditions, is not always a straightforward task. In addition to proposing the CE, results from a partial implementation using a GA were presented. A GA was employed to find the best scheme to operate under certain conditions. Even though, the GA searches only part of the search space, searching consumes resources as it is a trial and error process. Therefore, it is desired that the searching processes to be as efficient as possible. By addressing this issue, the need to use learning techniques for indentifying important system performance predictors (such as channel metrics) was indentified. Furthermore, it was concluded that searching and learning should both be employed as they provide different advantages to the CE's performance.

7. REFERENCES

[1] Mohinder Jankiraman, *"Space-Time Codes and MIMO Systems,"* Artech House, Norwood, 2004.

[2] B.D Van Veen, and K. M. Buckley, "Beamforming: a versatile approach to spatial filtering," *IEEE ASSP Magazine*, vol.5, no.2, pp.4-24, Apr 1988

[3] Arogyaswami Paulraj, Rohit Nabar, and Dhananjay Gore, *"Introduction to Space-Time Wireless Communications,"* Cambridge University Press, Cambridge, 2003.

[4] Sankar K. Paul and Simon C. K. Shiu, *"Foundations of Soft Case-Based Reasoning,"* John Willey & Sons, New Jersey 2004.

[5] Stuart Russel and Peter Norvig, *"Artificial Intelligence: A Modern Approach,"* Second Edition, Pearson Education, New Jersey 2003