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Approximation Knowledge-Based Recurrent Neural Network for Estimating N-Terminal Reliability

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Abstract— The main problem dispersed with in this paper is to find a novel method for the improvement in the reliability analysis of Computer Network. Reliability prediction are estimated during the life cycle of a computer network with the aim of estimating failure. In designing a variable size network, the serviceability, availability and reliability of the any network is a primary consideration. The reliability calculation in varying size network is a problem of NP-hard; it requires more calculation and effort with the amplifying no of nodes and links. Many different approaches have been taken for reliability and probability calculation for triumphant communication between any pair of computers. The paper presents a method for identifying n-terminal network reliability based on RNN technique. The method derived in this paper preceding inputs which increases the speed of computation. The approach works efficiently and overcome the difficulties of the previous approaches defined with neural network model and other reliability estimation techniques. It is proposed that the RNN model be used to replace the most time-consuming component of the system reliability evaluation approach. A variable-length sequence input can be handled by RNN. The main goal of this paper is to predict asperity of reliability which is highly correlated with performance of network in any unfavorable conditions.

Keywords- NP-Hard, All-terminal network reliability, estimation, neural network, RNN, spatio-temporal

I. INTRODUCTION

The reliability of any communication path between any specified pair of the node in a computer communication network is the primary design consideration. Generally, it is fully dependent on the topology of a network and other communication facilities [1]. The tailed treatment of successful communication is fully dependent on various factors. Reliability is the communication between the nodes of the network [2]. Practically it is difficult to exact reliability calculation in growing variable sized, highly increasing networks from very small to large network size.

The reliability optimization problem concerned with the ability to identify a design that meets less cost and more reliability. The maximizing reliability problem in system networks has taken huge rise due to the designing of complex systems. The component of a network is n object of a network. The problem of finding and maximizing reliability in a network of is declared as the communication of each node of a network. Mostly, the network reliability calculation is of two types: all-terminal and source-sink reliability [11]. There are many methods and techniques used for network reliability calculation. Most of these methods are simulation or analytical based, which requires significant computational effort. These methods are simple and very effective for the network of smaller size. For highly increasing and variable sized growing networks, these techniques are not suitable, because, most of these techniques require simulations to be repeated numerous times which costs significant computational effort [3].

Approaches designed earlier have few major drawbacks exact estimation of reliability, probability of successful communication and long vector length and it cannot work efficiently if the network is of varying size. Failure predictions must be sound in nature that they represent all the uncertainties involved. The novelty in this paper is the usage of RNN with LSTM version for estimation of network reliability. The paper provides an approach using Long Short-Term Memory Networks. The LSTM solves the problem by merging the network parameters with the hidden node. RNN outperforms LSTM because it activates states in response to network events.

The successful communication probability between any two specified pair of vertices is defined as.

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$$P_C\left[V_S, V_T\right] = \sum_{k=0}^{n} C_{s,t}(k)(1-p)^k\, p^{(n-k)} \quad (1)$$

Where $C_{s,t}$ *is* the no. of combination of k links, those operative and there is at least one path is available between specified pair of vertices (C_1 and P_{1}). So failure probability rate is calculated as

$$P_f\left[V_S, V_T\right] = 1 - P_C\left[V_S, V_T\right] \quad (2)$$

It means that $P_f\left[V_S, V_T\right]$ requires examination of all the specified path and cut-sets between V_s, V_T .It means there is no more communication can take place only in one condition when all links do not have the same failure probability. Serviceability, Availability and Reliability (SAR) are the main aspects for designing an efficient network. The problem is NP-Hard to find and estimate reliability of varying size networks [11]. The assumptions used in this paper are as follows:

a) Assume that all nodes are functioning,
b) All nodes are independently decision making
c) All links are reliable.

Because RNN employs a loop, it can be used for both forward and backward signal processing. Figure 1 illustrates the concept of "unrolling" for time steps in an RNN. Each time step, the previous hidden states as well as the current input vector activate every neuron in the hidden layer. As a result, the output of the current time step is influenced by the previous input vectors.

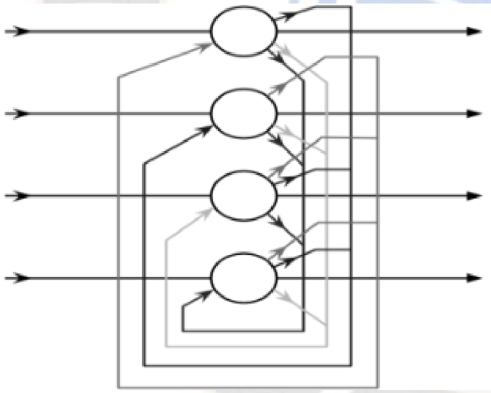

Figure 1: The basic structure of RNN

The paper contains five sections. In Section II, the Literature Review is specified. The Problem definition and assumptions are well defined in section III. Proposed methodology is explained in section IV. Section V and VI defines Results and Conclusions. Problem is well implemented in Python with a dummy network topology connection set of 2 to 256 nodes.

II. LITEARTURE SURVEY

Vijay Kumar [1] explained the performance of ARQ with help of Markov model. Yi-Kuei Lin [2]works on stochastic-flow network, and consider that each node and arc have capacities and may fail in certain conditions, which permits transmission from the source to the sink. Nader Samaan[3]presents reliability analysis method for composite power systems. The method proposed by is based on Genetic Algorithms (GA). Binary encoded algorithm is used to represent composite power system network. Anup Kumar [4] explains a new methodology for the optimization of network by adding new links. Berna Dengiz [5] use of computer networks has been rapidly increasing recently to share expensive various resources, and provides access to main systems from distant locations. Shuai Lin[6] explains how component failures may lead to more related component malfunction and ultimately how it impacts on reliability reduction. Kerri Morgan [7] clarifies reliability polynomial with the failure probability 1-p.. Om Prakash Yadav [8] presents a method for estimating the reliability by using ANN. Baijnath Kaushik [9][15] gives an optimization algorithm that work on amalgam feature of combinatorial spectrum with neural network.

III. PROBLEM DEFINITION AND ASSUMPTIONS

The primary design consideration is the first independent step to evaluate network performance in any unfavorable conditions. The calculation of the failure probability P_f, of a varying size system under given agitates conditions is a challenging task of reliability engineering. This segment of paper declares an explanation of the problem that how a computer network which is reliable can be designed so that the network can be work properly in any worst condition. Various application of neural network has been extensively used for prediction and estimating the reliability of a network but till now there is no algorithm that works on the feedback network approach. There is no known algorithm dealing with advance reliability technique as well as recurrent neural network approach to calculate exact reliability of varying size network. Main goal is to design a network that's having a capability of self-healing.

This paper presents a special algorithm for teetotally estimation of reliability; predict a failure and healing reporting by using RNN algorithm. A graph represent the network topology and represented as G = (V, E), network graph of N=1......n vertices, vertices set V={v_1, v_2, ---- v_n} and Link set L={ l_1, l_2, - l_k } the network reliability capacity can be estimated by using formula given below:

$$\text{Minimize Cost}(X) \text{ and } R_i(X) \geq R_0 \quad (3)$$

Where $X=(X_{12},\ldots,X_{i,j},\ldots,X_{N-1,,N})$, $R_0=(R_{01},\ldots,R_{0,j},\ldots,R_{0N})$ and N= Number of nodes (components)

L= communication path between nodes or vertices and P_c= Link probability/reliability

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A Graph network (G) with nodes n can be represented by n x n matrix which is adjacency matrix A(G), where $A_{ij} = 1$ if v_i is connected to v_j ($i \neq j$) and $A_{ij} = 0$ otherwise.

The adjacency matrix A (G) is symmetric or not a symmetric depends on the conditions. The number of links pointing in towards is In-degree $d_{in}(v)$ and number of links pointing out from, a node is out-degree $d_{out}(v)$. The minpath is just a path between $v_s$and v_t in two-terminal reliability. A spanning tree is a minpath for all-terminal reliability and k-terminal reliability. If the inputs are in discrete random fashion then the performance function μ R is represented as $\mu : R^m \rightarrow R$.

The main objective of this paper is to design a fidelity network with more reliability.

It can be stated using formula which is as follows:

$$\text{Minimize } Z(X) = \sum_{i=1}^{t} \sum_{j=i+1}^{n_i} C_{ij} \; X_{ij} \quad (4)$$

Some assumptions must be before designing a layered or structured network

1. Consider the failure of node and link at random time interval t.
2. The calculated minimal cut of the graph is connected and no formation of cycle.
3. The link between x and indicator function is not explicitly know than system reliability function is known as probability of failure and denoted as

$$p_F = P(x \epsilon F)$$

4. To evaluate μ(x) the effort is required for each value of x.
5. The above two steps helps to reduce function evaluations.

This paper proposes a new technique based on connectivity-based reliability measure instead of network resilience measure.

Notation and pre-assumption used:

The problem studied above is generally having some parameters like: node to node connectivity, cost of link, reliability of Node & reliability of link, increasing a network resilience measure and network design cost. The following are the underlying postulation kept in mind while solving the issues

(a). Consider a Transportation network with no articulation vertex.
(b). If network have articulation vertex, then add a parallel edge and make it functioning.
(c). Remove all the pendant nodes ($deg(v_i)=1$)
(d). Graph G = (V, E) with N nodes, where each link is having its flow_capacity (link)>0.
(e). Each node must be in operational state with initial probability value.
(f). Each link must be in operational state with initial probability value.
(g). Failures of Links and Nodes are independent.
(h). Parallel link must be avoided in between nodes.
(i). *Network resilience* level =1

Common notations for defending paper are as follows

(a) n,l :Denotes nodes and link of network graph
(b) (v_i,v_j) :component (v_i,v_j).
(c) $L(v_i,v_j)$:component (v_i,v_j) is undirected link
(d) Link :((i,j) = (j,i)
(e) (v_i,v_i) :denotes node i.
(f) $x(v_i,v_j)=1$: Operational state
(g) $x(v_i,v_j)=0$: Not in operational state
(h) $R_i(v_i,v_j)$:Reliability of component (v_i,v_j)
(i) R_S : Reliability of System
(j) P_f : Probability of Component(v_i,v_j)
(k) P_f : $1-R_b$
(l) λ_i : failure rate

General Terms used:

(a) Generally speaking, the reliability computation is a useful metric for making decisions in the flawlessly optimum design of networks.
(b) In all terminal networks with operational edges, every pair of connecting nodes has a communication path.

The most used lifetime distributions approach is (c) Weibull distribution. It is employed as a result of its adaptability and relative ease. Assume that all four identical modules in the system are operating correctly (at least one operational module).

The overall system reliability is given as below formula assuming each module reliability as .95, then is:

$$R(t) = 1 - \prod_{i=1}^{n} R_i\,(t)$$

$1-[1-.95]^4 = 0.99999375$

Our proposed methodology is based on the Recurrent Neural Network .RNN overcomes the complexity of existing reliability estimating techniques.

IV. Proposed Methodology

RNN technology for reliability estimation needs assistance from previous reliability estimation techniques. RNN was inspired by the following: robustness power and flexibility of the biological neuron. RNN were neutrally implemented and mathematical model. RNN consists of many simple mathematical elements. Neurons called summing element.

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Weighted connections are called weights both can work together in parallel and in series. Functions in RNN begin in a random state and learnt by using repeated processing of a training data set. Training data set contains input and target data set value. The RNN reliability estimation functions in designing of network are tested by evaluating it to a simply predicted bound and exact calculation. The backpropagation training method because it's having a powerful approximation capacity [6]. Simple ANN methods are having various limitations of unexplained behavior, network structure, duration of the network and so on [17]. The limitation discussed above can be overcome by using RNN (Recurrent Neural Network) technique for exact reliability estimation. The paper presents an algorithm named AKRNN (Approximation Knowledge-based Recurrent Neural Network) to effectively estimate all-terminal reliability measure and the reliability of networks self-healing and protection network. This allows RNN to display temporal dynamic behavior.

Below is the block diagram with input node, output node and link pairs.

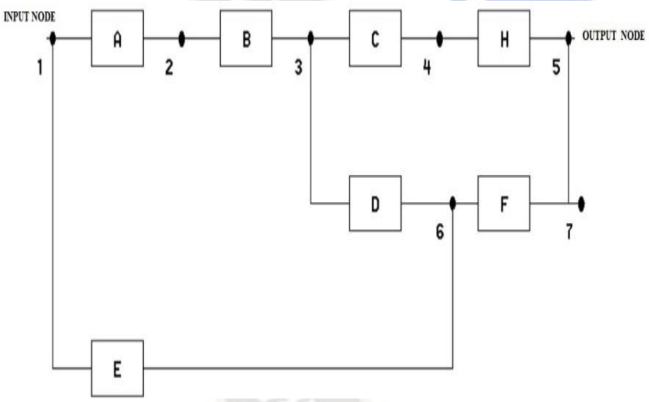


Figure 2: Serial-Parallel Network with 7 node and 7 Modules.

Initial reliability to each module than the total reliability of system is calculated by the above formula R_a=0.81, R_b=0.83, R_c=0.85, R_d=0.87, R_e=0.89, R_f=0.91, R_g=0.93, R_h=0.91, R_S = 0.89387. The paper assumes that all failures are statistically independent. The probability $P_C\left[V_S, V_T\right] = \sum_{k=0}^{n} C_{s,t}(k)(1-p)^k\, p^{(n-k)}$ is used for successful communication between any pair of nodes. In designing a variable size network, the serviceability, availability and reliability of the any network is a primary consideration but followings are the milestone while designing such kind of reliable network.

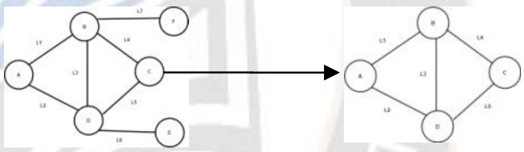
What is the probability that a vertex (v_i) is communicate with another vertex (v_j)?

- How the network overflow will be estimated?
- How transmission rate can manage [13-14]?
- Where are the weak points of network?
- What is the network failure exact calculation?
- What is the average delay?
- What is the probability of loss?
- How is traffic load distributed over the network?

The aforementioned issues are fixed, predefined, and have a network where a node can join or leave at any time, necessitating the use of a powerful algorithm to determine exact reliability. System needs an algorithm that can solve the optimal network design problem in the shortest possible time for static and networks of variable sizes. Predicting reliability over the threshold of 0.91 and fault-tolerant optimal design are the major goals. There are other techniques available for determining the polynomial-time all-terminal network dependability, but our algorithm complexity is substantially higher than that of all other algorithms. Algorithm proposed in this paper has various phases, test the result at each and every phase and compare it with the existing solution motivates us to move forward to next step.

Phase 1: Direct Decomposition (DD)

1. Consider a network graph if a network contains an articulation vertex, pendent vertex then applies pre - assumption rule.
2. Remove all the pendant nodes (deg(vi)=1)
3. Graph G = (V, E) with N nodes, where each link L_e is having its flow capacity c (e) > 0.



(a) (b)

Figure 3: (a) Original Graph before reduction (b) Graph after reduction

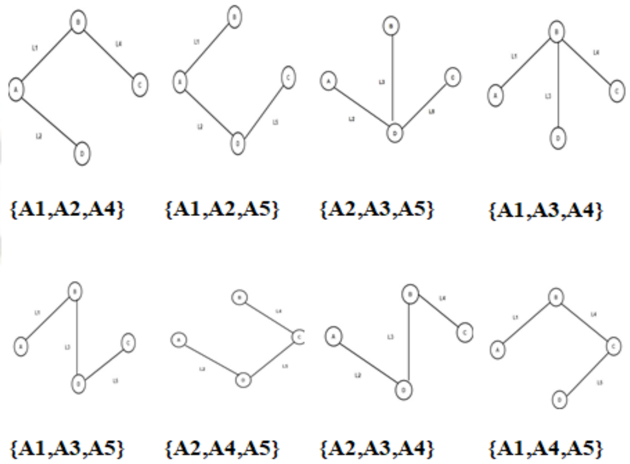


Figure 4: Set of arbitrary paths or spanning trees of fig. 3(b).

To calculate reliability communication of all nodes is been required. A network component is either failure or operational. Failure state is denoted by binary values 0 and the operational state is denoted by binary value 1. The minimal cut and

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minimal path of a network decide the operational or failure status of the system. The reliability of above graph will be calculated as:

$$R_S = P_{L1}P_{L2}P_{L4} + P_{L1}P_{L2}P_{L5} + P_{L2}P_{L3}P_{L5} + P_{L1}P_{L3}P_{L4} + P_{L1}P_{L3}P_{L5} + P_{L2}P_{L4}P_{L5} + P_{L2}P_{L3}P_{L4} + P_{L1}P_{L4}P_{L5} + - 2 P_{L1}P_{L2}P_{L4} - 2 P_{L1}P_{L2}P_{L3} P_{L5} - 3 P_{L1}P_{L2}P_{L4}P_{L5} - 2 P_{L1}P_{L3}P_{L4} P_{L5} - 2 P_{L2}P_{L3}P_{L4} P_{L5} + 4 P_{L1}P_{L2}P_{L3} P_{L4} P_{L5} \quad (7)$$

Where: R_s is the system reliability and R_i is the component reliability. In above formula R_S is the reliability of graph R (G). Here reliability depends on the reliability of an individual component and its position in a graph. The reliability polynomial R(G, p) is the probability that the undirected graph G = (V, E) is connected, assuming all edges of G fail independently with probability 1-p. If the network is of varying size, then number of possible topologies in terms of space size complexity is defined as:

$$K^{\frac{(|N|\times(|N|)-1)}{2}} \quad (8)$$

K is the number of choices for the links to be connected in growing variable size networks. The main problem in this paper is based on the type of link either connections–fixed or variable link connections.

After decomposition RNN approach is applied which is then compared with RNN approach.

ANN Approach for Reliability estimation

Step 1: Assign random weight and learning rate to all the links to initiate the algorithm. Set the following parameters to ANN model

- The number of networks,
- Number of O/P signals,
- I/P and target,
- Layers count,
- hidden layers count & rate of learning.

All the parameters will be set as design parameter.

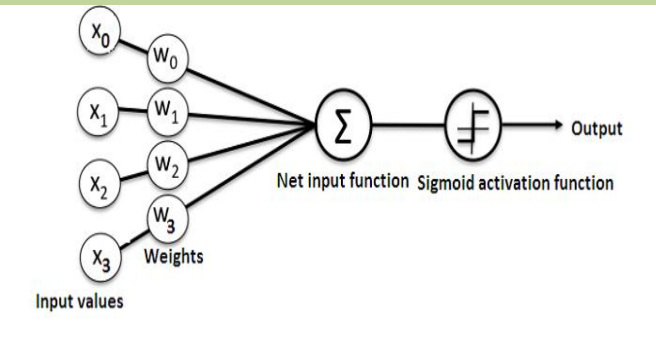

Figure 4: Simple Artificial Neuron

Step 2: Using the input X_i and the ($X_i \rightarrow N_h$) linkages. Assign X_i to N_h and record the O_R of N_h in separate array.

- Prepare an orthogonal array (O_R).
- Arrange the orthogonal array column according to design parameter.

Step 3: Assign specific values to the followings

- Connection weights
- Values for tolerance
- Rate of Learning
- Trails count to achieve epochs,

Each H_r sums its weighted input signals to calculate net input (where r = 1 to k)(H_r-Hidden unit)(N_h- Hidden Nodes)

$$H_{inr} = V_{or} + \sum_{i=1}^{n} X_i V_{ir} \quad (9)$$

Find the A_R of output nodes. Compute output of the H_r by applying A_f_function and feed the output signal from the H_r to the output unit.

$$H_r = f_a(H_{inr}) \quad (10)$$

Step 4: Recalibrate the weights between hidden nodes and input nodes

Step 5: Repeat the process until the reliability is not matched with the threshold.

Step 6: Using the final linkage weights score the A_R of the output nodes.

Step 7: Trained the network by using Back-Propagation algorithm.

Step 8: Use variance test for statistical analysis.

Step 9: The neural network is reconfigured on the basis of significant parameter, (perform the optimization process).

Step 10: Stop the training after specified number of epochs.

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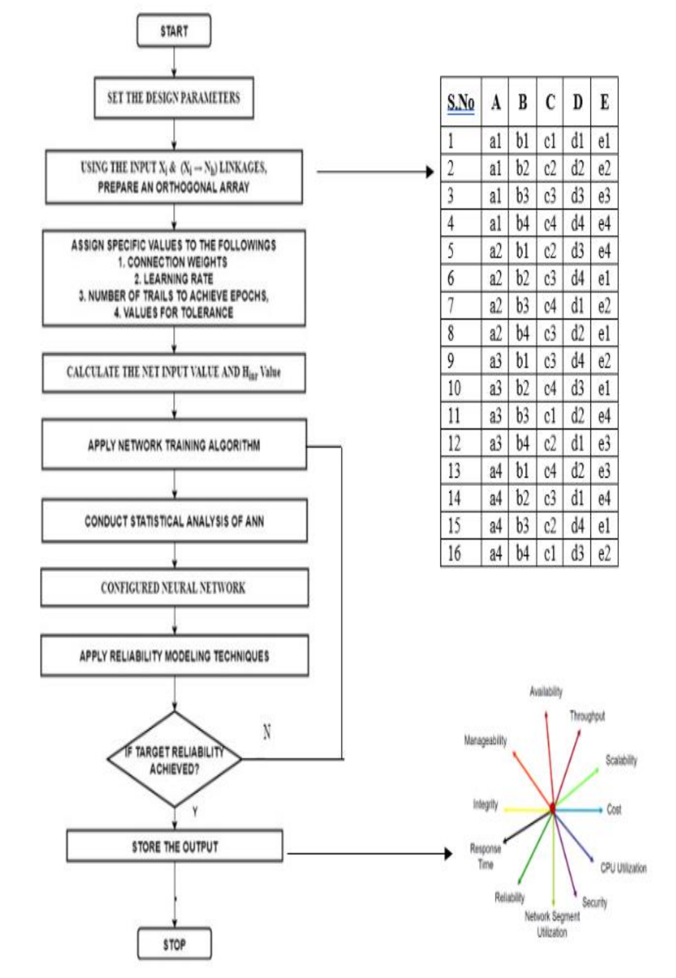

S.No	A	B	C	D	E
1	a1	b1	c1	d1	e1
2	a1	b2	c2	d2	e2
3	a1	b3	c3	d3	e3
4	a1	b4	c4	d4	e4
5	a2	b1	c2	d3	e4
6	a2	b2	c3	d4	e1
7	a2	b3	c4	d1	e2
8	a2	b4	c3	d2	e1
9	a3	b1	c3	d4	e2
10	a3	b2	c4	d3	e1
11	a3	b3	c1	d2	e4
12	a3	b4	c2	d1	e3
13	a4	b1	c4	d2	e3
14	a4	b2	c3	d1	e4
15	a4	b3	c2	d4	e1
16	a4	b4	c1	d3	e2

Figure 3: ANN Approach for Reliability estimation

The paper uses an approach and tested for 255+ nodes with link reliabilities. ANN is an approximation method and sometimes it produces different results. Main advantage of ANN is that if a network is trained with a very minute fraction of interval, it can be used without restriction during network design for a topology of a fixed number of nodes.

Recurrent neural network approach for Reliability estimation.

To overcome the limitation of traditional ANN this paper presents a novel method of RNN. It is a special kind of learning algorithm based on an approach for sequential information or its main working is based on how sequential information is been used in RNNs. RNNs computes the same task for every element of a sequence and called *recurrent* . It is another type of learning algorithm (Deep-Learning) which follows a sequential loom (or cycle). Traditional ANN assume that all input values and output values are independent of each other.

But in so many cases their independent nature is not applicable and sufficient like for predicting the next stage in a series of events you well known which event will occur. The Mathematical computations RNN perform in sequential manner [5]. When working with longer data sequences, standard a vanishing gradient problem causes short-term memory in recurrent neural networks (RNNs). We utilize the RNN LSTM version. The feature of LSTM is to store information for long durations. .

The complete RNN will get formed by repetitive NN. In traditional RNNs, the repeating module will have a pretty simple form.

The first stage of LSTM is which is completed by using sigmoid function to decide whether information to be be excluded in that time step. The sigmoid function determines this. The function is computed using the prior state (ht-1) and the current input.

$$f_t = \sigma\left(W_f\ [h_{t-1}, x_t] + b_f\right)$$

f_t is the forget gate, which decides which information from the previous phase should be deleted.

The second layer consists of two components. The sigmoid and tanh functions are two completely different functions. Which values are allowed to pass is determined by the sigmoid function (0 or 1). The tanh function gives the input values weight, indicating their relative importance (-1 to 1)

$$i_t = \sigma(W_t\ [h_{t-1}, x_t] + b_i)$$

$$C_t = tanh(W_c\ [h_{t-1}, x_t] + b_c)$$

it is the input gate that determines which data to pass based on its importance in the current time step.

The output will be determined at the third stage. A sigmoid layer is first utilised to identify which pieces of the cell state make it to the output. The Multiplication of the cell state is been done with sigmoid gate output and delivered via tanh to compel the values to be between -1 and 1.

$$o_t = \sigma(W_o\ [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

The output gate, Ot, permits the information sent in to affect the output in the current time step.

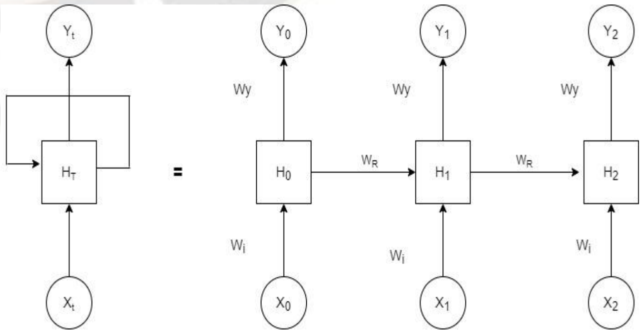

Figure 5: Simple Recurrent Neural Network

The recurrent neural network is been train by following steps-

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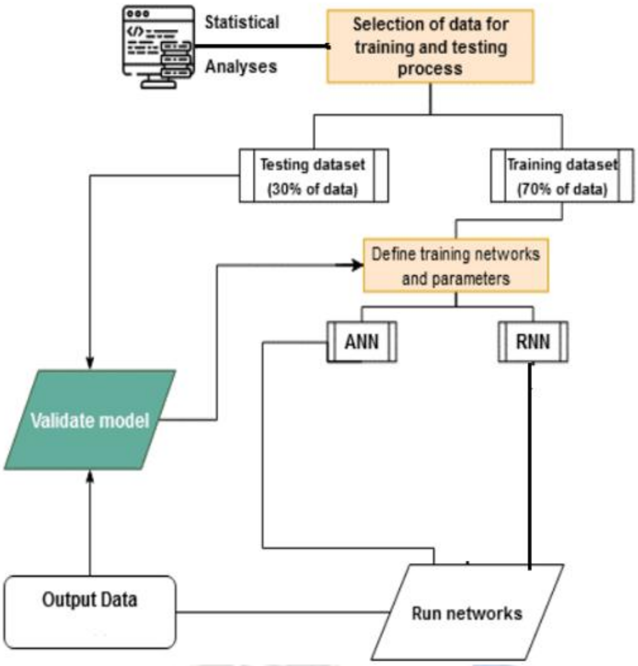

Figure 6: RNN Approach for Reliability estimation

Step 1- Prepare raw dataset to RNN.

Step 2: Initialized the entire variable according to threshold value.

Step3- Set a dummy Reliable network as an input and compute some results H_0 at time t from randomly initialized variable of raw data sets.

$$H_0^t = g_H (w_i x^t + w_R H^{t-1} + Bv_H) \tag{11}$$

Bv_H: Biased Value.

$$Y_0^t = g_Y(w_Y H^t + Bv_Y) \tag{12}$$

Step 4: Predicated result is computed.

Step 5: Compare the result with threshold value (expected value) and compute error if produced.

Step 6: Compute error by using the following formula

$$Err = \Sigma \text{ (Actual o/p- D\_reliable o/p)}^2 \tag{13}$$

D_reliable: dummy Reliable network

Step 7: Repeat the steps (3 to 6) until not achieved target output.

Step 8: A forecast output is made by putting these variables to get new unseen input

V. RESULTS

Experiment performs in this paper uses total**T** trials meet to measure the optimal design of a network. In the experimental trail total 3.4×10^{10} from **K** trails are considered. The main advantage of this method is that it reduces time in respect to previous existing methods (where T=128 and K=102). This section of the paper introduces cross validation n-Folds value of upper bounds with 100% confidence.

TABLE 1: Results of cross validation n-folds (n=5) maker for fixed link network

RELIABILITY ESTIMATION FIXED LINK NETWORK			
S.NO	**Training**	**Testing**	**Upper-bound**
1	0.039505	0.052791	0.076615
2	0.038225	0.049315	0.089575
3	0.038765	0.041367	0.08021
4	0.039586	0.042315	0.07569
5	0.039527	0.048776	0.07896
Average	**0.0391216**	**0.0469128**	**0.08021**

TABLE 1: Results of cross validation n-folds maker(n=5) for varying link network

RELIABILITY ESTIMATION VARYING LINK NETWORK			
S.NO	**Training**	**Testing**	**Upper-bound**
1	0.060521	0.06059	0.09965
2	0.052345	0.05788	0.09095
3	0.053672	0.05777	0.09979
4	0.051231	0.05858	0.09379
5	0.052441	0.05959	0.09813
Average	**0.054041**	**0.05888**	**0.096462**

TABLE 1: Results analysis of Fixed link Vs Varying link network

FOLD NO	RELIABILITY ESTIMATION FIXED LINK NETWORK			RELIABILITY ESTIMATION VARYING LINK NETWORK		
	T_1	T_2	AUBV	T_1	T_2	AUBV
F1	0.03343 600	0.0393 4200	0.0695 5400	0.0491 9400	0.0550 1000	0.0876 8400
F2	0.03912 160	0.0469 1280	0.0802 100	0.0540 4100	0.0588 800	0.0964 6200
F3	0.02915 200	0.0372 5000	0.0705 1000	0.0400 2600	0.0483 0600	0.0816 2600
F4	0.02804	0.0363	0.0655	0.0360	0.0451	0.0747

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	840	8600	2400	8200	0000	9200
AVG (F1-F4)	0.03256 562	0.0396 9800	0.0705 0300	0.0442 2450	0.0518 2450	0.0851 3200
AUBV: Approximate Upper-Bound Value						

For experiment purpose we use Training data set T_1(70%) and T_2 (30%)is testing data set value. This paper presents an optimal design method of RNN to estimation reliability from varying sized networks.

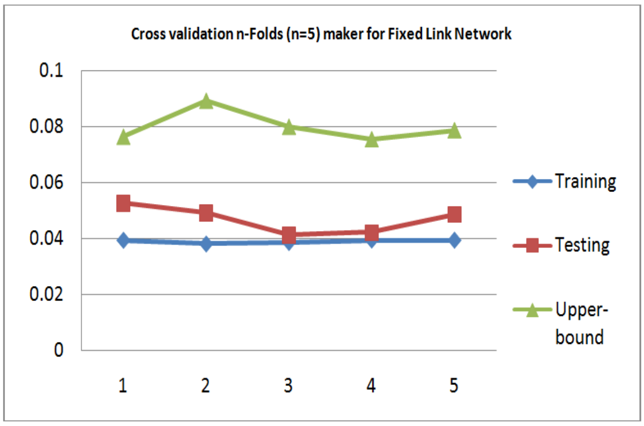

Figure 7: Illustrationof cross validation n-folds for Fixed link network

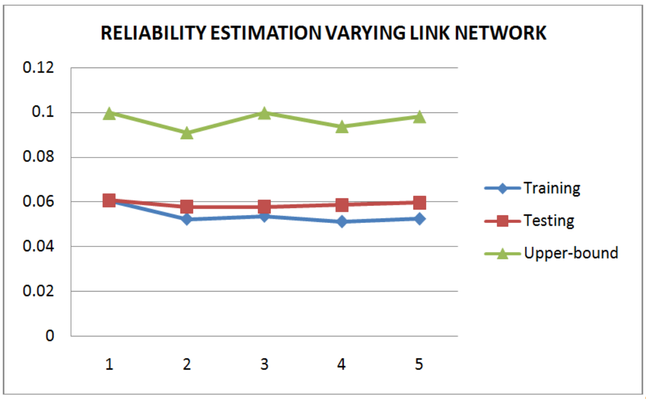

Figure 8: Illustrationof cross validation n-folds for Varying link network

VI. Conclusion

To discover the most dependable network with N nodes and L links, we have created a novel technique. Use the suggested method to demonstrate that the algorithm's efficiency is substantially higher than that of existing algorithms and that its time complexity is polynomial in N and L. We also assert that the RNN technique makes it simple to identify the N nodes and L links network that is the most trustworthy. As a result of the inherent mistake in the reliability assessment, our results may only be taken as approximations. The algorithm shows that if the network size is high, the difference in reliability between two networks topologies with the same number of nodes and links is tiny, and the search for the most reliable network unquestionably calls for a larger number of experiments. In order to satisfy the constraint on the total number of links=L for the experimental setup, we first build a method using a basic network structure and add further links as needed. This is followed by a search using rewiring or utilising. The suggested algorithm's main drawback is a little mistake in the reliability estimation. For networks with a size between 2 and 255, the technique operates effectively.

References

[1] Vijay Kumar et.al (2011), "Markov Model for Reliable Packet Delivery in Wireless Sensor Networks", IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 3, No. 1, ISSN (Online): 1694-0814

[2] Yi-Kuei Lin (2002)"Two-commodity reliability evaluation for a stochastic-flow network with node failure", Computers & Operations Research, 1927–1939 www.elsevier.com/locate/dsw.

[3] Nader Samaan,(2005) "Using Genetic Algorithms for Reliability Calculations of Complex Power Systems", 0-7803-8834-8/05, IEEE 10.1109/ISCAS.2005.1465555

[4] Kumar, R. M. Pathak and Y. P. Gupta, (1995) "Genetic-algorithm-based reliability optimization for computer network expansion," in IEEE Transactions on Reliability, vol. 44, no. 1, pp. 63-72, March 1995, doi: 10.1109/24.376523.

[5] Dengiz Berna, Altiparmark Fulya and Smith Alice E.,(1997) "Genetic algorithms design of networks considering allterminal reliability", The Sixth Industerial Engineering Research Conference Proceedings IERC'97, Miami Beach, Florida, USA, May 17-18, pp. 30-35.

[6] Shuai Lin "Hindawi Complexity Volume (2018), "System reliability assesment based on failure propogation process",Article ID 9502953, 19 pages https://doi.org/10.1155/2018/9502953

[7] Kerri Morgan,(2016) "An infinite family of 2-connected graphs that have reliability factorisations", http://dx.doi.org/10.1016/j. dam. 2016. 11.006 0166-218X Elsevier B.V.

[8] Om Prakash Yadav (2020) "All-terminal network reliability estimation using convolutional neural networks", proc IMechE Part O: J Risk and Reliability 1–14 March 2020, https://doi.org/10.1177 /1748006X20 969465

[9] Baijnath Kaushik,(2015) "Performance evaluation of approximated artificial neural network (AANN) algorithm for reliability improvement", Applied Soft Computing 303–314 Http://dx.doi.org/10.1016/j.asoc.2014.10.002 1568-4946/©

[10] Leemis, L.M.,(1995) Reliability - Probabilistic Models and Statistical Methods, Prentice Hall, Inc., Englewood Cliffs, New Jersey,

[11] Om Prakash Yadav(2020), "All-terminal network reliability estimation using convolutional neural networks", Journal of Risk and Reliability. https://doi.org/10.1177/1748006X20969465

ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5898
***Article Received**: 05 October 2022 **Revised**: 08 November 2022 **Accepted**: 05 December 2022*

[12] Khanna G, Chaturvedi SK, Soh S (2019) "On computing the reliability of opportunistic multihop networks with mobile relays.", Qual Reliability Eng Int. https://doi.org/10.1002/qre.2433
[13] Khanna G, Chaturvedi SK (2018) "A comprehensive survey on multihoop wireless networks: milestones, changing trends and concomitant challenges", Wireless PersCommun. https://doi.org/10. 1007/s11277-018-5711-8
[14] ZhifuLuan(2017) "Calculation and Simulation of Transmission Reliability in Wireless Sensor Network Based on Network Coding", International Journal of Online Engineering (IJOE).
[15] Baijnath Kaushik(2015) "Performance evaluation of approximated artificial neural network (AANN) algorithm for reliability improvement", Applied Soft Computing 26 (2015) 303–314.
[16] Chakraborty S, Goyal NK(2015). Irredundant subset cut enumeration for reliability evaluation of flow networks. IEEE Transactions on Reliability 2015;64(4):1194–1202.
[17] S. Chakraborty and N. K. Goyal(2015), "Irredundant subset cut enumeration for reliability evaluation of flow networks," IEEE Trans. Rel., vol. 64, no. 4, pp. 1194–1202,
[18] F. Altiparmak, B. Dengiz(2014) "Design of reliable communication networks: A hybrid ant colony optimization algorithm" IIE Transactions, 42:4, 273-287, DOI: 10.1080/07408170903039836
[19] B Kaushik(2013) "Achieving maximum reliability in fault tolerant network design for variable networks", Applied Soft Computing 13 (7), 3211-3224.
[20] Wei-Chang et.al (2010), "A Particle Swarm Optimization Approach Based on Monte Carlo Simulation for Solving the Complex Network Reliability Problem", IEEE Transactions on Reliability 59(1):212 – 221
[21] Mutawa, A. M., Alazemi, H. M. K., &Rayes(2009), A. "A novel steady-state genetic algorithm approach to the reliability optimization design problem of computer networks". International Journal of Network Management, 19(1), 39–55. doi:10.1002/nem.687, (2009).

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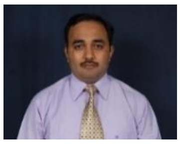

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