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# Estimation for Faults Prediction from Component Based Software Design using Feed Forward Neural Networks

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**Abstract:** As far as the software system is concerned, the reliability is one of the important quality attributes in software development process. The recently growing trends in software development process witnessed the paradigm shift to component based software. The reliability of component based software is difficult to estimate directly by taking the reliability of individual components into account and measuring the component reliability in software is not an easy task alike. In this paper we propose a method to estimate the reliability of the software consisting of components by using different neural network architectures. The proposed method considers software consisting of components divided into different sets and observes the number of faults encountered over a cumulative execution time interval for the known set of components and after this we estimate the number of faults predicted for the randomly chosen set of components in software over next cumulative execution time interval. In this process, we estimate the faults prediction behavior in the set of components over a cumulative execution time interval besides this the prediction of faults is estimated for the complete software. We apply the feed forward neural network architectures & its generalization capability to predict the faults in each component of the software with the prediction of faults for the complete software for given cumulative execution time.

**Keywords:** software reliability estimation, component based software reliability, feed forward neural network, fault prediction.

## 1. INTRODUCTION:

Component based software reliability estimation is an emerging and still a trust area of software engineering. The architecture of software in itself emerges with motivation for predicting reliable behavior of overall system [1].The reliability of the component based software reflects the interdependency with reliability of components. It is one of the possibilities that overall software system reliability effects with the functioning of its components. On the other aspect the overall reliability of the software does not affect with the failure of any component. The reliability tolerance limit must specify in this aspect. Software system design is a high level abstraction of a software system; its components and their connection. Thus software system design complements component definition which focuses on the individual components and their interfaces. The failure occurrence in any component may cause the failure in whole software system design, this gives the connection between components and system design. It is natural to extend contacts to the level as architectural specification and worthwhile to develop specialized methods for the prediction of reliability for component based software system design [2]. The model of software reliability prediction for component based software should consider the nature of fault population contained within the whole software as well as in the components of software. Therefore, due to these faults the software exhibits the

failure behavior. It is well defined that the most useful reliability criteria are residual fault density or the failure intensity. There are various different

Software reliability growth models have also been proposed [3, 4, 5]. Every model has its own limitation and criteria for predicting the reliability of software. As far as concerns of component based software, the mean time to failure occurrence will consider for whole software as well as for each component of the software. These proposed models are considered to model the failure process and to characterize how software reliability varies with time and other factors. These models are used not only to estimate the current values of the reliability measures such as the residual fault density, the failure intensity and mean time to failure but also to predict their future values. It is found with empirical evidence [6,7] that different models have different predictive accuracy at different phases of testing and there is no single analytic model that can be relied on for accurate prediction in all software . Therefore, the selection of particular model is very important in software reliability estimation. The selection of the model can consider in two ways (i) by generating the applicability of

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software reliability growth models by analyzing their predictability across a broad range of dataset and (ii) by developing an adaptive model building system [8]. The problem in first approach is the issue of generalization which remains partially unanswered due to the lack of availability of sufficient data sets for software as well as for its various components. The second approach i.e. adaptive model, which does not depend on assumed parameters and based on only the last failure history of the software system as whole and also failure history of its each component. The failure history of components of software produces an immense effect for predicting the future failures by the software depending on the failure history and so that the adaptive model should consider the failure history of complete software system with the failure history information of each component to predict the possible future failures by the software. In the literature, the adaptive model or non-parametric models like neural network and support vector machine (SVM) based on statistical failure data such as cumulative failure detected, failure rate, time between failures, next time to failure etc. [9, 10]. There are various attempts have been reported in literature review for using neural network techniques to model the software reliability prediction. In [11] the first time neural network is used to predict software reliability. In this work, feed forward neural network and recurrent neural networks along with Elman neural network and Jordan neural network is used for predicting the cumulative number of detected faults by using execution time as input. This work also discussed the effects of various training procedures applied to neural network namely data representation methods, architectural issues concluding that neural network can construct models with varying complexity and adaptability for different datasets in a realistic environment. In [12] the two methods are described for software reliability prediction, first neural networks and second recalibration for parametric models that were compared by using common predictability measure and common data sets. The comparative results revealed that neural network could be used for better trend prediction. In [13], the effectiveness of the neural back propagation network method (BPNN) is investigated for software reliability assignment and prediction using multiple recent inter failure times as input to predict the next failure time. In this work the performance of neural network architecture with various numbers of input nodes, hidden nodes is evaluated and concluded that the effectiveness of a neural network method depends on the nature of data sets up to a larger extent. In [14], a modified Elnan recurrent neural network is proposed to model and predict software failure trends. In [15], the artificial neural network is implemented to software reliability modeling and examined several conventional software reliability growth models by eliminating some unrealistic assumption. In [16], the feed forward back propagation algorithm is applied to predict the software reliability. In this work different failure data sets collected from several standard software projects has been applied to neural network model. It has also been seen in [17] that the neural network model is considered as a better estimator for the software reliability predictor rather than statistical approaches. In most of the previous works the neural network is trained with the data sets of past history of failures in the software for the specific period of time [18, 19, 20]. The trained neural network is expected to predict the occurrence of failure for the time period which has not presented in the data sets. Thus, the prediction of software reliability is depending upon the occurrence of failures in the given time period used in the training data set. This approach is working quite effectively for the simple software system design. The same approach could not work with so effectively for predicting the reliability of component based software. Reliability prediction for the component based software will not only depend upon the failure history of software but also on the reliability of each interdependent component. The software reliability for each component is predicted with occurrence of failures in the given time period for the component. The estimated reliability of components is further used to estimate the reliability of the whole software. Therefore, in this present work the feed forward neural networks are used to predict the reliability of component based software. In this approach a dataset of failure occurrence for each component in given time period is considered as the local training set. Thus, each component has its own local training set. These training sets consist with occurrence of failure for the component in specific period of same time. There is feed forward neural network corresponds to each component. These neural networks are trained with local training sets of respective components. The prediction of reliability for each component is considered from respective trained neural network architecture. Thus, we have the set of trained neural network corresponds to each component in the software. The output of these neural networks and the failure history of the software for a specific period of time are now used to construct the global training set for the main neural network which is predicting the expected failure for the time period not used in the global training set. Thus, this neural network is used to estimate the reliability of component based software for the presented time period. This is obvious that the prediction of reliability for component software depends on the reliability state of each component and previous failure information about the software.

The rest of the paper is organized in four sections. The section 2 discusses about the multilayer neural network and back propagation learning rule, section 3 of the paper presents the simulation and implementation details, section 4 incorporates the results & discussion. Section 5 considers the conclusion followed by references.

## 2. Multilayer Feed Forward Neural Network:

The multilayer feed forward neural network can be used to capture the classification explicitly in the set of input output pattern collected during an experiment and simultaneously expected to model the unknown system or

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function from which the prediction can be made for the new or unknown set of data [2]. The collected input-output pattern pairs are presented to neural network on repeated basis to accomplish the training of the neural network for capturing the implicit relation function between input and output pattern pairs. Once the mapping function between the input-output pair is captured or estimated the network can be used to predict the future projection for any unknown set of input pattern(test pattern set), which has not been provided during the training. The network produced the output for this unknown input pattern, this output will be an interpolated version of the output patterns corresponding to the input training patterns close to the given test input pattern. Thus, the network can be used for the prediction after the effective training or learning. The neural network architecture requires the training set of sample examples of input-output pattern pairs to accomplish the learning. A feed forward neural network architecture as shown in figure 1 is needed to perform the task of training.

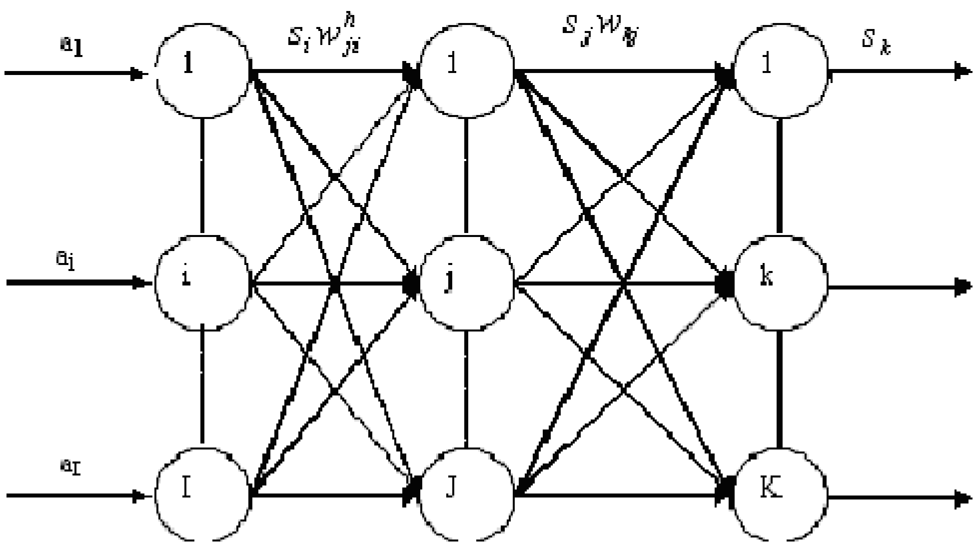


Figure 1: Feed Forward Multilayer Neural Network Architecture

This neural network consist of differentiable continuous but non linear output function in all processing units [22] of output and all hidden layer. The number of processing units in the input layer corresponds to the dimensionality of the input pattern vectors are linear. The number of processing units in the output layer corresponds to the number of distinct classes in the pattern classification. The number of processing units in the hidden layers and the number of hidden layers in the network correspond to the convex of classes. All the processing units of input layer are interconnected to all the processing units of the hidden layers and all the processing units of the hidden layer are interconnected to the processing units of the output layer and weight is associated with each connection. We can use supervised leaning method i.e generalized delta learning rule so that a network can be trained to capture the mapping explicitly in the set of input output pattern collected during an experiment and simultaneously expected to model the unknown system or function from which the prediction can be made for the new or unknown set of data not used in the training set [23]. The possible output pattern class would be approximately an interpolated version of the output pattern class corresponding to the input learning pattern close to the given test input pattern. This method involves the modification of the weight between the processing units of successive layers. For such an updating of weight in the supervisory mode, it becomes necessary to know the desired output for each unit in the hidden and output layers so that the instantaneous squared error (the difference between the desired and actual output for the current presented input pattern from each unit of the output layer) may be used to guide the updating of the weights. We propagate the error from output layers to successive hidden layers for updating the weights. This leaning method is known as back-propagation learning [24, 25] based on the principle of gradient descent along the error surface in weight space. In this proposed neural network architecture the activation value and output values of the units of output layer and hidden layer are shown with following set of equations.

The activation and output signal for the $j^{th}$ units of output layer for the presented input pattern at the $k^{th}$ iteration can represent as:

$$y_j^k = \sum_{h=1}^{H} S_h(q_h^k) W_{jh} \tag{2.1}$$

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$$S_j\left(y_j^h\right) = f\left(y_j^h\right) = \frac{1}{1+e^{-y_j^k}} \quad (2.2)$$

The activation and output signal for the $h^{th}$ unit of hidden layer for the presented input at the $k^{th}$ iteration can represent as:

$$q_h^k = \sum_{i=1}^{n} S_i\left(x_i^h\right) W_{h_i} = \sum_{i=1}^{n} x_i^k\, W_{h_i} \quad (2.3)$$

$$S_{h\left(q_h^i\right)} = f\left(q_h^k\right) = \frac{1}{1+e^{-q_h^k}} \quad (2.4)$$

The instantaneous squared error (SE) for the presented input pattern at the iteration k can represent as:

$$E_k = \frac{1}{2}\sum_{j=1}^{n}\left(d_j^k - S_j\left(y_j^k\right)\right)^2 \quad (2.5)$$

Where $d_j^k$ is the desired output pattern at the $j^{th}$ unit for the given input-output pattern pair.

So that, in this paper we use the back-propagation learning rule to train the system for capturing the implicit relationship function between input and its corresponding output pattern. This functional mapping used to establish a generalize relationship between input output pattern pair of training set. This generalized mapping is used to predict the failure intensity likely to occur for the given time period from each component of the software. The reliabilities of each component is estimated from its corresponding neural network with prediction of failure intensities. This estimated reliability with failure history of the software for the specific time period is used to predict or estimate the reliability of whole software for the specific time period which is not used during the training. Hence the number of independent neural network architecture is depending upon the number of components in the software. Thus, for each component there is neural network architecture with its local training set. Every local training set involves the data of previous failure in specific period of time for the respective component. The estimated software reliability from each component with the data of previous failure in specific time for the whole software is now used to predict the reliability of the whole software.

### 3. Neural Network Modeling for Failure Prediction:

It has been discussed in previous section of paper that the back-propagation learning rule for the feed forward neural network is used to capture the implied functional relationship between input pattern and corresponding output pattern. Thus a widely used feed forward neural networks trained with back propagation learning rule can be represented as a mapping $N{:}I^n \rightarrow O^m$, where $I^n$ is a point in the n dimensional input space and $O^m$ is point in the m dimensional output space. Generally this mapping is performed with multilayer feed forward neural network. The training procedure is a mapping operation $T{:}I_k \rightarrow O_k$ in which $(I_k, O_k) = \{(i,o) \mid i \in I^n \text{ and } O \in O^m\}$ is a subset of k stimuli-response pairs sampled from $(I^n, O^m)$ spaces. The function T is an approximation to neural network. The problem of prediction can be formulated as a mapping $f{:}I_l \rightarrow O_l$ in which $I_l$ represent a sequence of $I^{th}$ recent samples of the stimuli and $O_l$ the predicted output corresponding to a future moment. Once we train the network within a certain prespecified error tolerance we can make the network predicts an output by feeding $i_{k+d} \in I^n$ as stimulus input. The input $i_{k+d}$ corresponds to future stimuli with a time difference of d consecutive random intervals from the $k^{th}$ moment. For d=1 the prediction is called the next step prediction and for $d = n(\geq 2)$ consecutive intervals it is known as the n-step ahead or long term prediction [26].

Thus we can formulate our software reliability prediction problem in terms of a feed forward neural network mapping as:

Hence to consider the problem of component based software reliability prediction we consider the number of feed forward neural networks as the number of components. Let we have the r components in the software so that we consider the r number of neural network architectures. Each neural network will predict the reliability of the corresponding component. Therefore, for each component software reliability prediction a sequence of cumulative execution time $((t_1,t_2,\ldots\ldots\ldots t_k) \in T_k$ and the corresponding observed accumulated faults $((\mu_1,\mu_2,\ldots\ldots\mu_k) \in F_k)$ upto the present time $t_k$ is required as the input-output sample patterns in the local training set for the corresponding component. Thus, for each component we consider a different training set which we are calling as local training sets. In each local training set of the component, the input pattern information i.e. cumulative execution time remains same but the corresponding observed accumulated faults are different. The global training set which is used to train the main neural network for the prediction of software reliability for the complete software contains with sequence of cumulative execution time $(t_{k+1},\ldots\ldots\ldots t_{k+q}) \in T_{n+q}$, number of predicted faults in each component $(f_1,f_2,\ldots..f_r) \in F_r$ and the corresponding observed accumulated faults $((\mu F_1,\mu F_2,\ldots\ldots\ldots..\mu F_n) \in F_k)$.

$$N{:}\{((T_{k+q},f_r),\mu F_k\} \rightarrow \mu F_{k+h} \quad (3.1)$$

Where $((T_{k+q},f_r), \mu F_k)$ represents the failure history of the software system at time $t_{k+q}$ with predicted faults from each component at time $t_k$ used to train the network and $\mu F_{k+h}$ the network's prediction. Similarly, we can also formulate the software reliability prediction problem for each component in terms of local feed forward neural network mapping as:

$$N_r: \{(T_k, F_k)_r, t_{k+h}\} \rightarrow \mu_{k+h}^r \quad (3.2)$$

Where $(T_k, F_k)_r$ represents the failure history of r[th] component of the system at time $t_k$ used to train the r[th] network and $\mu_{k+h}^r$ the r[th] network prediction for the r[th] component of the software. Thus, on the successful training of neural network, it can be used to predict the total number of faults to be detected at the end of a future test session k+h feeding $t_{k+h}$ as its input. In the process of training, the two techniques are used to exhibit the predictive capability of neural network. The first method is used in the generalization training. This is the standard way in which most of the feed forward neural networks are trained. During training, each input $i_t$ at time t is associated with the corresponding output $O_t$. Here, the network learns to generalize the actual functionality between the input variable and the output variable. The second regime is used in the prediction training. It refers to an approach used in training recurrent networks. Under this training the value of the input variable $i_t$ at time t is associated with the value of the output variable $O_{t+1}$ corresponds to the next time step t+1. Here the network learns to predict output anticipated at the next time step rather than computing outputs corresponding to the present input [27].

Hence for the prediction or estimation for the expected number of faults, we consider a component based software for which we are interested in estimating the reliability. Let the software consists of r individual components. Each component has cumulative execution time and its own accumulated faults. Therefore, we consider the r different neural network architecture. Now we consider the arbitrary r[th] component from the components of software. The r[th] component considers the $t_1^r, t_2^r, \ldots \ldots \ldots \ldots \ldots \ldots t_k^r$ cumulative execution times and $f_1^r, f_2^r, \ldots \ldots \ldots \ldots f_k^r$ are observed accumulated faults. This set of execution time and accumulated faults consider the training set of the r[th] component and in such a way each component has its own training set. Thus at any instant of time we have the r local training sets. Therefore individual r neural networks are trained with corresponding local training set and predict the expected number of faults in the next instant of execution time. Hence the training set for r[th] component is represented as:

$$T^r = \{(t_1^r, f_1^r), (t_2^r, f_2^r), \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (t_n^r, f_r^n)\} \quad (3.3)$$

The r[th] neural network is initialized with random weights prior to learning. In the process of learning for input-output pattern pairs of training set $T^r$, patterns are presented on repeated basis. Suppose an arbitrary input pattern $t_l^r$ is presented at iteration m on the current values of weights. The neural network $n^r$ produces the output pattern:

$$N^r = \{S_1(y_1^r(l), S_2\left(y_2^r(l), \ldots S_j\left(y_j^r(l)\right) \ldots S_p\left(y_p^r(l)\right)\right\} \quad (3.4)$$

Suppose number of units in the output layer is P so that the instantaneous square error at l[th] iteration is defined as:

$$E_l^r = \frac{1}{2}\sum_{j=1}^{P}(f_l^r - S_j\left(y_j^r(l)\right)^2 \qquad (3.5)$$

The weights will converge to optimal weights by modification in the weights during the training process of network for capturing the required mapping function. The training process is in such a way that the weight changes at current iteration will proportional to the gradient descent along the instantaneous error surface i.e.

$$\Delta W_{jh}(l) = -\eta_0 \frac{\partial E_l^r}{\partial W_{jh}(l)} \quad for\ output\ layer \quad (3.6)$$

And $\Delta W_{hi}(l) = -\eta_h \frac{\partial E_l^r}{\partial W_{hi(l)}} \quad for\ hidden\ layer \quad (3.7)$

Hence with the chain rule in limit of stochastic gradient method we have:

$$\frac{\partial E_l^r}{\partial W_{jh(l)}} = \frac{\partial E_l^r}{\partial y_j^r(l)} \cdot \frac{\partial y_i^r(l)}{\partial W_{ih(l)}} = \frac{\partial E_l^r}{\partial y_j^r(l)} \cdot S_h(q_h^r(l))$$

or

$$\frac{\partial E_l^r}{\partial W_{ih(l)}} = \frac{\partial E_l^r}{\partial S_j(y_j^r(l))} \cdot \frac{\partial S_j(y_j^r(l))}{\partial y_j^r(l)} \cdot S_h(q_h^r(l))$$

$$= \Delta_l^r \cdot S_h(q_h^r(l) \qquad (3.8)$$

Where $\Delta_l^r = \frac{\partial E_l^r}{\partial S_j(y_j^r(l)} \cdot \frac{\partial S_j(y_j^r(l)}{\partial y_j^r(l)}$

Now, $\Delta_l^r = \frac{\partial E_l^r}{\partial S_j(y_j^r(l)} \cdot S_j(y_j^r(l))(1 - S_j\left(y_j^r(l)\right))$

$$= -\sum_{j=1}^{p}\left(f_{jl}^r - S_j\left(y_j^r(l)\right)\right) S_j\left(y_j^r(l)\right)(1 - S_j(y_j^r(l)))$$

So that from equation (3.6) we have

$$\Delta W_{jh}(l) = \eta_0 \Delta_l^r \cdot S_h\left(q_h^r(l)\right) \qquad (3.9)$$

$$\text{And } W_{jh}(l+1) = W_j h(l) + \eta_0 \Delta_l^r S_h\left(q_h^r(l)\right) \qquad (3.10)$$

Similarly, from equation (3.7) we have

$$\frac{\partial E_l^r}{\partial W h_i(l)} = \frac{\partial E_l^r}{\partial q_h^r(l)} \cdot \frac{\partial q_h^r(l)}{\partial W h_i(l)}$$

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$$= \frac{\partial E_l^r}{\partial q_h^r(l)} . t_k^r(l)$$
$$= \frac{\partial E_l^r}{\partial S_h\,(q_h^r(l)}.\frac{\partial S_h(q_h^r(l)}{\partial q_h^r(l)}.t_k^r(l)$$
$$= \frac{\partial E_l^r}{\partial S_h\left(q_h^r(l)\right)}.S_h\left(q_h^r(l)\right)\left(1-S_h\left(q_h^r(l)\right)\right).t_k^r(l)$$
$$= \frac{\partial E_l^r}{\partial y_j^r}.\frac{\partial y_j^r(l)}{\partial S_h(q_h^r(l)}.S_h(q_h^r(l))(1-S_h\left(q_h^r(l)\right).t_k^r(l)$$
$$= \Delta_l^r.W_{jh}.S_h\left(q_h^r(l)\right)(1-S_h(q_h^r(l))).t_k^r(l)$$

Therefore, from equation (3.7) we have

$$\Delta W{h_i}(l) = \eta_h \Delta_l^r.W_{jh}.S_h\left(q_h^r(l)\right)\left(1-S_h\left(q_h^r(l)\right)\right).t_k^r(l) \qquad (3.11)$$

and

$$W_{hi}(l+1) = W_{hi}(l) + \eta_h \Delta_l^r.W_j h.S_h\left(q_h^r\,(l)\right)\left(1-S_h\left(q_h^r(l)\right)\right).t_k^r(l) \qquad (3.12)$$

Hence in this way all the neural networks i.e. l to r are combined for the learning process with their local training sets. Thus, these r neural networks are able to predict reliability of each components in generalize way.

After this, we consider our global training set to accomplish the training of main neural network architecture for the prediction of software reliability for the complete software. This training set consists of sequence of cumulative execution time i.e. ($t_{k+1}$, $t_{k+2}$,……………$t_{k+q}$ ∈ $T_k$), the number of possible predicted faults in each component and the corresponding observed accumulated faults ($\mu F_1$, $\mu F_2$,………….. $\mu F_n$) ∈ Fn from the whole software i.e.

$$GT = \{(t_{k+1},(f_1^{k+1},\dots\dots f_r^{k+1}),\mu F_{k+1}),$$
$$(t_{k+2},(f_1^{k+2}\dots\dots f_r^{k+2}),\mu F_{k+2}\dots\dots\left(t_{k+q}\left(f_1^{k+q}\dots,f_r^{k+q}\right)\right),\mu F_{k+q}\} \qquad (3.13)$$

Now this training is presented to neural network architecture which is predicting the reliability of the whole software. This prediction depends upon number of failures in cumulative execution time and predicted faults in each component. During the training process the weight update in neural network architecture for output and hidden layer can define in similar manner of equation (3.10) and (3.11). Hence we have:

$$\Delta W_{h_i}(l) = \eta_h \Delta_l W_{jh}.S_h\left(q_h(l)\right)\left(1 - S_h\left(q_h(l)\right)\right).x_i^l \qquad (3.14)$$

and $$W h_{jh}(l) = \eta_0 \Delta_l S_h\left(q_h(l)\right) \qquad (3.15)$$

where

$$\Delta l = -\sum_{j=1}^{p}\left(\mu F_j^{k+l} - S_j\left(y_j^l\right)\right).S_j(y_j^l)(1-S_j\left(y_j^l\right)) \qquad \forall\, d = 1 \text{ to } q$$

and

$$x_i^l = t_{k+d}^i + \sum_{j=1}^{r} f_{ij}^{k+d} \qquad \forall\, i = 1 \text{ to } n \text{ and } d = 1 \text{ to } q \quad (3.16)$$

Thus, the set of neural network i.e. r in number are used to predict failures in the presented time as input pattern through the captured implied function relationships by the network. This predicted information is used with cumulative execution time to predict the reliability of whole software. Therefore, it is now required to consider the formation of local training sets and global training set with proper encoding for cumulative execution time and accumulated faults to accomplish the implementation and simulation of proposed method.

## 4. Implementation Detail and Simulation Design:

In this section of implementation detail and simulation design we consider the input-output pattern representation for training with the selection of various required parameters & architecture to accomplish the training for prediction of reliability in component based software. So that before we attempt to use neural network it is necessary to encode the patterns in a form that is suitable for the training pattern to the neural network. As we know that the neuron state variable in feed forward networks is restricted to 0 to 1.0 or -1.0 to +1.0 due to the sigmoid single function use in the units of hidden and output layers. Hence the input/output variables of the problem should be encoded to conform to this range. It is obvious that for prediction problem where input/output variable may range over a large numerical value and to use the direct binary encoding is a trivial form. However, such a direct scaling may result both in the lost of prediction accuracy and the network failure to discriminate different output values. Some of such schemes are found in literature [28] to address this situation. A better generalization and prediction is obtained [6,7] using gray coding when compared to binary encoding representation. Thus the gray coding is used to eliminate hamming clifts in the input representation. Thus in our application we employ a

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simple gray code representation because our data set represents a sequence of increasing numerical values and prediction is near this kind of hamming clift resulted in very high error and this anomaly reduced with the use of Gray coding. Therefore, in order to simulate the experiment for the prediction of reliability in component based software model, we have combined the individual neural network architecture for each component with its local training set. The global training set for the neural network which is used to predict the reliability for whole software includes extra values in terms of predicted faults from the components of software. Therefore the number of units used in the input and the output layer is determined by the number of bits used to encode the input and the output variables used in our experiments for the components in the software and for the complete software. Tables from 1.1 to 1.10 are showing the encoding used for the components and their corresponding observed faults.

Table 1.1: Coding for 1st software(SW1) containing 10 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 4+3+3 | 3+5+6 | 000000.0110.0010.0010 | 00010.00111.00101 |
| $t_6$-$t_{10}$ | 4+3+3 | 2+4+5 | 000001.0110.0010.0010 | 00011.00110.00111 |
| $t_{11}$-$t_{15}$ | 4+3+3 | 2+3+8 | 000010.0110.0010.0010 | 00011.00010.01100 |
| $t_{16}$-$t_{20}$ | 4+3+3 | 0+4+4 | 000011.0110.0010.0010 | 00000.00110.00110 |
| $t_{21}$-$t_{25}$ | 4+3+3 | 1+2+1 | 000110.0110.0010.0010 | 00001.00011.00001 |

Table 1.2: Coding for 2nd software(SW2) containing 20 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 8+5+7 | 14+6+9 | 000000.1100.0111.0100 | 01001.00101.01101 |
| $t_6$-$t_{10}$ | 8+5+7 | 11+8+8 | 000001.1100.0111.0100 | 01110.01100.01100 |
| $t_{11}$-$t_{15}$ | 8+5+7 | 6+6+6 | 000011.1100.0111.0100 | 00101.00101.00101 |
| $t_{16}$-$t_{20}$ | 8+5+7 | 8+4+3 | 000010.1100.0111.0100 | 01100.00110.00100 |
| $t_{21}$-$t_{25}$ | 8+5+7 | 5+2+1 | 000110.1100.0111.0100 | 00111.00011.00001 |

Table 1.3: Coding for 3rd software(SW3) containing 30 components with faults.

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 7+14+9 | 11+20+9 | 000000.0100.1001.1101 | 01110.11110.01101 |
| $t_6$-$t_{10}$ | 7+14+9 | 8+22+7 | 000001.0100.1001.1101 | 01100.11101.00100 |
| $t_{11}$-$t_{15}$ | 7+14+9 | 5+17+10 | 000011.0100.1001.1101 | 00111.11001.01111 |
| $t_{16}$-$t_{20}$ | 7+14+9 | 7+11+6 | 000010.0100.1001.1101 | 00100.01110.00101 |
| $t_{21}$-$t_{25}$ | 7+14+9 | 4+9+2 | 000110.0100.1001.1101 | 00110.01101.00011 |

Table 1.4: Coding for 4th software(SW4) containing 09 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 4+3+2 | 14+7+8 | 000000.0110.0010.0011 | 01001.00100.0110 |
| $t_6$-$t_{10}$ | 4+3+2 | 11+8+9 | 000001.0110.0010.0011 | 01110.01100.01101 |
| $t_{11}$-$t_{15}$ | 4+3+2 | 6+6+9 | 000011.0110.0010.0011 | 00101.00101.01101 |
| $t_{16}$-$t_{20}$ | 4+3+2 | 7+4+8 | 000010. 0110.0010.0011 | 00100.00110.01100 |
| $t_{21}$-$t_{25}$ | 4+3+2 | 1+5+2 | 000110. 0110.0010.0011 | 00001.00111.00011 |

Table 1.5: Coding for 5th software(SW5) containing 25 components with faults.

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 8+10+7 | 11+9+20 | 000000.1100.1111.0100 | 01110.01101.11110 |
| $t_6$-$t_{10}$ | 8+10+7 | 6+11+8 | 000001. 1100.1111.0100 | 00101.01110.01100 |
| $t_{11}$-$t_{15}$ | 8+10+7 | 2+4+9 | 000011. 1100.1111.0100 | 00011.00110.01101 |
| $t_{16}$-$t_{20}$ | 8+10+7 | 17+10+5 | 000010. 1100.1111.0100 | 11001.01111.00111 |
| $t_{21}$-$t_{25}$ | 8+10+7 | 7+22+8 | 000110. 1100.1111.0100 | 00100.11101.01100 |

Table 1.6: Coding for 6th software(SW6) containing 12 components with faults

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| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 5+4+3 | 15+11+12 | 000000.0111.0110.0010 | 01000.01110.01010 |
| $t_6$-$t_{10}$ | 5+4+3 | 12+15+11 | 000001.0111.0110.0010 | 01010.01000.01110 |
| $t_{11}$-$t_{15}$ | 5+4+3 | 15+18+0 | 000011.0111.0110.0010 | 01000.11011.00000 |
| $t_{16}$-$t_{20}$ | 5+4+3 | 1+8+16 | 000010.0111.0110.0010 | 00001.01100.11000 |
| $t_{21}$-$t_{25}$ | 5+4+3 | 16+15+3 | 000110.0111.0110.0010 | 11000.01000.00010 |

Table 1.7: Coding for 7th software(SW7) containing 24 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 10+8+6 | 6+5+4 | 000000.1111.1100.0101 | 00101.00111.00110 |
| $t_6$-$t_{10}$ | 10+8+6 | 5+4+1 | 000001.1111.1100.0101 | 00111.00110.00001 |
| $t_{11}$-$t_{15}$ | 10+8+6 | 15+14+13 | 000011.1111.1100.0101 | 01000.01001.01011 |
| $t_{16}$-$t_{20}$ | 10+8+6 | 13+15+5 | 000010.1111.1100.0101 | 01001.01000.00111 |
| $t_{21}$-$t_{25}$ | 10+8+6 | 5+6+19 | 000110.1111.1100.0101 | 00111.00101.11010 |

Table 1.8: Coding for 8th software(SW8) containing 37 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 11+12+14 | 0+9+12 | 000000.1110.1010.1001 | 00000.01101.01010 |
| $t_6$-$t_{10}$ | 11+12+14 | 14+11+4 | 000001.1110.1010.1001 | 01001.01110.00110 |
| $t_{11}$-$t_{15}$ | 11+12+14 | 9+8+8 | 000011.1110.1010.1001 | 01101.01100.00100 |
| $t_{16}$-$t_{20}$ | 11+12+14 | 3+3+9 | 000010.1110.1010.1001 | 00010.00100.01101 |
| $t_{21}$-$t_{25}$ | 11+12+14 | 10+11+12 | 000110.1110.1010.1001 | 01111.01110.01010 |

Table 1.9: Coding for 9th software(SW9) containing 13 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 3+2+8 | 12+13+14 | 000000.0010.0011.1100 | 01010.01011.01001 |
| $t_6$-$t_{10}$ | 3+2+8 | 6+7+8 | 000001.0010.0011.1100 | 00101.00100.01100 |
| $t_{11}$-$t_{15}$ | 3+2+8 | 9+10+16 | 000011.0010.0011.1100 | 01101.01111.11000 |
| $t_{16}$-$t_{20}$ | 3+2+8 | 9+10+11 | 000010.0010.0011.1100 | 01101.01111.01110 |
| $t_{21}$-$t_{25}$ | 3+2+8 | 2+7+1 | 000110.0010.0011.1100 | 00011.00100.00001 |

Table 1.10: Coding for 10th software(SW10) containing 18 components with faults

| Time | Number of Components | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 5+6+7 | 4+5+6 | 000000.0111.0101.0100 | 00110.00111.00101 |
| $t_6$-$t_{10}$ | 5+6+7 | 7+4+2 | 000001.0111.0101.0100 | 00100.00110.00011 |
| $t_{11}$-$t_{15}$ | 5+6+7 | 11+14+9 | 000011.0111.0101.0100 | 01110.01001.01101 |
| $t_{16}$-$t_{20}$ | 5+6+7 | 16+9+5 | 000010. 0111.0101.010 | 11000.01101.00111 |
| $t_{21}$-$t_{25}$ | 5+6+7 | 8+6+7 | 000110.0111.0101.0100 | 01100.00101.00100 |

The number of units used in the neural network for complete software in the input and output layer is determined by the number of bits used to encode one input for execution time & number of bits to express predicted faults from each component and the output variables as the number of total actual faults in the complete software in presented cumulative execution time. Table 2.1 to 2.10 shows the encoding used in our experiments for the complete software.

Table 2.1: Detected faults in cumulative execution time for software(S/W1)

| Time | No. of Components in Software one | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 10 | 31 | 000000.001111 | 010000 |
| $t_6$-$t_{10}$ | 10 | 20 | 000001.001111 | 011110 |
| $t_{11}$-$t_{15}$ | 10 | 37 | 000011.001111 | 110111 |
| $t_{16}$-$t_{20}$ | 10 | 28 | 000010. 001111 | 010010 |
| $t_{21}$-$t_{25}$ | 10 | 15 | 000110. 001111 | 001000 |

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Table 2.2: Detected faults in cumulative execution time for software(S/W2)

| Time | No. of Components in Software two | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 20 | 38 | 000000.011110 | 110101 |
| $t_6$-$t_{10}$ | 20 | 36 | 000001.011110 | 110110 |
| $t_{11}$-$t_{15}$ | 20 | 30 | 000011.011110 | 010001 |
| $t_{16}$-$t_{20}$ | 20 | 24 | 000010.011110 | 011101 |
| $t_{21}$-$t_{25}$ | 20 | 08 | 000110.011110 | 001100 |

Table 2.3: Detected faults in cumulative execution time for software(S/W3)

| Time | No. of Components in Software three | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 25 | 15 | 000000.010101 | 001000 |
| $t_6$-$t_{10}$ | 25 | 11 | 000001.010101 | 001110 |
| $t_{11}$-$t_{15}$ | 25 | 17 | 000011.010101 | 011001 |
| $t_{16}$-$t_{20}$ | 25 | 14 | 000010.010101 | 001001 |
| $t_{21}$-$t_{25}$ | 25 | 08 | 000110.010101 | 001100 |

Table 2.4: Detected faults in cumulative execution time for software(S/W4)

| Time | No. of Components in a whole Software four | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 30 | 39 | 000000.010001 | 110100 |
| $t_6$-$t_{10}$ | 30 | 47 | 000001.010001 | 111000 |
| $t_{11}$-$t_{15}$ | 30 | 39 | 000011.010001 | 110100 |
| $t_{16}$-$t_{20}$ | 30 | 29 | 000010.010001 | 010011 |
| $t_{21}$-$t_{25}$ | 30 | 17 | 000110.010001 | 011001 |

Table 2.5: Detected faults in cumulative execution time for software(S/W5)

| Time | No. of Components in Software five | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 35 | 18 | 000000.110010 | 011011 |
| $t_6$-$t_{10}$ | 35 | 17 | 000001.110010 | 011001 |
| $t_{11}$-$t_{15}$ | 35 | 20 | 000011.110010 | 011110 |
| $t_{16}$-$t_{20}$ | 35 | 22 | 000010.110010 | 011101 |
| $t_{21}$-$t_{25}$ | 35 | 10 | 000110.110010 | 001111 |

Table 2.6: Detected faults in cumulative execution time for software(S/W6)

| Time | No. of Components in Software six | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 40 | 28 | 000000.111100 | 010010 |
| $t_6$-$t_{10}$ | 40 | 25 | 000001.111100 | 010101 |
| $t_{11}$-$t_{15}$ | 40 | 28 | 000011.111100 | 010010 |
| $t_{16}$-$t_{20}$ | 40 | 30 | 000010.111100 | 010001 |
| $t_{21}$-$t_{25}$ | 40 | 20 | 000110.111100 | 011110 |

Table 2.7: Detected faults in cumulative execution time for software(S/W7)

| Time | No. of Components in Software seven | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 45 | 28 | 000000.111011 | 010010 |
| $t_6$-$t_{10}$ | 45 | 32 | 000001.111011 | 110000 |
| $t_{11}$-$t_{15}$ | 45 | 22 | 000011.111011 | 010010 |
| $t_{16}$-$t_{20}$ | 45 | 15 | 000010.111011 | 010001 |
| $t_{21}$-$t_{25}$ | 45 | 08 | 000110.111011 | 011110 |

Table 2.8: Detected faults in cumulative execution time for software(S/W8)

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| Time | No. of Components in Software eight | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 50 | 35 | 000000.101011 | 110010 |
| $t_6$-$t_{10}$ | 50 | 40 | 000001.101011 | 111100 |
| $t_{11}$-$t_{15}$ | 50 | 32 | 000011.101011 | 110000 |
| $t_{16}$-$t_{20}$ | 50 | 30 | 000010.101011 | 010001 |
| $t_{21}$-$t_{25}$ | 50 | 28 | 000110.101011 | 010010 |

Table 2.9: Detected faults in cumulative execution time for software(S/W9)

| Time | No. of Components in Software nine | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 55 | 32 | 000000.101100 | 110000 |
| $t_6$-$t_{10}$ | 55 | 28 | 000001.101100 | 010010 |
| $t_{11}$-$t_{15}$ | 55 | 25 | 000011.101100 | 010101 |
| $t_{16}$-$t_{20}$ | 55 | 24 | 000010.101100 | 011101 |
| $t_{21}$-$t_{25}$ | 55 | 20 | 000110.101100 | 011110 |

Table 2.10: Detected faults in cumulative execution time for software(S/W10)

| Time | No. of Components in Software ten | Faults Detected | Input Encoding | Output Encoding |
|---|---|---|---|---|
| $t_1$-$t_5$ | 60 | 44 | 000000.100010 | 111010 |
| $t_6$-$t_{10}$ | 60 | 40 | 000001.100010 | 111101 |
| $t_{11}$-$t_{15}$ | 60 | 38 | 000011.100010 | 110101 |
| $t_{16}$-$t_{20}$ | 60 | 32 | 000010.100010 | 110000 |
| $t_{21}$-$t_{25}$ | 60 | 28 | 000110.100010 | 010010 |

Since for each prediction we have the two experiments one for the components and the other one for the complete software. As far as first experiment is concerned we consider the cumulative execution time as a free variable and the corresponding cumulative faults count as the dependent variable. Therefore, we trained the network for components with the execution time as the input and observed fault count as the target output. It is considered that the training ensemble at time $t_k^i$ consists of complete failure history of the i$^{th}$ component since t=0. As the feed forward neural network cannot predict well without any exposure to the failure history of the component, we imposed a limit on the minimum size of the training ensemble. Thus in our first experiment the minimum ensemble size was restricted to 3 data points i.e. the components are assumed to be at first 3 sessions of test are over. Hence after successful training for each neural network with failure history up to $t_{k_1}$, we fed the future cumulative time as test input patterns i.e. $t_{k+1}^i$ to the neural network of i$^{th}$ component to get the predicted number of faults. These predictions are observed up to $t_q$. Now we consider our second experiment. In this we trained the neural network with the cumulative execution time $t_{k+1}$ to $t_{k+q}$ and predicted faults of components from first experiment as the input and the observed faults count from the complete software as the target output. Hence, after successful training to the network with failure history up to $t_{k+q}$ and predicted faults from each component up to $t_{k+q}$, we fed the network with future cumulative execution time as input patterns from $t_{k+q+1}$ to $t_{k+q+u}$ to get the network's prediction. Single hidden layer is considered with 10 neurons for the neural network architecture used for the components and two hidden layers with 10 and 5 neurons in each is considered for the neural network used to predict faults from complete software. These selection are based on the heuristic criteria, which indicates that the number of inputs are more in global training set with respect to local training sets. Therefore, the problem of mapping in complete software is much complex with respect to the problem of mapping for neural networks of components. The number of units in hidden layers is selected as per the suitability of effective performance of neural network as good generalization and approximation.

## 5. RESULTS AND DISCUSSION

In our experiment, we consider the different neural network architectures for predicting the faults in future cumulative execution time as a free variable. The first architecture consists of 18 input units, one hidden layer with ten neurons and one output layer with 15 units. The second neural architecture is used for predicting the number of faults for whole software consists of 10 units and 5 units in hidden layer and one output layer with 6 units. We conducted the whole simulation in two phases for two different situations. In first phase, we consider the components for ten different software consisting of different number of components. In this simulation, we consider the cumulative execution time as a free variable for each of the software, the number of components in the software and corresponding cumulative faults count for each component of the software as the dependent variable.

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We have trained the neural network with the execution time, components as input after encoding these inputs in Gray code as input pattern vector of size 18x1. The observed faults count for each component are considered as output pattern vector of size 12x1 after encoding of observed faults in Gray code. In this training, the input patterns are provided in cumulative time interval from $t_1$-$t_{25}$ with the step of five and this training is continued for each of the software and training graphs for epochs of convergence are shown from figure 5.1 to figure 5.10.

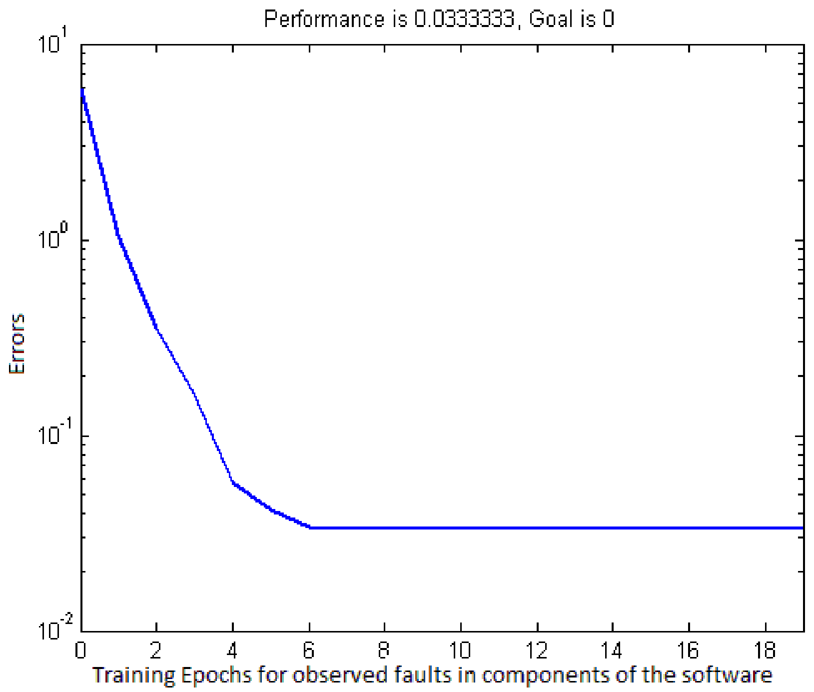


**Figure 5.1**

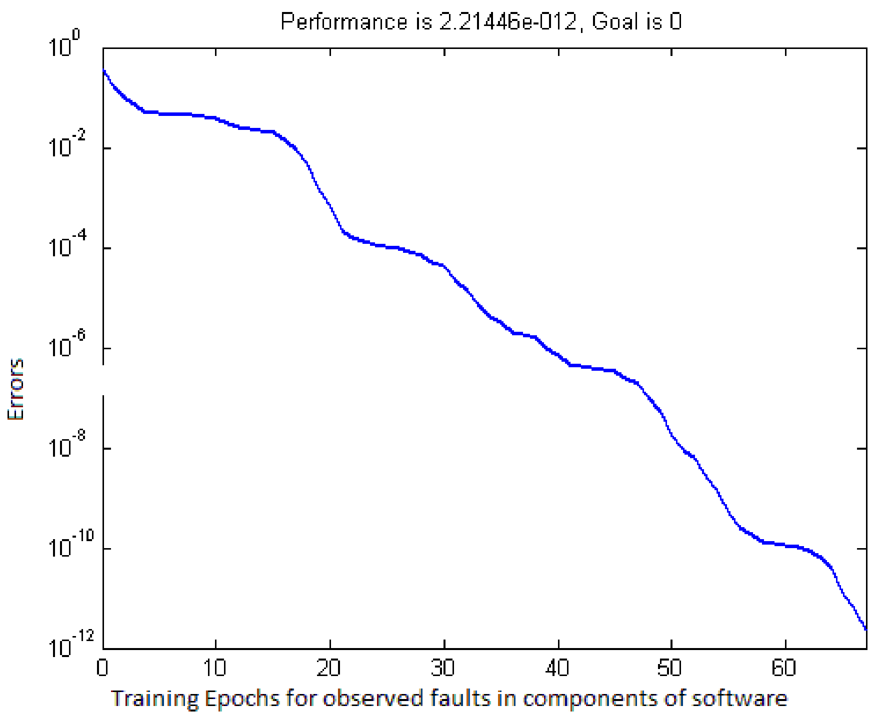


**Figure 5.2**

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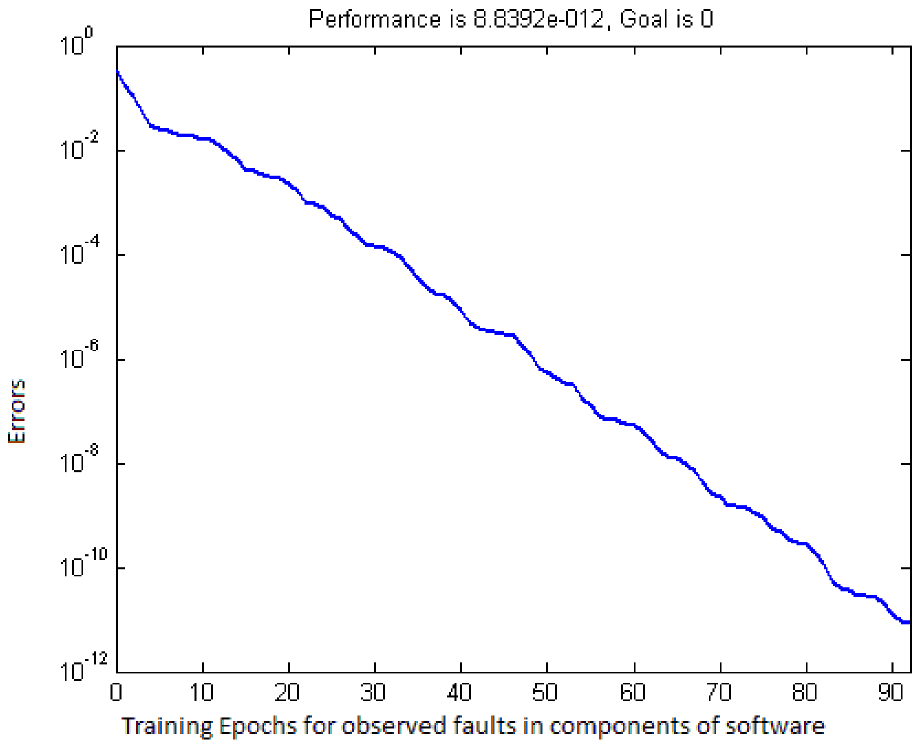


**Figure 5.3**

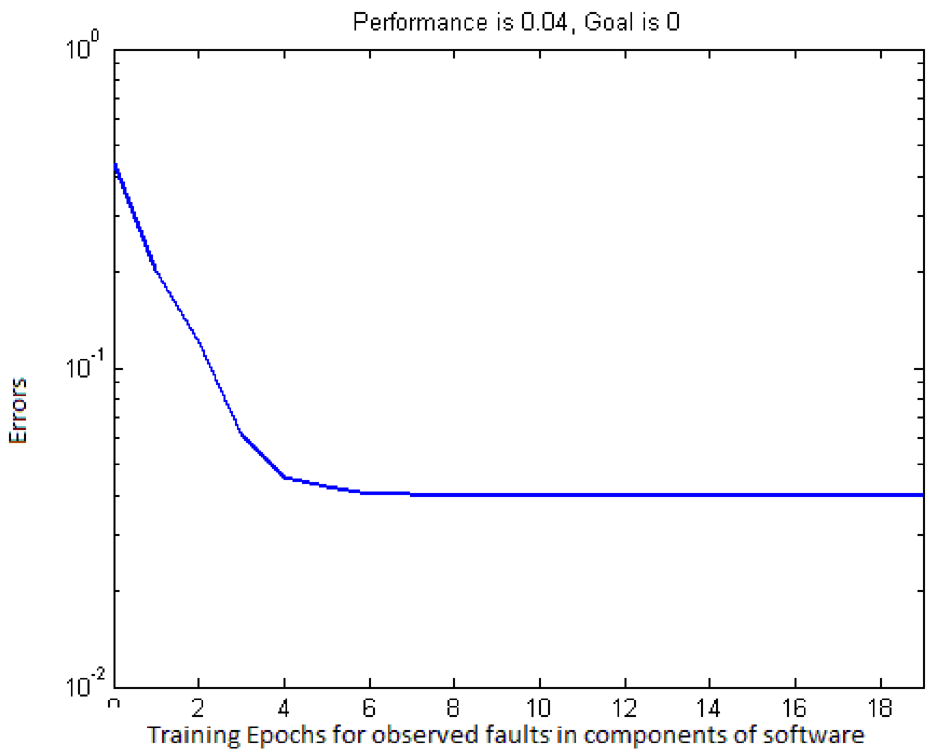


**Figure 5.4**

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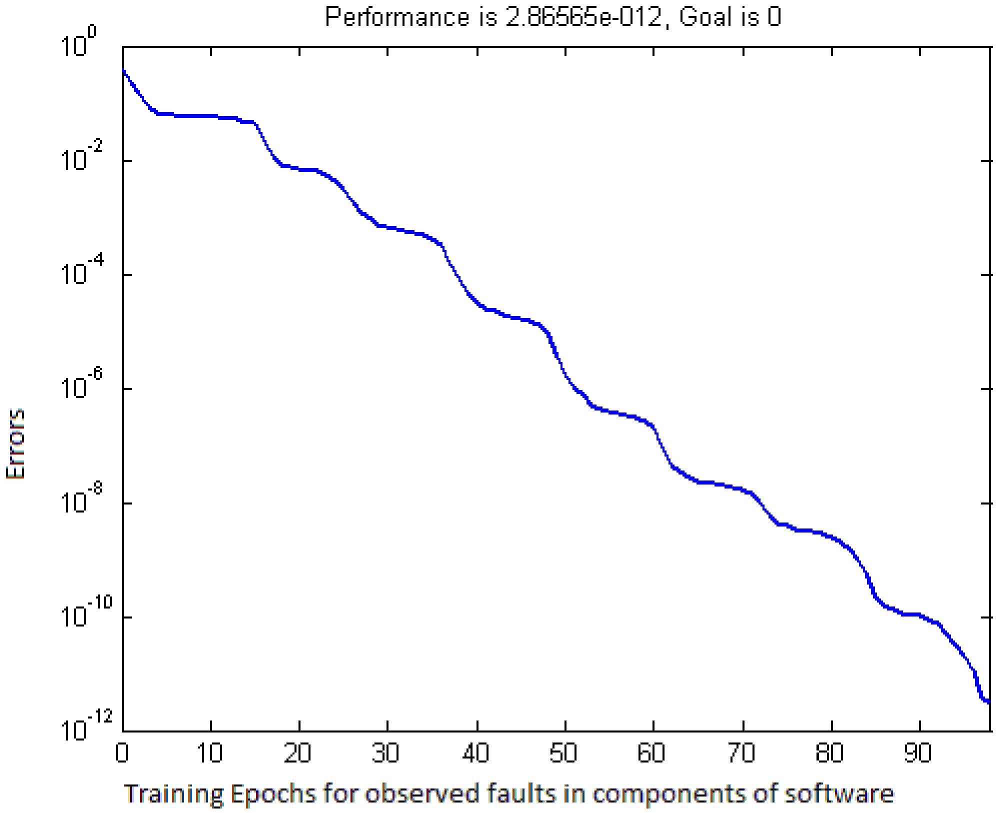


**Figure 5.5**

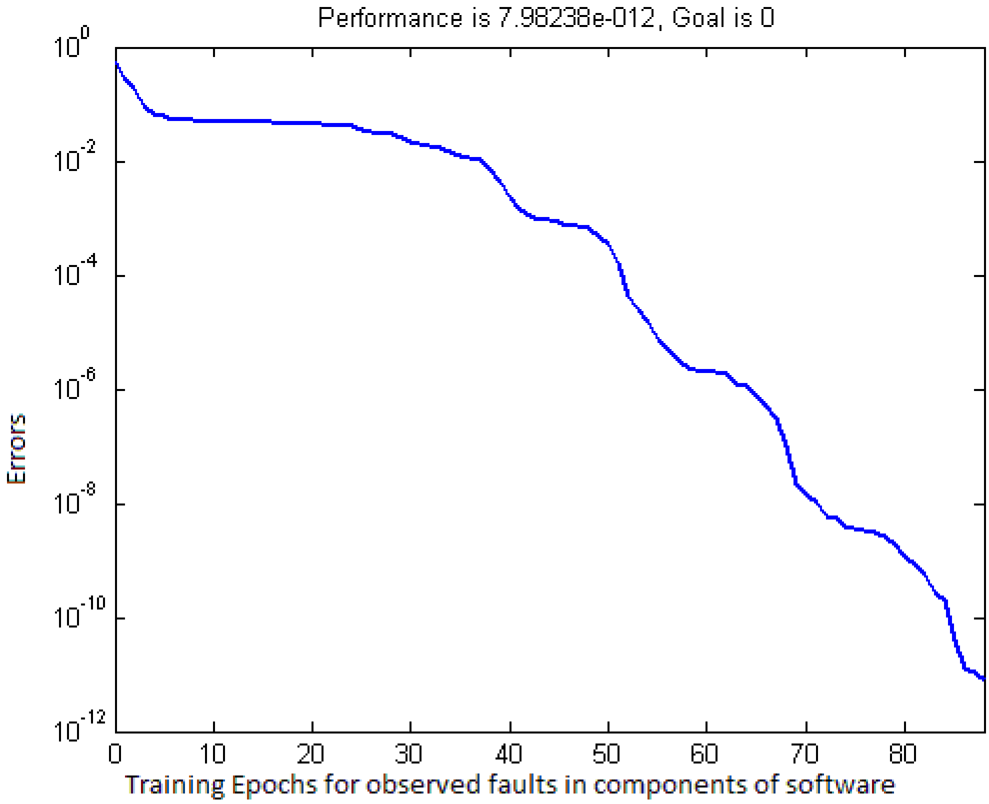


**Figure 5.6**

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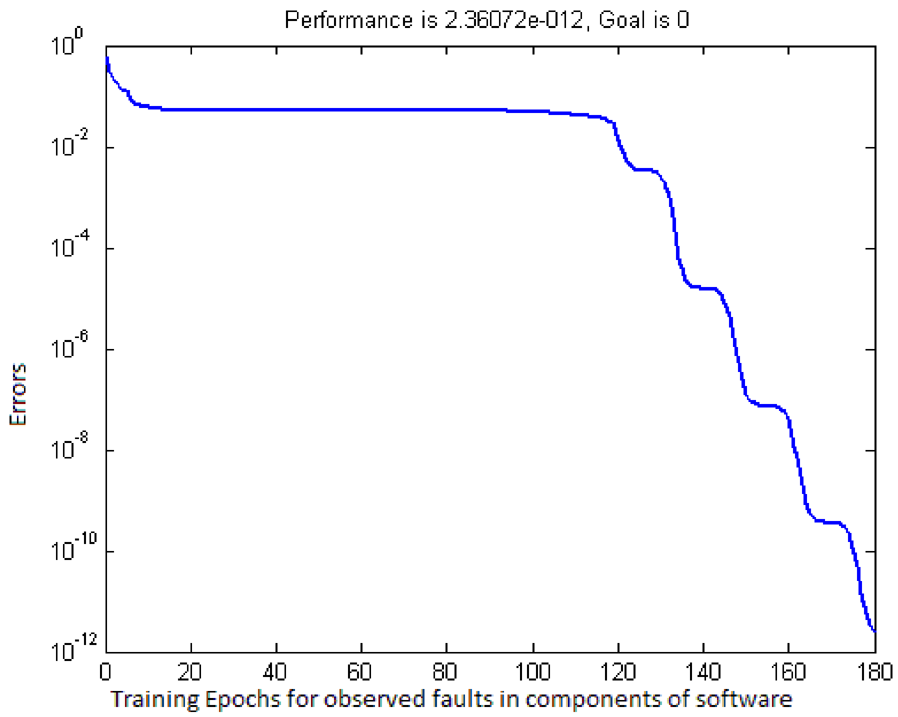


**Figure 5.7**

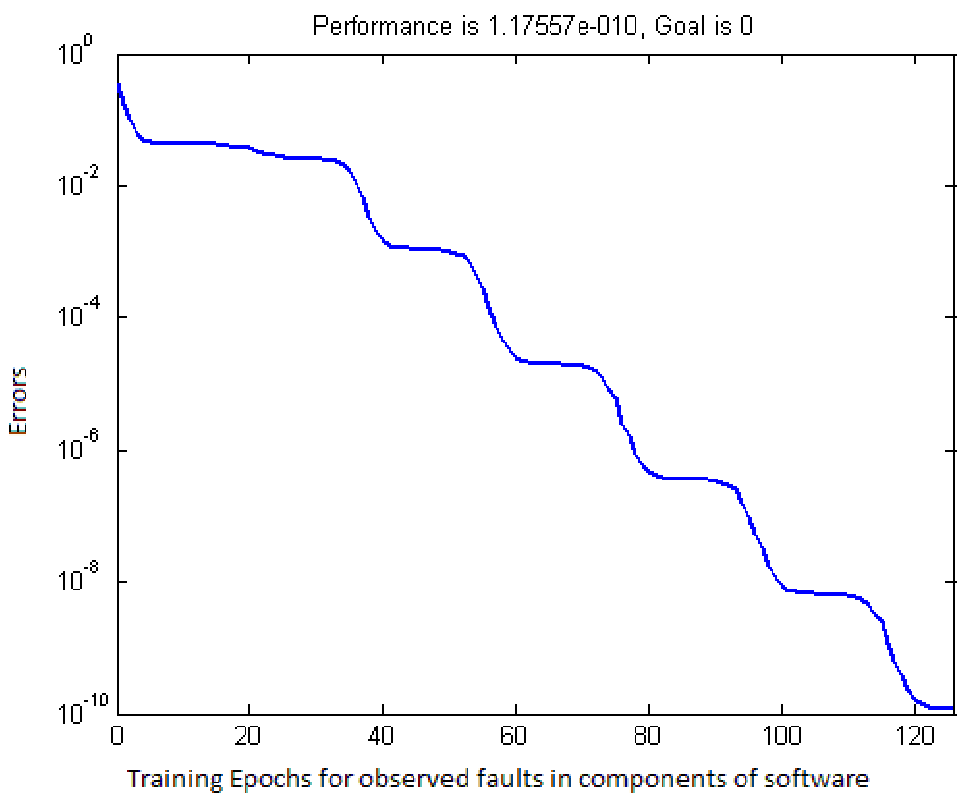


**Figure 5.8**

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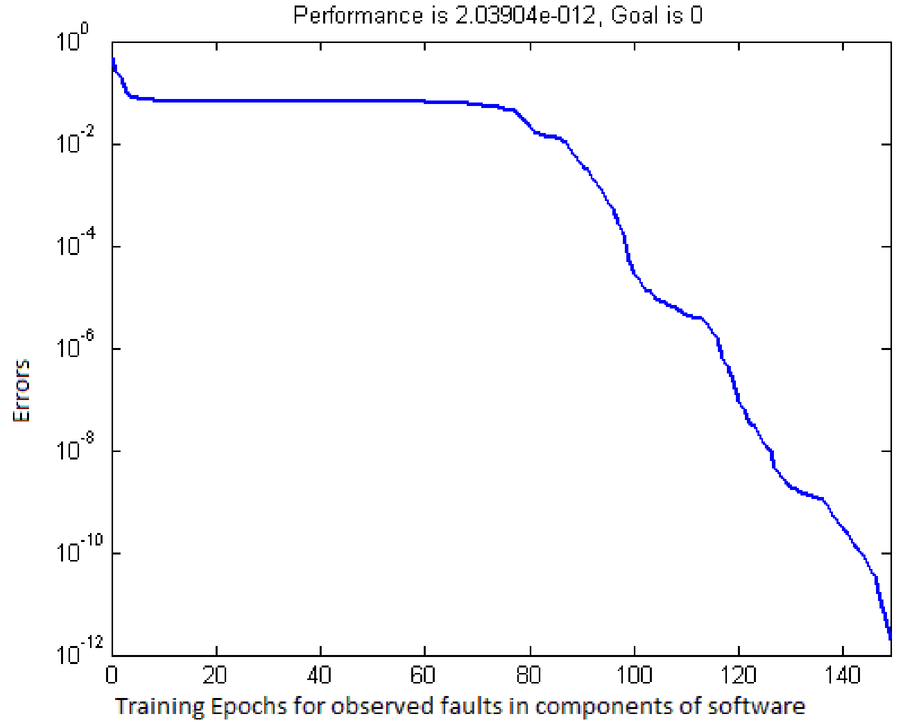


**Figure 5.9**

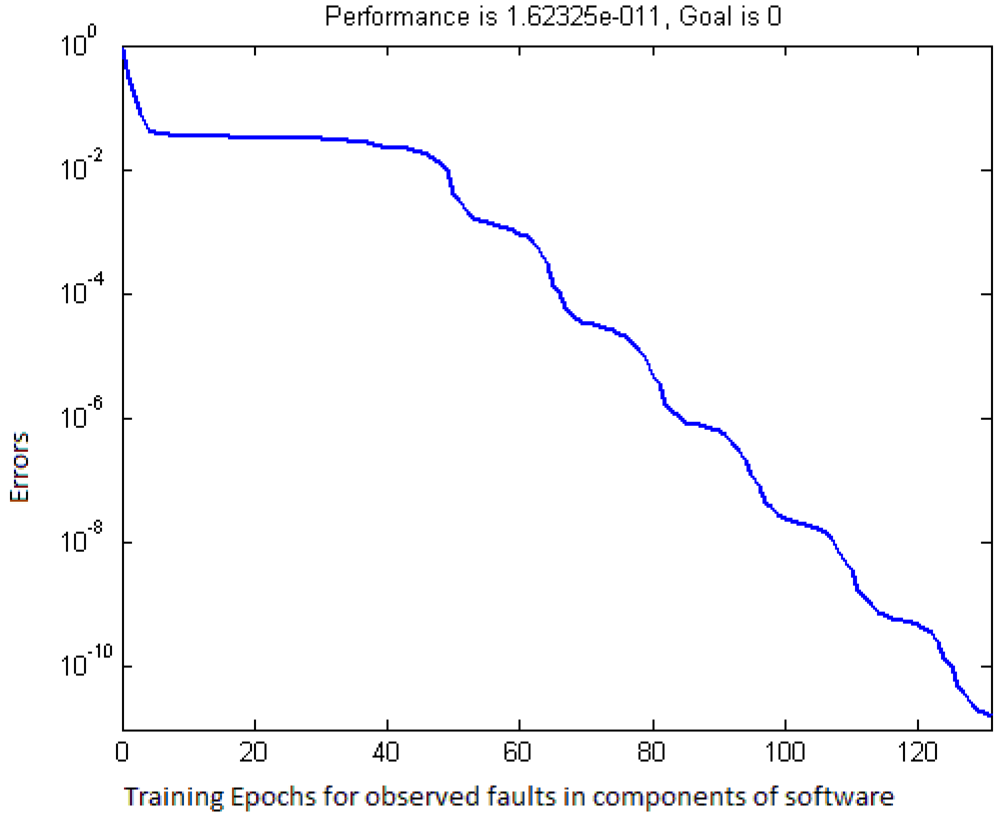


**Figure 5.10**

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After this the second phase of first experiment was started for the prediction of detected faults in next cumulative execution time interval. Here the next cumulative execution time interval means that the time which is not being used in our training set. Thus to predict the faults we consider the cumulative execution time interval from $t_{26}$-$t_{50}$. The trained neural network considered this unknown next cumulative execution time interval with the number of components as input pattern vector for simulation. The simulation behavior of trained neural network is exhibiting the predicted faults. These predictions of faults for different software are shown in the figures from 5.11(a) to 5.15(a). These figures 5.11(a) to 5.15(a) are representing the graphs for number of faults observed in the components for software in given cumulative execution time interval whereas figures 5.11(b) to 5.15(b) are representing the number of predicted faults in components in the software for future cumulative execution time interval.

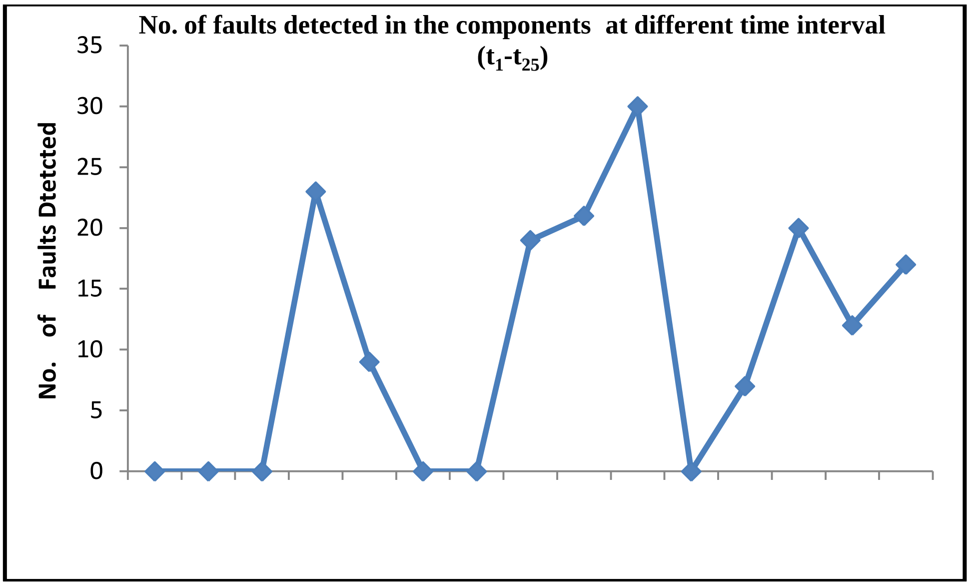


**Figure 5.11(a)**

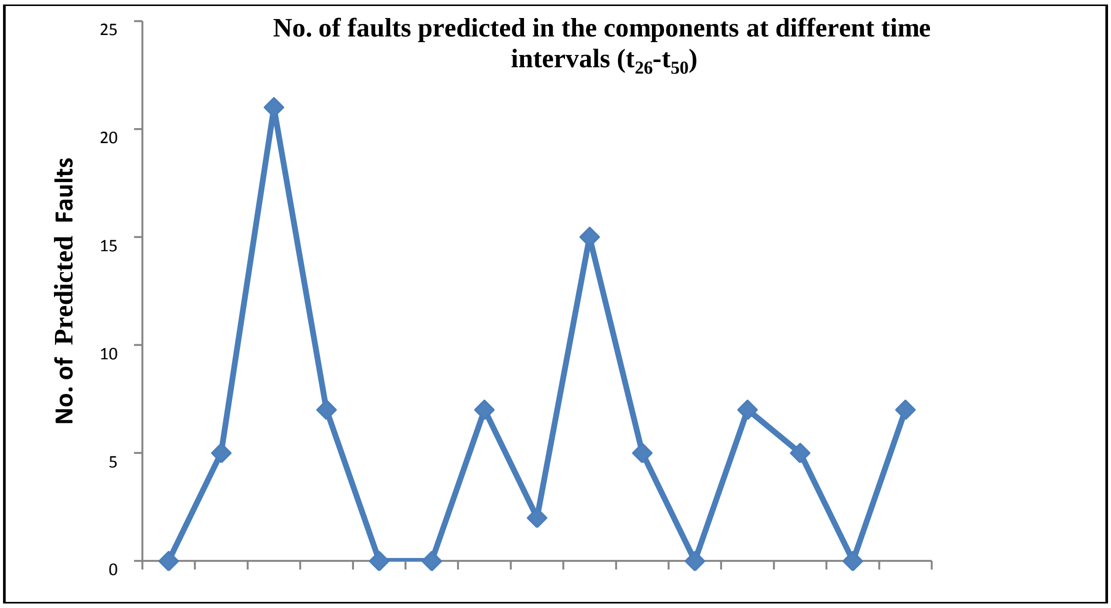


**Figure 5.11(b)**

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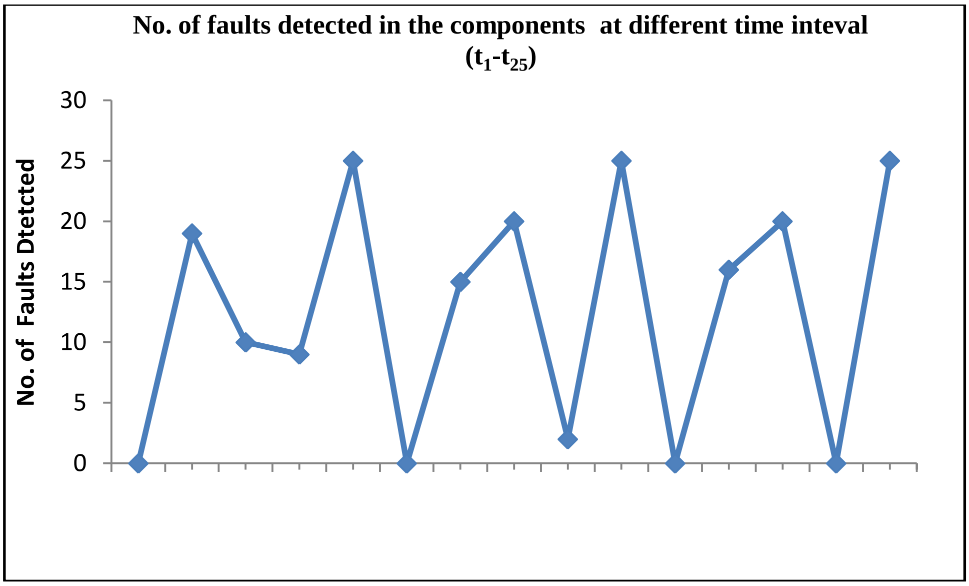


**Figure 5.12(a)**

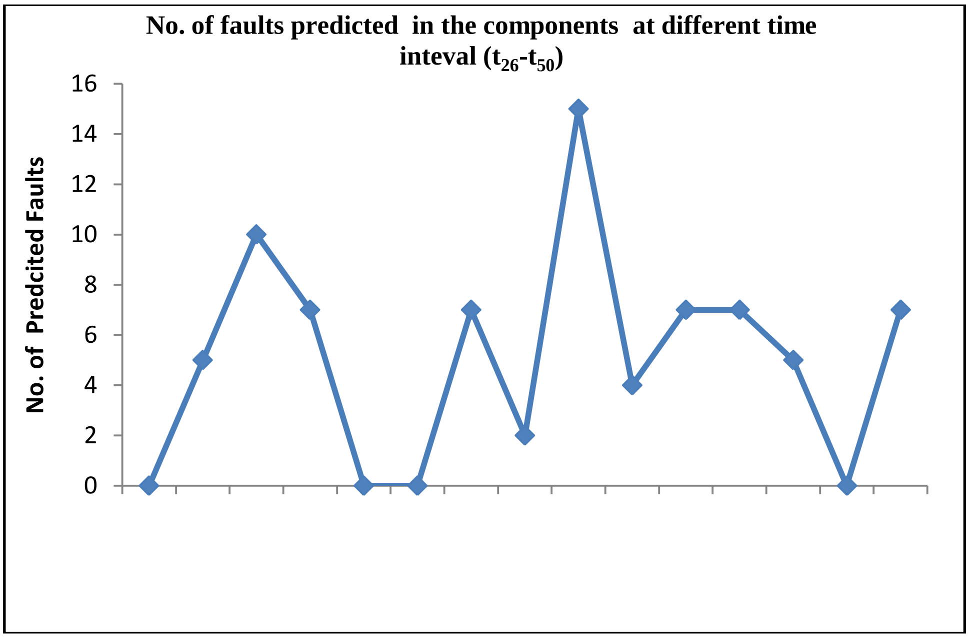


**Figure 5.12(b)**

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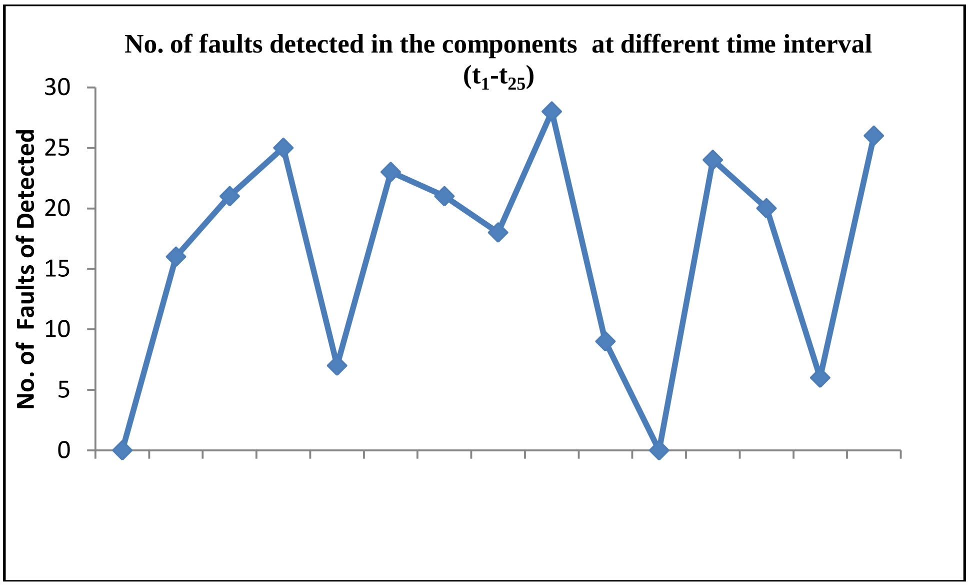


**Figure 5.13(a)**

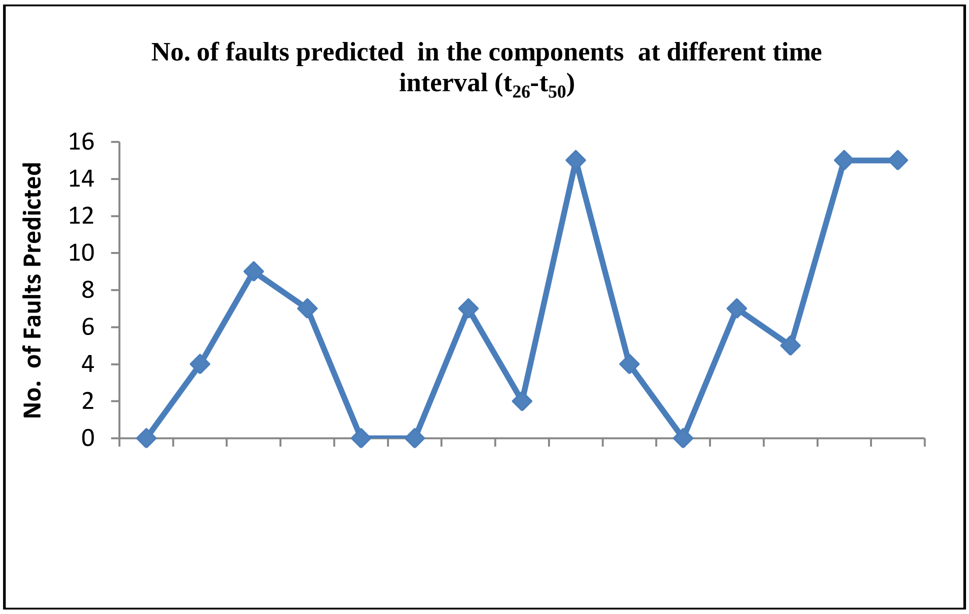


**Figure 5.13(b)**

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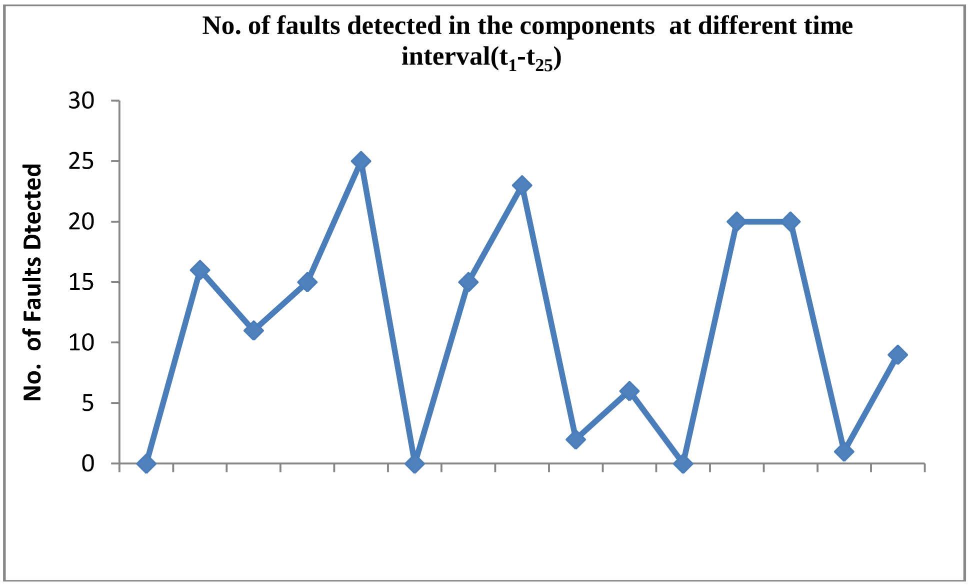


**Figure 5.14(a)**

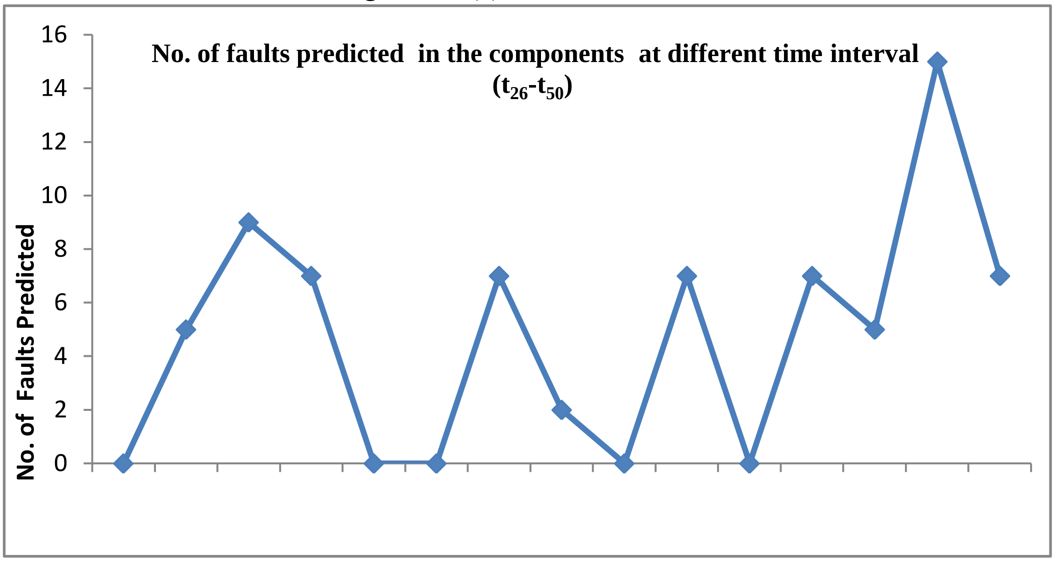


**Figure 5.14(b)**

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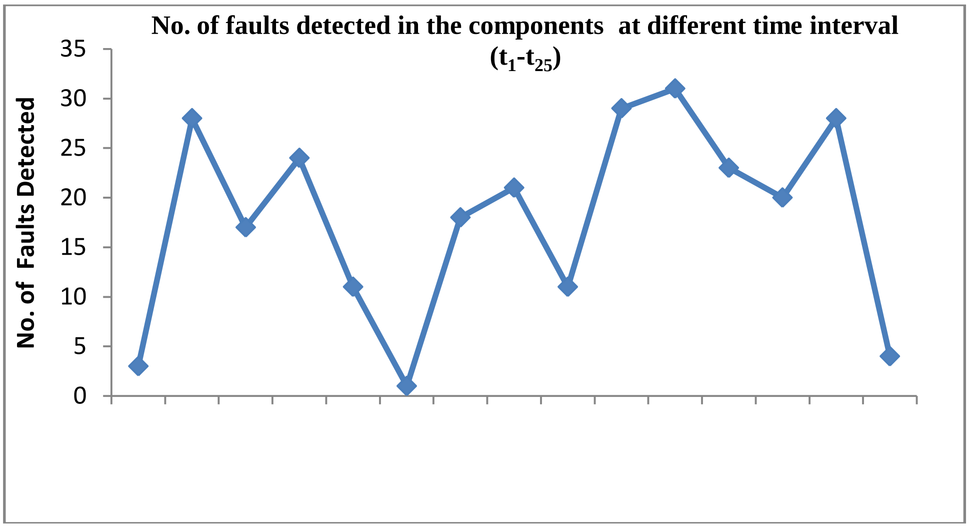


**Figure 5.15(a)**

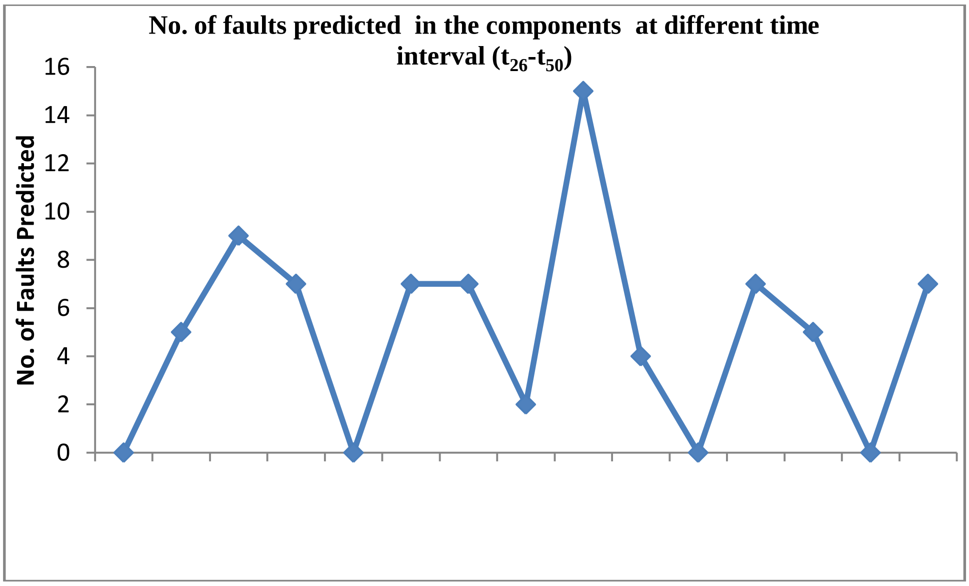


**Figure 5.15(b)**

In the analysis of the results it can be seen that the behavior of faults prediction is a generalized approximation of the observed faults. Thus it shows that the predicted faults are approximately tends to interpolated from observed faults in given cumulative execution time interval. Now, the first phase of the second experiment is started in the same manner as previous experiment with the change that in place of components, the dependent Variable i.e. observed faults are considered for complete software in the same cumulative execution time interval. Here in this experiment the input pattern vector of 12x1 is presented to the neural network with 6x1 pattern vector as target output for training. The training is accomplished for each of the software on same cumulative execution time interval as it used for its components. The performance of neural network for complete software is shown in the figure 5.16 to figure 5.25.

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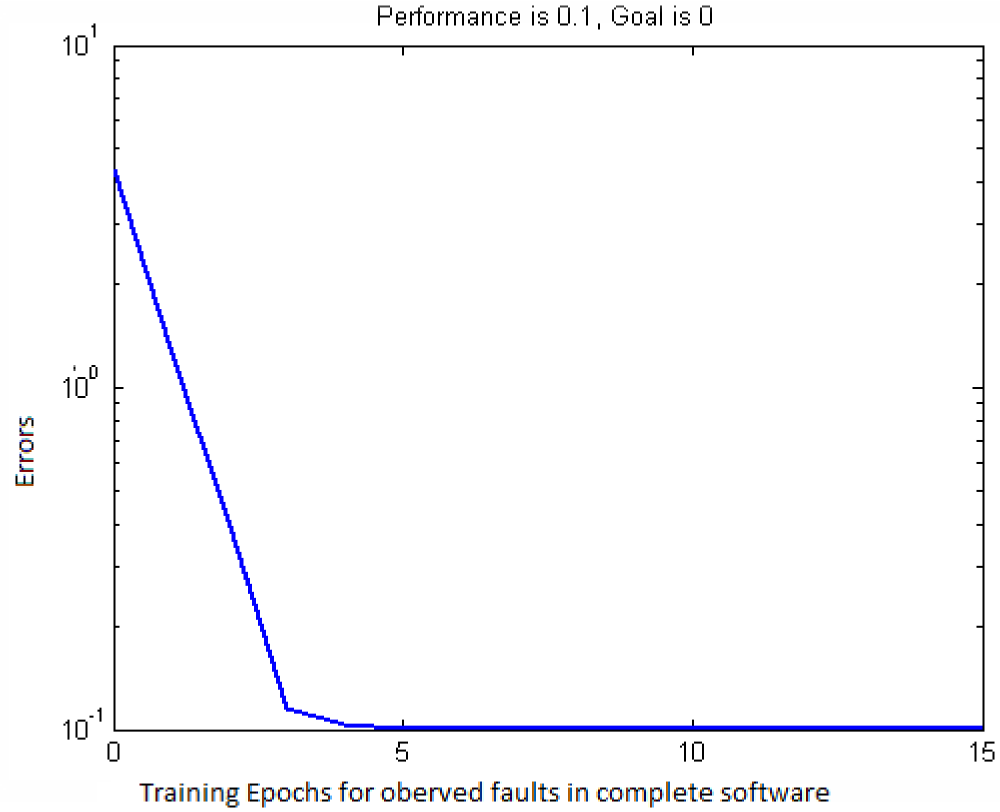


**Figure 5.16**

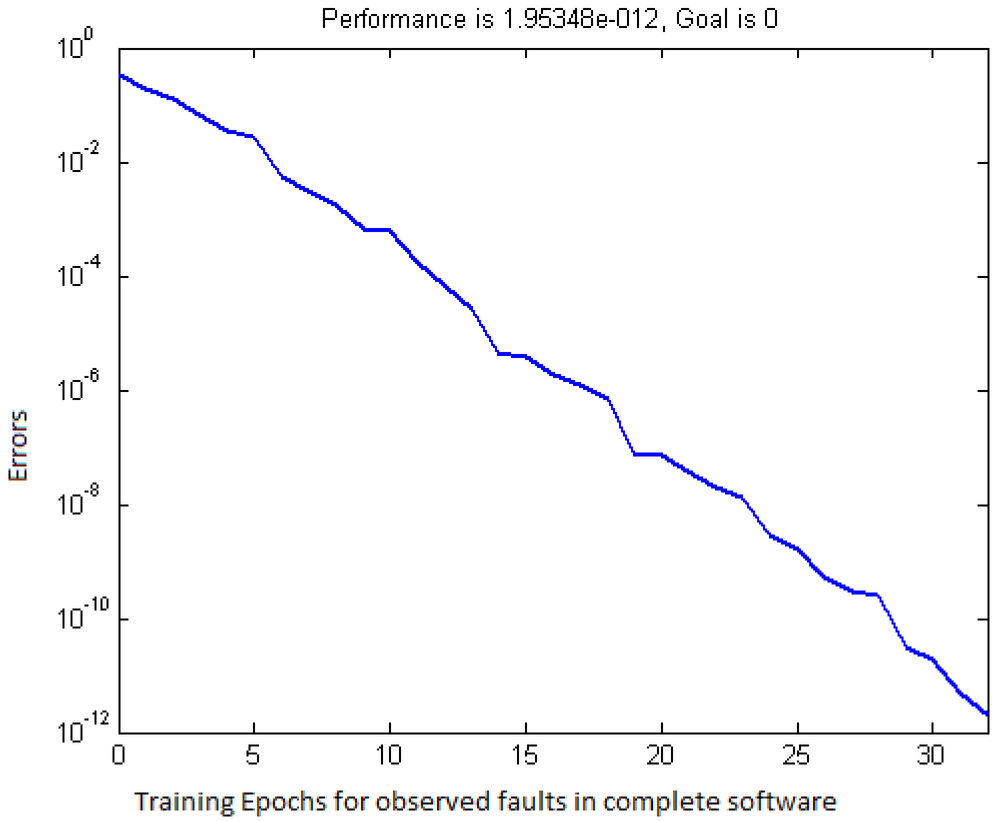


**Figure 5.17**

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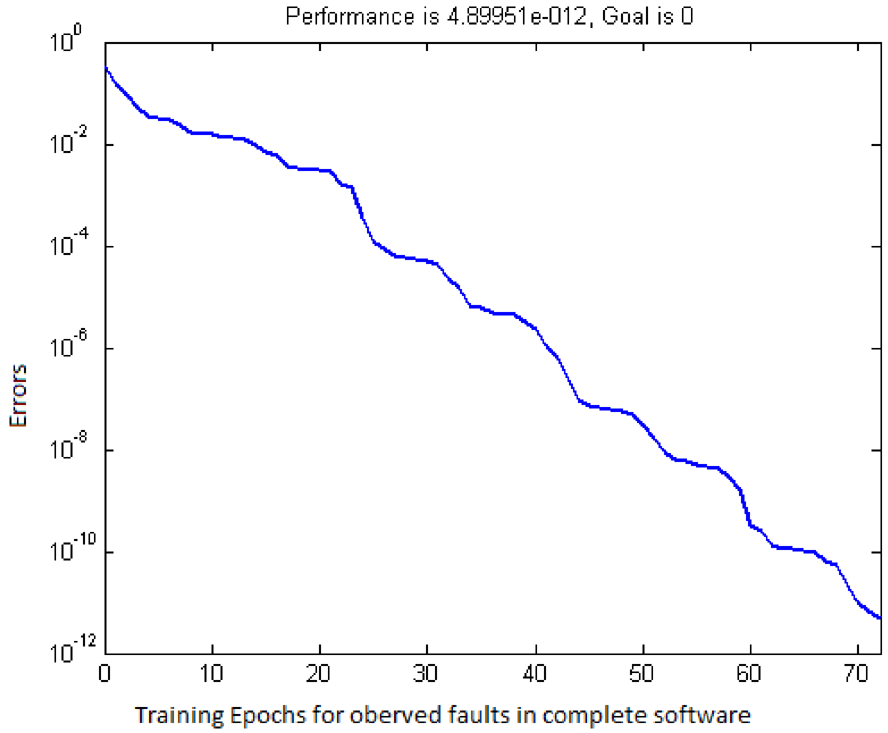


**Figure 5.18**

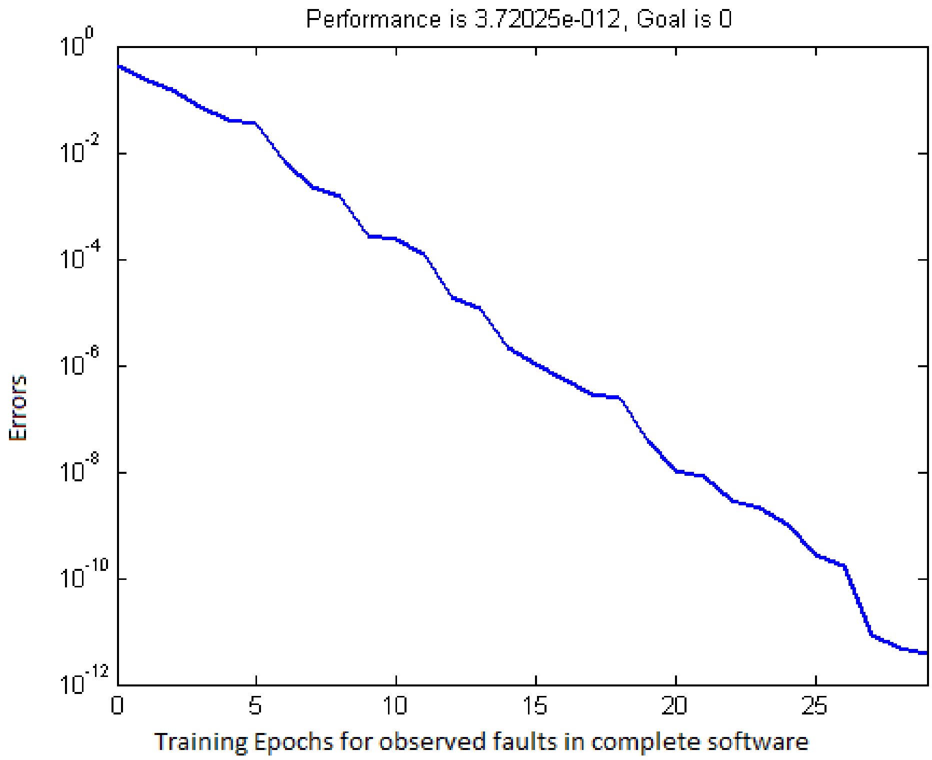


**Figure 5.19**

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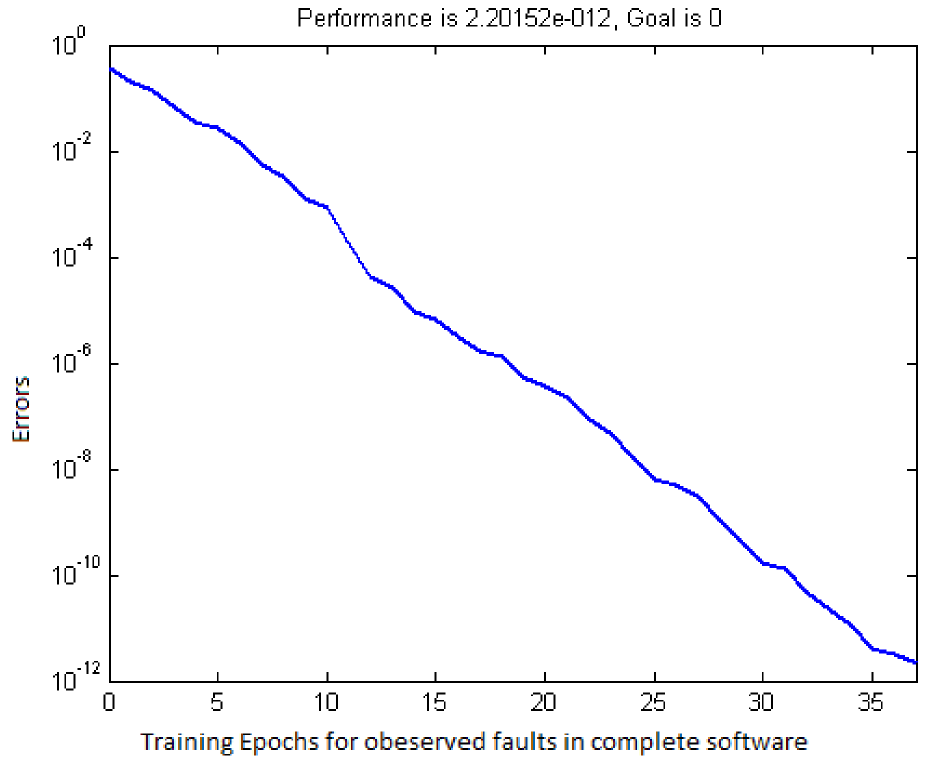


**Figure 5.20**

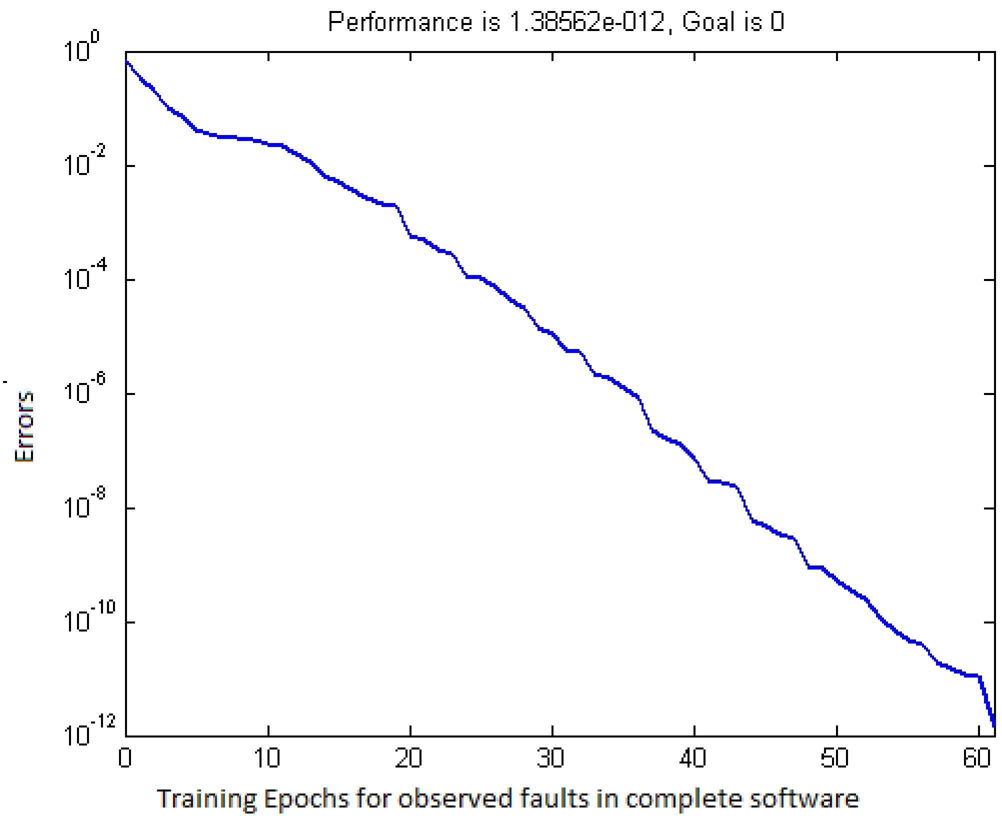


**Figure 5.21**

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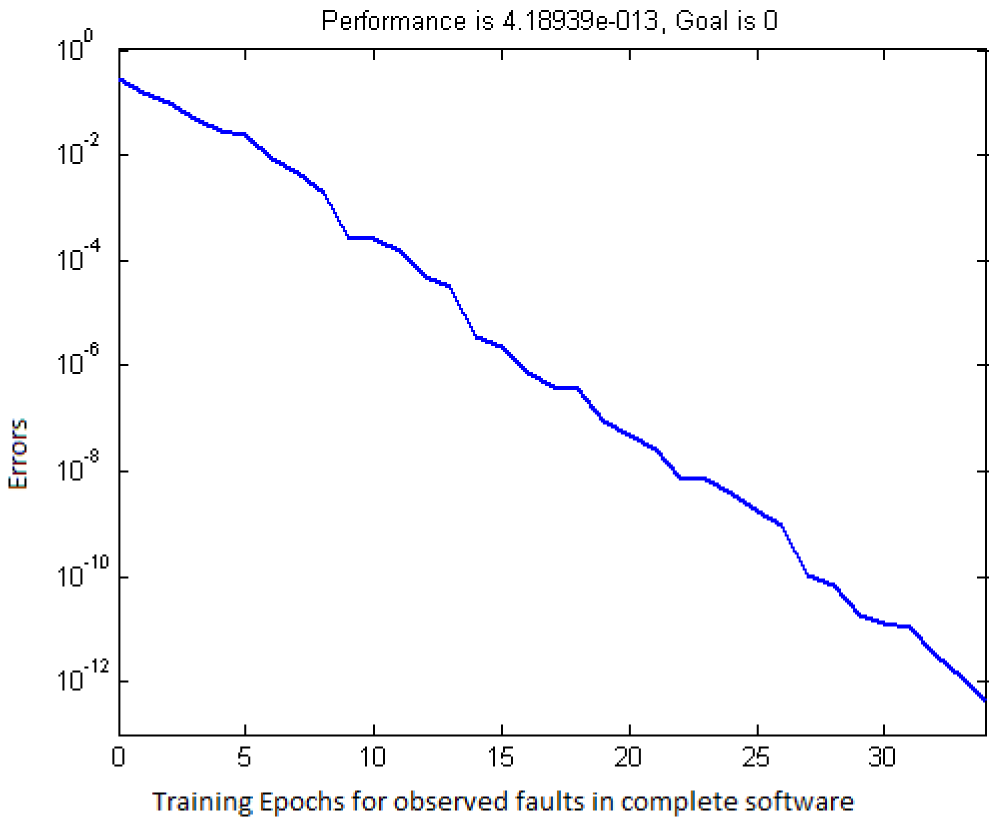


**Figure 5.22**

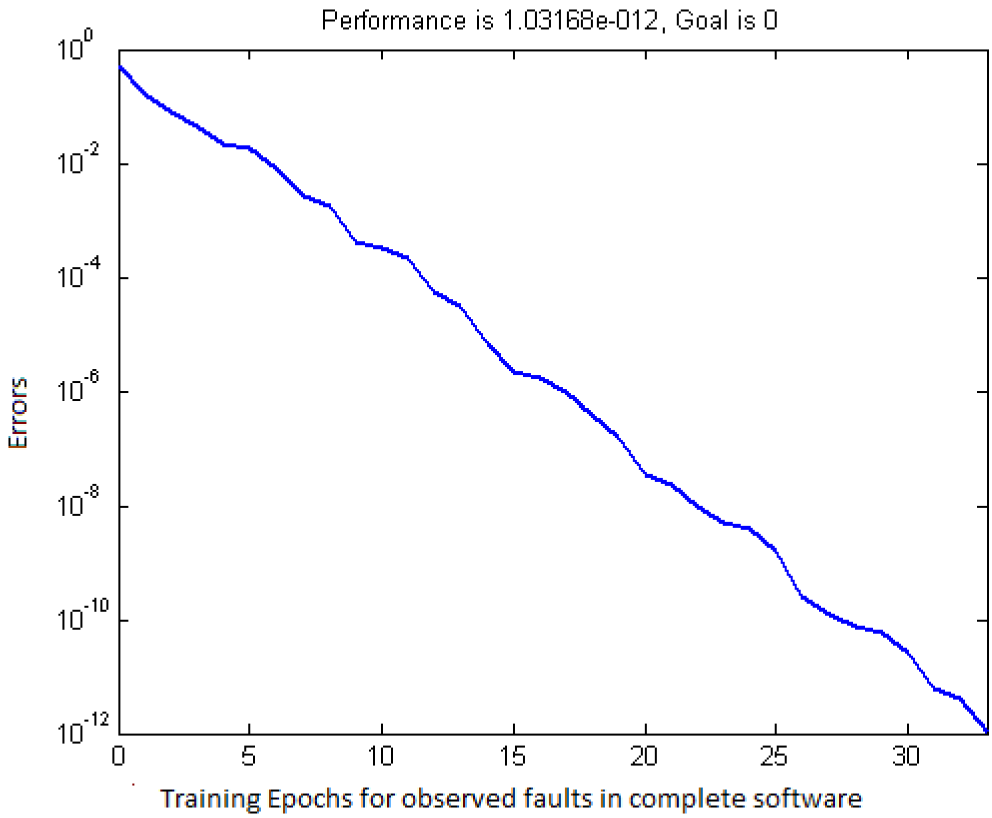


**Figure 5.23**

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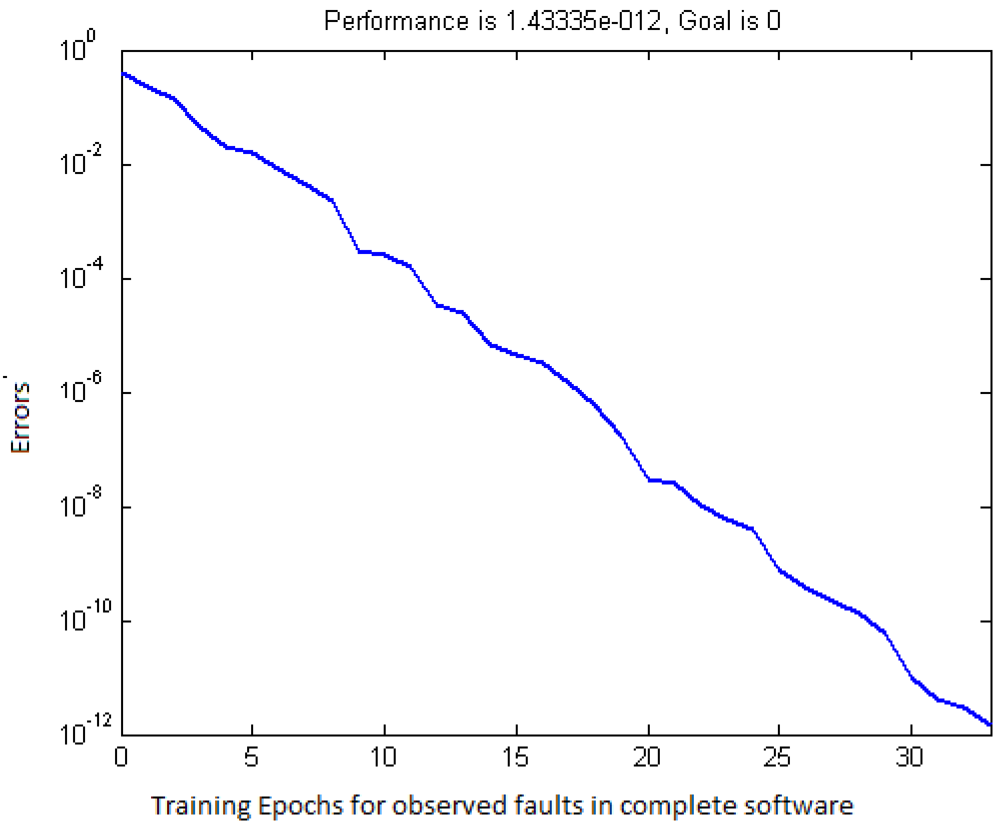


**Figure 5.24**

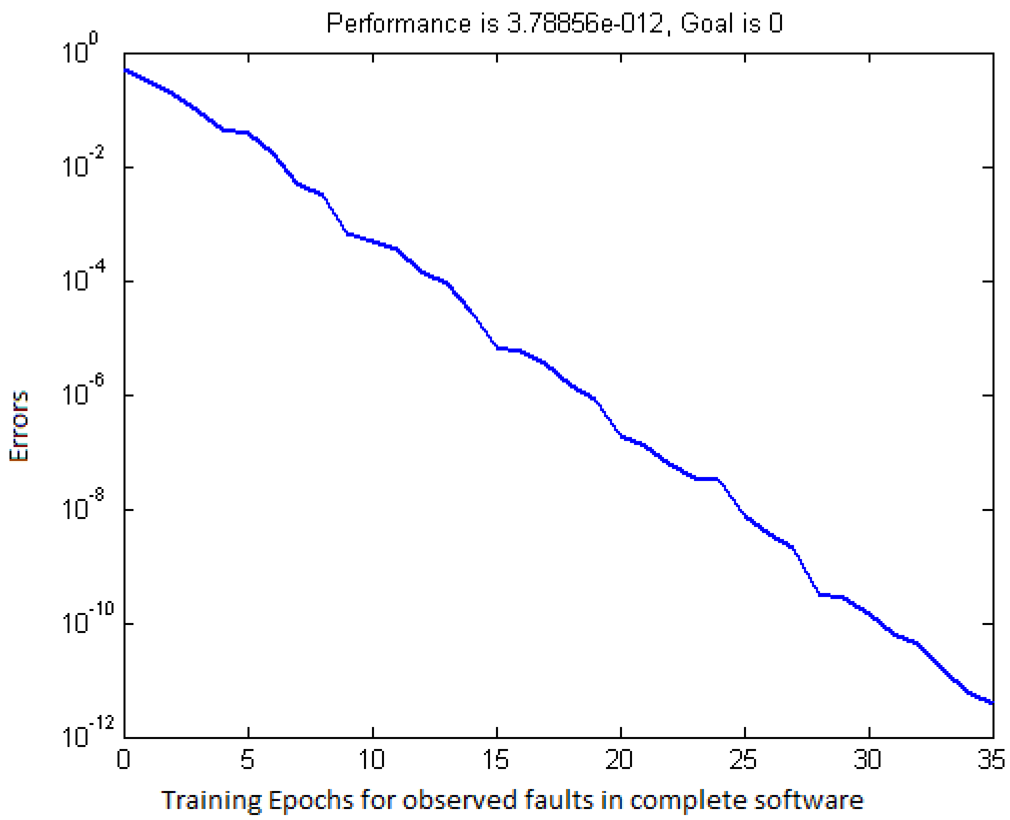


**Figure 5.25**

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After this training the neural network is simulated for predicting the number of faults in next cumulative execution time interval. Thus for evaluating the performance of trained neural network, we consider the next cumulative execution time interval $t_{26}$-$t_{50}$. The simulated behavior of the neural network exhibited the number of detected faults as it can be seen from figure 5.26 to figure 5.35. The graph of figure 5.26 to figure 5.30 are representing the no. of observed faults for given cumulative execution time interval whereas the graph of figure 5.31 to figure 5.35 are representing the number of predicted faults in whole software for unknown next cumulative execution time interval.

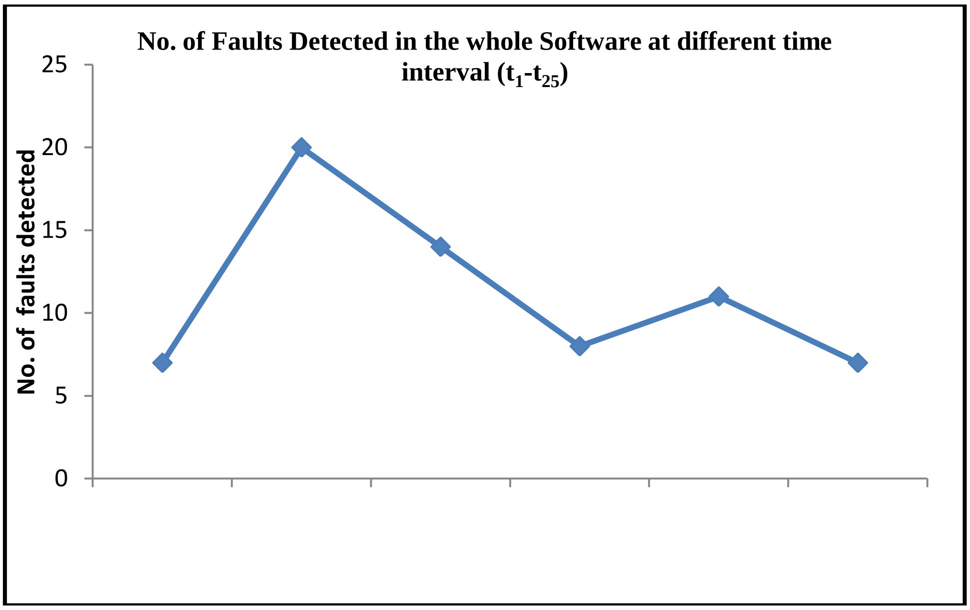


**Figure 5.26**

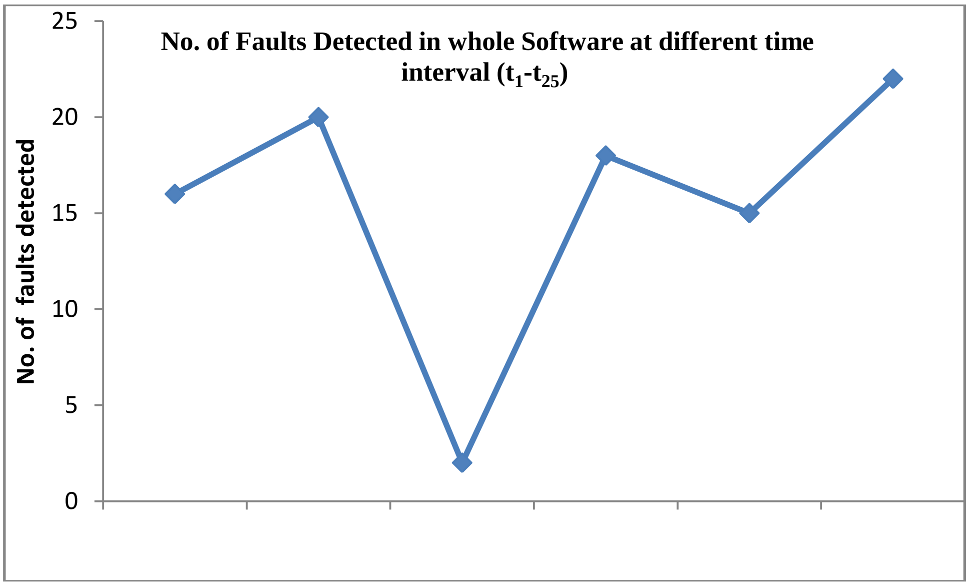


**Figure 5.27**

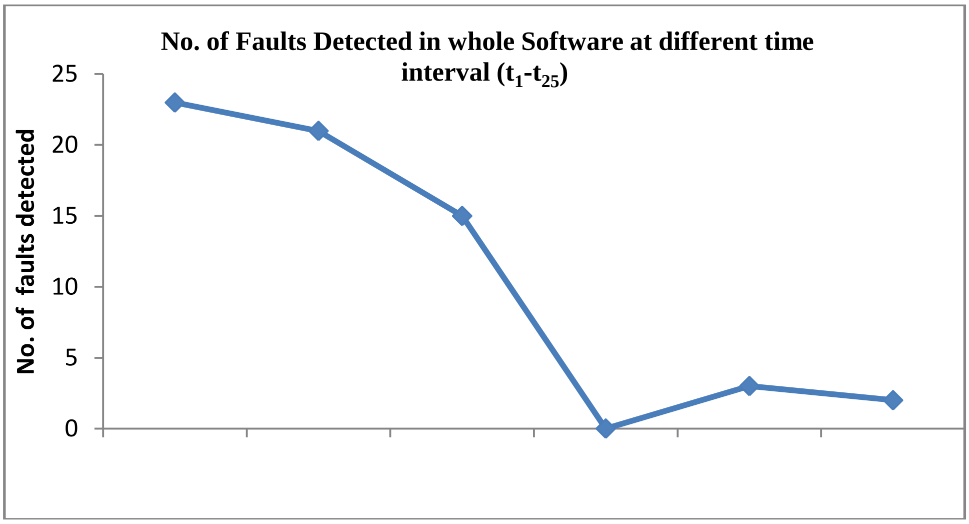


Figure 5.28

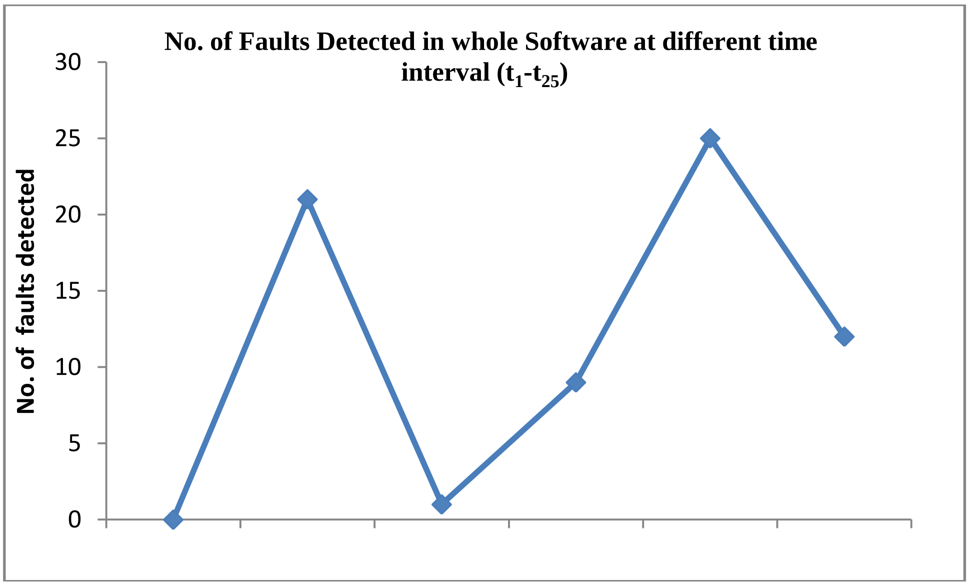


Figure 5.29

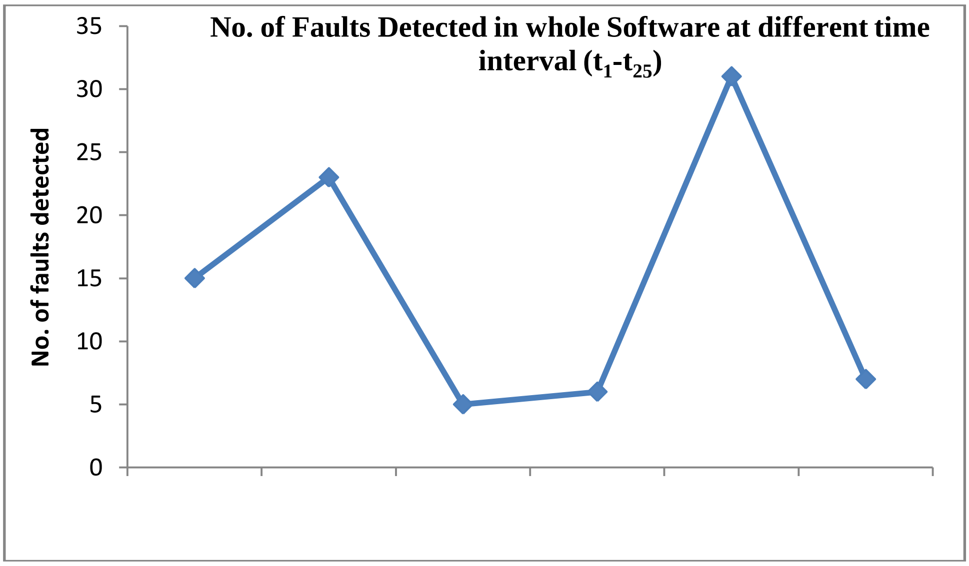

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**Figure 5.30**

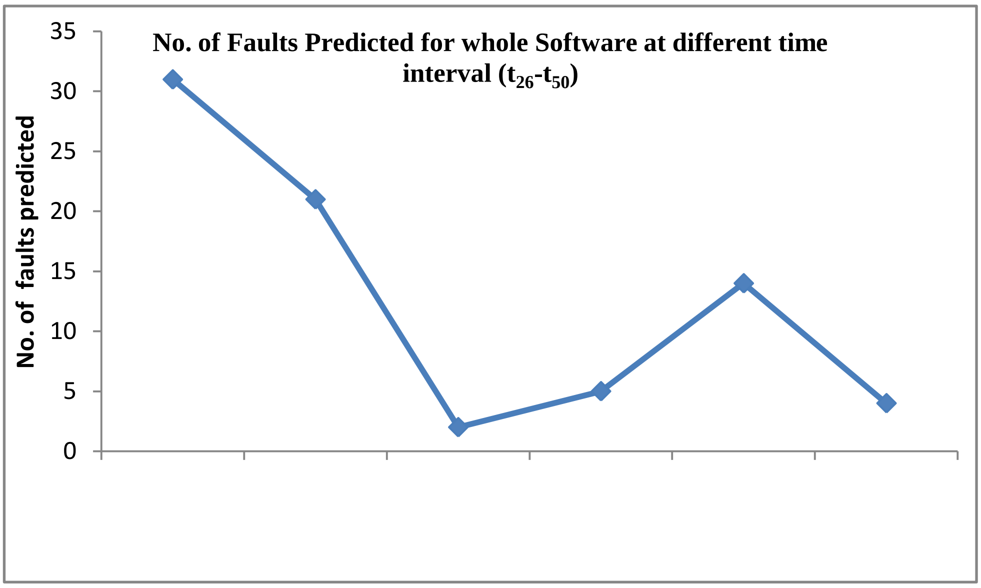


**Figure 5.31**

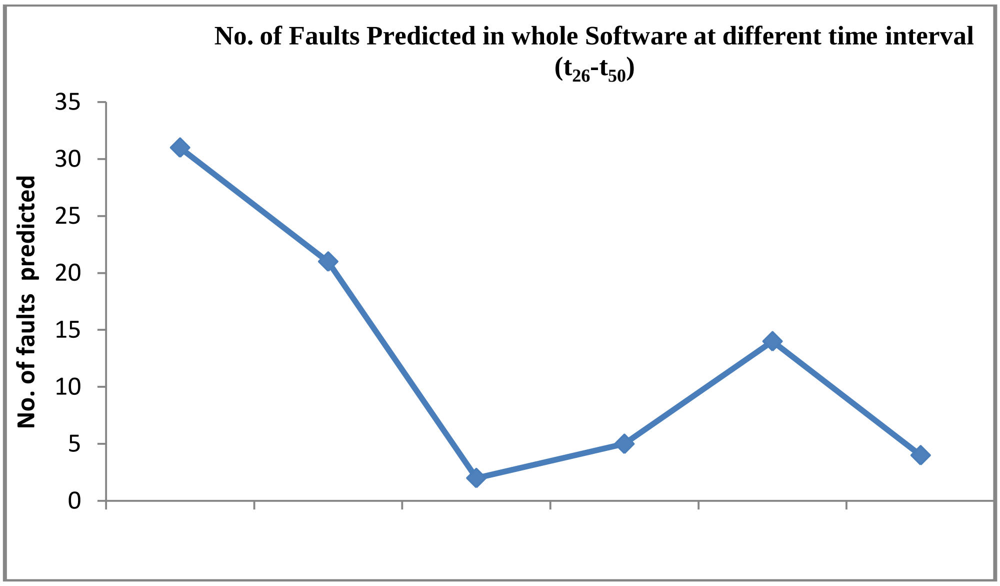


**Figure 5.32**

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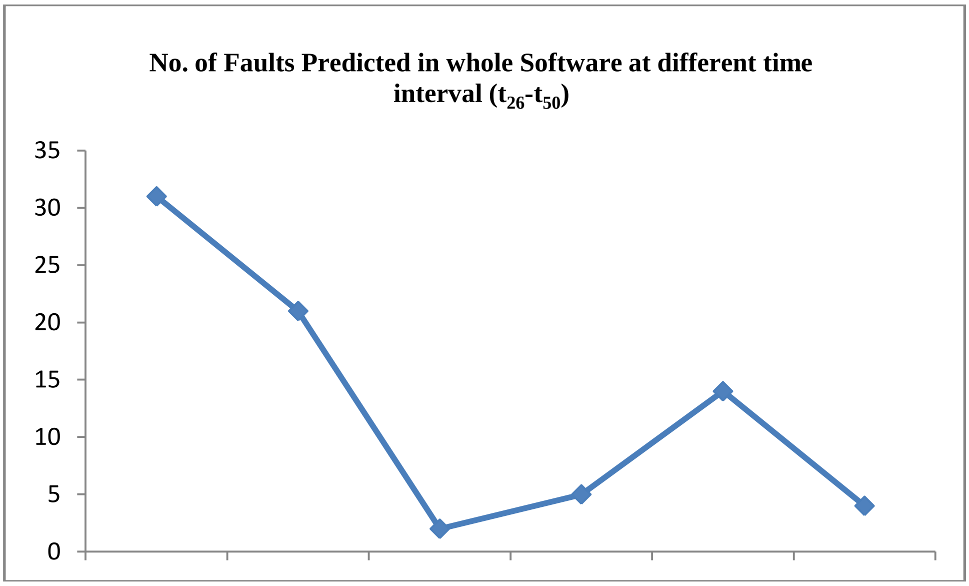


**Figure 5.33**

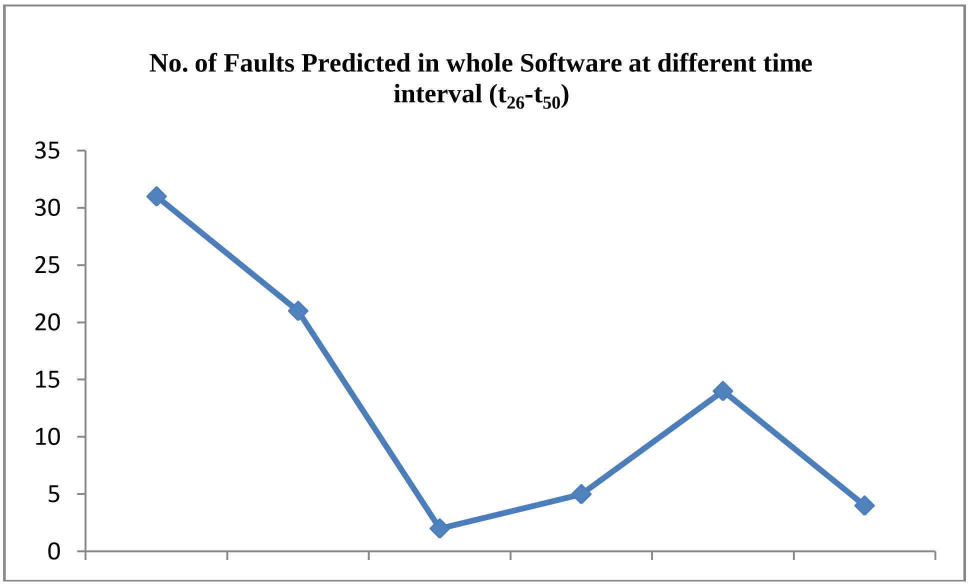


**Figure 5.34**

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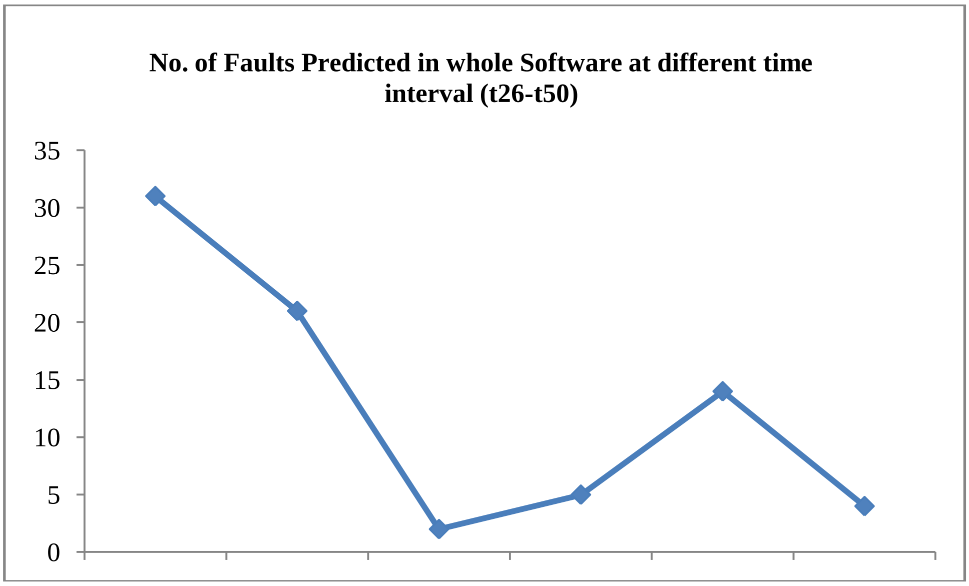


**Figure 5.35**

The graph of predicted faults for each of the software is same, but it is representing the generalized approximations of corresponding graphs of number of detected faults in that software. The characteristics of predicted faults for each of the software is consistent, it means the prediction of faults for the software is not behaving in the same manner as the prediction of faults for the components. Thus the behavior for predicting the faults in the software indicates the prediction is independent from the fault prediction of the components of the software. This observation concretes the concepts that the software reliability of software may not depend upon the behavior of components.

## 6. CONCLUSION

We know that the software reliability is effective technique for measurement of software quality over a time period. In this paper, we employed the feed forward neural architecture for estimating the reliability of component based software. This estimation of reliability is considered in two phases. The first phase included the prediction of faults in each component of the software for cumulative execution time. In second phase the faults were predicted for the complete software. Two stages of feed forward neural network architecture were used. The first stage of neural networks architecture is used to predict the faults from each component. There is as much neural network architecture as the number of components in the software. The predictions of faults were based on the generalized behavior of trained neural network for given training sets. The final neural network architecture is used for the prediction of faults from the complete software. This neural network architecture used the predicted faults from components as input with cumulative execution time to estimate the number of predicted faults. The following observations are drawn from the simulation of proposed method.

(i) We have considered the software consisting of components divided into different sets and observed the number of faults encountered over a cumulative execution time interval separately for the known set of components. After that, we estimated the number of faults predicted for the randomly chosen set of components in software over next cumulative execution time interval. On comparing the detected faults and predicted faults, we have found a generalized faults prediction behavior or a expected number of faults in the set of components over a cumulative execution time interval and this can be useful in estimating the reliability for the set of components over a next cumulative execution time interval.

(ii) Secondly, we have applied the neural network architecture for the software as a whole. In case of complete software, we have observed the number of faults detected by assuming all the components in the software as a single unit over cumulative execution time interval. After that, we observed the predicted number of faults in randomly chosen software consisting of components over the next cumulative execution time interval. In doing so, we have noticed very little variation in number of predicted faults for randomly chosen different software of small size over next cumulative execution time interval. We can conclude that with the help of proposed method we may estimate the software reliability for the small size software very effectively as a result of properly trained neural network architecture and observe a very little variation in the pattern of number of estimated faults in the software as single unit of number of components.

(iii) There is an interesting behavior is observed during the simulation. The predicted faults from the complete software were approximately same in given cumulative execution time. This behavior was not found for their components. Thus, the predicted faults for cumulative execution time from each component were different. It indicates that the number of predicted faults from the complete software may approximately independent from the predicted number of faults from the component. Therefore, it is not necessary that if

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components of software are predicting more number of faults than the complete software will also consider the increased number of faults. It is observed from the simulation of our proposed method that the number of predicted faults of complete software does not increase with increased predicted faults of its component. Thus, estimation of faults for complete software may not depend upon the estimation of faults prediction from its components.

In the future, we can extend and explore the pattern of behavior of number of detected faults and predicted faults to estimating the software reliability for the software consisting of tightly interdependent and a very large number of components.

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