



# Design Novel CMOL Architecture in Terabit-scale Nano Electronic Memories Technology

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## ABSTRACT

We have calculated the minimum chip area overhead and hence the bit density reduction. In this approach, the number of faults in each line of a memory block (matrix) is counted, and the lines having the largest number of defects are replaced with the spare lines. This method achieved by memory array reconfiguration (bad bit exclusion), combined with error correction code techniques, in prospective terabit-scale hybrid semiconductor/nanodevice memories, as a function of the nanodevice fabrication yield and the micro-to-nano pitch ratio. The results show that by using the best (but hardly practicable) reconfiguration and block size optimization, hybrid memories with a pitch ratio of 10 may overcome purely semiconductor memories in useful bit density if the fraction of bad nanodevices is below ~15%, while in order to get an order-of-magnitude advantage in density, the number of bad devices has to be decreased to ~2%. For the simple 'Repair Most' technique of bad bit exclusion, complemented with the Hamming-code error correction, these numbers are close to 2% and 0.1%, respectively. When applied to purely semiconductor memories, the same technique allows us to reduce the chip area 'swelling' to just 40% at as many as 0.1% of bad devices. We have also estimated the power and speed of the hybrid memories and have found that, at a reasonable choice of nanodevice resistance, both the additional power and speed loss due to the nanodevice subsystem may be negligible.

**KEYWORDS:** ECC, Memories, CMOS, FPGA, RTL, MCS, Semiconductor, Nanodevice.

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## I. INTRODUCTION

The recent spectacular advances in molecular electronics, in particular the demonstration of single-molecule single electron transistors by several groups, offer the hope for a practical introduction of hybrid semiconductor/nanodevice circuits, first of all for terabit-scale memory applications. In such memories, nanodevices (e.g., single molecules) would be used as single-bit memory cells, while the semiconductor transistor subsystem would perform all the peripheral (input/output, coding/decoding, line driving, and sense amplification) functions that require relatively smaller number of devices (scaling as  $N/2$ , where  $N$  is the memory size in bits).

The first experimental steps toward the implementation of the hybrid memories have

already been made. The main architectural challenge faced by the hybrid memories is the anticipated substantial fraction of 'bad' nanodevices, limited by both the integration technique (e.g., the chemically-directed molecular self-assembly, and the vulnerability of Nanoscale devices to random charged defects). The main approach to addressing this problem in semiconductor memory technology is reconfiguration, the replacement of memory array lines (rows or columns) containing bad cells by spare lines.

The effectiveness of the replacement depends on how good its algorithm. The Exhaustive Search approach (trying all possible combinations) finds the best repair solution, though it is not practicable because of the exponentially large execution time. A more acceptable choice is the 'Repair Most'

method that allows a simple hardware implementation and an execution time scaling linearly with the number of bits.

In semiconductor memories the ECC is reserved mainly for the suppression of soft rather than the hard errors, for insuring the memory fault tolerance rather than defect tolerance. However, for the prospective hybrid memories the defect tolerance is expected to be a much more acute problem, and ECC may need to be involved at the initial repair process as well.

The technical analysis of the opportunity, carried out in the pioneering work has been limited to the exclusion of just a few spare lines. Figure 1 shows the assumed general structure of the hybrid memory. It is essentially a matrix of  $L$  memory blocks, while each block is in turn a rectangular array of  $(n + a) \times (m + b)$  memory cells. Here  $a$  and  $b$  present redundant resources that are being used for bad bit replacement at the initial test and repair stage, so that the final number of used memory cells is  $L \times n \times m$ . The good cells, addressed at each particular time step, form a row with one cell per block.

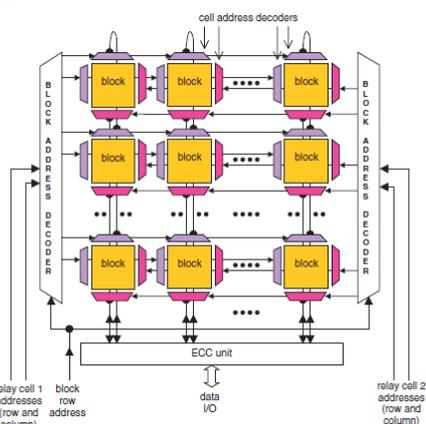


Figure: 1.1 Top structure of the analyzed hybrid memory

At each instance, block address decoders allow one to send the cell row and column addresses to a single row of blocks. The cell addresses are then processed by decoders of each block.

They have the same external word and bit addresses in each block, though due to the internal re-routing during the initial reconfiguration process, the real physical location of the used cell may be different in each block. The objective of our work is a study of the bad component exclusion techniques extended to an arbitrary number of redundant rows and columns of the matrix blocks, applied both with and without the error correction.

We have calculated the chip real estate overhead necessary for the fabrication of spare rows, columns, and auxiliary circuits, as a function of

the bad bit fraction  $q$  and the ratio  $R$  of critical dimensions of the semiconductor transistors and nanodevice components. The results for  $R = 1$  are also presented, since we believe that they are important for the evaluation of scaling prospects of purely semiconductor memories.

In contrast to the memory top structure (figure 1.1), the block architecture is substantially different from the traditional ‘uniform’ (semiconductor) memories. At each elementary operation, the block decoders address two vertical and two horizontal lines implemented in the CMOS layers of the integrated circuit, thus selecting a pair of ‘relay’ CMOS cells. The difference between the CMOL approach and the earlier suggestions (which seem hardly feasible from the fabrication point of view) is in the interfacing between the nanowires and the underlying CMOS-level wires in CMOL it is provided by sharp-pointed pins that are distributed all over the circuit area.

## II. EXISTING SYSTEM

The objective of our work is a study of the bad component exclusion techniques extended to an arbitrary number of redundant rows and columns of the matrix blocks, applied both with and without the error correction. We have calculated the chip real estate overhead necessary for the fabrication of spare rows, columns, and auxiliary circuits, as a function of the bad bit fraction  $q$  and the ratio  $R$  of critical dimensions of the semiconductor transistors and nanodevice components. The results for  $R = 1$  are also presented, since we believe that they are important for the evaluation of scaling prospects of purely semiconductor memories.

### 2.1 Cmos Memory Architecture

The block architecture (figure 4.1) is substantially different from the traditional ‘uniform’ (semiconductor) memories. At each elementary operation, the block decoders address two vertical and two horizontal lines implemented in the CMOS layers of the integrated circuit, thus selecting a pair of ‘relay’ CMOS cells.

### 2.2 Circuit Behavior

At every single contraction series  $t_i$ , the early period of our two-stage pipelined filter performs the pursuing procedures for the input example  $X$ : compute the new rank of every single cell, insert  $X$  in a cell that encompasses the token, and bypass the token to the subsequent cell. This way that for all  $P_i$ ,  $R_i$ , and  $T_i$  lists, their new benefits will be

computed and ambitious at this period so that they can be notified at the subsequent series  $t_{i+1}$ . At the alike period, the subsequent pipeline period computes the median worth for the input example that enters the window at the preceding series  $t_{i-1}$ . That is, for the output list  $Y$ , its new worth will be computed at this period so that it can additionally be notified at the subsequent series  $t_{i+1}$ .

For every single cell  $c_i$ , the benefits of its  $P_i$ ,  $R_i$ , and  $T_i$  lists are all shown in the figure. Initially, at series  $t_0$ , to make the early input example be stored in the early cell  $c_1$ , the last cell  $c_5$  is projected to encompass the token ( $T_5 = 1$ ). The rank and example benefits ( $P_i$  and  $R_i$ ) of every single cell, alongside the benefits of the two input/output lists  $X$  and  $Y$ , are all reset to be zero.

When the early example 12 enters the window at series  $t_1$ , the token has been advanced from  $c_5$  to  $c_1$  ( $T_1 = 1$  and  $T_5 = 0$ ). The worth of  $P_5$  has additionally been notified to be 5 as the early zero of  $X$  (now stored in  $R_5$ ) is indulged as an adjacent example at the early series  $t_0$ . To design for the subsequent series  $t_2$ , the new worth of  $R_1$  will be ambitious as 12 to store the input example as  $c_1$  encompasses the token. The new worth of  $P_1$  will be computed as 5 as example 12 (to be stored in  $R_1$ ) is larger than the example benefits of the supplementary four cells. Finally, the new benefits of  $T_1$  and  $T_2$  will be ambitious as 0 and 1, suitably, to indicate that the token will be advanced from  $c_1$  to  $c_2$ . All the benefits of  $P_i$ ,  $R_i$ , and  $T_i$  will next be notified at the subsequent series  $t_2$ . After the window is fully inhabited alongside valid data at series  $t_6$ , cell  $c_1$  holds the token once more ( $T_1 = 1$ ). The new worth of the median output  $Y$  for the subsequent series  $t_7$  will be ambitious as the worth of  $R_4$  (47) as rank  $P_4$  is equal to 3, i.e.,  $(5 + 1)/2$ . As the counseled design is a two-stage pipeline, after  $Y$  is notified to be 47 at series  $t_7$  for the input example 66, the benefits of all  $P_i$ ,  $R_i$ , and  $T_i$  will additionally be notified at this series for the subsequent input example 52. It can be perceived from this example that after an input example is inserted into the window, the aged example in every single cell will not be moved. Instead, the rank of every single cell is recalculated so that the new median can be obtained in a cell whose rank is equal to  $(N + 1)/2$ .

### 2.3 Rank Updating

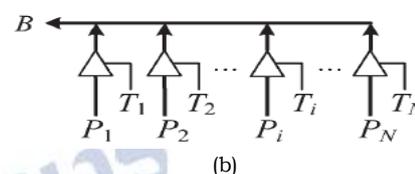
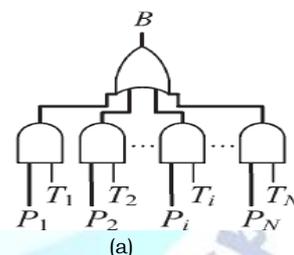
This section explains how to determine the new rank for each cell. Two types of cells will be separately discussed: a cell with the token and a cell without the token

Clk	Input Reg $X$	Cell Registers															Output Reg $Y$	
		$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$R_1$	$R_2$	$R_3$	$R_4$	$R_5$	$P_1$	$P_2$	$P_3$	$P_4$	$P_5$		
$t_0$	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
$t_1$	12	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
$t_2$	59	0	1	0	0	0	12	0	0	0	0	5	0	0	0	0	0	4
$t_3$	35	0	0	1	0	0	12	59	0	0	0	4	5	0	0	0	0	3
$t_4$	47	0	0	0	1	0	12	59	35	0	0	3	5	4	0	0	0	2
$t_5$	66	0	0	0	0	1	12	59	35	47	0	2	5	3	4	1	0	12
$t_6$	52	1	0	0	0	0	12	59	35	47	66	1	4	2	3	5	0	35
$t_7$	38	0	1	0	0	0	52	59	35	47	66	3	4	1	2	5	0	47
$t_8$	18	0	0	1	0	0	52	38	35	47	66	4	2	1	3	5	0	52
$t_9$	26	0	0	0	1	0	52	38	18	47	66	4	2	1	3	5	0	47

**Table.1. Example illustrating the insertion of nine input samples into a window.**

### 2.4 Ranksel and Mediansel Modules

The RankSel module is accountable for transferring the rank  $P_i$  of a cell  $c_i$  to its output  $B$  if  $c_i$  encompasses the token; i.e., after  $T_i = 1$ . Fig. 2(a) displays an easy implementation of this module employing AND/OR gates. It can additionally be requested by tri-state buffers in Fig. 2(b), whereas  $B$  is the output of a globe data bus that accumulates the output signals of all the tristate buffers. As there exists precisely one cell that encompasses the token at each time; i.e., there exists precisely one  $T_i$  signal whose worth is equal to 1, the worth of  $B$  will always be valid.



**Fig.3. Implementation of the RankSel module. (a) Using AND/OR gates. (b) Using tristate buffers.**

The MedianSel module can additionally be requested in a comparable way. It transfers the worth of  $R_i$  to the output list  $Y$  if  $R_i$  is the median; i.e., after  $Y_i = 1$ . Though, if it is requested by tristate buffers, the median will be valid merely after there exists at least  $(N + 1)/2$  samples in the window; or else, it will stay in an elevated impedance state.

### 2.5 Rankgen and Rankcal Modules

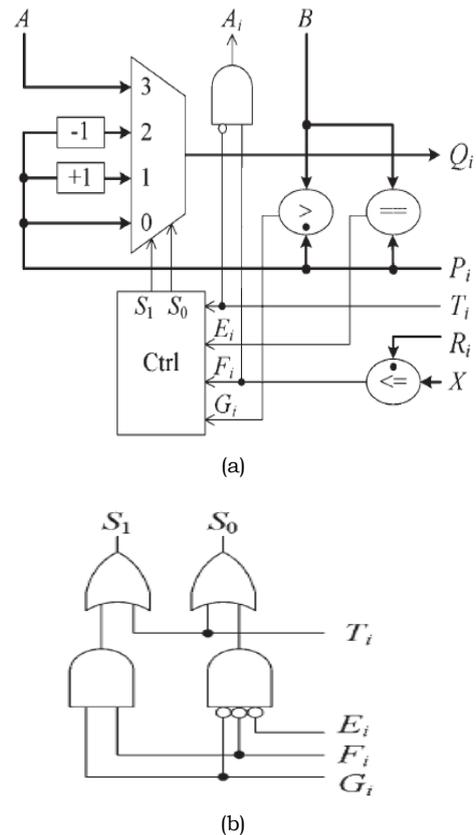
For the RankGen module in a cell  $c_i$ , its implementation is given in Fig. 4(a). signal  $F_i$  is the output of a comparator module " $\leq$ ," that assesses the worth of  $R_i$  alongside that of the input example  $X$  so that  $F_i = 1$  if  $R_i$  is less than or equal to  $X$  ( $R_i \leq X$ ), else  $F_i = 0$  ( $R_i > X$ ). Signal  $A_i$  is the output of a logic AND gate so that  $A_i = 1$  if  $T_i = 0$  and  $F_i = 1$ ; i.e., if cell  $c_i$  does not encompass the token and  $R_i$  is less than or equal to  $X$ , else  $A_i = 0$ . The  $A_i$  signal of every single cell is related to the RankCal module, that computes the new rank of a cell that encompasses the token. New rank is computed as  $K + 1$ , whereas  $K$  is the number of cells, that does not encompass the token and whose example worth is less than or equal to  $X$ ; i.e.,  $K$  is equal to the number of logic 1's on the  $A_i$  signals of all the cells.

The RankCal module can be requested by a multi-input adder that adds all the  $A_i$  signals and next increments the sum by 1. If cell  $c_i$  encompasses the token, the output  $A$  of the RankCal module will be its new rank at the subsequent series. On the contrary, if cell  $c_i$  does not encompass the token, its new rank will be ambitious by the supplementary signals. Signal  $G_i$  is the output of a comparator module " $>$ ," that assesses the worth of rank  $P_i$  alongside that of signal  $B$  so that  $G_i = 1$  if  $P_i$  is larger than  $B$ , else  $G_i = 0$ . As the worth of  $B$  is the rank  $P_j$  of one more cell  $c_j$  that encompasses the token, the meaning of  $G_i$  can additionally be delineated as  $G_i = 1$  if  $P_i$  is larger than  $P_j$  ( $P_i > P_j$ ), else  $G_i = 0$  ( $P_i \leq P_j$ ). signal  $E_i$  is the output of a compactor module " $=$ ," that additionally assesses the worth of  $P_i$  alongside that of  $B$  so that  $E_i = 1$  if  $P_i$  is equal to  $B$ , else  $E_i = 0$ . Likewise, the meaning of  $E_i$  can be delineated as  $E_i = 1$  if  $P_i$  is equal to  $P_j$  ( $P_i = P_j$ ), else  $E_i = 0$ . Joining these two signals  $E_i$  and  $G_i$ , for the three relations amid  $P_i$  and  $P_j$  ( $P_i > P_j$ ,  $P_i = P_j$ , and  $P_i < P_j$ ), the corresponding worth of  $E_i G_i$  will be 01, 10, and 00, respectively.

**2.6 CTRL Module**

For a cell  $c_i$ , since there are four possible sources to update its rank, a 4-to-1 multiplexer is used to select one of these sources for signal  $Q_i$  in Fig. 3(a). Then, the worth of rank  $P_i$  will be notified by the worth of  $Q_i$  at every single cycle. The multiplexer is manipulated by two selection signals  $S_1$  and  $S_0$ ; and these two signals, that are generated by the Ctrl module, are ambitious by four signals  $T_i$ ,  $E_i$ ,  $F_i$ , and  $G_i$ . If cell  $c_i$  encompasses the token ( $T_i = 1$ ), its new rank is obtained from the output  $A$  of the RankCal module; i.e., the worth of  $S_1 S_0$  ought to be 11 when  $T_i = 1$ . If cell  $c_i$  does not encompass the token ( $T_i = 0$ ), there are five cases for this. In Case 1 after  $P_i > P_j$  ( $E_i G_i = 01$ ) and  $R_i \leq X$  ( $F_i = 1$ ), the rank of  $c_i$  will be

decremented by 1; i.e., the worth of  $S_1 S_0$  should be 10 after  $E_i F_i G_i = 011$ . Comparably in Case 2, after  $P_i < P_j$  ( $E_i G_i = 00$ ) and  $R_i > X$  ( $F_i = 0$ ), the rank of  $c_i$  will be incremented by 1; i.e., the worth of  $S_1 S_0$  ought to be 01 when  $E_i F_i G_i = 000$ . Finally, after  $P_i < P_j$  ( $E_i G_i = 00$ ) and  $R_i \leq X$  ( $F_i = 1$ ) in Case 3,  $P_i > P_j$  ( $E_i G_i = 01$ ) and  $R_i > X$  ( $F_i = 0$ ) in Case 4, and  $P_i = P_j$  ( $E_i G_i = 10$ ) in Case 5, the rank of  $c_i$  will be retained unchanged; i.e., after  $E_i F_i G_i = 010, 001$ , or  $1 - 0$ , the worth of  $S_1 S_0$  ought to be 00. Fig.4(b) depicts a easy implementation of the Ctrl module.



**Fig.4. (a) Implementation of the Rank Gen module. (b) Implementation of the Ctrl module.**

**III. PROPOSED SYSTEM**

**3.1 Adaptive Median Filter**

The Adaptive Median Filter is projected to remove the setbacks confronted alongside average median filter. The frank difference amid the two filters is that, in the Adaptive Median Filter, the size of window encircling every single pixel is variable. This variation depends on the median of the pixels in the present window. If the medians of pixel worth are an impulse, next the size of the window is expanded. Otherwise, more processing is completed on portion of the image inside the present window specifications. 'Processing' the image basically entails the following: The center pixel window is assessed to confirm whether it is an impulse or not. If it is an impulse, next new worth of that pixel in

filtered image will be the median worth of the pixels in that window. If, though, the center pixel is not an impulse, next the worth of the center pixel is retained in the filtered image. Thus, unless the pixel being believed is an impulse, the gray-scale worth of the pixel in the filtered image is the alike as that of the input image. Thus, the Adaptive Median Filter solves the dual intention of removing the impulse noise from the image and cutting distortion in the image. Adaptive Median Filtering can grasp the filtering procedure of a picture corrupted alongside impulse noise of probability larger than 0.2. This filter additionally smoothens out supplementary kinds of noise, therefore, providing a far larger output image than the average median filter.

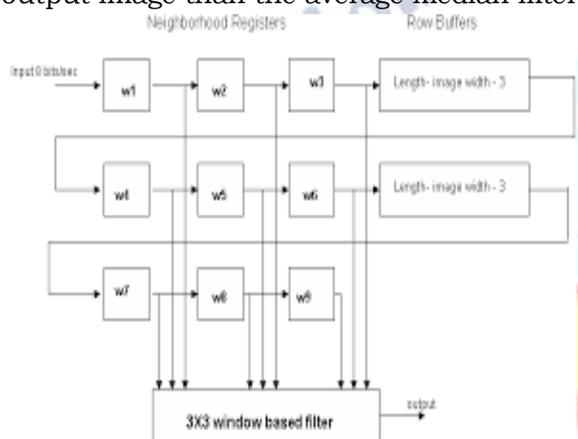


Fig.5. Implementation of a 3\*3 filter window

### 3.2 Parallel Sorting strategy

To make fair analogy of parallel sorting strategy opposing wave sorter strategy in words of the finished number of needed steps sort an array, it is vital to ponder the steps utilized to elucidate data from recollection and the steps needed to store sorted data back to memory. The counseled way is established on alike construction of lists array utilized in the wave sorter strategy. With this kind of array, data can be stored in the array by dispatching a datum to the early list and afterward, after subsequent datum is dispatched to the early list, the worth on the early array is advanced to subsequent register. Thus, for every single datum dispatched to the array to be stored, benefits in lists advanced to their corresponding adjacent registers. This procedure needs to  $n$  steps. The alike number of steps is needed to seize data out from the array. This way permits store a new set of data in the array as the preceding set is being dispatched back into the memory. As remarked in serving 2, suffix sorting could imply extra than one sorting iterations. If  $k$  sorts are needed, next parallel sorting needs  $((n+n/2) * k + n)$  to sort an array of  $n$  data.

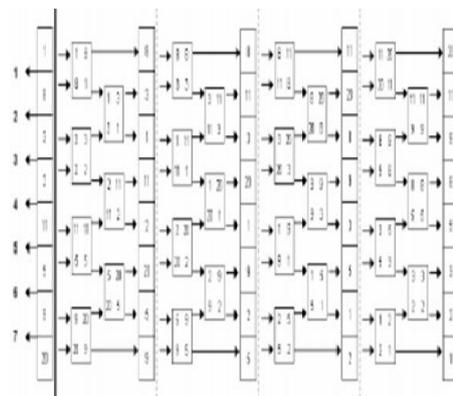


Fig.6. Parallel sorting.

## IV. RESULTS AND CONCLUSION

To summarize, our results show that a simple combination of array reconfiguration (bad line exclusion) and Hamming-code error-correction techniques may make hybrid CMOS/nanodevice memories tolerant to a substantial fraction of bad nanodevices. However, the fabrication technology still has to reduce this fraction to below  $\sim 0.1\%$  before terabit-scale memory chips, exceeding purely semiconductor memories in bit density by an order of magnitude, become possible. Possibly, this threshold may be moved up by almost an order of magnitude by the development of novel reconfiguration algorithms that would combine the simplicity and speed of the Repair Most exclusion with a higher repair quality (comparable to that of the Exhaustive Search). Under this approach, candidate solutions are modified by employing many small changes and occasionally large jumps. As a result, CS can substantially improve the relationship between exploration and exploitation, still enhancing its search capabilities. Despite such characteristics, the CS method still fails to provide multiple solutions in a single execution.

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