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Neural Network System Design for Predicting MIN Reliability

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Abstract: ***Efforts have been made to examine and study different path and multi-path Multistage Interconnection Networks (MIN) possessing regular or irregular topology. Numerous strategies for establishing fault-tolerance in MINs have also been studied. These studies have provided us help to understand the strength and weakness of the existing static and dynamic and regular and irregular MINs. Application of Neural Networks leads to the development of MINs with improved performance and study of its Reliability In this paper ANN based system has been developed which will help in the study of metrics required for enhancing and predicting the reliability of MINs. In this paper Number of iterations are conducted to improve the ANN based system to predict the reliability of MINs by changing the number of neurons and the number of layers.***

Keywords: ***Multistage Interconnection Network(MIN), Artificial Neural Network (ANN), Mean time to failure (MTTF), Neurons, Layers.***

I. INTRODUCTION

The topological and functional characteristics of interconnection nets used to link the processor or the processor with the memory have long been the subject of the analysis.There are essentially two forms of IN that can be loosely defined as: Dynamic and Static. Static networks are easy to construct and extend and provide a standard architecture with a certain routing algorithm. Even with a single error, however, a network of this kind fails, because the network has no redundancy.[1]. Many static networks have been suggested in literature such as the Baseline Network and the Omega Network, the Cube Network, the Butterfly Network, the Flip Network, etc. [1, 2]. A dynamic network makes it possible to spread the nodes unequally, accomplished through any switching process. For eg, the four tree networks, the random shuffle swap and other busses are complex networks [3, 4]. Multistage interconnection networks are capable of being a complex interconnecting network with low cost and latency and good capacity and bandwidth, and offers a balance between a more costly crossbar network and a cheaper bus-based network.

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Multi-stage Interconnection Networks incorporating small crossbar switches in evenly spaced phases are organized on a regular basis. In the last three decades research was published and used a large amount of network mechanisms based on the Clos[5] and Benes[6] networks.The majority of the standard MINs in the literature are typically designed by using the smallest 2x2 interchangeable switch with two inputs and 2 outputs with n = log2N stages, with N/2 SEs in any stage. In contrast to O(N2, for an interbar network, the cumulative number of switches in the NXN Network is N/2 (log2N). Much of the standard MINs are self-routing, i.e. routing takes place spread by the "routing tag".The frequency of the daily MIN network is still the same. In comparison, intermittent MIN topologies have different lengths, which greatly decreases the overall latency[7,8]. The special routing feature in MINs allows simple routing.However, maximum connectivity capacity is lost by the loss of a single part with a considerable likelihood for broad networks. [9]. The fundamental principle for fault tolerance is to have several routes for the input-output pair in case of faults. A variety of multipath MINs have been developed in the literature[9-11] to provide highly efficient contact and to be fault-tolerant. Yet there are also difficulties in embracing modern fault-tolerant architectures to boost efficiency and durability. The implementation of redundancy in a given topology is part of numerous methods studied and used for fault tolerance[9]. Network connectivity deficiencies can contribute to lower performance, which is declining sharply as network sizes increase. Many enhancements in efficiency, such as the use of concomitant links and several sub-networks have been introduced [4, 5, 13-14]. Most normal structures with redundant topology are present in the literature[9, 14]. However, the precise estimation of their durability is challenging, because it is difficult to translate such complicated systems into basic block diagrams or redundancy graphs. There is also a need for a program that will calculate the precise strength of such networks in order to achieve a better understanding of them.An effort has been made in this paper to construct a program based on neural networks that can predict reliability based on MIN parameters. Neural Networks have proven themselves to be capable classifiers and to tackle non-linear problems particularly well[26-28]. Despite the non-linear complexity of real-world experiments, such as estimating MIN efficiency, neural networks are definitely a strong choice for problem-solving. Predefined topologies have been used for training purposes to construct such a neural network-based system. This paper aims to predict the number of neurons and the number of layers for optimal neural network architecture. Section 2 provides a concise overview of existing topologies used in neural network science.

The paper is organized in the following manner.Section 3 explains the determination of the efficiency of such networks. The technique used for the creation of the neural network system was described in Section 4. The findings for the optimum number of neurons and layers needed are planted in Section 5, and the hypothesis and potential scope of Section 6 are provided.

II. BACKGROUNDS AND PRILIMINARIES

A. *Omega Network*

Omega network is a simple non redundant network consisting of *2X2* crossbar switching elements (SE) with *N/2* SE in each stage. There are $n=log_2N$ switching stages in omega network with total complexity of $N/2(log_2N)$. it is a unique path MIN. so all SE are considered to be in series to achieve full connectivity of the network[9, 12, 14-15].

B. *Extra Stage Network*

The increasing stage cube is developed by adding an additional phase into the network from the Generalized Cube Network. The input and output points are connected to multiplexers and demultiplexers. The capacity for errors is improved, even as the length and complexity of the network are decreased [10, 13].

C. *Indra network*

Fault-Tolerant Networks have multiple versions of the same unique route network installed. The INDRA network incorporates double copies of the basic path network, mainly an omega network with its initial distribution. This has an RXR crossbar transition (logRN+1) number of phases [11, 16]

D. *Multiplexer Demultiplexer Replicated MIN (MDRMIN)*

Mux-Demux Replicated Multistage Interconnection Network (MDRMIN) is a k number of similar specific route multistage networks in k planes with k-3:1 multiplexers and 1:3-k multiplexers at input and exit, respectively, for linking N origins and destinations to have k parallel routes. It renders the device robust and fault-tolerant[18].

E. *3- Replicated MIN(3-REP MIN)*

3-REP MIN uses three unique path MIN in parallel which provides three paths between each source-destination pair [19].

III. MEAN TIME TO FAILURE (MTTF)

MTTF is specified as the predicted period the network will operate until the loss of one of its network paths under normal operating conditions[16, 20-25]. Mathematically MTTF of all above five networks may be defined by the following expressions:

$$MTTF(Omega) = \int_0^\infty e^{-\lambda t N/2(\log_2 N)} dt \quad (1)$$

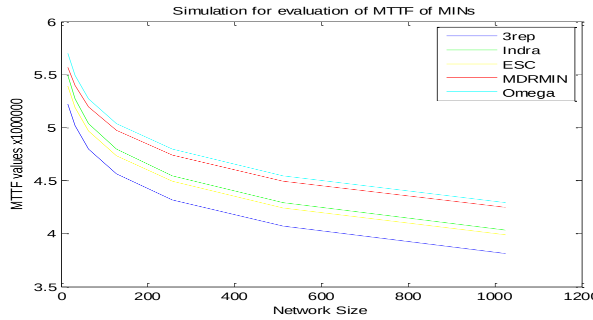
$$MTTF(ESC) = \int_0^\infty \left[1 - \left(1 - e^{-\lambda t 2N/4(\log_2 N-1)+N}\right)\right] dt \quad (2)$$

$$MTTF(3-REP) = \int_0^\infty \left[1 - \left(1 - e^{-\lambda t 3N/2(\log_2 N)}\right)\right] dt \quad (3)$$

$$MTTF(INDRA) = \int_0^\infty \left[1 - \left(1 - e^{-\lambda t 2N/2(\log_2 N+1)}\right)\right] dt \quad (4)$$

$$MTTF_{(MDRMIN)} = \int_0^\infty \left[1 - \left(1 - e^{-\lambda t k N 2k(\log_2 N/k)}\right)\right]\left[1 - \left(1 - e^{-\lambda t k/4k2N/k}\right)\right] dt \quad (5)$$

All these parameters define the perform ability of respective MINs. Here λ is the failure rate of MIN at time t and N is the number of inputs and outputs.



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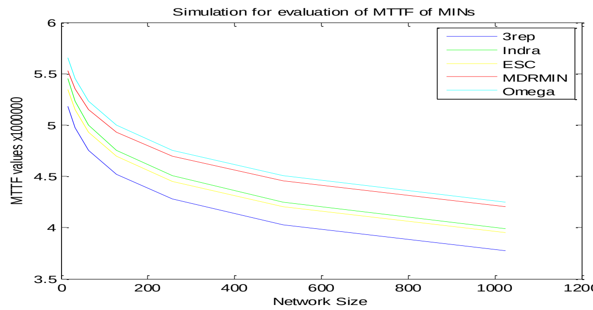

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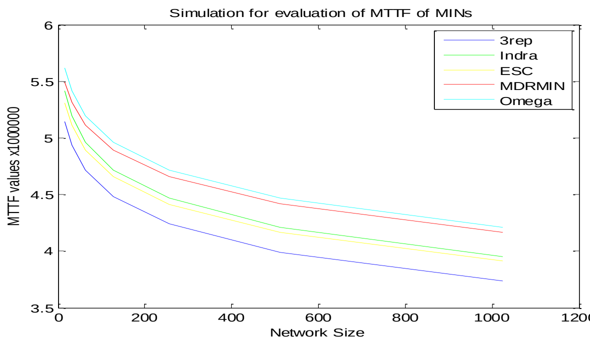

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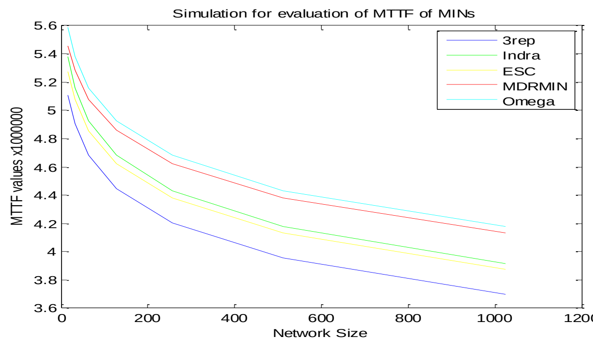

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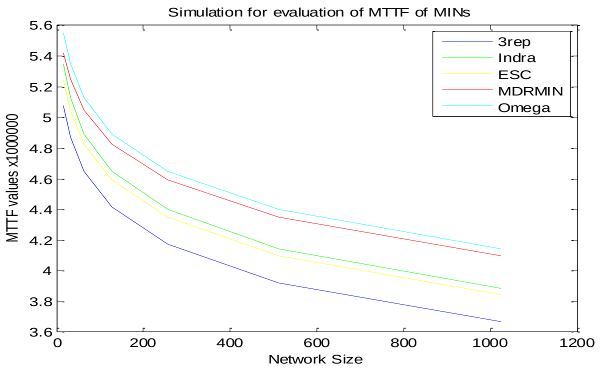

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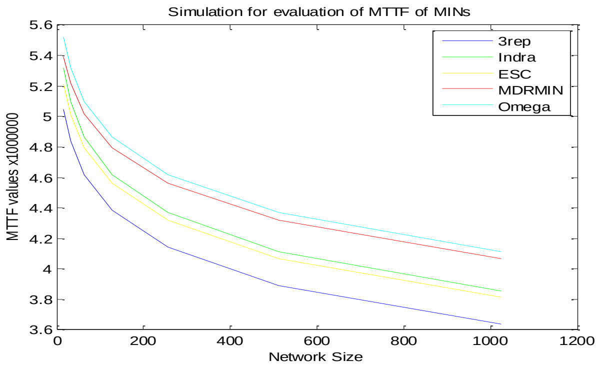


(f)

Fig 1: MTTF plots for different MIN topologies as a function of network size for failure rate (λ)= a) 0.000001, b) 0.0000011, c) 0.0000012, d) 0.0000013, e) 0.0000014 and f) 0.0000015

IV. DESIGN OF NEURAL NETWORK BASED SYSTEM

Neural networks have demonstrated their competence and are particularly ideal for solving non-linear problems [26-28], like predicting reliability in MIN,In this paper attempt has been made to build a system that can predict the reliability based on MIN parameters. Different parameters defined by the equation (1) to equation (5) of the MIN have been considered. These parameters were used as ingredients in a neural network and reliability prediction is the objective. The neural network will assess whether or not the efficiency has been enhanced in light of the input which constitutes the six computed values for the MIN parameters mentioned above. It is done when previously recorded MIN parameters are inserted into the neural grid and modified to produce the appropriate goal outputs. This approach is regarded as the planning of neural networks. The samples have been individually collected, analyzed and checked. It instruction is used to educate the network. The teaching. Education should proceed until the network raises the range of validity. A genuinely independent network efficiency metric can be included in the assessment list. In comparison with the required goal response, the network answer was used to construct a classification matrix that provides a comprehensive image of system performance.

There are a number of representations in the training data set, each with values for a range of input and output variables. Second, what variables should be weighed and how many (and when) instances will be used.

The variables choice (at least initially) is intuitive. Experts have information regarding the possible consequences of input variables. In the first stage it is important to include all variables that could influence the dimension of the design process of each selection. Networks struggle with predictive details within a reasonably limited framework. This raises the question of whether the data were inconsistent, whether the results are missing or not. Fortunately, each of these issues is faced with strategies. Numerical results are changed to the right region for the network and missing values may be substituted in the other available testing situations by using the mean (or other) meaning of the attribute. It is quite difficult to handle non-numeric data. Trivial value variables like Outcome={Transfer, not transfer} are the most popular category of non statistical data. The empirical analysis of minimal variables is essential. However, neural networks do not look nice with limited variables and have a great deal of possible values. Any non-numerical types of data are either converted or discarded in numerical ways. Dates and times can be converted into the offset number, if necessary, from the start date / period. Prices for currencies may be converted easily. Unrestricted fields of text (for example names) can not be read and removed. There are also problems with the numbers of cases needed for neural network training. Many heuristic principles exist in the amount of situations expected by the network size (the simplest of which is to provide ten times as many links in the network). However, the necessary quantities also contribute to the (Unknown) complexity of the process underlying the simulation and variation of the noise of additives by the network. The amount of non-linear cases needed decreases with expanded variables such that only relatively few (perhaps fifty or fewer) variables are necessary. The issue is known to be the spatial curse. For most practical trouble areas, hundreds or thousands of cases may be required. More could be expected for very complex situations, but that should be fewer than 100 cases for an odd (even trivial) problem.

It may not be enough to train a network if the data is smarter than the information, so the safest thing to do is fit a linear model. When there is a greater and still limited set of data, of which the average of the network forecasts may be paid to a certain extent by forming a network set, each equipped by a different re-sample of the available data. Many technical issues emerge from untrustworthy data: certain variables may be corrupted with noise or values may be entirely missing. Noise resistance is also observed in neural networks. Nevertheless, this flexibility is limited; if the outliners of a variable are unusual well outside the normal range of values, research may be biasable. Defining and removing these outliers (whether by discarding the case or transforming the outliers into a lost value), is the easiest approach. If the outliers are difficult to find, a city block error can be used, but this guidance to tolerance is less effective than the normal form. The neural networks also take numerical input and deliver numerical output. Input through any range and output in a closely specified region (it's squeezing) is typically chosen to transmit the system function. While it could be in a variety, the sensor responds only to stimuli within a very limited amount of saturation.

In the accompanying illustration, the logistic function (often called the sigmoid function, though simply speaking it really is an example of the sigmoid-shape function) is one of the most common communication mechanisms. The performance in this situation is below range (0,1) and the input does not surpass (-1,+1). The function is also simple to find and smooth to allow network training algorithms to operate.

The small selection of numerical responses along with the fact that the data will be in numerical form requires the usage of neural solutions in real applications. We will counter two issues:

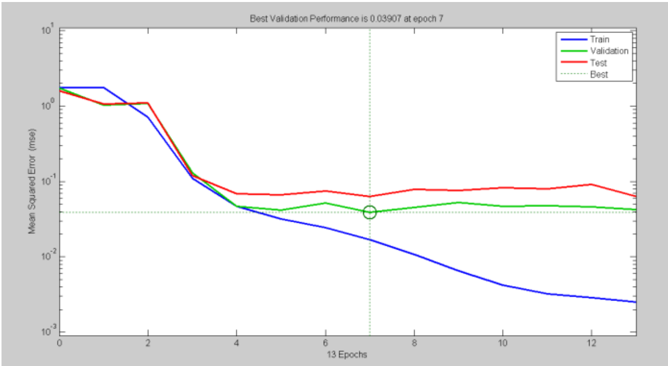
A spectrum suitable for the network must be optimized with quantitative values. The actual vector values typically are linearly distributed. Non-linear scaling can be necessary in certain cases (for example, you would be able to use the logarithm because you realize the sum is exponentially distributed). Nonlinear scaling is not endorsed in ST Neural Networks. Rather, the STATISTICA data transformation facility enables the matrix to be portable until the tests are transferred to the ST neural networks.

For two (e.g. Effect = {Success, losses}) or more (e.g. more than two) situations, proportional variables may be included. A conditional two-state vector is useful for a subjective significance representation (e.g. output = 0 Failure = 1). Other nations are more complicated to deal with. We are translated with ordinal text, but this implies that the nominal rule is (probably) incorrect.A easier way to use a series of numerical variables is to use a specific encoding value known as one-of-N encoding. The number of integer variables is equal to the number of potentials; one of the N is fixed; the remaining variables are omitted. ST Neural Networks require the modification of both conditional two-state and multi-state variables for usage within the neural network. Unfortunately, a simple variable comprising a huge number of statements allows it easy to use prohibitive numerical criteria for one-of-N encoding, raise the network size and avoid instruction. In this case, a minimal variable can be modeled using a single numerical order (though not satisfactory), and the better approach is to search for different ways to provide details.The goal is to decide every input case belongs to a number of different classes in group. Two State tasks are the most common classification tasks, although other State tasks still are not unknown. In addition, a variety of classification functions can be carried out at once by neural networks, but usually each network does just one. In this scenario the network will have one vector of output.

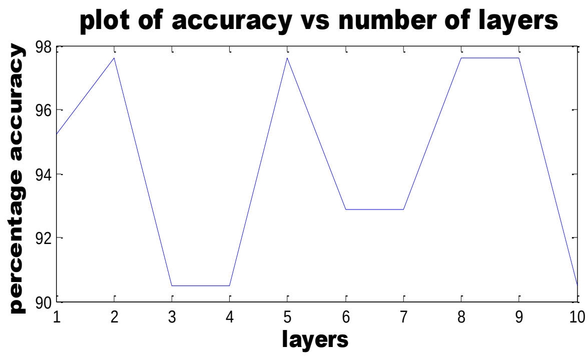
Multilayer Perceptron is the type of network in which each instrument performs a partially weighted number of inputs and sends this sum via a transfer mechanism. They generate and the units are grouped into a layered topology feed. The network is therefore explicitly described as a form of input-output function, with free interface parameters for weights and thresholds (biases).Such networks can model almost random functions with the number of layers and the number of units per layer that determines the system's complexity. The key issues in the design of the Multilayer Perceptron (MPP) are estimation of the number of hidden layers and the amount of layers.

V. RESULT AND DISCUSSION

There is a calculation of the number of inputs and output units (the inputs for usage may be misleading). Furthermore, the input variables are considered to be logical and significant. A hidden layer with a unit number equal to half the amount of inputs and outputs is used for a fair starting point.



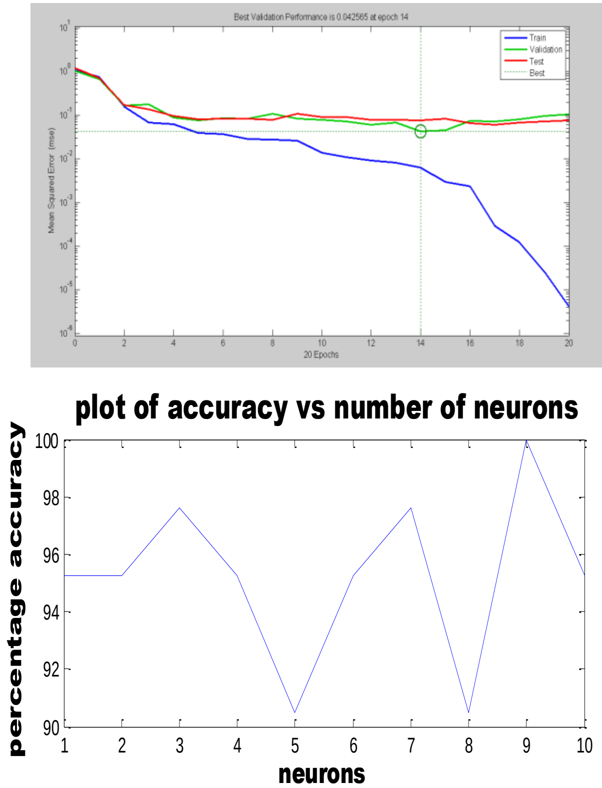
(a)



(b)

Fig 2: a) Training of neural network for no. of Layers and b) Plot for accuracy of neural network

This article utilizes unary encoding to represent the transfer of symbols. The first column of data reflects the attributes of the MIN. The 7th column shows whether or not the MIN is accurate. The data were randomly generated. The next step is to analyze the data before using it in a neural network. Next move is to create a neural network and figure out whether the function is to be moved or not. The samples assumed to be separated into planning, processing and data sets instantly. The test set includes a fully different predictor of the neural network output to identify the transition. With the study samples the trained neural network was tracked. This offers an example of how effectively the network will operate in combination with data from the globe. The tests are seen in fig. (b) in the fig. 2(a) and (b). The following are 3(a) and (b). From then on, a minimum of 2 layers and 9 neurons is necessary to create a system with the highest precision, which can be used for the further measurement of the reliability of MIN for either normal topology or abnormal topology. Preparation and testing of the neural network are given in figures 2(a) and 3(a). The total number of neurons and the minimum number of layers needed are shown in figs 2(b) and 3(b) respectively.



(b)

Fig 3: a) Training of neural network for no. of neurons and b) Plot for accuracy of neural network

VI. CONCLUSION AND FUTURE SCOPE

Neural networks have proven to be a possible candidate to interpret non-linear data generated by the real world. Determines an algorithm for forecasting efficiency if the Pos is based on the Pos parameters. Most work has been done to assess the reliability of MINs and too many techniques have been used to measure the reliability of MINs. In this article, a neural network architecture with a minimal number of neurons and layers has been established that can be used to efficiently test the efficiency of MIN networks. A number of modifications have been made to render the method successful in predicting reliability based on practical non-linear results.The device built uses the minimal equipment, i.e. the reduced number of neurons (9 neurons) and layers (3 layers) and the tests demonstrate that the device measures the MIN efficiency effectively. The neural network method was educated using the reliability feature of normal MIN architectures. In the future, this device can be improved to measure the efficiency of abnormal MIN frameworks.

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