

# Genetic Algorithm Implementation of Multi-User Detection in SDMA-OFDM Systems

Mohammed Alansi, Ibrahim Elshafiey and Abdulhameed Al-Sanie

Electrical Engineering Department, King Saud University

PO Box 800, Riyadh, 11421, Saudi Arabia

**Abstract**— Number of supported users in the orthogonal frequency division multiplexing (OFDM) systems can be increased considerably using powerful multi-user detector (MUD) combined with space division multiple access (SDMA) techniques. This paper presents the results of implementing MUD in SDMA-OFDM systems based on an advanced genetic-algorithm (GA) optimization tool. The hardware implementation is performed using Field Programmable Gate array (FPGA) devices which allow the real time performance of the proposed tool. Results show that the GA scheme enhances the performance and provides BER near to that attained using maximum likelihood (ML) detector at considerably lower computation complexity. Investigation of the GA population size is presented and FPGA implementation is described based on the shared memory approach.

**Keywords**- Genetic Algorithms; Multi-User Detection; SDMA; FPGA; Shared Memory.

## I. INTRODUCTION

Space division Multiple Access (SDMA) is one notable application of Multiple Input Multiple Output (MIMO) and it can be employed for supporting multiple users, where higher bandwidth efficiency can be achieved in comparison to conventional multiplexing techniques. In these systems a number of transmitted signals coming from a group of different users are separated at the base-station (BS) with the aid of their unique, user-specific spatial signature, which is constituted by the element vector of channel transfer factors between the users equipped with a single transmit antenna each and the receiver antenna elements at the BS. Flat-fading channel conditions are assumed in each of the Orthogonal Frequency Division Multiplexing (OFDM) subcarriers.

The user-specific spatial signature in SDMA is used to differentiate amongst the user signals. Accurate channel estimation as well as powerful Multi-User Detector (MUD) should be available at the receiver in order to support high number of users.

Different MUD schemes at the Base Station (BS) receiver have been proposed to separate the user signals based on their spatial signature as explained in [1]. The most common scheme is the Minimum Mean Squared Error (MMSE). The Maximum Likelihood (ML) detector is approved as the optimal detector with the ability to provide low Bit Error Rate (BER) and high performance. ML detector however suffers from the computational complexity, which increases

exponentially with increase of the number of users and constellation size [2].

Advanced optimization techniques such as the genetic algorithms (GAs) can be used to enhance the performance of MUD schemes. GAs have been proposed for use as MUD in [3], where the initial population to the algorithm is obtained using MMSE. However, the time requirements of the GAs, although less than that of ML can still be large. Hardware implementation of the GAs provides an attractive tool to expedite GA process.

This work proposes use of Field Programmable Gate Arrays (FPGAs) as implementation technique for the GAs as an optimization tool for MUD. Hardware co-simulation in the Xilinx Vertex-6 environment is adopted [4]. Results of the MMSE detector are used to generate the initial genes to be tested in estimating the transmitted signal. After the evolution of the algorithm, the best gene in terms of minimizing the error function is chosen as the detector estimate of the original transmitted signal. Simulation results show that the potential of the GAs in enhancing the performance of MUD techniques.

The rest of the paper is arranged as follows. Section II describes the SDMA model, whereas in Section III a variety of MUD techniques are illustrated. The FPGA implementation model of the GAs is introduced in Section IV. Section V presents simulation results, and conclusions are drawn in Section VI.

## II. SDMA SYSTEM MODEL

The capacity enhancement in SDMA system comes from the exploitation of spatial signature which makes the possibility for identify the individual users; even when they are operating in the same time, frequency and code domains. Moreover, the orthogonal OFDM can be used to mitigate the channel impairments and transforms a frequency-selective channel into a set of frequency-flat channels.

Fig. 1 shows the SDMA uplink channel systems where it consists of  $L$  simultaneous uplink mobile users employed single antenna for each one transmitting signals and the BS has  $P$  receive antennas [1]. The received signal was corrupted by the Gaussian noise at the antenna array elements yielding

$$y = Hx + n \quad (1)$$

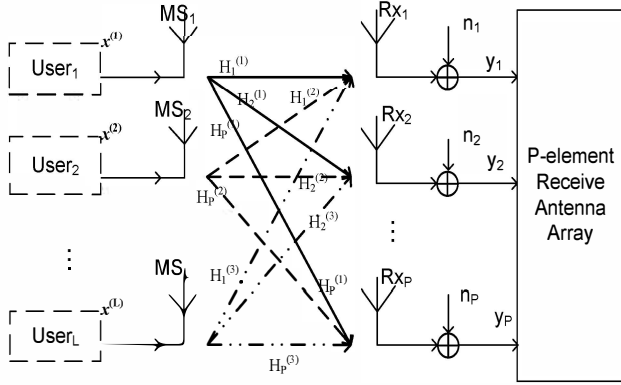


Fig. 1. Schematic model of SDMA uplink channel system.

where  $y = [y_1, y_2, \dots, y_P]$  is the received signals vector,  $x = [x^{(1)}, x^{(2)}, \dots, x^{(L)}]$  is the transmitted signals vector and  $n$  is the dimensional noise vector. The frequency domain channel transfer function matrix (FD-CHTFs)  $H$  is constituted by the set of channel transfer function vectors  $H^l$  where  $l = 1, \dots, L$  users:

$$H = [H^1, H^2, \dots, H^L] \quad (2)$$

### III. MULTI-USER DETECTION SCHEMES

MUD techniques are used at the BS for detecting the different user's transmitted signals with the aid of their unique, user-specific spatial signature constituted by their FD-CHTFs. The estimate  $\tilde{x}$  of the transmitted signal vector  $x$  of the  $L$  simultaneous users is generated by the MUD upon linearly combining the signals received  $y$  by the different antenna elements  $P$  at the BS with the aid of the array weight matrix  $W$ , resulting in

$$\tilde{x} = W^H y \quad (3)$$

By substituting from (1) to (3) and considering the  $l^{th}$  user's associated vector component, we will arrive at

$$\tilde{x}_l = \tilde{x} + W_l^H n \quad (4)$$

where the weight vector  $W_l$  is the  $l^{th}$  column of the weight matrix  $W$ .

A variety of linear MUD has been proposed for performing the separation of users. The standard linear detection methods include the Zero-Forcing (ZF) technique and the MMSE technique, where the MMSE-MUD is the most popular SDMA receiver design strategy, noting that the MMSE receiver requires the statistical information of noise  $\sigma_n^2$  [5]. The MMSE weight matrix is used to maximize the post-detection signal to interference plus noise ratio (SINR) is

$$W_{MMSE} = (H^H H + \sigma_n^2)^{-1} H^H \quad (5)$$

In the linear detection methods, Successive Interference Cancellation (SIC) is an attractive method, where the principle is to successively detect and cancel the data layer by layer. The detected symbol is then cancelled from the

received signal vector and the procedure is repeated until all the symbols are detected. The performance of SIC can be improved by selecting the user data with the highest SINR at each detection stage using the Ordered Successive Interference Cancellation (OSIC) [6].

ML detector achieves the optimal performance as a MUD technique, and it is considered as a reference to other detection methods [7]. The ML method minimizes the Euclidean distance between the received signal vectors and the product of all possible transmitted signal vectors with the given channel. The ML detection methods determine the estimate of the transmitted signal vector  $x$  as

$$\tilde{x}_{ML} = \underset{x}{\operatorname{argmin}} \|y - Hx\|^2 \quad (6)$$

Where  $\|y - Hx\|^2$  corresponds to the ML metric. The numbers of evaluations that will be done in ML detector depend on the number of users in the system and the set of constellation symbol point. The ML detector has a complexity on the order of  $O^{(2L \cdot \log_2 M)}$ , where  $M$  represents the constellation size. Thus when the number of users increases, ML detector quickly becomes infeasible.

In comparison to the ML detector, GAs provide an advanced optimization tool that can be used to enhance the performance at lower complexity. Moreover, it was approved in [3], and [8] that the GAs have the ability of maintaining near-optimum performance in SDMA-OFDM systems.

The optimum ML detector based decision metric of (6) can be used in the GA MUD for the sake of detecting the estimated transmitted symbol vector  $\tilde{x}_{GA}$ , where the decision metric required for the receive antenna, namely the antenna specific fitness function is defined by:

$$\Omega_p(x) = |y_p - H_p x|^2 \quad (7)$$

where  $y_p$  is the received symbol at the input of the  $p^{th}$  receiver, while  $H_p$  is the  $p^{th}$  row of the channel transfer function  $H$ . Therefore the decision rule for the optimum MUD associated with  $p^{th}$  antenna is to choose the specific  $L$ -symbol vector  $x$ , which minimizes the metric given in (7). Thus, the estimated transmitted symbol vector based on the knowledge of the received signal at the  $p^{th}$  receiver antenna is given by:

$$\tilde{x}_{GA} = \underset{x}{\operatorname{argmin}} |\Omega_p(x)| \quad (8)$$

### IV. FPGA IMPLEMENTATION OF GENETIC ALGORITHM

GAs provide computer simulation methods in which a population representing candidate solutions to an optimization problem evolves toward better solutions and the algorithm thus optimizes a given fitness function. For many real-world applications the GA process can be time-consuming, even when it is executed with a high performance computing facility.

Recent advances in FPGA allow an attractive tool for hardware implementation of the GAs, which can considerably reduce the processing time.

For Xilinx FPGA, *System Generator* provides a system-level modeling tool that facilitates hardware design. It is based on MATLAB-Simulink design tool [9] for Xilinx's line of FPGAs and complex digital circuits have been developed using multiple Hardware Description Language (HDL) modules. The hardware simulation token is generated using the system generator tool for a design captured that will co-simulate with the rest of the simulink system to provide up to a 1000x simulation performance increase. Also, the hardware co-simulation using the system generator makes the possibility to incorporate a design running in an FPGA directly into a simulation [4].

In this work the FPGA Xilinx Virtex-6 is used to design and implement GA using hardware co-simulation in order to optimize the performance of MUD in the system. Fig. 2 shows the block diagram of the proposed system to implement GA in FPGA hardware environment. The system consider that there eight users transmitting data and the BS has eight antenna receivers. MATLAB initial simulation program is used to generate the channel where it was assumed to be perfectly known at the receiver and 16-QAM modulation is used in the transmitter. Furthermore, the initial estimated points from the output of MMSE detector is used to get five initial population points around the transmitted signal for each transmitter, which is used in the Form Genes subsystem to generate the genes. The various implementation stages are shown in Fig. 2.

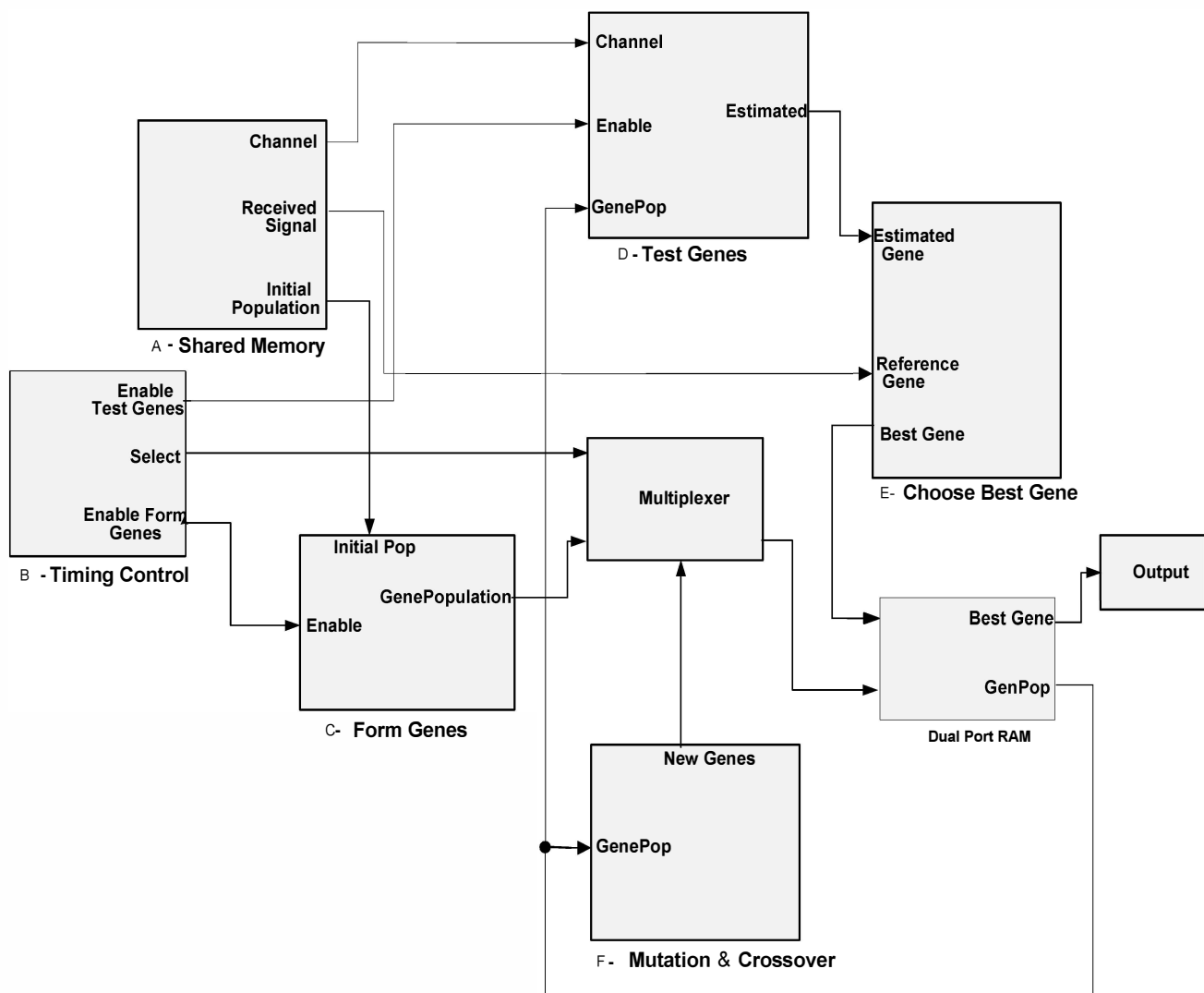


Fig 2. Proposed Implementation Block Diagram for GA Optimization Technique of MUD in SDMA-OFDM Systems.

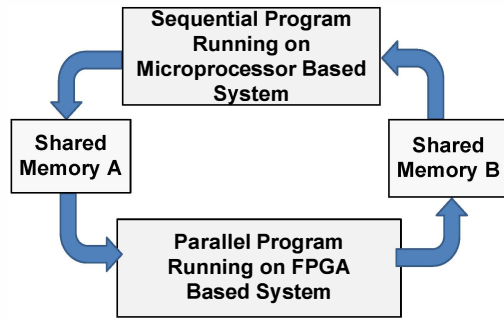


Fig 3. Schematic of Hardware Co-Simulation and Shared memory.

The shared memory block is used to transfer the data between the host PC and FPGA, where the received signal and the channel vectors are transferred from the PC to FPGA. Hardware co-simulation interfaces allow shared memory to be compiled and co-simulated in FPGA hardware. These interfaces make it possible for hardware based shared memory resources to map transparently to common address spaces on the host PC and these shared memories can help facilitate high-speed data transfers between the host PC and the FPGA. Xilinx shared memory block can be included in the design to implement Random Access Memory (RAM) that can be shared among multiple designs in the implementation.

Fig. 3 shows the principle of the shared memory approach and hardware co-simulation in Xilinx FPGA system. The parallel GA will be running on the FPGA platform, and the parameters and results are stored in the shared memory to be accessed by the FPGA in addition to the sequential program running on the host PC.

Timing Control subsystem is proposed in order to adjust and control the timing for all the subsystems and blocks and make the system more efficient and use all possible resources in a proper way.

Form Genes subsystem generates and form all the possible genes i.e. possible estimated solutions for the transmitted signal using the initial population that already transferred to the shared memory from the simulation program running on the PC and using counters to get all the states of the solutions. Since the system assumed that eight users are applied, it can be seen that the number of possible solutions i.e. number of generated genes will be  $p^8$ , where  $p$  is the number of initial sphere points surrounding the transmitted signal and they are used to generate the initial population.

Test Genes subsystem use the genes population to obtain the estimated signal. Complex multiplier is used to get the channel effect on each gene to get the estimated received signal.

Choose Best Gene subsystem calculates the error between the received and estimated signals. The best gene is selected according to the rule of getting the minimum error in comparison to all other genes and thus identifying

the best gene and representing the detected signal for all users.

Mutation & Crossover subsystem are used to implement these two main processes of creating new generations from the old ones in the GA. A generator is used to obtain random numbers that help decide the location of the mutation bits and the crossover points. The outputs of Form Genes subsystem and the Mutation & crossover subsystem are stored in the Dual Port RAM, where the Multiplexer block chooses one of these two outputs to be written into the RAM.

Finally, it is important to mention here that it is important to decrease the communication time for reading and writing data to the FPGA. For our system, shared memories allow high speed of writing and reading data to & from the FPGA and we notice that the reading time was approximately 0.0015 second and the writing time was also approximately  $2.1206 \times 10^{-4}$  second.

## V. SIMULATION RESULTS

Simulation for the SDMA-OFDM system and the MUD techniques including the GA applied using Matlab simulation program. The simulation considers 16-QAM modulation and Rayleigh channel where it is assumed to be known from the perfect channel estimation at the BS. Table 1 shows the parameters used in the simulation, where the Tap-Power, Tap-Delay, and Doppler frequency of the standard ITU channel model for high delay spread vehicular test environment is applied [10]. The output of MMSE detector is used as an initial population of the GA.

Fig. 4 portrays the BER performance of MUD schemes (MMSE, GA, and ML) in the SDMA-OFDM system. Three users are assumed ( $L=3$ ), each one has a single transmitter antenna, and three receiver antenna elements are considered at the BS. It can be observed that the GA enhance the performance of MMSE and get a near optimum performance to that attained by the optimum ML detector.

Table 1. Parameters used in model simulation.

Channel	Tap-Power (dB)	Tap-delay (ns)	Doppler (Hz)
	[0 -1 -9 -10 -15 -20]	[0 310 710 1090 1730 2510]	400 (120 Km/hr)
Genetic Algorithm	Max Num. Generations	Population Size	mutation probability (per bit)
	50	100	0.0833
	Crossover Type	Gene Length	Max Fitness Tolerance
	Uniform	12bits	1e-4

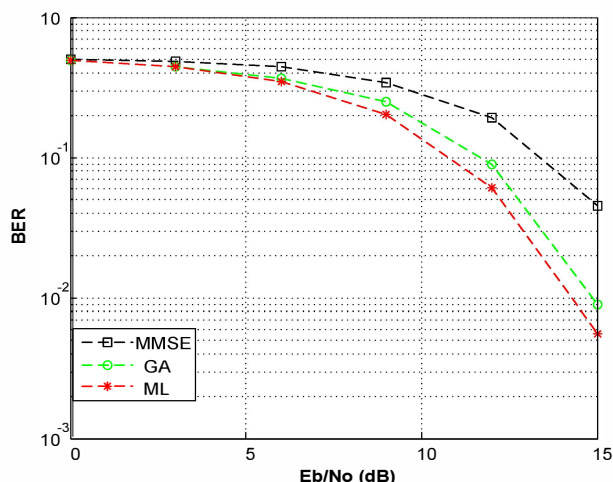


Fig 4. Performance of the MUD schemes when  $L=3$  &  $P=3$ .

In order to investigate the performance of the genetic algorithm, the population size (maximum number of genes) and the maximum allowed number of generations have been investigated. Fig. 5 shows the effect of increasing the population size and the number of generations in enhancing the performance of the GAs. Both the number of users and the number of receiver antenna elements are taken to be two. The first GA implementation (GA-1) has 20 for the population size and also the number of generations, whereas, the second implementation (GA-2) employed 100 for the population size and the number of generations. The increase of the population size and number of generations in the second case allowed better investigation of the search space and provided lower BER result as shown in the figure.

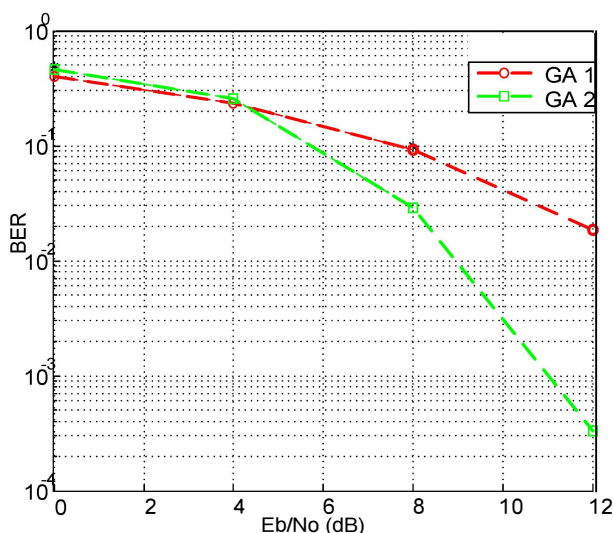


Fig 5. Performance of GA scheme for two cases of population size and number of generations.

## VI. CONCLUSIONS

SDMA-OFDM systems provide an attractive tool to enhance the capacity of future communication systems. GA optimization technique has the ability to enhance the performance of SDMA-OFDM and achieve a close performance to the optimum ML, at considerably lower computation complexity. However, the GA requires enough population size and large number of generations to be able to get an enhancement for the performance particularly for high number of users. This requirement motivate the research to develop the hardware implementation based on FPGA environment in order to improve the ability of using GA as an optimization tool for MUD providing real time close-to-optimal performance.

## ACKNOWLEDGMENT

This work is funded by the National Plan for Science and Technology, Kingdom of Saudi Arabia, under project number: 08-ELE262-2.

## REFERENCES

- [1] L. Hanzo, M. M<sup>u</sup>nster, B. Choi, and T. Keller, *OFDM and MC-CDMA for Broadband Multi-user Communications WLANs and Broadcasting*, John Wiley and IEEE Press, Ed., 2003.
- [2] M. Alansi, I. Elshafiey and A. Al-Sanie, "Multi User Detection for SDMA OFDM Communication Systems," in *Electronics, Communications and Photonics Conference (SIEPCP)*, 2011 Saudi International , 2011, pp. 1-5.
- [3] M. Jiang and Lajos Hanzo, "Genetically Enhanced TCM Assisted MMSE Multi-User Detection for SDMA-OFDM," in *Proc.2004 IEEE 60th Vehicular Technology Conf. (VTC '04 Fall)*, Los Angeles, CA.
- [4] Xilinx company web site. [Online]. <http://www.xilinx.com/support/documentation/virtex-6.htm>
- [5] R. and Verdú, "Linear multiuser detectors for synchronous code division multiple-access channels.," *IEEE Transactions on Information Theory*, vol. 34, no. 1, 1989.
- [6] J. Ylions, "Iterative detection, decoding, and channel estimation in MIMO-OFDM," University of Oulu, Finland, Academic dissertation 2010.
- [7] J. Proakis, *Digital Communications*.: McGraw-Hill, 2008.
- [8] P. A. Haris, E. Gopinathan, and C. K. Ali, " Performance of Some Metaheuristic Algorithms for Multiuser Detection in TCM-Assisted Rank-Deficient SDMA-OFDM System," *EURASIP Journal on Wireless Communications and Networking*, 2010.
- [9] <http://www.mathworks.com/>. [Online]
- [10] K. Vaiapury, M. Nagarajan, S. Kumaran, "Performance Evaluation of Preamble Detection under ITU and SUI Channel Models in Mobile WiMAX," in *The First International Conference on COMmunication Systems and NETworks COMSNETS* , Bangalore, India, Jan 2009.