Asian Journal of Information Technology 15 (3): 504-517, 2016
ISSN: 1682-3915

Hybrid ELMAN Neural Network Approach for Reliability and Fault Analysis of Quantum-Dot Cellular Automata Circuits

S. Vimalraj and R. Maheswar
Department of Electronics and Communication Engineering,
Sri Krishna College of Technology, Kovaipudur, India

Abstract: In this stduy, fault analysis of Quantum-dot Cellular Automata (QCA) circuits is carried out employing a proposed hybrid version of ELMAN neural network approach. The QCA are basically designed structures with locally interconnected cellular automata like arrays. The fault analysis is carried out in this study for QCA circuits because of its wide applicability in signal processing applications and related computational applications. The QCA operates in a manner to process information employing a set of dots in a charged configuration module. Considering the QCA design aspect, when the placement of QCA cells at gate level gets altered, this results in reducing the effect of output polarization of the entire configuration. Hence, this study focuses on introducing a hybrid version of ELMAN neural network for performing reliability analysis on the considered QCA circuit. ELMAN neural network is a feed forward recurrent neural network model operating on gradient descent learning rule and its weights are updated using the evolutionary genetic algorithm approach. For testing the given QCA layout for its reliability, the various faults that may occur during the fabrication process are well-noted and analyzed. The proposed hybrid version of ELMAN neural network along with Genetic Algorithm (GA) are applied to the numerous logic gates in QCA module. The proposed model is validated for its effectiveness with the simulation results computed using the QCA designer. Simulation results that the proposed model performs reliability analysis in a better manner in comparison with that of the other methods considered for comparison form the literature.

Key words: QCA circuit, reliability, fault analysis-and-OR inverter, NAND-Nor inverter, ELMAN Neural Network, Genetic algorithm

INTRODUCTION

Von Neumann introduced the concept of cellular automata and an extension of this concept related to quantum computing is the development of Quantum-dot Cellular Automata (QCA). QCA is noted to be an emerging module in micro and nano electronics technology (Tougaw and Lent, 1996). Fundamentally, cellular automata operate on a uniform grid of cells and form a finite state machine. Here, at a particular discrete time instant one cell can be located at only one finite number of states. The approach of cellular automata is more developed on software modules and to implement and model it physically is the development of quantum-dot cells. This was first fabricated and implemented in the year 1997. This QCA is an important paradigm in contrast to that of the transistor paradigm. The QCA basically operates based on the adjustment of electrons within a minimal boundary area of hardly small amount of square nanometers in contrast to the transport of electrons. Currently, QCA has become an important emerging area of research in the past decade and the early works reported in the literature is presented in this study.

Turvani *et al.* (2014) present an innovative test environment for NML technology. The test algorithm is integrated in ToPoliNano and it is specifically tailored to support the analysis of faults in large complexity circuits. This methodology applied to NML circuits can also be applied to QCA technology. Das, etc. in 2013 introduced the logic synthesis with tile nanostructure in QCA. The Coupled Majority-minority Voter (CMmV) is most promising QCA tile structure which is actually used for designing n-variable symmetric functions. Dey *et al.* (2015) discussed the probability analysis of switching activity of an Electrostatic Quantum-dot Cellular Automata (EQCA) cell. The algebraic method is used to find the reliability using Probabilistic Transfer Matrix (PTM).

Sen *et al.* (2013) developed sequential circuits in QCA under multilayer framework to build an efficient

Corresponding Author: S. Vimalraj, Department of Electronics and Communication Engineering, Sri Krishna college of Technology, Kovaipudur, India

methodology to achieve high device density as well as minimum delay in logic realization. The proposed multilayer design achieves 77% improvement in device density simultaneously with 50% improvement in delay than that of the existing conventional design approaches. Mahdavi *et al.* (2009) investigated the effects of Single Event Upsets (SEU) on QCA circuits and the defects which may occur. Ganguly, etc., intended to see how optimized QCA designs perform in the presence of the manufacturing defects, i.e., to find the tolerance level of the QCA designs where clock zones have been optimized for speed. The proposed design optimization methodologies can generate a QCA implementation, not only faster but also defect tolerant. A QCA full adder is as an example for this analysis. Hanninen and Takala (2008) studied the relationship between system reliability and component failure rates, in the case of a binary multiplier unit on quantum-dot cellular automata nanotechnology. The analysis is based on a decomposition of probabilistic transfer matrices, a versatile framework for computing the conditional probability of system failure. The result indicates that passive wiring dominates the reliability of arithmetic designs on the nanotechnology.

Aghababa *et al.* (2008) described the design of an asynchronous circuit as an example to discuss the rules for translating a classical circuit to its QCA counterpart. Dysart and Kogge (2007) examined reliability considerations of several sample circuits when implemented in a molecular QCA technology. It is found that component error rates must be at or below 10-4 for an adder to function with 99% reliability and that the straight wire and majority gate are the most critical components to each circuit's reliability. Huang *et al.* (2007) analyzed the defect characterization of sequential devices and circuits implemented by molecular Quantum-dot Cellular Automata (QCA). The defect characterization shows that defects affect the functionality of basic QCA devices resulting mostly in unwanted inversion and majority voter acting as a wire at logic level.

Sikdar (2006) evaluated the effectiveness of state-of-the-art VLSI test mechanisms and investigates the possibility of more defect coverage through N-detectability in QCA designs. The experimental results shows that the conventional test technique for CMOS designs is also effective in QCA based designs. Huang *et al.* (2004) proposed a novel complex and universal QCA gate: the And-Or-Inverter (AOI) gate, which is a 5 input gate consisting of 7 cells. Design implementations using the AOI gate are compared with the conventional CMOS and the majority voter-based QCA methodology.

Hayati and Rezaei (2014) presented two methods, e.g., artificial neural network and a mathematical algorithm based on the QCA cell-cell response function named Tansig method are used for the modeling and simulation of QCA circuits at the cell level. Ganesh *et al.* (2007) proposed the use of Hopfield neural network design of simple QCA cells and study device level uncertainties like stable polarization at the output cell, near to ground state configuration of QCA cells. The proposed study is helpful to synthesize the QCA system for achieving high speed and errorless circuit. Neto *et al.* (2007) proposed the use of computational intelligence techniques in the simulation and in the automatic synthesis of QCA circuits. The optimization done by the proposed method reduces the possibility of failures and guarantees higher speed. Fortuna and Porto (2004) considered coupled quantum-dot cells for Quantum-dots Cellular Automata (QCA) to build Cellular Nonlinear Networks.

Khademi *et al.* (2014) presented a novel method for optimal implementation of three variable Boolean functions by using Ant Colony Optimization (ACO) algorithm. Simulation results demonstrate that the proposed method outperforms GA-based methods in the average number of required gates and levels for implementing three variable Boolean functions. Caires *et al.* (2013) proposed to synthesize QCA circuits using a Genetic algorithm that considers device robustness against external influences. The results obtained demonstrate that the method proposed is able to efficiently and automatically produce robust circuits with a reduced number of cells. Kamrani *et al.* (2012) proposed an efficient method based on Genetic Algorithms (GAs) to design Quantum Cellular Automata (QCA) circuits with minimum possible number of gates. The results show that the proposed approach is very efficient in deriving NAND based QCA designs.

Beiki *et al.* (2012) proposed an approach based on Genetic algorithm which reduces the area size of QCA circuits. Simulation results show that the proposed method is able to reduce area in QCA circuits design. Houshmand *et al.* (2011) proposed a method to minimize Boolean functions with an arbitrary number of outputs. Simulation results for the circuits with three, four and five outputs shows that the proposed method on the average results in 25.41, 28.82, 30.89% decrease in the number of required gates in comparison with optimizing each output independently. Houshmand *et al.* (2009) presented a method to reduce the number of primitive gates in a multi-output Boolean circuit based on genetic algorithm for converting sum of product expressions into a reduced number of QCA primitive gates in a single-output Boolean circuit. Simulation results show that the proposed method is able to reduce the number of primitive gates.

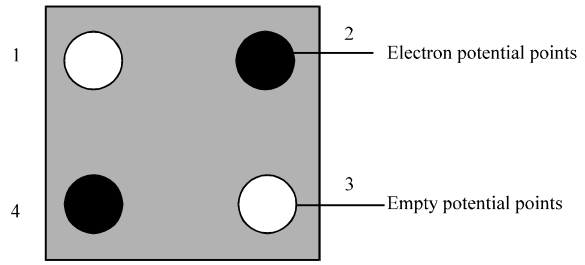

Fig. 1: Four site QCA cell

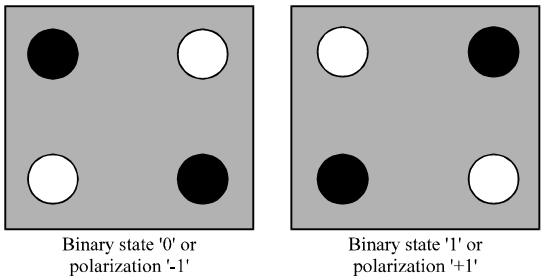

Fig. 2: States and polarization points of a QCA cell

Bonyadi *et al*. (2007) proposed a novel and efficient method for majority gate-based design. This method is based on genetic algorithm and can reduce the hardware requirements for a QCA design. The proposed approach is very efficient in deriving the simplified majority expression in QCA design.

Based on the above presented literature studies on the area of QCA, this study contributes a hybrid genetic algorithm based ELMAN neural network to perform fault and reliability analysis of QCA circuits. The features of GA approach are combined with that of the ELMAN neural modeling to obtain better simulation results. The proposed approach is also designed to ensure the robustness of the QCA devices and circuits. The physical coupling in QCA is carried out by Coulomb interaction between the electrons and not based on wired connections, i.e., it is noted that the flow of information in QCA is based on Coulomb interaction between two or more cells. ELMAN neural network with its weights optimized using genetic algorithm converges to obtain a minimal error rate and proving higher reliability of the considered quantum cell dots.

QCA cell and Gate modeling; an overview: Basically in QCA, the coupling between the cells is with respect to their physical interaction and not by means of the wired inter-connections. The implementation of QCA is carried out with respect of the quadratic cells which are also called as the QCA cells. Figure 1 represents a basic four site QCA cell. From Fig. 1, it can be noted that there exists four potential points on each corner of the QCA cell. In four dot QCA cell, two dots on one of the diagonal corner represents the electron potential points and the other two on the dots falling on the other diagonal part represents an empty operational point.

In Fig. 1, the solid dots represent the two electron points located diagonally. Here, between the individual quantum dots within a cell, the electrons are allowed to jump with the concept of Coulomb force and quantum tunneling (Snider *et al*., 1999). All the potential points in Fig. 1 are connected together by electron tunnel junctions and by employing a clock signal they will allow the electrons to travel within their stipulated boundaries. With respect to the Coulomb force which embodies between the electrons, they get separated from each other without any other external forces acting on these electrons. Henceforth is the case that they get embodied in the potential points that are located diagonally as they are the maximum possible distance that can separate each other. The QCA cell occurs in the form a square and as well known, there exists two diagonals in a square meaning that the electrons can embody in atleast two possible locations of the QCA cell. These two possibilities are defined as binary 1 or polarization +1 and as binary 0 or polarization -1, i.e., each of the QCA cell can be in either of the two binary states or on the polarization points. Basically, it is adaptable to the Boolean logic as employed in computers and in this case a high voltage is represented by polarization +1 or binary 1 and a low voltage is denoted by polarization -1 or binary 0. Figure 2 shows the two states of a four state QCA cell.

The polarization in QCA denotes a measure of the charge alignments along the cell diagonals. As in Fig. 1 and 2, if the cells 1 and 3 are occupied then it can be noted that the polarization is '-1' and if the cells 2 and 4 are occupied then the polarization is '+1'. In QCA cell, a superposition based on equal weights of the considered configurations results in a ground state and at this point the net polarization point becomes zero.

QCA majority voter and QCA Gates: In QCA modeling, the cell state can be transferred to multiple neighboring cells (Lent and Isaksen, 2003). The operation with multiple neighboring cells is carried in the similar way as that of the individual cells, but the sequential neighboring cells should have their junctions open at the same time which enables faster transfer. This makes the information transfer possible for large distances. The basic gate of QCA is the three input majority voter and this is constructed with five cells of individual four state QCAs. In QCA majority voter, when the entire input cell's Coulomb force corresponding to the electrons gets added, the centre cell located gets adjusted to that of the input cells. At the end, the final cell shown in blue color in

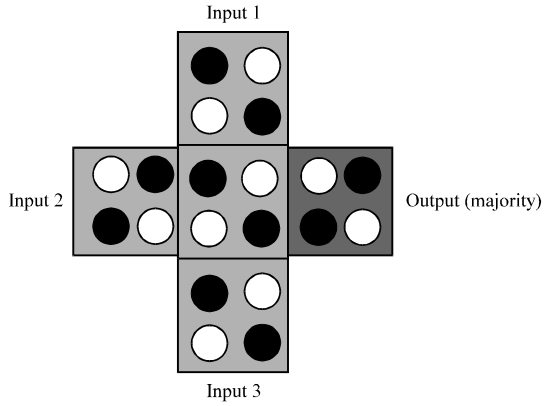

Fig. 3: Majority QCA voter

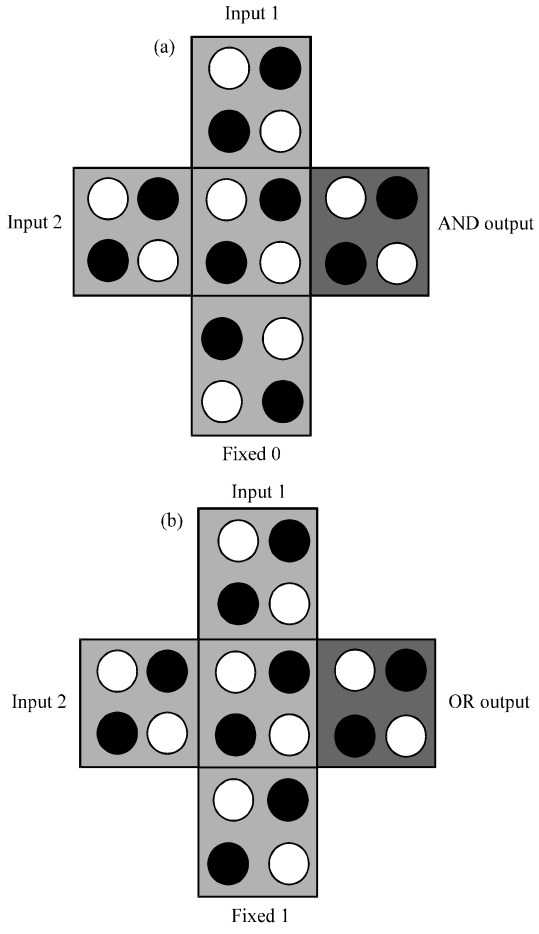

Fig. 4: a) QCA AND gate and b) QCA OR gate

Fig. 3 gets adjusted with respect to the centre cell and the majority votes resulting state is computed from the output cell. Figure 4 shows the QCA AND and QCA OR gate derived using the resultant Coulombs force on the positional states of the electron movements.

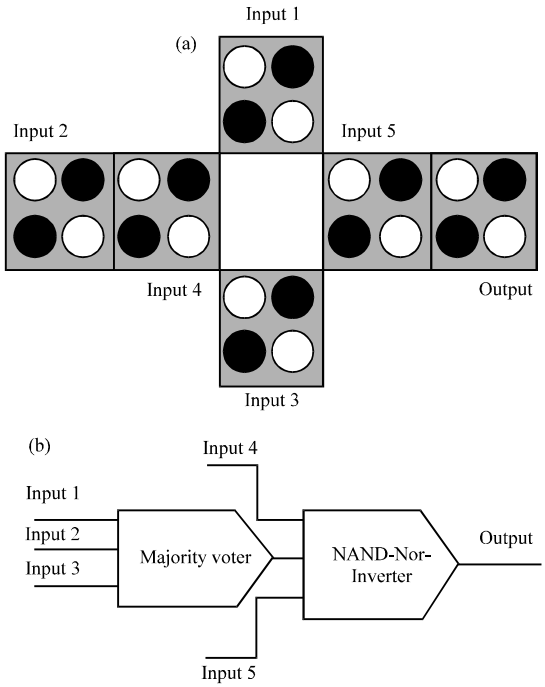

Fig. 5: a) QCA NAND-NOR Inverter module and b) QCA AND-OR-Inverter module

In QCA AND gate, the two inputs of the majority voter acts as the input to the AND gate and the third input forms always a 0 state and is a fixed cell and the voter should not come out with a 1, if only one input of the two inputs is 1. In case of both inputs becoming 1, it results in summing with a stronger Coulomb force than that of fixed cell input and the AND gate output is achieved. In QCA OR gate, fixed cell is always designed with a 1 state and this fixed cell adds to a larger Coulomb force with a single other input adjusted to 1, henceforth the OR gate produces an output 1 when any of the free inputs is 1. The QCA computing is carried out by mapping the physical ground state of the QCA array and that of the logical solution state of that of the computational problem under consideration. Figure 5 shows the NAND-NOR-Inverter and AND-OR-Inverter obtained using the majority voter.

Faults in QCA circuits: To design a QCA logic gate circuit, the four phase clocking signals are employed switch, relax, hold and release. Because of these four phase clocking signals this QCA gate circuit is noted to possess clock conflict errors. For example, in case of majority voter, all the cells should be in the same clock zone and making some cells present in different clock zones will lead to wrong results. In majority voter, the

three inputs, the centre cell and the output cell should always be in the same clock zone to avoid clock conflict error. The faults may tend to occur during the phases of chemical synthesis and deposition. Faults in QCA circuit means any ambiguities that tend to occur during the VLSI design phase. Faults occur during the fabrication phase as well. The most important faults that occurs in the QCA circuits involves:

- Additional deposition over the cells
- Deposition on the cells getting misplaced at other cell locations
- Deposition not made at the respective cells during the chemical synthesis and deposition phase of fabrication

This study aims to handle these errors and provide a solution for fault analysis of QCA circuits employing the proposed GA based ELMAN neural network model.

Formulating QCA dynamics (Porod *et al.*, 1999): Let the two basic states of the QCA cell be represented by ρ_1 and ρ_2 and these two states are polarized in nature. With respect to the basic states, the quantum state is:

$$\mu = \lambda\rho_1 + \beta\rho_2 \tag{1}$$

where, λ and β are the quantum amplitudes. Based on these quantum amplitudes, the cell polarization is given by:

$$P_c = |\lambda|^2 - |\beta|^2 \tag{2}$$

The quantum cell dynamics is given by:

$$i\bar{h}\omega/\omega|\mu| = H(\mu) \tag{3}$$

where, 'H' specifies the Hamiltonian specifier. Thus, for applying the proposed algorithms the cell polarization employed in Eq. 2 is used as the objective function to perform the iterative process and convergence to a reliability solution.

MATERIALS AND METHODS

Proposed hybrid ELMAN neural network model for QCA reliability analysis: This study focuses on developing a Hybrid Genetic algorithm based ELMAN neural network model to perform fault analysis and test the reliability nature of the quantum-dot cellular automata circuits. ELMAN neural network being a recurrent feed forward neural network is fed with the training data set of the position of the electrons located in the cell array and the testing dataset comprises of the new model of the developed QCA circuits for which the reliability test is to be done. In general, for a fundamental ELMAN neural network the weights that exist between the interconnected links are randomly assigned during the process flow and this random assignment leads to the occurrence of local minima problem and increases the elapsed training time of the network. Hence, in this study attempt is taken to optimize the weights to the ELMAN neural network employing the evolutionary approach Genetic algorithm. Genetic algorithm by its virtue of selection, crossover and mutation operations tends to compute the optimal weights and enhances the faster convergence of the ELMAN neural network model. The proposed hybrid GA based ELMAN neural network model is presented in this study.

Genetic algorithm-an outline (Sivanandam and Deepa, 2008): Genetic algorithm noted to be a evolutionary population based stochastic optimization approach operating on the principle of natural selection and is utilized to solve non-deterministic hard polynomial problems and as well combinatorial optimization problems. In the past few decades, GA has thrown its light in solving numerous optimization problems due to the fact of avoiding the derivatives of the considered objective functions. Henceforth, GAs is designed to solve problems with non-continuous cost functions and discrete models. GAs is capable of handling single objective as well multi objective optimization problems. The three main process involved in genetic algorithm flow includes selection (reproduction), crossover and mutation. These three operators of GA flow tend to produce new offsprings which are better than their parents. The process of GA flow is carried out for several generations and this procedure stops on identifying the individual with the optimal solution or as the termination condition is reached. The algorithmic steps involved for GA flow is as follows:

- Step 0: Start
- Step 1: Initialize the necessary parameters for the GA process like no. of populations, generations, crossover rate, mutation rate and type of selection process
- Step 2: Randomly generate populations (specified no. of chromosomes)
- Step 3: Compute the fitness of the generated chromosome in the population
- Step 4: Create a new population by performing the following steps until the new population is generated

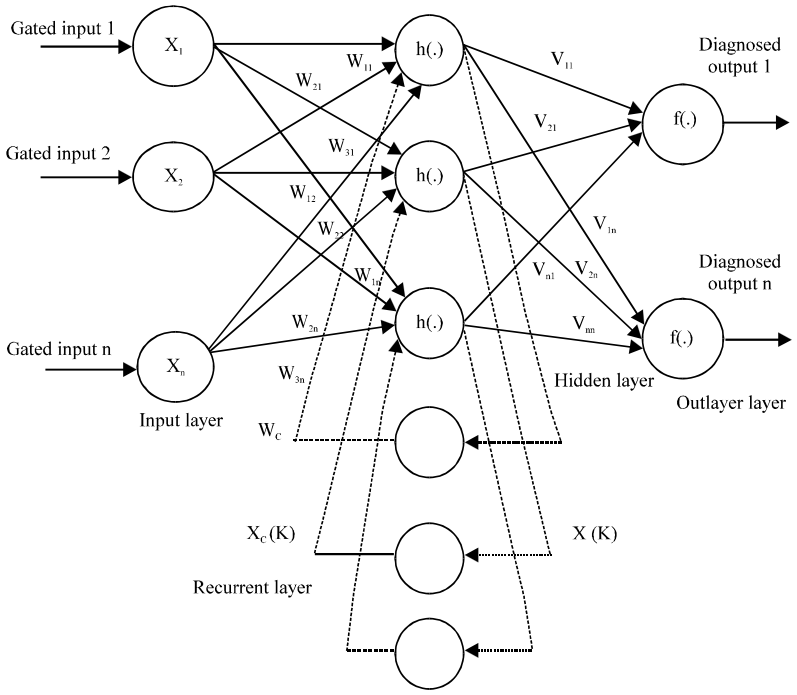

Fig. 6: The ELMAN neural network model for fault analysis

- Step 4(a): Selection; two parent chromosomes will be selected to participate in the process from a population according to their fitness (the one with the better fitness has the highest chance to get selected)
- Step 4(b): Crossover; perform cross over between the parents to generate new offspring. When no crossover takes place, then the offspring is the exact copy of parents
- Step 4(c): Mutation-mutate new offspring at each locus, i.e., the position in chromosome
- Step 4(d): Replacement, the developed new offspring would enter the new population
- Step 5: Employ the newly generated population to carry out the further process
- Step 6: If the termination condition is satisfied, stop and then return the best solution in current population, else
- Step 7: Go to step 3 to evaluate fitness function

In this study, the presented genetic algorithm is employed to determine the optimal weights of the recurrent feedforward ELMAN neural network and so as to identify the fault mechanisms of the designed QCA circuits.

ELMAN Neural Network model: ELMAN neural network (Lin and Hong, 2011) is a recurrent Neural Network Architecture model in which the recurrent links are incorporated into the hidden layer as feedback connection. The fundamental layers of ELMAN neural network include input, hidden, recurrent link and output layer. The design of recurrent layer is in a manner to follow one step delay of that of the hidden layer. The output of ELMAN neural network model is computed from its hidden layer. The complete information pertaining to the ELMAN hidden layer is stored in the recurrent link layer and this link layer retains the memory of the network. The hidden layer employs hyperbolic tangential sigmoidal activation function and the output layer uses purelin activation function. In case of the QCA fault analysis problem considered, the inputs are the gate signals under consideration and are binary or bipolar (polarization) in nature. Henceforth, the number of input neurons in ELMAN model depends on the gated input signals of the QCA circuit. As well as the output neurons in this case will be the existence of fault or not, so even a signal output neuron in the output layer would satisfy the need. The proposed ELMAN model for performing fault analysis is as shown in Fig. 6.

In Fig. 6, it is noted that each of the neuronal layers perform independent computation on the received data and that passes the results to the subsequent layers and finally the output is computed for the network. The gated input signals are transmitted through the hidden layer wherein the optimal weights computed employing GA

Table 1: Parameters in ELMAN Neural Network model

Parameters used in the network architecture	Description of parameters
$X_1, X_2, X_3, \ldots, X_n$	Gated input signals
$Y_1, Y_2, \ldots, Y_n$	Diagnosed output
$W = (W_{11}, W_{12}, \ldots, W_{1n}, W_{21}, W_{22}, \ldots, W_{2n}, \ldots, W_{31}, W_{32}, \ldots, W_{3n})$	Weighted interconnection between the input and the hidden layer
$V = (V_{11}, V_{12}, \ldots, V_{1n}, V_{21}, V_{22}, V_{23}, \ldots, V_{2n}, \ldots, V_{n1}, V_{n2}, \ldots, V_{nn})$	Weighted interconnection between the hidden and the output layer
$W = (W_{c11}, W_{c12}, \ldots, W_{c1n}, W_{c21}, W_{c22}, \ldots, W_{c2n}, \ldots, W_{c31}, W_{c32}, \ldots, W_{c3n}$	Weight interconnection of recurrent link layer to input vector
$X_c(K) = X(K-1)$	Input entering recurrent link layer

gets multiplied with the continuous hyperbolic tangential sigmoidal function. The recurrent link neural network learns the function based on current input along with the record of already diagnosed output. Added to this, the value X(k) gets transmitted through the second connection multiplied with that of the purelin activation function. Table 1 presents the parameters employed in the designed ELMAN neural network controller model for fault analysis of QCA circuits.

Algorithmic steps of ELMAN Neural Network model: The algorithmic procedure followed in the process of ELMAN Neural Network (NN) model is as given below.

Step 1; initialization process: Initialize the various parameters like learning rate, initial weights and activation functions of the ELMAN neural model. The necessary inputs from the considered QCA gates are also initialized.

Step 2; Data scaling: Min-Max technique is used to perform scaling operation, which scales within the range of [0 1]. The Min-Max technique is used for scaling of input data. The scaling of data is done by Eq. 4:

$$\phi_i' = \left(\frac{\phi_i - \phi_{min}}{\phi_{max} - \phi_{min}}\right)(\phi'_{max} - \phi'_{min}) + \phi'_{min} \quad (4)$$

where, ϕ_i, ϕ_{min} and ϕ_{max} are the actual input data, minimum and maximum input data and ϕ'_{min}, ϕ'_{max} are the minimum and maximum desired target value. In QCA circuits, since the gated inputs may be either in binary or bipolar as a result scaling operation may not be required.

Step 3; Design of ELMAN network: The various parameters like number of inputs, hidden and output neurons are to be assigned. Hidden layer neurons are set as half that of the input neuron. The input arguments get transmitted through the hidden layer wherein it gets multiplied with the weights and the hyperbolic sigmoid function is applied over it. The output is noted to get transmitted through the second connection and this gets multiplied with weights by purelin activation function. As the training progresses, past information is observed to reflect on the ELMAN neural network model. The termination condition for the neural network algorithm includes reaching the minimum error point or a fixed number of iterations.

Step 4; Training and computing performance of ELMAN NN model: The input data is presented into the designed neural network model and the learning process is initiated. The training data of the input QCA gate signals are used to develop reliability models and the diagnosed output determines whether or not the clock conflict error or misplaced deposition of cells occurs. Mean Square Error (MSE) is used as the criteria to perform effective training process. MSE is given by:

$$MSE = \sum_{i=1}^{N} \frac{(Y_i' - Y_i)^2}{N} \quad (5)$$

Where:
Y_i = Specifies the predicted output
Y'_i = Specifies the actual output
N = Gives the number of samples considered

Thus, this ELMAN network develops a fault analysis model to implement the action on the considered QCA gate circuit. Further, in the ELMAN Neuronal model Genetic algorithm technique is hybridized for tuning the optimal weights of the output layer and hidden layer and as well, the weights between the hidden layer and input layer. Figure 7 depicts the flowchart of the proposed methodology employing ELMAN neural network model to carry out reliability analysis of QCA circuits.

Proposed hybrid GA based ELMAN Neural Network model for fault analysis: This study proposes the approach of hybridizing ELMAN Neural Network model and Genetic algorithm to perform reliability analysis of QCA gate circuits under consideration. The ELMAN performs the synthesis action and the weights of ELMAN neural network are tuned for optimality to achieve minimum square error and faster convergence employing Genetic algorithm. In ELMAN NN model, the initial weights between all the layers including the recurrent layer are randomly initialized. This random initialization and random process of weight updation gets stuck up with the local and global minima during the training process of the network. Also, since randomness exist in

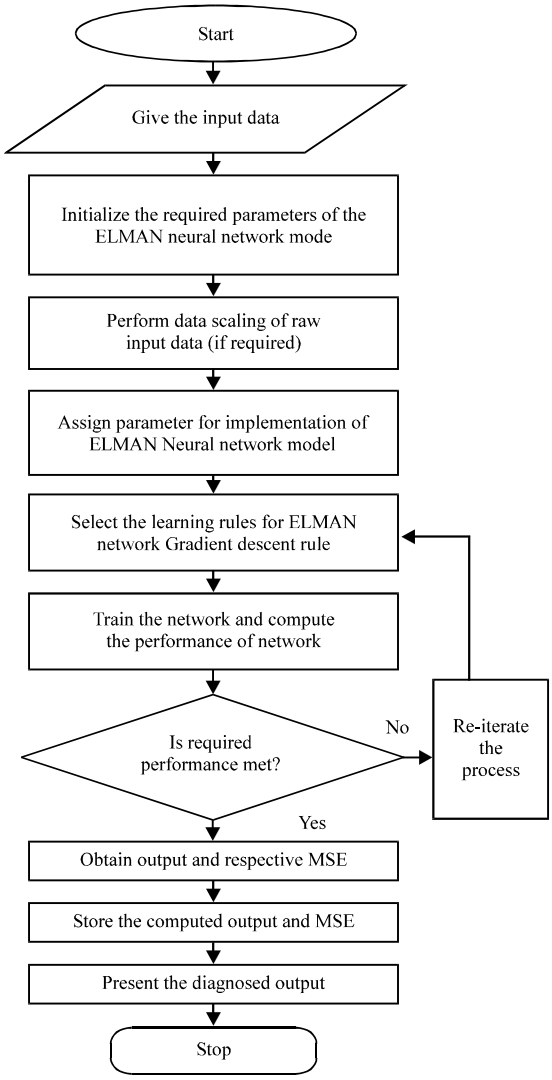

Fig. 7: Flowchart for the designed ELMAN neuronal model for QCA circuit analysis

the network, this leads to premature convergence of the neural network model. Henceforth, this paper aims to build a hybridized ELMAN neural model with that of the genetic algorithm approach to tune for the optimal weights resulting in faster convergence and avoiding the problems of local and global minima. The algorithm developed for the proposed hybrid GA-ELMAN NN model is as given below:

- Step 1: Initialize the necessary GA parameters no. of populations, crossover rate, mutation rate and so on
- Step 2: Compute the fittness of the problem considered (MSE) and sort the population from best to worst
- Step 3: While the termination condition criteria is not met do
- Step 4: Perform selection; fitest individual is selected to participate in the next process
- Step 5: Perform crossover; generate new offspring with the information of parents
- Step 6: Perform mutation; mutate the crossover strings to obtain another set of new offsprings
- Step 7: Evaluate the fitness and sort the population from best to worst. Reject the unfit population strings
- Step 8: Input the values related to best fitness to tune the weights
- Step 9: With the tuned weights, perform learning rule process of ELMAN neural network
- Step 10: Evaluate the mean square error of the network
- Step 11: Perform weight updation and compute the training performance
- Step 12: Sort the population strings
- Step 13: Check for feasibility of the computed soltuion
- Step 14: Stop the algorithmic process

The above presented hybrid GA based ELMAN neural network approach is used to perform fault and reliability analysis on the QCA Gate circuits. This ensures better solution and will not be over run and as well result in faster convergence towards the necessary action of the QCA problem domain.

Proposed hybrid ELMAN test model for reliable QCA design: The proposed hybrid GA based ELMAN neural network is employed in this paper to perform the fault analysis and test the reliability of QCA device at the gate level and circuit level. The developed hybrid ELMAN model is tested for its effectiveness by comparing it with the simulation carried over in the literature by QCA designer. Figure 8 shows the proposed hybrid GA-ELMAN model for QCA reliability analysis.

In this study, possible QCA layouts for a given logic are examined with necessary simulation studies over three fault factors additional cell deposition fault, random cell displacement fault and Missing cell depositional fault. To depict the applicability of the proposed hybrid ELMAN model with its optimal weights tuned using GA, test criterion is developed for three input majority voter with the specified three different faults. Extra cells are imposed on the three input majority voter around the inputs covering the maximum possible radius of effect over the QAC device cell as shown in Fig. 9.

Figure 9 shows the majority voter with three inputs; input 1, 2 and 3 and four extra cells as shown by extra cell 1 to extra cell 4. These four extra cells are noted to be mounted over the three input majority voter. The extra cell 1 is imposed between the input 1 and input 2, extra cell 4

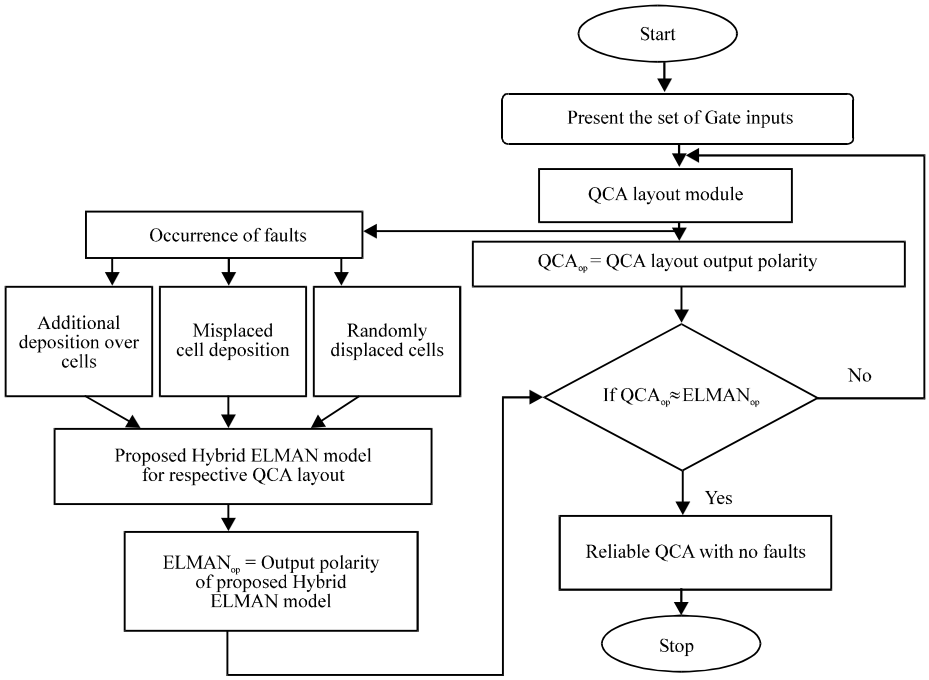

Fig. 8: Proposed hybrid GA-ELMAN model for QCA layout design analysis

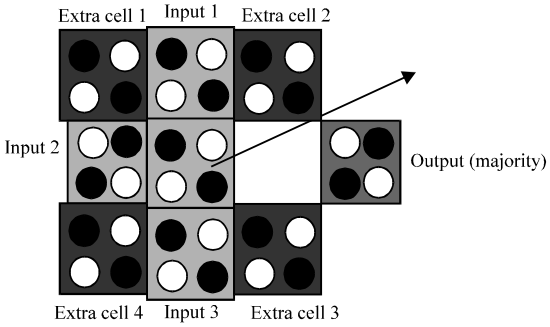

Fig. 9: Three input majority voter with 4 extra cells mounted

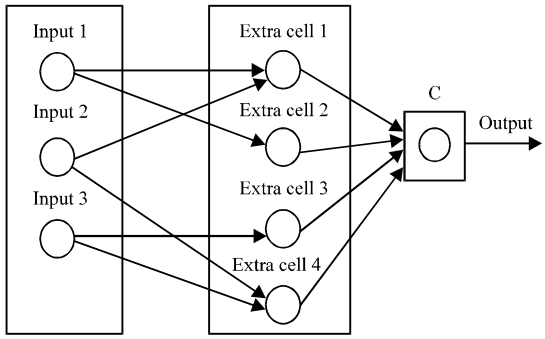

Fig. 10: Proposed Hybrid ELMAN model for 3 input QCA majority voter

is imposed between the input 2 and 3 and the extra cell 2 and 3 occurs near to input 1 and input 3, respectively. The complete effect of polarization of all the three inputs; input 1-3 with that of the four extra cells are imposed on the centre cell C and this polarization developed in 'C' cell is carried towards the output of the majority voter. Figure 10 shows the proposed hybrid ELMAN model of 3-input majority voter.

RESULTS AND DISCUSSION

Simulation results: The simulation results present the measurement of prediction of fault tolerance at the time of fabrication of three input majority voter. The faults occur in the three input majority voter at the time of deposition phase like the additional cell deposition, missing cell deposition points and misplacement of deposition in another cell positions. The computed simulation results considering the fault cases are presented in this study.

The realization of 3 input majority voter using the proposed hybrid GA based ELMAN model is performed in the following manner. To start with the weights of all the three inputs are taken to be +1 and the net input is calculated. Extra cell 1 and 4 generates a+2 and the Extra cell 2 and 3 generates a+1. The cumulative sum at C is noted to be >0, resulting in the polarization to be +1.

Table 2: Proposed hybrid GA - ELMAN Neural Network parameters

Parameters of the ELMAN NN model	Set values	Parameters of GA process	Set values
Number of output neurons	1.00	No. of populations	30
No. of hidden layer	1.00	No. of generations	100
No. of Epochs	100	Crossover rate	0.1
Threshold	1.00	Mutation rate	0.01
Learning rate parameter	0.10	Selection	Roulette wheel
Activation function	Tangential sigmoidal	Crossover	Two-point crossover

Table 3: MSE evolved during generations

Generations	Mean square error values
10	0.3576
20	0.3145
30	0.2579
40	0.1999
50	0.1865
60	0.1022
70	0.0772
80	0.0247
90	0.0155
100	0.0039

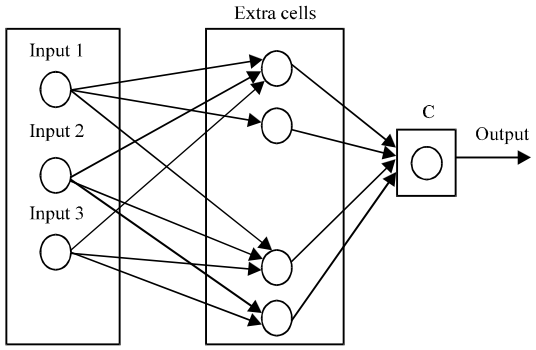

Fig. 11: Proposed GA ELMAN model for 3 input majority voter (extra cell deposition)

When the weights of the inputs are changed to that of -1, the cumulative sum obtained at the 'C' point is noted to be less than zero and results a polarization of -1. All the possible randomly generated weights are chosen for the three inputs and the realization process is carried out by simulation and the optimal weights tuned by GA process. Table 2 shows the parametric values of the proposed hybrid GA ELMAN model employed for fault analysis of QCA circuits. Table 3 gives the MSE values generated during the training process of three input majority voter module.

Additional cell deposition: In this case of extra cell deposition, to analyze the fault condition eight additional cells are deposited on the three input majority voter. Figure 11 shows the proposed hybrid ELMAN model for the tiled three input majority voter. Table 4 presents the computed simulation results employing the proposed approach and that of the solution from QCA designer. The comparison of the simulated results obtained

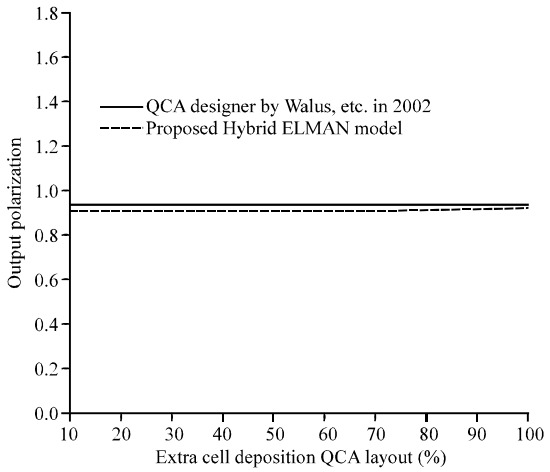

Fig. 12: Convergence plot of the proposed model (extra cell deposition case)

using the proposed approach and that from the QCA designer from the existing literature is given in Fig. 12. The computed results prove the effectiveness of the proposed model and it justifies the significance with that of the simulation of QCA designer for fault of extra cell deposition.

Missing cell deposition: With respect to the missing cell deposition, it can be noted that the device cell is missing in the three input majority voter. Figure 13 shows the missing cell in 3 input majority voter and as well the proposed ELMAN model of the same. In case of the proposed Hybrid ELMAN model, the input polarization of all the inputs are noted to be imposed on the driver cell as specified by CR. This CR cell tends to calculate the weighted sum of the inputs and determine the output polarization. Table 5 shows the computed results using the QCA designer as available in the literature and as that computed from the proposed model. The simulated results prove that employing the proposed model, it can be noted that the output polarization gets decreased but tend to remain same using the QCA designer. The decrease in output polarization using the proposed model proves that the reliability is reduced with the missing cell deposition occurrence. Hence, the proposed model diagnoses that with the noted fault of missing cell deposition, the reliability of the QCA circuit gets reduced which is

Table 4: Simulation result of extra cell deposition of three input majority voter

Inputs for three input majority voter					
Input 1	Input 2	Input 3	Extra cell deposition from the exact layout (%)	Output polarization with QCA designer by Walus etc. in 2002	Output polarization using proposed model
1	1	-1	10	+0.959	+0.900
1	1	-1	20	+0.959	+0.912
1	1	-1	30	+0.959	+0.937
1	1	-1	50	+0.959	+0.941
1	1	-1	75	+0.959	+0.949
1	1	-1	100	+0.959	+0.951

Table 5: Simulation result of missing cell deposition of three input majority voter

Inputs for three input majority voter					
Input 1	Input 2	Input 3	Extra cell deposition from the exact layout (%)	Output polarization with QCA designer by Walus etc. in 2002	Output polarization using proposed model
1	1	-1	10	+0.942	+0.950
1	1	-1	20	+0.942	+0.903
1	1	-1	30	+0.942	+0.826
1	1	-1	50	+0.942	+0.791
1	1	-1	75	+0.942	+0.645
1	1	-1	100	+0.942	+0.527

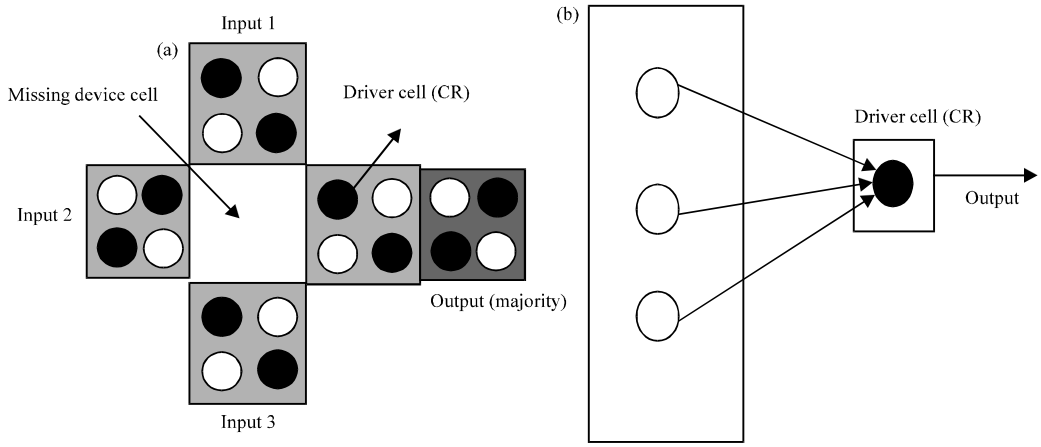

Fig. 13: a) Configuration of missing cell in 3 input majority voter and b) Proposed model of missing cell deposition

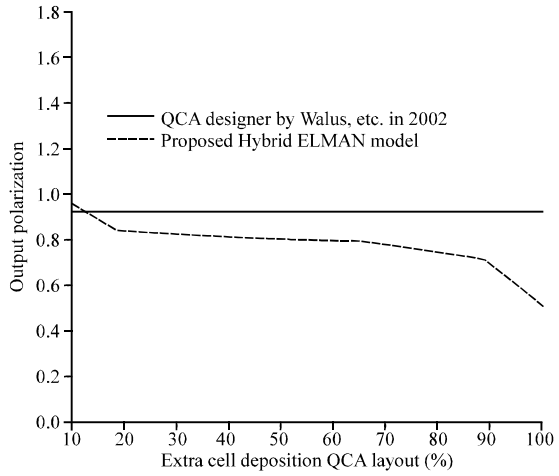

Fig. 14: Convergence plot of the proposed model (missing cell deposition case)

indicated by the decrease in value of output polarization. Figure 14 shows the results of output polarization obtained using the proposed model and its comparison with the results of QCA designer.

Misplacement in the cell deposition: This type of misplacement fault is noted to occur during the deposition phase of the fabrication process. In this case for analyzing, lets consider that the cells are misplaced around up/down and left/right in the exact QCA layout. The misplacement of cell position is studied in this study of 10% cell to that of 100% cell with the displacements defined as<5 nm and between 5-7 nm. Table 6 shows the simulated results computed using the proposed model and as well that of the traditional QCA designer module. The misplacement of cell position is as shown in Fig. 15 along with the proposed model and Fig. 16 shows the convergence plot of the output computed.

Table 6: Simulation result of misplacement cell deposition of three input majority voter

Inputs for three input majority voter			Misplacement cell (<5 nm) deposition from the exact layout	Output polarization with QCA designer by Walus, etc. in 2002	Output polarization proposed using model	Misplacement cell (5-7 nm) deposition from the exact layout	Output polarization with QCA designer by Walus etc in 2002	Output polarization proposed using model
Input 1	Input 2	Input 3						
1	1	-1	10	+0.931	+0.930	10	+0.873	+0.870
1	1	-1	20	+0.872	+0.851	20	+0.849	+0.824
1	1	-1	30	+0.756	+0.737	30	+0.827	+0.819
1	1	-1	50	+0.739	+0.724	50	+0.800	+0.765
1	1	-1	75	+0.726	+0.709	75	+0.769	+0.738
1	1	-1	100	+0.703	+0.685	100	+0.717	+0.698

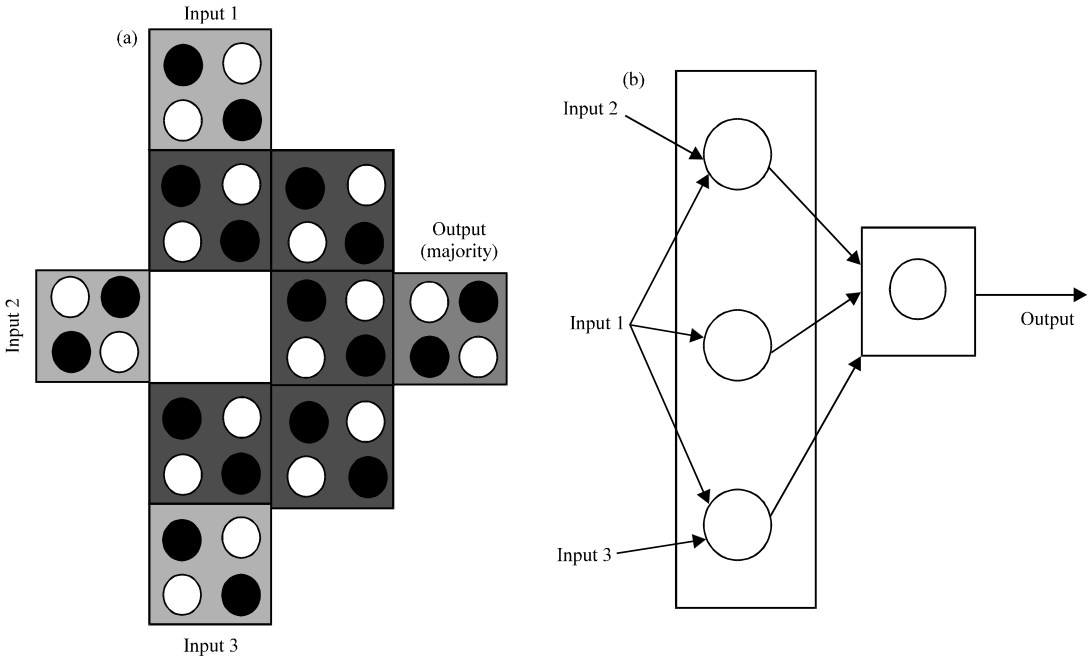

Fig. 15: a) Configuration of misplaced cell in 3-input majority voter and b) Proposed model of misplaced cell deposition

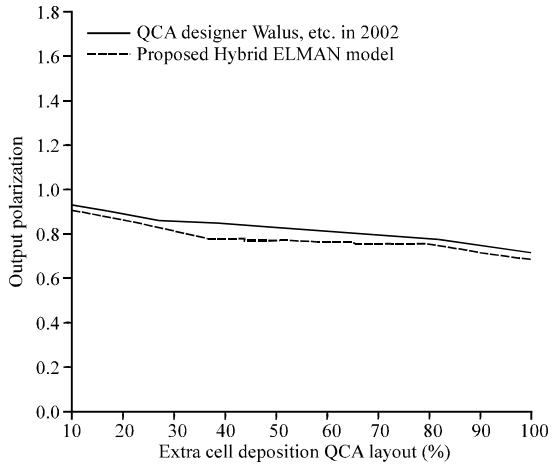

Fig. 16: Convergence plot of the proposed model (misplacement cell deposition <5 nm)

Discussion on the simulated results: The simulated results are computed employing the proposed model for the considered fault cases of extra cell deposition, missed cell deposition and misplaced cell deposition of three input majority voter. From the computed simulation results, the following observations are made. With respect to the occurrence of extra cell deposition on the three input majority voter, the results show that the proposed model achieves steady increase in output polarization rate in comparison with that of the traditional QCA designer which remains the same for all extra cell deposition rates. In connection with that of the missed cell entity wherein the device cell is vanished and the existence of driver cell is noted which drives towards the output cell. The obtained results show that there is a higher reduction rate in the output polarization employing the proposed model which substantiates that the reliability and robustness has got decreased which is not been observed when using the regular QCA designer. Thus, the proposed model achieves and analyses the reliability nature of the system. The case of misplaced cells, the results are obtained for <5 nm misplacement and between 5-7 nm cell

misplacement. There is a steady decrease in the output polarization rate of the proposed model proving the reduction in robustness and reliability nature of the system and it analyses in a better way than that of the regular QCA designer. Thus, the convergence plots of each of the three fault cases of the majority output voter proves an effective analysis is made on the reliability and robust nature of the QCA circuit.

CONCLUSION

A Hybrid Genetic algorithm based ELMAN Neural Network model is developed in this study to carry out fault analysis and test the reliability nature of the QCA circuits. QCA circuits are basically operating on cell mechanisms and their respective movements. This study explores the three input majority voter circuit of QCA module. In the three input majority voter, the located faults that can occur during the fabrication phase are analyzed; extra cell deposition, missed cell deposition and misplacement cell deposition. The proposed ELMAN model is trained for the optimal weights employing the Genetic algorithm approach and the simulation results are computed for basic three input majority voter and as well with the specified three faults included. The obtained simulated results prove the effectiveness of the proposed model in determining the reliability nature of the considered QCA circuit.

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