FAILURE PREDICTION OF CRITICAL ELECTRONIC SYSTEMS IN POWER PLANTS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: This paper presents an Artificial Neural Network (ANN) model for failure prediction of critical electronic systems in power plants. Reliability modeling of electronic circuits can be best performed by the stressor – susceptibility interaction model. A circuit or a system is deemed to be failed once the stressor has exceeded the susceptibility limits. For on-line prediction, validated stressor vectors may be obtained by direct measurements or sensors which after preprocessing and standardization is fed into the ANN. ANN is trained using the stressor sets obtained using Monte Carlo Analysis (MCA) and is then combined with the susceptibility limits for failure prediction of the circuit or system. The ANN reads the incoming stressor set and recalls the trained pattern and predicts the result. The performance of the proposed method of prediction is evaluated by comparing the experimental results with the actual failure model values.

Keywords: Stressor, susceptibility, Monte Carlo analysis, failure prediction, neural networks

1. INTRODUCTION

Real time monitoring of the healthiness of complex critical control circuits of power plants is a difficult challenge to both human operators and expert systems. Artificial Neural networks are well known for its robustness and fault tolerant prediction and classification [3], [8], [10]. Once the neural network is trained to recognize the various stressor sets associated with the susceptibility limits, it can easily predict the healthiness of the state.

The new technique of failure prediction using stressor- susceptibility interaction [1], [6] is briefly discussed in Section 2. This technique can be extended to simple electronic components and for complicated electronic circuits and equipment. Section 3 presents some of the common failure mechanisms in practical situations. The derivation of stressor sets using Monte Carlo Analysis is given in Section 4 followed by Section 5 wherein the procedures for obtaining stressor sets by practical measurements are discussed. Section 6 is devoted for the architectural representation of the proposed neural network, experimental results and performance. Finally conclusions are provided in Section 7.

2. CONCEPT OF STRESSOR – SUSCEPTIBILITY INTERACTION

Stressor is a physical entity influencing the lifetime of a component or circuit. A stressor, indicating a physical entity *x* will be denoted as ψ_x. Stressors can be broadly classified into three main groups. First group contains the electrical stressors, parameters related to the electrical behavior of the circuit. Second group of stressors is the mechanical stressors, which are related to the mechanical environment of the component. Third group of parameters influencing the lifetime of components is related to the thermal environment of the component. Susceptibility of a component to a certain failure mechanism is defined as the probability function indicating the probability that a component will not remain operational for a certain time under a given combination of stressors. The susceptibility related to the failure mechanism "y" is usually defined as S_y (t, ψ_p, ψ_q,ψ_r).

Failure probabilities require detailed analysis of both stressors and susceptibility. Most components tend to have more than one failure mechanism, resulting in more than one "failure probability". It can be shown that there is a strong correlation between the various failure mechanisms existing within a component. Figure 1 illustrates the stressor - susceptibility interaction for a single failure mechanism. It is clear that the main source of problem is the overlap between stressor and susceptibility density. The first step is to calculate the failure probability for this stressor distribution on a failure mechanism with a single, one variable, time independent catastrophic susceptibility model. This results in the following probability

$$f_{fail,y,\Psi}(\Psi_0) = \int_{\Psi_0}^{\infty} f_y(\Psi)d\Psi$$

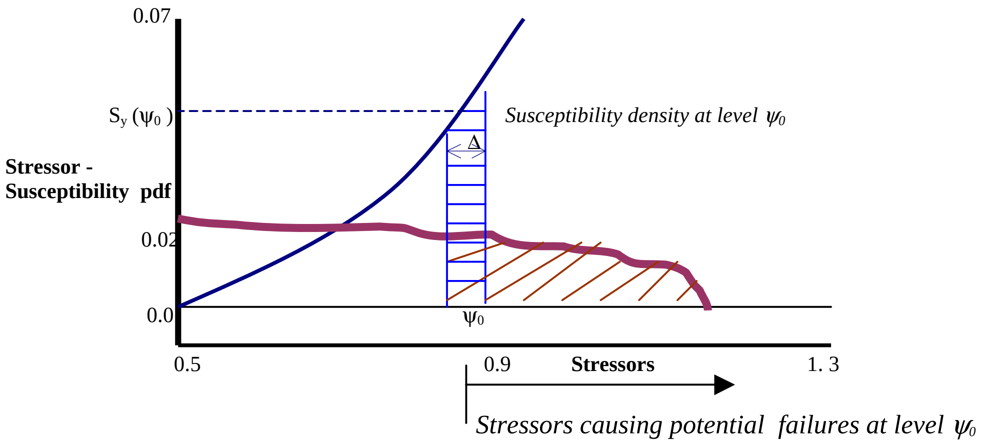

Fig 1. Stressor- Susceptibility interaction for single failure mechanism

To calculate the failure probability as a function of more complex susceptibility model, it will be necessary to calculate the failure probability of a part of the susceptibility model, for a certain stressor interval Δ, characterized by its mean value ψ_o and the corresponding susceptibility density function at that point $S_y(\psi_o)$. Considering the probability that a part has failed at a lower susceptibility level, result in the possibility to predict the failure probability per time interval of a certain failure at stressor level ψ_0 using the following relation

$$f_{fail,y,\Psi}(\Psi_0) = \Delta(S_Y(\Psi_0)\int_{\Psi_0}^{\infty} f_y(\Psi)d\Psi)\left(1-\int_{0}^{\psi_0-\Delta} f_{fail,y}(\psi)d\psi\right)$$

The last term is introduced to subtract failures caused by stressors at a lower susceptibility level. As, most often, failure probabilities are very small, in many cases the previous expression will simplify to

$$f_{fail,y,\psi}(\psi_0) = \Delta(S_y(\Psi_0)\int_{\Psi_0}^{\infty} f_y(\Psi)d\Psi)$$

when $(1-\int_{0}^{\psi_0-\Delta} f_{fail,y}(\psi)d\psi) = 1$.

Since the susceptibility is defined as the probability that a component will not remain operational during a certain time, it is therefore possible to calculate the failure probability during a certain observation time t_{obs}

$$f_{fail,y,\psi}(\psi_0) = t_{obs} * \Delta * (S_y(\Psi_0)\int_{\Psi_0}^{\infty} f_y(\Psi)d\Psi)$$

The important requirement for using of the above equation is that the observation time t_{obs} must be larger than the total elapsed sampling time to obtain an ergodic description of the associated stressors $t_{total\ sample}$ ($t_{obs} > t_{total\ sample}$); $f_{ail,\ y,\ \psi,}(t, \psi)$ is assumed to be constant during the time interval t_{obs}.

From the previous equation it is possible to calculate the failure probability of a part per fail mechanism per time interval using the relation

$$f_{fail,y} = \int_0^{\infty} f_{fail,y,\psi}(t,\psi)d\psi$$

The above equation can now be used to calculate the part failure probability per time interval

$$f_{fail} = \sum_{i=1}^{n} f_{fail,i}$$

Using the previous assumptions it is also possible to calculate the probability that a component survives from time "*t*" to "*t+dt*". The following expression can be used to calculate the failure probability for one single failure mechanism within one single device

$$R(t \ldots. t+\Delta t) = \frac{\sum_{i=1}^{k} Devices\_operational\_at\_time\_(t+\Delta t)}{\sum_{i=1}^{n} Devices\_operational\_at\_(t)} = R(t)F(\Delta t) = R(t)\Delta t f(t)$$

As for large series of components, the physical structures of the individual components will be different for every component, the survival probability of such a series of components will also show individual differences. The stress on a component may vary with time due to circuit behavior and circuit use. The circuit behavior will differ amongst a series of circuits due to physical differences in the individual circuit components, the physical structure of a circuit, the use of a circuit and the environment (electrical, thermal, etc.) of the circuit. To summarize the variety of effects it is useful to describe stressors as stochastic signals with properties depending on the influencing factors mentioned above. These assumptions make it possible to derive the failure probability and reliability of a component using a Markov approach.

For Markov approach the following requirements should be fulfilled

- Susceptibility of all failure mechanisms in a component is known and is constant in the time interval (t, $t+\Delta t$).
- All stressors $\psi_a(t)$, $\psi_b(t)$, … are known as stochastic signals for the time interval (t, $t+\Delta t$).
- The failure probability (or reliability) is known at a certain (initial) time t.

Using these properties it is possible to calculate the reliability and failure probability for components, derived from internal failure mechanisms for time $t+\Delta t$. For this purpose the following relationships are used

$$\vec{P}(t+\Delta t) = \vec{P}(t) ✪ (\Delta t)$$

$$= \vec{P}(t) \begin{pmatrix} P_{x\to x} & \ldots & \ldots & P_{x\to y} \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ P_{y\to x} & \ldots & \ldots & P_{y\to y} \end{pmatrix}$$

where $\vec{P}(t)$ is the state probability vector of a component. This state probability vector is defined as

$$\vec{P}(t) = \begin{cases} P_{operational}(t) & \text{Probability that part is operational at time } t \\ P_a(t) & \text{Probability that part fails due to failure mechanism a at time } t \\ P_b(t) & \text{Probability that part fails due to failure mechanism b at time } t \\ \ldots & \ldots \quad \ldots \\ P_n(t) & \text{Probability that part fails due to failure mechanism n at time } t \end{cases}$$

$$\sum_{j=1}^{n} P_j(t) = 1$$

$$P_1(t) = P_{operational}(t) = R(t)$$
$$P_{2\ldots.n}(t) = P_{fail,\,2\ldots\,n}(t) = F_{fail,\,2\ldots.\,n}(t)$$
$$P_{x\rightarrow y} = P_{(y\,(t+\Delta t)\,|\,x\,(t))} = f_y(t)\,\Delta t\;P_x(t)$$

It is possible to replicate this calculation process for a whole batch of circuits. In this case for every circuit the individual stressor/ susceptibility interaction is calculated thus simulating batch behavior. Using this method it is possible to derive the failure probability for many parts in many practical situations, also in cases where considerable differences (in stressors and susceptibility) exist within a batch.

3. STRESSOR SETS AND SUSCEPTIBILITY MODELS – PRACTICAL APPROACH

There are two different categories of failure mechanisms applicable to electronic components. First, the failure mechanisms that are related to the electrical stress in a circuit. Second there are failure mechanisms related to the intrinsic aspects of a component. Table 1 shows some of the typical failure mechanisms and their causes with associated stressors [2],[4-6], [9], [11-12], [14].

Table 1. Some common Failure mechanisms with associated causes and stressors

No.	Failure Mechanism	Influencing aspect or associated stressors
1	Thermal Failure (general)	• Dissipated power • Environmental Temperature • Thermal resistance • Thermal capacitance
2	Current Breakdown (Hot spot melting)	• Resistivity of the material • Impurities/ mechanical distortions in the material causing increase in current density. • Thermal resistivity coefficient.
3	Power breakdown (Thermal cracks)	• Thermal expansion coefficient of the materials. • Thermal resistivity coefficients of the materials.
4	Impact Ionization	• Electric field
5	Avalanche breakdown	• Electric field (positive temperature coefficient)
6	Zener breakdown	• Electric field (negative temperature coefficient)
7	Corrosion	• Environmental temperature (negative influence on susceptibility) • Dissipated power • D C Voltage
8	Electromigration	• Current density • Environmental temperature
9	Secondary diffusion	• Temperature
10	Switch on pulse power dissipation (for bipolar junctions)	• Voltage slope dV/dt • Current slope dI/dt
11	Switch off pulse power dissipation (for bipolar junctions)	• Voltage slope dV/dt • Maximum reverse junction current • Applied reverse voltage • Storage charge Q's in the diode at the moment of polarity reversal.
12	Forward bias second breakdown (for power transistors)	• Collector emitter voltage • Slope of the base current during switching on dI_b/dt • Slope of the collector current during switching on dI_c/dt • Environmental temperature
13	Reverse bias second breakdown (for power transistors)	• Collector emitter voltage • Discharge speed dI_b/dt (optimum value) • Stored charge at the moment of transistor switch off (closely related to collector current at the moment of switch off). • Environmental temperature

There are two possible ways to obtain stressor sets for practical circuits. The First possibility involves usage of computer simulation models to derive all circuit signals using one single simulation. Second possibility is to derive stressor sets from practical measurements. In those cases where sufficient systems are available it is possible to do a statistical evaluation of the individual stressor functions existing in individual systems. As the stressor sets are dependent on the conditions of use and the operation modes of a system it is important that the measured stressor is based on all the possible operation modes of a circuit and all the possible transitions between the various operation modes. This can become a quite tedious job as the entire operation is to be repeated for a number of systems to obtain an accurate statistical mean stressor model. Accurate description of a stressor set needs a sampling frequency of at least twice the highest frequency in the stressor frequency spectrum. Accurate description of a stressor set will require a number of samples sufficient to cover all the different states of the system. As a signal has often more than one quasi-stationary states, each characterized by their stressor set, it is possible to derive the overall stressor set function from the individual state stressor sets using [6]

$$f_{str,y(x)} = \sum_{i=1}^{n} \frac{T_i}{T_{total}} f_{str,y,i(x)}$$

$f_{str,y\,(x)}$ is the stressor probability density function of quasi-stationary state i. T_i / T_{total} is the fraction of time that the stressor is in quasi-stationary state i.

4. MONTE CARLO ANALYSIS (MCA) FOR DERIVING STRESSOR SETS

In a Monte Carlo analysis, a logical model of the system being analyzed is repeatedly evaluated, each run using different values of the distributed parameters [13]. The selection of parameter values is made randomly, but with probabilities governed by the relevant distribution functions. Statistical exploration covers the tolerance space by means of the generation of sets of random parameters within this tolerance space. Each set of random parameters represents one circuit. Multiple circuit simulations, each with a new set of random parameters, explore the tolerance space. Statistically the distribution of all random selections of one parameter represents the parameter distribution.

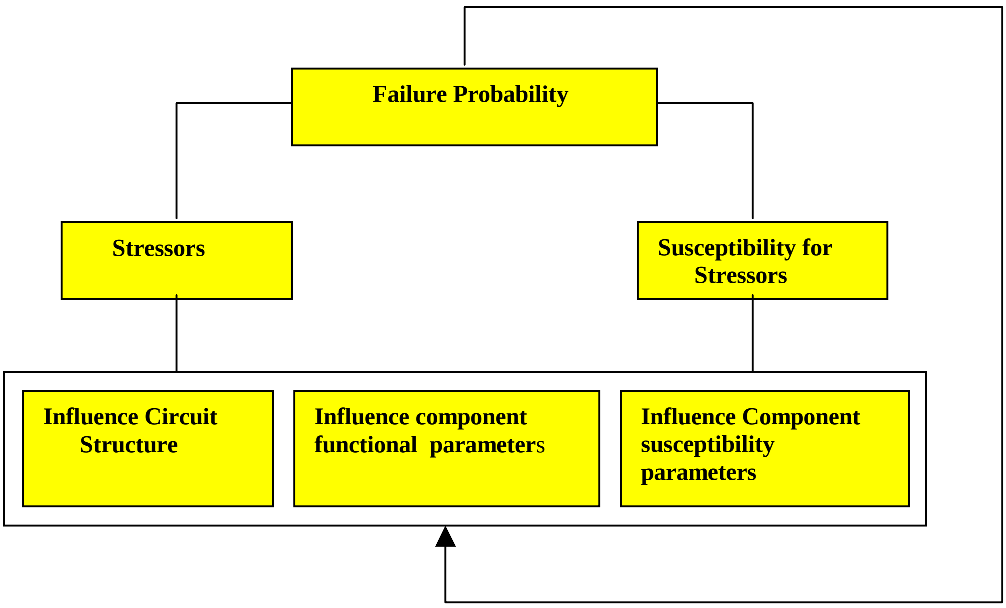

Fig 2. Monte Carlo Analysis

Although the number of simulations required for MCA is quite large, this analysis method is useful, especially because the number of parameters in the failure prediction of circuits is often too large to allow the use of other techniques. Figure 2 illustrates the MCA. With MCA it is possible to simulate the behavior of a large batch of circuits and derive stressor sets. The next phase will be the combination of the derived stressor sets with the component susceptibilities in order to decide whether a component will fail or not. As for the failure prediction, the most important aspect is to prevent failures, susceptibility will be expressed using the susceptibility limit. To distinguish circuits where failures are possible any circuit in the MCA causing to exceed a susceptibility limit are marked as fail. Circuits where no stressors exceed susceptibility limit are marked as pass.

5. PRACTICAL STRESSOR - SUSCEPTIBILITY INTERACTIONS

The analysis was carried out on a power circuit and the main cause of the failure of the circuit was a Schottky diode. Analysis shows that the main failure mechanisms are leakage current and excess crystal temperature.

Parameter	Susceptibility limit
T crystal	125^o Celsius
dV/dt	10^9 V/s
dI/dt	0.51×10^9 A/s
I (reverse)	-1.5 A

Using the procedure described earlier, it was possible to derive a complete individual stressor set for the failure mechanism of this diode. Figure 3 shows the joint stressor – susceptibility interaction model in terms of voltage and current. The susceptibility limit for leakage current is set at -1.5A.

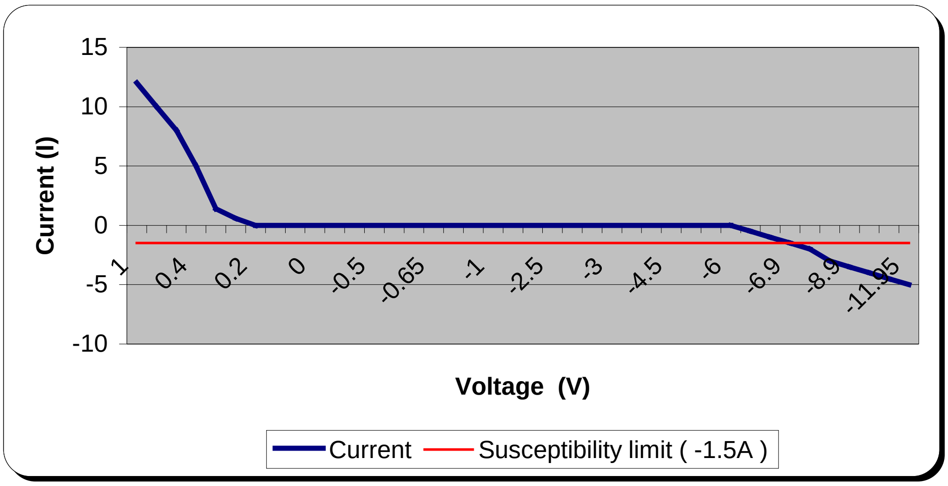

Fig 3. Stressor - susceptibility interaction model

6. ARTIFICIAL NEURAL NETWORK MODEL

Artificial Neural Networks (ANNs) have been developed as generalizations of mathematical models of biological nervous systems. Networks may be distinguished on the basis of the directions in which signals flow. There are two types of networks: feedforward and feedback. A network in which signals propagate in only one direction (left to right) from an input stage through intermediate neurons to an output stage is called a feedforward network. Feedback networks, on the other hand, are networks in which signals may also propagate from the output of any neurons to the input of any neuron.

A neural network is characterised by the network architecture, the connection strength between pairs of neurons (weights), node properties, and updating rules. The updating or learning rules control weights and/or states of the processing elements (neurons). Normally, an objective function is defined that represents the complete status of the network, and its set of minima corresponds to different stable states of the network. It can learn by adapting its weights to changes in the surrounding environment, can handle imprecise information, and generalise from known tasks to unknown ones. Each neuron is an elementary processor with primitive operations, like summing the weighted inputs coming to it and then amplifying or thresholding the sum. There are three broad paradigms of learning: supervised, unsupervised (or self-organised) and reinforcement (a special case of supervised learning). In supervised learning, adaption occurs when the system directly compares the network output with a known correct or desired answer. The network is initially randomized to avoid imposing any of our own prejudices about an application on the network. The training patterns can be thought of as a set of ordered pairs $\{(x_1, y_1), (x_2, y_2), \dots, (x_p, y_p)\}$ where x_i represents an input pattern and y_i represents the output pattern vector associated with the input vector x_i .The process of training the network then proceeds according to the following algorithm [7], which is derived as a natural result of finding the gradient of the error surface (in weight space) of the actual output produced by the network with respect to the desired result .

1. Select the first training vector pair from the training pair vectors. Call this the vector pair (x,y).
2. Use the input vector ,x, as the out put from the input layer of processing elements.
3. Compute the activation to each unit on the subsequent layer.

4. Apply the appropriate activation function, which we denote as $f(net^h)$ for the hidden layer and as $f(net^0)$ for the output layer, to each unit on the subsequent layer.
5. Repeat steps 3 and 4 for each layer in the network.
6. Compute the error, δ^o_{pk}, for this pattern p across all K output layer units by using the formula: $\delta^o_{pk} = (y_k - o_k) f'(net^o_k)$
7. Compute the error δ^h_{pj}, for all J hidden layer units by using the recursive formula. $\delta^h_{pj} = f'(net^h_j) \sum_{k=1}^{K} \delta^o_{pk} w_{kj}$
8. Update the connection weight values to the hidden layer by using the equation: $w_{ji}(t+1) = w_{ji}(t) + \eta \delta^h_{pj} x_i$. Where η is a small value used to limit the amount of change allowed to any connection during a single pattern training cycle.
9. Update the connection weight values to the output layer by using the equation: $w_{kj}(t+1) = w_{kj}(t) + \eta \delta^o_{pk} f(net^h_j)$.
10. Repeat steps 2 to 9 for all vector pairs in the training set. Call this one training epoch.

Steps 1 to 10 are to be repeated for as many epochs as it takes to reduce the sum squared error to a minimal value according to the formula $E = \sum_{p=1}^{P} \sum_{k=1}^{K} (\delta^o_{pk})^2$

Figure 4 shows a typical *L*-layer feed-forward network (the input nodes are not counted as a layer) consists of an input layer, (*L*-1) hidden layers, and an output layer of nodes successively connected in a feed-forward fashion with no connections between neurons in the same layer.

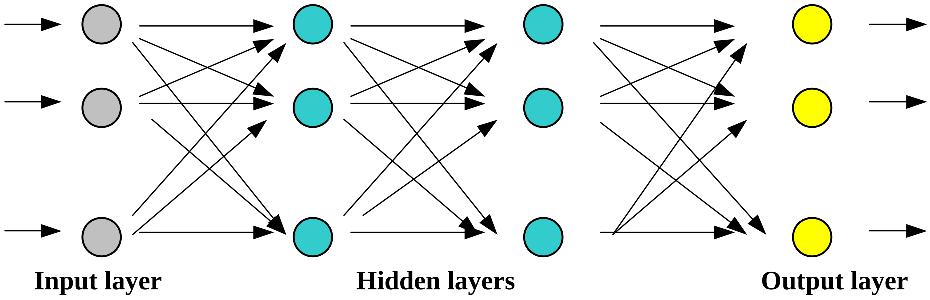

Fig 4. A Typical Three-layer Feedforward Network Architecture

6.1 Overview of the ANN failure prediction system

The experimental system consists of three stages: Modeling the stressor – susceptibility interaction and data simulation, network training and performance evaluation.

- **Modeling the stressor – susceptibility interaction and data simulation**

The stressor – susceptibility interaction model was analyzed in detail and the main causes of failures were identified. Analysis showed that the main cause of the failure was excess junction temperature and leakage current. A mathematical model was built relating the failure probability, leakage current and junction temperature. A failure simulation was carried out and the data set was generated.

- **ANN training and prediction**

Deciding the network architecture and training is the crucial task. We used a feedforward back propagation network with 2 hidden layers in parallel. The input layer had 2 neurons corresponding to the input variables and output layer consists of 3 neurons. Each of the 2 input neuron was directly connected to each of the neurons in the 2 hidden layers. The predicted outputs were failure probability, leakage current and junction temperature. The network was trained using 80% of the simulated data and the remaining 20% data was used for testing and validation. Initial weights, learning rate and momentum used were 0.3, 0.1 and 0.1 respectively. The system error was set at 0.0001.

- **Performance and results achieved**

Predicted outputs are the Junction temperature, failure probability and leakage current. Figures 5, 6 and 7 illustrate the test results for the three predicted outputs.

Training time taken:	*36 seconds (on Gateway Solo Intel 233MHz Pentium platform)*
Learning epochs:	*1203*
Error achieved:	*0.0000963 (Training set), 0.0000752 (Test set)*
Correlation:	*0.9993 (Temperature), 0.9999 (Failure probability), 0.9993 (Leakage current)*
R squared:	*0.9987 (Temperature), 0.9998 (Failure probability), 0.9987 (Leakage current)*

From the experimental results, it is clear that the proposed neural network performed extremely well in predicting the output parameters.

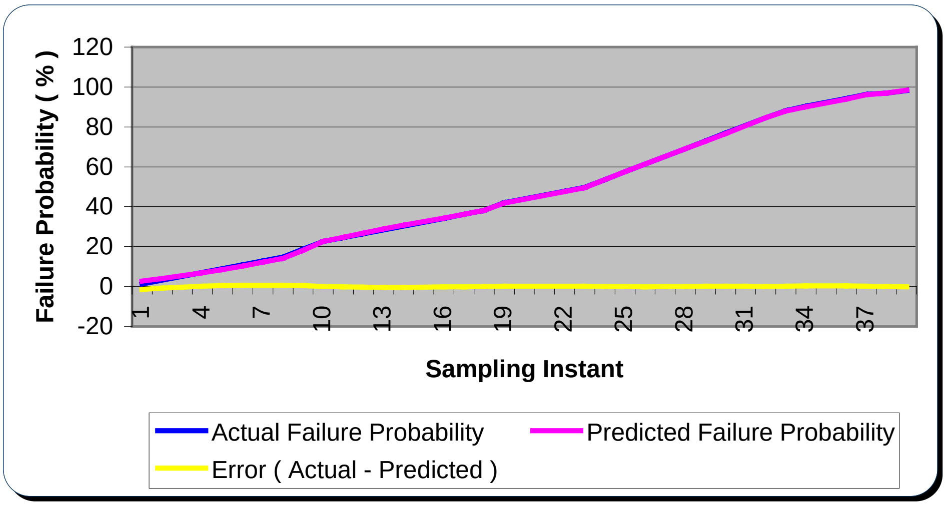

Fig 5. Test Result - Failure Probability prediction

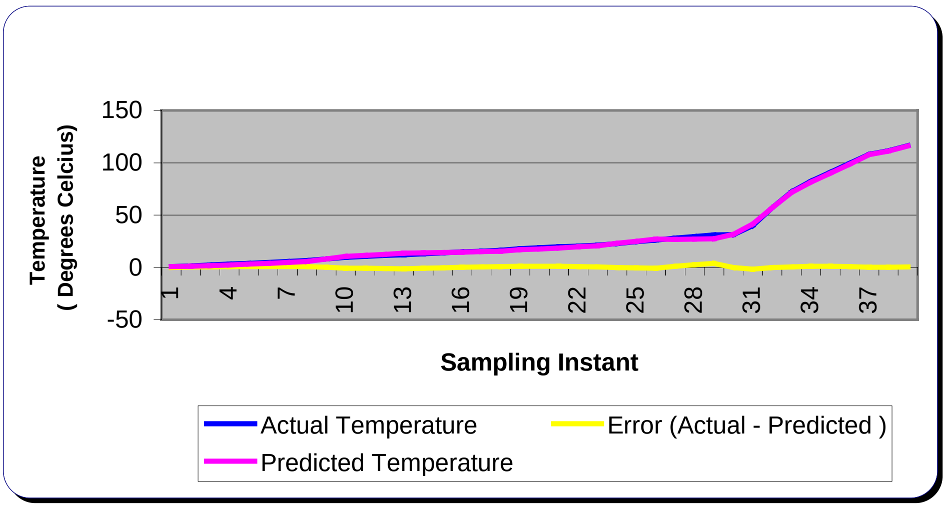

Fig 6. Test Result - Predicted Temperature

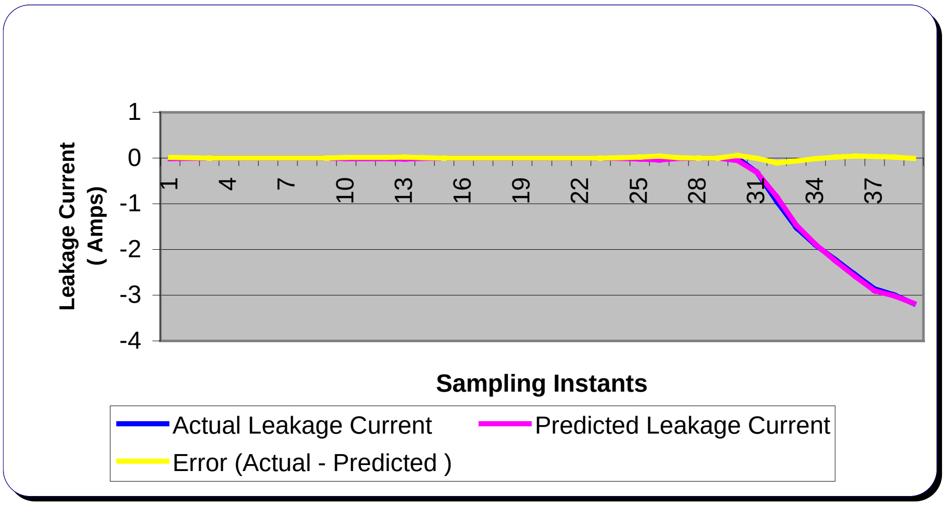

Fig 7. Test Result - Leakage current prediction

7. CONCLUSIONS

In this paper we attempted to predict the failure probability of electronic circuits using artificial neural networks. For the predicted failure probability, temperature and leakage current the values obtained for R-squared were 0.9998, 0.9987 and 0.9987 respectively, the high values indicate the learning power and computational ability of ANN. The problem modeling using stressor – susceptibility interaction method can be widely applied to a wide range of electronic circuits or systems. However, it requires intense knowledge on the circuit behavior to model the various dependent input parameters to predict the results accurately. At present ANN design still relies heavily on human experts who have sufficient knowledge about ANNs and the problem to be solved. As the problem become more complicated, designing the architecture and weights manually may become more difficult and unmanageable. Design of optimal architecture and weights can be formulated as a search problem whereby mutation operators are applied sequentially and selectively to evolve the architecture and connection weights of ANNs. Evolutionary Artificial Neural Networks (EANNs) represent a special class of ANNs in which simulated evolution is another fundamental form of adaptation in addition to learning [15]. Hence when the problem become really complicated EANNs may prove to be useful.

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