NEURAL NETWORK FOR THE RELIABILITY ANALYSIS OF A SERIES – PARALLEL SYSTEM SUBJECTED TO FINITE COMMON-CAUSE, FINITE HUMAN ERROR AND FINITE ENVIRONMENTAL FAILURES

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Abstract: *In the existing environment, no machine is cent percent accurate as there are many parameters causing failures, so that the reliability of the machine tends to zero. In series –parallel system there are many parameters causing failure to the systems such as common-cause, human error and environmental error. The traditional methods gives less accurate solution to the series-parallel system or a solution with error. So we use artificial network method to solve a series-parallel system to achieve high computation rates.*

In this paper we present artificial network method to find reliability analysis of a series-parallel system subjected to finite common cause, finite human error and environmental error.

Keywords: Markov model, environmental error, Common cause, human error,series –parallel system.

1.INTRODUCTION

In the present Electronic era, the efficiency of a system is the combination of properties that determine the degree of suitability of the system for the fulfillment of the task. There are many parameters to measure the systems efficiency such as reliability, survivability, availability, maintainability etc. Reliability is defined as the ability to perform its intended function satisfactorily of the system under some operating conditions i.e. the reliability R(t) of a system is the probability that the component will not fail for a time t.

A system is a combination of many modules (components). Sometimes under the some identical conditions, different systems fail at different times, making failures with some probability distribution such as weibull, Gamma and Normal distribution.

The reliability of the system depends on how the individual components with their individual failure rates are arranged. If the 'n' components of a system is arranged in series i.e. if the components are arranged so that the failure of any component causes the system failure, then the reliability of the system, R is given by $R=R_1R_2R_3......R_n$,where R_i denotes the reliability of the i^{th} component is exponentially distribution with parameter λ_i then reliability of the system R is given by

$$R= e^{-(\lambda_1+\lambda_2+....+\lambda_n)t}$$

If the n-components of a system are arranged in parallel i.e the system fails only when all the components fail then the reliability of the system is given by

$$R=1-[(1-R_1)(1-R_2)......(1-R_n)]$$

If the failure rates of components are exponentially distributed with parameters λ_i, i=1,2,3....n then the reliability of the system is given by

$$R= 1-[(1-e^{-\lambda_1 t})(1-e^{-\lambda_2 t})......(1-e^{-\lambda_n t})\ ]$$

Reliability Function R(t): The reliability function R(t) is defined as

R(t)=prob{system up-time in (0,t)/system up at t=0}

Failures of a system is mainly due to the failure of its components common cause, human error and environmental error are some parameters causes failure to the system.

Anandarajachari and sasthri(1) have studied availability analysis of two component system with common-cause failures. Recently Dhillon and etall(2) have also studied the effect of common cause failures on reliability of the system. A detailed literature in common cause failures can be found in Dhillon(2).

Human error is an error due to the performance of a normal task with wrong input. Dhillon(3) in his book on human reliability states various studies have indicated that a significant proportion of system failures are due to human errors.

Environmental error is a sudden, unexpected failure due to the environmental situations such as Tsunami, earthquake etc., The probability of failure is very less hence it is not considered many times, but error due to environment is also effects the system. In this paper we consider environmental error also for any parallel series system.

Over past 15 years a new has energed that computing based on models inspired by our understanding of the biological neural networks, they hold the key to the success of solving intelligent tasks by machines, the new field is called ANN'S it is more to describe parallel and distributes. ANN'S is based on the working of human brain by making the right connections can be initiated using silicon wires as living neurons and dendrites.

The inventor of the first neuro computer Dr. Robert Neilson defines neural networks as "A computing system made up of a number of simple, highly interconnected processing elements which process information by their dynamic state response to external inputs".

The human brain is composed of 100 billion nerve cells called neurons, which are connected to other thousand cells by axons, stimuli from external environment or input from sensory organs are accepted by dendrites. These inputs create electric impulses which quickly travel through the neural network, a neuron can send the message to other neuron to handle the issue or does not send it forward.

ANN'S are composed of multiple nodes, which initiate biological neurons of human brain, the neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations in the data. The result of these operators is passed to other neurons. The output at each node is called its activation or node value each link is associated with weight, ANN'S are capable of learning which takes place by alternating weight values.

1.1 Feed Forward Networks:

The first layer serves only to distribute a weighted version of the input vector to the neurons in the inner layer. Neurons in the inner layer called hidden neurons respond to the accumulated effects of their inputs and propagate their response signals to neurons in the output layer. There are several powerful algorithms(4,5) available for adopting the strengths of the inter connections between neurons in feed forward network so that the network learns to map input patterns into derived output patterns.

1.2 Feed Back Networks:

Neural models that permit feedback have been employed to develop networks capable of unsupervised learning, self-organization, retrieving stored memory patterns and computing solutions to a variety of optimization problems.

2. Markov model:

In the Markov model approach we assumed that behavior of the system must be same at any point of time. Thus it is uniquely characterized as stationary or homogeneous process. This means that the probability of making a transition from one state to another is same. Therefore the Markov approach is applicable to those systems, whose behavior can be described by probability distribution namely poisson and exponential which is based on constant failure rate. The literature on Markov random process and its applicability to the reliability analysis is discussed in Cox(6).

Series-Parallel System:

Consider the markov model of a series-parallel system consisting n units.

ASSUMPTIONS

The following assumptions are associated with the system under study:
(q) Failures are statistically independent.
(r) All system units are active, identical and form a parallel network.
(s) A unit failure rate is constant.
(t) A Common - Cause failure or a critical human error or a environmental error leads to system failure.
(u) A Common - Cause failure or a critical human error or a environmental error can occur when one (or more) unit is operating.
(v) Critical human error, environmental failure and Common - Cause failure rates are constant.
(w) Failed system repair rates are constant / non-constant.
(x) At least one unit must operate normally for the system's success

SYMBOLS

The following symbols are associated with this model :
n - Number of units in the parallel system
λ - constant failure rate of a unit
i - system up state as shown in boxes of fig 4.5
i = 0 (all units operating normally),
i = 1 (one unit failed, (n-1) operating),
i = 2 (two units failed, (n-2) operating),
i = 3 (three units failed, (n-3) operating),
i = 4 (four units failed, (n-4) operating),
i = k (k units failed, (n-k) / one operating).
K - number of failed units in the system and corresponding up state of the system,
for k = 1, 2.........(n-1)

λc_{1i}, λc_{2i} - Constant Common Cause failure rate from system up state i,
for i = 0, 1, 2......k
λh_{1i}, λh_{2i} - Constant critical human error rate from system up state i ,
for i = 0, 1, 2, ...k
λe_{1i}, λe_{2i} - Constant environmental error rate from system up state i ,
for i = 0, 1, 2, ...k
i= System down state as shown boxes
j=n (all units failed other than due to a common-cause failure or a critical human error or a environmental error)
j = c_1,c_2 ...c_k (system failed due to Common Cause failure)
j = h_1, h_2...h_k (system failed due to a critical human error)
j= e_1,e_2......e_k(system failed due to a critical environmental error)

Pi(t) - Probability that the system is in up state i, at time t, for i = 0, 1, 2, 3,........k
Pj(t) - Probability that the system is in down state j at time t, for j = n, c_1,c_2,.....c_k, h_1,h_2,.....h_k,e_1,e_2,......e_k.
Pi - Steady state probability that the system is in up state i, for i = 0, 1, 2,.........k
Pj - Steady state probability that the system is in down state j, for j = n, c_1,c_2,.....c_k, h_1,h_2,.....h_k,e_1,e_2,......e_k.
R1(x),r_2(x),.....r_k(x),q_{c1}(x),q_{c2}(x),.....q_{ck}(x)-repair rate and probability density function of repair times respectively when the failed system is in states c_1c_2.....c_k and has an elapsed repair time of x.
Z_1 (x),z_2(x),.....z_k(x),q_{h1}(x),q_{h2}(x),.....q_{hk}(x)-repair rate and probability density function of repair times respectively when the failed system is in states h_1h_2.....h_k and has an elapsed repair time of x.
y1(x),y_2(x),.....y_k(x),q_{e1}(x),q_{e2}(x),.....q_{ek}(x)-repair rate and probability density function of repair times respectively when the failed system is in states e_1e_2....e_k and has an elapsed repair time of x.
$\mu(x), q_n(x)$- repair rate and probability density function of repair times respectively when the failed system is in state n and has an elapsed repair time of x.
M, R1(x),r_2(x),.....r_k(x), Z_1 (x),z_2(x),.....z_k(x) ,y1(x),y_2(x),.....y_k(x)-constant repair rates from the failed system states n, c_1,c_2,.....c_k, h_1h_2.....h_k, e_1e_2....e_k

GENERAL MODEL

The system transition diagram is shown in fig 4.5

The discrete time equations for the Markov model are given by

$$p_0(t+\Delta t) = p_0(t)[1-n\lambda\Delta t-\lambda_{c10}\Delta t-\lambda_{c20}\Delta t-\lambda_{c30}\Delta t-\lambda_{ck0}\Delta t-\lambda_{h10}\Delta t \\ \lambda_{h20}\Delta t-\lambda_{h30}\Delta t-.....-\lambda_{hk0}\Delta t-\lambda_{e10}\Delta t-\lambda_{e20}\Delta t-\lambda_{e30}\Delta-......-\lambda_{ek0}\Delta t]+ \\ p_1(t)n\lambda\Delta t+p_{c1}(t)\lambda_{c10}\Delta t+......+p_{ck}(t)\lambda_{ck0}\Delta t$$

$$p_{c1}(t+\Delta t) = p_0(t)r_1\Delta t + p_{c1}(t)[1-r_1\Delta t]$$

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$$p_{ck}(t+\Delta t) = p_0(t)r_k\Delta t + p_{ck}(t)[1-r_k\Delta t]$$

$$p_{h1}(t+\Delta t) = p_0(t)z_1\Delta t + p_{h1}(t)(1-z_1\Delta t)$$

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$$p_{hk}(t+\Delta t) = p_0(t)z_k\Delta t + p_{hk}(t)[1-z_k\Delta t]$$

$$p_{e1}(t+\Delta t) = p_0(t)y_1\Delta t + p_{e1}(t)[1-y_1\Delta t]$$

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$$p_{ek}(t+\Delta t) = p_0(t)y_k\Delta t + p_{ek}(t)[1-y_k\Delta t]$$

$$p_1(t+\Delta t) = p_{c1}(t)\lambda_{c11}\Delta t + p_{c2}(t)\lambda_{c21}\Delta t + p_{c3}(t)\lambda_{c31}\Delta t+...+ \\ p_{ck}(t)\lambda_{ck1}\Delta t + p_{h1}(t)\lambda_{h11}\Delta t+...+p_{hk}(t)\lambda_{hk1}\Delta t+p_{e1}(t)\lambda_{e11}\Delta t+...+ \\ p_{ek}(t)\lambda_{ek1}\Delta t + p_2(t)(n-1)\lambda\Delta t + p_1(t)[1-\lambda_{c11}\Delta t-\lambda_{c21}\Delta t-......- \\ \lambda_{ck1}\Delta t-\lambda_{h11}\Delta t-\lambda_{h21}\Delta t-...-\lambda_{hk1}\Delta t-\lambda_{e11}\Delta t-\lambda_{e21}\Delta t-....- \\ \lambda_{ek1}\Delta t-(n-1)\lambda\Delta t]$$

$$p_2(t+\Delta t) = p_{c1}(t)\lambda_{c12}\Delta t+...+p_{ck}(t)\lambda_{ck2}\Delta t+p_{h1}(t)\lambda_{h12}\Delta t+...+ \\ p_{hk}(t)\lambda_{hk2}\Delta t+p_{e1}(t)\lambda_{e12}\Delta t+.....+p_{ek}(t)\lambda_{ek2}\Delta t+p_3(t)(n-2)\lambda\Delta t \\ +p_2(t)[1-\lambda_{c12}\Delta t-\lambda_{c22}\Delta t-......-\lambda_{ck2}\Delta t-\lambda_{h12}\Delta t-\lambda_{h22}\Delta t-... \\ -\lambda_{hk2}\Delta t-\lambda_{e12}\Delta t-\lambda_{e21}\Delta t-....-\lambda_{ek2}\Delta t]$$

$$p_3(t+\Delta t) = p_{c1}(t)\lambda_{c13}\Delta t+p_{c2}(t)\lambda_{c23}\Delta t+p_{c3}(t)\lambda_{c33}\Delta t+... \\ +p_{ck}(t)\lambda_{ck3}\Delta t+p_{h1}(t)\lambda_{h13}\Delta t+...+p_{hk}(t)\lambda_{hk3}\Delta t+p_{e1}(t)\lambda_{e13}\Delta t+... \\ +p_{ek}(t)\lambda_{ek3}\Delta t+p_3(t)[1-\lambda_{c13}\Delta t-\lambda_{c23}\Delta t-......-\lambda_{ck3}\Delta t-\lambda_{h13}\Delta t \\ -\lambda_{h23}\Delta t-...-\lambda_{hk3}\Delta t-\lambda_{e13}\Delta t-\lambda_{e23}\Delta t-....-\lambda_{ek3}\Delta t-(n-3)\lambda\Delta t]$$

$$p_k(t+\Delta t) = p_{c1}(t)\lambda_{c1k}\Delta t+p_{c2}(t)\lambda_{c2k}\Delta t+p_{c3}(t)\lambda_{c3k}\Delta t+... \\ +p_{ck}(t)\lambda_{ckk}\Delta t+p_{h1}(t)\lambda_{h1k}\Delta t+...+p_{hk}(t)\lambda_{hk1}\Delta t+p_{e1}(t)\lambda_{e1k}\Delta t \\ +.....+p_{ek}(t)\lambda_{ekk}\Delta t+p_{k+1}(t)(n-k)\lambda\Delta t-p_k(t)[1-\lambda_{c1k}\Delta t- \\ \lambda_{c2k}\Delta t-......-\lambda_{ckk}\Delta t-\lambda_{h1k}\Delta t-\lambda_{h2k}\Delta t-...-\lambda_{hkk}\Delta t-\lambda_{e1k}\Delta t- \\ \lambda_{e2k}\Delta t-....-\lambda_{ekk}\Delta t-(n-k)\lambda\Delta t]$$

$$p_n(t+\Delta t) = p_0(t)\mu\Delta t + p_n(t)(1-\mu\Delta t)$$

The Neural Network For a series –parallel system

A feed forward cascade recursive network is set to represent the parallel system. As shown in fig the network consists of two layers of neurons: one form by input and other forms the output, the number of neurons in each layer equals to the number of states, in Markov model.

$W_{12} = \lambda_{c10}\Delta t \qquad W_{21} = r_1\Delta t$

$W_{3K+2,K+1} = \lambda_{C1K}\Delta t$

$W_{12} = \lambda_{c10}\Delta t \qquad W_{21} = r_1\Delta t$

$W_{1,K+1} = \lambda_{ck0}\Delta t \qquad W_{K+1,1} = r_k\Delta t$

$W_{1,K+2} = \lambda_{h10}\Delta t \qquad W_{K+2,1} = Z_1\Delta t$

$W_{1,K+3} = \lambda_{hk0}\Delta t \qquad W_{2K+1,1} = Z_K\Delta t$

$W_{1,2K+2} = \lambda_{e10}\Delta t \qquad W_{2K+2,1} = Y_1\Delta t$

$W_{1,3K+1} = \lambda e_{k0}\Delta t \qquad W_{3K+1,1} = Y_K\Delta t$

$W_{3k+2,2} = \lambda c_{11}\Delta t \qquad W_{3K+3,2} = \lambda_{C21}\Delta t$

$W_{3k+3,2} = \lambda c_{21}\Delta t \qquad W_{3K+4,2} = \lambda_{C31}\Delta t$

$W_{3k+4,2} = \lambda c_{31}\Delta t \qquad W_{4K+1,2} = \lambda_{CK1}\Delta t$

$W_{4k+1,2} = \lambda c_{k1}\Delta t \qquad W_{3K+2,3K+3} = (n-1)\lambda\Delta t$

$W_{3K+3,2K+2} = \lambda_{e11}\Delta t \qquad W_{3K+3,3K+4} = (n-2)\lambda\Delta t$

$W_{3K+4,2K+2} = \lambda_{e21}\Delta t \qquad W_{3K+4,3K+5} = (n-3)\lambda\Delta t$

$W_{3K+4,2K+2} = \lambda_{e31}\Delta t \qquad W_{3K+3,3K+4} = (n-k)\lambda\Delta t$

$W_{3K+n+1,1} = \mu\ \Delta t$

$W_{3K+4,2K+2} = \lambda_{ek1}\Delta t$

$W_{4K+1,3K+1} = \lambda_{ekk}\Delta t$

$W_{3K+2,3K+2} = 1 - W_{3k+2,1}$

$W_{3K+2,3K+3} = 1 - W_{3k+3,1}$

$W_{4K+1,4K+1} = 1 - W_{4k+1,1}$

$W_{3K+4,K+1} = \lambda_{C3K}\Delta t$

$W_{3K+2,2K+1} = \lambda_{h1K}\Delta t$

$W_{3K+3,2K+1} = \lambda_{h2K}\Delta t$

$W_{3K+4,2K+1} = \lambda_{h3K}\Delta t$

$W_{4K+1,2K+1} = \lambda_{hKK}\Delta t$

$W_{3K+2,K+2} = \lambda_{h11}\Delta t$

$W_{3K+2,K+2} = \lambda_{h21}\Delta t$

$W_{3K+4,K+2} = \lambda_{h31}\Delta t$

$W_{4K+1,K+2} = \lambda_{hK1}\Delta t$

$W_{3K+2,3K+1} = \lambda_{e1k}\Delta t$

$W_{3K+3,3K+1} = \lambda_{e2k}\Delta t$

$W_{3K+4,3K+1} = \lambda_{e3k}\Delta t$

$W_{11} = 1 - \left[W_{12} + W_{1,K+1} + W_{1,K+2} + W_{1,K+3} + W_{1,2K+2} + W_{1,3K+1}\right]$

$W_{22} = 1 - W_{11}$

$W_{K+1,K+1} = 1 - W_{K+1,1}$

$W_{K+2,K+2} = 1 - W_{K+2,1}$

$W_{2K+1,2K+1} = 1 - W_{2K+1,1}$

$W_{2K+2,2K+2} = 1 - W_{2K+2,1}$

$W_{3K+1,3K+1} = 1 - W_{3K+1,1}$

$$W_{2K+n+1,2K+n+1} = 1 - W_{2K+n+1,1}$$

At any time 't' during operation of the system

$$X_1 = P_0(t) \qquad Y_1 = P_0(t+\Delta t)$$

$$X_2 = P_{C1}(t) \qquad Y_2 = P_{C1}(t+\Delta t)$$

$$X_{k+1} = P_{Ck}(t) \qquad Y_{k+1} = P_{Ck}(t+\Delta t)$$

$$X_{k+2} = P_{h1}(t) \qquad Y_{k+2} = P_{h1}(t+\Delta t)$$

$$X_{2k+1} = P_{hk}(t) \qquad Y_{2k+1} = P_{hk}(t+\Delta t)$$

$$X_{2k+2} = P_{e1}(t) \qquad Y_{2k+2} = P_{e1}(t+\Delta t)$$

$$X_{3k+1} = P_{ek}(t) \qquad Y_{3k+1} = P_{ek}(t+\Delta t)$$

$$X_{3k+2} = P_1(t) \qquad Y_{3k+2} = P_1(t+\Delta t)$$

$$X_{3k+3} = P_2(t) \qquad Y_{3k+3} = P_2(t+\Delta t)$$

$$X_{3k+4} = P_3(t) \qquad Y_{3k+4} = P_3(t+\Delta t)$$

$$X_{4k+1} = P_k(t) \qquad Y_{24k+1} = P_k(t+\Delta t)$$

$$X_{3k+n+1} = P_n(t)$$

$$Y_{3k+n+1} = P_n(t+\Delta t)$$

The initial conditions are given by

$$X_1 = 1, X_2 = X_3 = X_4 = X_5 = \dots\dots = X_{3K+n+1} = 0$$

The basic equation of the neural network are

$$Y_1 = W_{11}X_1 + W_{21}X_2 + W_{K+1,}X_{K+1} + W_{K+2,1}X_{K+2} + W_{2k+1,1}X_{2K+1} + W_{2K+2,1}X_{2K+2} + W_{3K+1,1}X_{3K+1} + W_{3K+n+1,}X_{3k+n+1}$$

$$Y_2 = W_{12}X_1 + W_{22}X_2 + W_{3K+2,2}X_{3K+2} + W_{3K+3,2}X_{3K+3} + W_{3K+4,2}X_{3K+4} + \dots\dots\dots + W_{4K+1,2}X_{4K+1} + \dots\dots\dots + W_{3K+n,2}X_{3K+n}$$

$$Y_{K+1} = W_{3K+2,K+1}X_{3K+2} + W_{3K+3,K+1}X_{3K+3} + W_{3K+4,K+1}X_{3K+4} + \dots\dots + W_{4K+1,K+1}X_{4K+1}$$

$$Y_{K+2} = W_{3K+2,K+2}X_{3K+2} + W_{3K+3,K+2}X_{3K+3} + W_{3K+4,K+2}X_{3K+4} + \dots\dots + W_{4K+1,K+2}X_{4K+1}$$

$$Y_{2K+1} = W_{3K+2,2K+1}X_{3K+2} + W_{3K+3,2K+1}X_{3K+2} + W_{3K+4,2K+1}X_{3K+3} + \dots\dots + W_{4K+1,2K+1}X_{4K+1}$$

$$Y_{2K+2} = W_{3K+2,2K+2}X_{3K+2} + W_{3K+3,2K+2}X_{3K+3} + W_{3K+4,2K+2}X_{3K+4} + \dots\dots + W_{4K+1,2K+2}X_{4K+1}$$

$$Y_{3K+1} = W_{3K+2,3K+1}X_{3K+2} + W_{3K+3,3K+1}X_{3K+3} + W_{3K+4,2K+1}X_{3K+3} + \dots\dots + W_{4K+1,2K+1}X_{4K+1}$$

$$Y_{3K+2} = W_{3K+2,3K+3}X_{3K+3} + W_{3K+2,3K+2}X_{3K+2}$$

$$Y_{3K+3} = W_{3K+2,3K+3}X_{3K+2} + W_{3K+3,3K+3}X_{3K+3}$$

$$Y_{3K+4} = W_{3K+3,3K+4}X_{3K+3} + W_{3K+4,3K+4}X_{3K+4}$$

$$Y_{4K+1} = W_{3K+4,4K+1}X_{3K+4} + W_{4K+1,4K+1}X_{4K+1}$$

$$K = 2,3,4\dots\dots n-1$$

$$Y_{3k+n+1} = W_{3K,3K}X_{3K} + W_{3K+n+1,3k+n+1}X_{3K+n+1}$$

The energy function E for the neural network and update equations are obtained using the least mean square, gradient-descent learning procedure as follows:

$$E = \sum_{i=1}^{3k+n+1} [Y_i - D_i]^2$$

$$\Delta W_{12} = 2KX_1[E_2 - E_1]$$

$$\Delta W_{1,K+1} = 2KX_1[E_{K+1} - E_1]$$

$$\Delta W_{1,K+2} = 2KX_1[E_{K+2} - E_1]$$

$$\Delta W_{1,K+3} = 2KX_1[E_{K+3} - E_1]$$

$$\Delta W_{1,2K+2} = 2KX_1[E_{2K+2} - E_1]$$

$$\Delta W_{1,3K+1} = 2KX_1[E_{3K+1} - E_1]$$

$$\Delta W_{21} = 2KX_2[E_1 - E_2]$$

$$\Delta W_{K+1,1} = 2KX_{K+1}[E_1 - E_{k+1}]$$

$$\Delta W_{K+2,1} = 2KX_{K+2}[E_1 - E_{K+2}]$$

$$\Delta W_{2K+1,1} = 2KX_{2K+1}[E_1 - E_{2K+1}]$$

$$\Delta W_{2K+2,1} = 2KX_{2K+2}[E_1 - E_{2K+2}]$$

$$\Delta W_{3K+1,1} = 2KX_{3K+1}[E_1 - E_{3K+1}]$$

$$\Delta W_{3K+2,2} = 2KX_{3K+2}[E_2 - E_{3K+2}]$$

$$\Delta W_{3K+2,K+1} = 2KX_{3K+2}[E_{K+1} - E_{3K+2}]$$

$$\Delta W_{3K+2,K+2} = 2KX_{3K+2}[E_{K+2} - E_{3K+2}]$$

$$\Delta W_{3K+2,2K+1} = 2KX_{3K+2}[E_{2K+1} - E_{3K+2}]$$

$$\Delta W_{3K+2,2K+2} = 2KX_{3K+2}[E_{2K+2} - E_{3K+2}]$$

$$\Delta W_{3K+2,2K+2} = 2KX_{3K+2}[E_{2K+2} - E_{3K+2}]$$

$$\Delta W_{3K+3,2} = 2KX_{3K+3}[E_2 - E_{3K+3}]$$

$$\Delta W_{3K+3,K+1} = 2KX_{3K+3}[E_{k+1} - E_{3K+3}]$$

$$\Delta W_{3K+3,K+2} = 2KX_{3K+3}[E_{k+2} - E_{3K+3}]$$

$$\Delta W_{3K+3,2K+1} = 2KX_{3K+3}[E_{2k+1} - E_{3K+3}]$$

$$\Delta W_{3K+3,2K+2} = 2KX_{3K+3}[E_{2k+2} - E_{3K+3}]$$

$$\Delta W_{3K+4,2} = 2KX_{3K+4}[E_2 - E_{3K+4}]$$

$$\Delta W_{3K+4,K+1} = 2KX_{3K+4}[E_{K+1} - E_{3K+4}]$$

$$\Delta W_{3K+4,K+2} = 2KX_{3K+4}[E_{K+1} - E_{3K+4}]$$

$$\Delta W_{3K+4,2K+1} = 2KX_{3K+4}[E_{2K+1} - E_{3K+4}]$$

$$\Delta W_{3K+4,2K+2} = 2KX_{3K+4}[E_{2K+2} - E_{3K+4}]$$

$$\Delta W_{3K+4,K+2} = 2KX_{3K+4}[E_{K+1} - E_{3K+4}]$$

$$\Delta W_{4K+1,2} = 2KX_{4K+1}[E_2 - E_{4K+1}]$$

$$\Delta W_{4K+1,K+1} = 2KX_{4K+1}[E_{K+1} - E_{4K+1}]$$

$$\Delta W_{4K+1,K+2} = 2KX_{4K+1}[E_{K+2} - E_{4K+1}]$$

$$\Delta W_{4K+1,2K+1} = 2KX_{4K+1}[E_{2K+1} - E_{4K+1}]$$

$$\Delta W_{4K+1,2K+2} = 2KX_{4K+1}[E_{2K+2} - E_{4K+1}]$$

$$\Delta W_{3K+n+1,1} = 2KX_{3K+n+11}[E_1 - E_{3K+n+1}]$$

Where error $E_m = (Y_m - D_m)$ or the difference between the actual and the desired output of neuron m in the output layer.

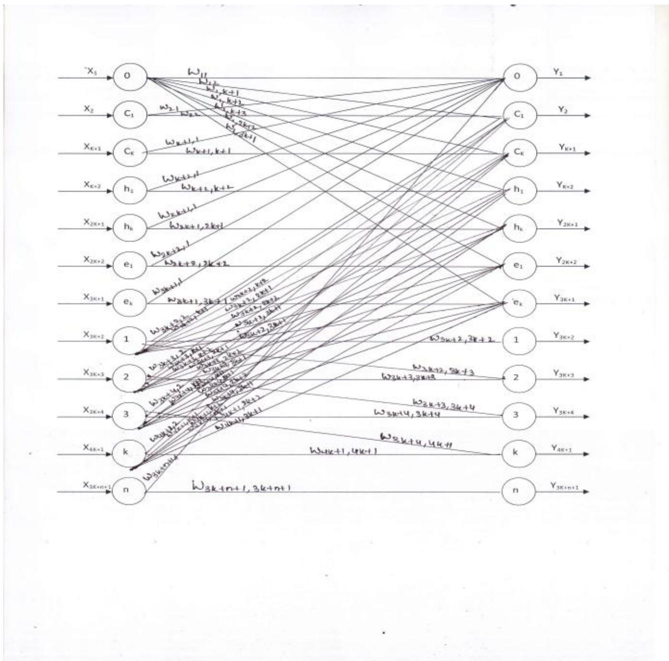

Figure: Neural Network

Table:

P_0 Desired	P_1 values	μ	r_1	r_2	r_3	r_4	r_5	r_6	z_1	z_2
0.18	0.18	2.2554	1.234	0.3555	0.233	2.945	1.245	0.153	2.415	0.7411
0.5	0.0310	1.5534	2.412	1.6334	2.212	1.450	0.765	2.134	1.565	2.835
0.094	0.25	1.1252	0.8142	0.4254	2.506	0.0296	0.026	1.515	2.959	1.707
0.40	0.23	3.3221	0.9159	2.996	0.728	0.895	0.745	1.870	1.340	2.949
0.38	0.28	3.2111	2.917	1.836	2.768	1.456	1.982	0.590	1.229	2.310
0.22	0.20	3.8456	0.9566	2.945	2.103	1.616	2.234	1.070	0.548	2.243
0.21	0.32	2.5318	3.91	0.9456	1.222	0.2341	2.289	0.113	1.224	1.049
0.55	0.43	2.6234	2.639	1.366	2.445	0.6151	1.239	0.632	2.212	0.1212
0.39	0.22	3.3319	2.650	2.950	0.3257	2.365	1.298	1.550	2.849	2.269

z_3	z_4	z_5	z_6	y_1	y_2	y_3	y_4	Y_5	Y_6	λ	λ_{c10}
2.345	1.198	2.950	2.964	2.456	0.8312	2.423	1.167	2.950	2.964	0.1811	0.002862
1.678	0.724	2.012	1.441	1.664	2.835	1.468	0.914	2.199	1.414	0.537	0.0001249
2.488	0.989	0.671	2.743	2.989	1.708	2.578	0.092	0.7617	2.753	0.285	0.00088
2.692	1.385	1.785	2.394	1.345	2.839	2.682	1.280	1.726	2.85	0.232	0.003254
2.855	0.165	2.446	0.719	1.311	2.450	2.950	1.142	2.546	0.909	0.363	0.005936
2.705	0.325	1.868	0.342	0.438	2.140	2.515	0.224	1.784	0.239	0.186	0.005273
1.659	0.888	2.065	0.042	1.414	1.039	1.829	0.819	2.259	0.0412	0.3952	0.002970
0.790	2.68	0.795	2.813	2.111	0.110	0.890	2.685	0.7812	2093	0.5740	0.004956
2.270	1.712	0.382	0.721	2.849	2.401	0.365	1.602	0.485	0.611	0.1201	0.00129

λ_{c11}	λ_{c12}	λ_{c13}	λ_{c20}	λ_{c21}	λ_{c22}	λ_{c23}	λ_{h10}	λ_{h11}
0.00047	0.0025	0.00759	0.00784	0.00357	0.000864	0.001825	0.003854	0.005940
0.00254	0.0025	0.00251	0.00155	0.00186	0.004515	0.001727	0.006853	0.002528
0.00349	0.0026	0.00435	0.00524	0.00686	0.005225	0.005899	0.004523	0.002364
0.00498	0.0018	0.00547	0.00564	0.00197	0.002430	0.003894	0.004282	0.001262
0.00472	0.0046	0.00145	0.00154	0.00378	0.001230	0.001514	0.004339	0.004256
0.00392	0.00425	0.00435	0.00345	0.00545	0.001530	0.002930	0.002636	0.004734
0.004218	0.00148	0.00541	0.00545	0.00517	0.005640	0.005250	0.007589	0.000958
0.005727	0.00258	0.00517	0.001233	0.00172	0.002450	0.003899	0.005496	0.000480
0.00418	0.00540	0.00170	0.00386	0.00527	0.001750	0.001427	0.004595	0.000650

λ_{h12}	λ_{h13}	λ_{h20}	λ_{h21}	λ_{h22}	λ_{h23}	λ_{e10}	λ_{e11}	λ_{e12}
0.006880	0.00434	0.002345	0.002569	0.000928	0.00327	0.0047	0.0069	0.0043
0.006540	0.00365	0.005826	0.001736	0.00148	0.00245	0.0073	0.0035	0.0032
0.001166	0.000498	0.004925	0.001685	0.00725	0.00195	0.0032	0.00032	0.00039
0.002971	0.006538	0.007250	0.004586	0.00735	0.00315	0.0051	0.00171	0.0069
0.001825	0.001821	0.003525	0.004582	0.00635	0.00984	0.00042	0.0051	0.0018
0.004523	0.004652	0.002718	0.0035826	0.001230	0.001584	0.0056	0.00563	0.0023
0.004625	0.003582	0.000869	0.004250	0.002450	0.002056	0.0075	0.000954	0.0051
0.007012	0.004253	0.006384	0.005750	0.00085	0.000928	0.0054	0.000478	0.0070
0.002545	0.002822	0.006848	0.005820	0.000526	0.004502	0.0058	0.000652	0.0035

λ_{e13}	λ_{e20}	λ_{e21}	λ_{e22}	λ_{e23}	Time	k	No. of iterations
0.0043	0.00323	0.00256	0.000978	0.00413	0.005	0.18	26
0.002729	0.00626	0.00183	0.001480	0.00241	0.001	0.29	20
0.000369	0.00591	0.00173	0.007255	0.001854	0.002	0.56	5
0.00694	0.00680	0.00542	0.007250	0.00367	0.004	0.087	32
0.00262	0.00342	0.00545	0.001958	0.00984	0.004	0.28	28
0.00465	0.00278	0.00366	0.002445	0.001589	0.003	0.26	30
0.00436	0.00086	0.00437	0.000845	0.002158	0.003	0.25	4
0.00425	0.00642	0.00585	0.000522	0.000928	0.004	0.12	2
0.00362	0.00742	0.00581	0.000386	0.004202	0.005	0.16	12

3. CONCLUSIONS

Computer software is developed for simulation of neural network representing the series-parallel system and is tested for 4-unit series parallel system. The initial failure and repair rates chosen within an attainable practical range. Samples of the results obtained from the simulation are shown in tables.

REFERENCES

[1] A. Anandarajachari and M. P. Sastry, "System reliability analysis in the presence of lethal and nonlethal common cause shock failures." International Journal of Management and System, Vol.10, 1994 pp.1-8.

[2] B. S. Dhillon and S. N. Rayapati, "Human error and common cause failure modeling of redundant system micro electronics and Reliability," Vol.8, 1986, pp.1139-1159.

[3] B. S. Dhillon, Human Reliability with Human factors. Pergomon press, Inc, Newyork, 1986.

[4] John Hertz, Andrskrogh, Richard G.Palmer, Introduction to the theory of neural computation, Addison-Wesley, publishing company, 1991.

[5] B. S. Dhillon and S. N. Rayapati, "Reliability Modeling of systems with human errors." Proceedings of the Twentieth Hawaii International Conference on System Sciences(HICSS-20),Honolulu,Hawaii,USA,VOL-3, 1987, pp.493-501.