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A Heuristic Approach for all-terminal Network Reliability using OANN

Anuradha[1], A.K. Solanki[2] and Harish Kumar Taluja[3]
[1]Assistant Professor, Department of Computer Science,
Meerut Institute of Engineering & Technology, Meerut (Uttar Pradesh), India.
[2]Assistant Professor, Department of Computer Science,
Bundelkhand Institute of Engineering & Technology, Jhansi (Uttar Pradesh), India.
[3]Associate Professor, Department of Computer Science,
Meerut Institute of Engineering & Technology, Meerut (Uttar Pradesh), India.

(Corresponding author: Anuradha)
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ABSTRACT: In current network reliability research, the concern is how to develop a standard network design. It is the probability that a network will perform adequately for a given period of time in favorable condition as well as in worse conditions. Existing methodology on assumptions about network design, *the probability of individual failures occurring.* All-terminal network reliability estimation contains polynomial-time hardness (NP-Hard); it means that for exact reliability estimation requires more computation efforts or estimation of exact reliability for complex and varying size network is NP-Hard. This paper presents a new approach to the reliability calculation of transportations networks with assorted source and destination nodes. The proposed OANN method in this paper for all terminal network reliability compares results with MCS, PSO and existing ANN approach for reliability estimation. The approach is completed into four phases. The first phase is for generating level 1 reliable network topology design with the addition of edges and nodes in order to turn into a structurally reliable system. The second phase is to enumerate a minimal cutset for topology layout. The third phase is to enumerate minimal cutset if require for Backtracking simulation. The fourth phase is for estimation of reliability for computational efficiency and accuracy by using advanced Heuristic Rules of neural network. The main focus of this paper is to predict asperity of reliability which is highly correlated with the performance of the network in any worst condition.

Keywords: ANN, backtracking, MCS, MC, MP, NP-hard, PSO, All-Terminal Reliability.

I. INTRODUCTION

The improvement in the reliability of complex system has acquired special importance in recent years. The reliability of the system is understood to mean the felicitousness of the network for the fulfillment of a planned task and the efficiency of utilizing the means put into it. Many advance applications such as transportation network, oil production, water the distribution system, distributed system reliability, reliability analysis in the large complex structural system, flow networks, computer & communication systems, coherent-system reliability, a series-parallel system, simplex system and in the wireless network requires reliability calculation for constructing a highly optimal layered or structured system having the maximal operational capability with minimum cost constraints [1-8, 14].

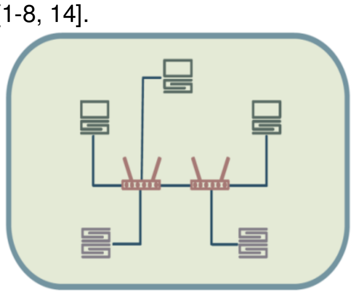


Fig. 1. A Simple Physical Network Diagram.

Fig. 1 represents the physical topology of a network. The reliability optimization problems of any network are anxious to fix scenarios that convene minimum cost and high reliability [6, 18]. The Fig. 2 defines the notion of a reliability topology which isn't a physical topology; this is an organization of devices inside of a network that shows how the system functions. Various communication paths can be formed from Fig. 2.

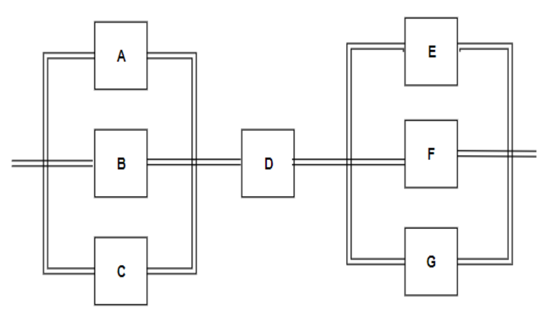


Fig. 2. Components in a network interact from a reliability Topology.

The Table 1 shows the path matrix for the Fig. 2 and conclude that column D contains all 1's it means that it represents that articulation vertex point.

Table 1: Path Matrix for Fig 2.

Path/Node	A	B	C	D	E	F	G
PC_1	1	0	0	1	1	0	0
PC_2	1	0	0	1	0	1	0
PC_3	1	0	0	1	0	0	1
PC_4	0	1	0	1	1	0	0
PC_5	0	1	0	1	0	1	0
PC_6	0	1	0	1	0	0	1
PC_7	0	0	1	1	1	0	0
PC_8	0	0	1	1	0	1	0
PC_9	0	0	1	1	0	0	1

It decreases the overall reliability of system. The reliability calculation is gaining very huge drive for designing complex and larger networks. For maximizing the reliability in real life network has gained huge momentum from its applicability. With the expansion of technologies in communication devices, we expect maximum utilization of devices and network. Networks are capable for success broadcast of data between the S_n (Source Node) to D_n (destination node). Networks are becoming more complex day by day due to huge expansion of demands. The computer network comprises the number of objects or components. Probability comes where Reliability is present. Testing and Maintenance are the essential part of Reliability [31, 34]. Generally, the Reliability computation is a valuable measure for decision making in optimal designing of network without fail. Reliability of the system R_s is evaluated by the given below equations [3, 24, 28, 33, 39].

$$R_s(t) = \prod_{i=1}^{n} R_i\,(t) \tag{1}$$

$$R_s(t) = \prod_{i=1}^{n}[\exp\,(-\lambda_i * (t))] \tag{2}$$

$$R_s(t) = \exp\,[-\sum_{i=1}^{n} \lambda * t] \tag{3}$$

$$R_s(t) = \exp\,[-\lambda_s\text{*t}] \tag{4}$$

Where component failure rate = λ_i.

If 6 sub-systems are arranged in a series to form a single system named S each subsystem having a specific reliability value in hrs. The reliability value for each subsystem is as follows: 65, 75,135, 85,125, 115. Reliability for 6000 minutes will be calculated by the equation number 1, 2, 3, 4.

T = 6000 Minutes = 6000/60=100 hrs.

MTBF = 600/6=100

$\lambda = 1/100$=0.01

$R_s(100) = exp\,[-0.01\text{*}100] = exp(-1)$

$R_s(100) \simeq 0.37$

So, rate for survival is 37%. Reliability of the system can be increased only by reducing the time interval. This method is having some limitations; those can be overcome by the Weibull Method. Weibull distribution is most commonly used lifetime distributions method. It is used due to its flexibility and relative simplicity [7]. *Three parameters of Weibull density functions are as follows:*

– Shape(β)

– Scale(η)

– Threshold value (ϒ)-location parameter

$$f(t)=\frac{\beta}{\eta}\left(\frac{T-\Upsilon}{\eta}\right)^{\beta-1} e^{-}\left(\frac{T-\Upsilon}{\eta}\right)^{\beta} \tag{5}$$

The ϒ is not used and its value is set to be zero. The shape (β) is also known as Weibull slope. Weibull *Probability density function (PDF)* is used as the mean, median, reliability function and failure rate [31].

$$R(T)=e^{-}\left(\frac{T-\Upsilon}{\eta}\right)^{\beta} \tag{6}$$

Failure rate is calculated as

$$\lambda(T) = \frac{f(T)}{R(T)} = \frac{\beta}{\eta}\left(\frac{T-\Upsilon}{\eta}\right)^{\beta-1} \tag{7}$$

MTBF is calculated as

$$\bar{T} = \Upsilon + \eta.\acute{\Gamma}\left(\frac{1}{\beta}+1\right) \tag{8}$$

The distribution method is used in life data analysis and reliability estimation. We assume that the reliability of a network is the probability (P_o) that a network will perform a desired operation for a time period (t) under a given condition (C_0) [7, 8, 14]. Consequently, Complex network design issues are solved by network reliability estimation and flow management. The ability of any communication network is to establish a path between specified pair of vertices. In layered or structured network communication between any pair of nodes is possible through specified path. The network reliability computation is depending on all-terminal reliability and source-sink (K-terminal) reliability [4, 16]. Another factor of reliability calculation is depending on traffic management and connectivity among nodes in any communication network. Reliability is the probability of non-failure over time ($D_{i,j}$- data transmission rate between node v_i and v_j) at time t from a specified network. In complex network design the probability failure of any component may be assessed in a sequential arrangement – from observed threshold rates. For designing a complex network structure, the probability of a component failure may be review in a frequentist manner from experimental failure rates. The No. of failures/component function hours is shown in Fig. 3.

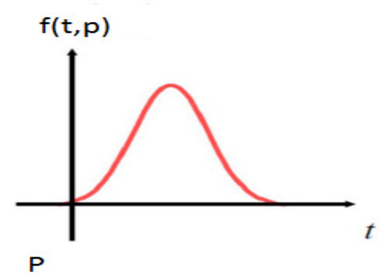


Fig. 3. Components Failure rate at a time t.

Reliability calculation can be done by using various methods such as simulation or analytical based, these methods can be applicable for small size networks but with a limitation of more computations are required to achieve the desired results. Monte Carlo Simulation techniques have been used for cracking various reliability issues or problem.MCS methods have been applied to estimate network reliability by focusing on how to design sampling plans to reduce the variance in terms of the known MP/MC [1, 9, 13, 20, 21]. Minimal Paths or Minimal Cuts calculation is itself a NP-Hard for variable size networks [3]. The afore mentioned techniques are not suitable, for varying size and frequently growing network because these techniques require more simulations to be repeated frequent n number of times. These methods have a big drawback that computation cost is increased with a computation factor (C_f) n times. For reliability calculation of highly increasing and variable sized growing networks we proposed a method that is based on Optimized Artificial

Neural Network (OANN). The method proposed in this paper present a simplification of network design.

The main target of this designing is to achieve maximum reliability of the network and main focus is to minimize the faults of network. To achieve the better results some prerequisites are required like nodes of the networks must be fully reliable and links failure is the only factor responsible for failure of network. The proposed model is having initial link (Bi-directional) value at the beginning and if a link is repaired once in life time it cannot be reusable. If the nodes of a network are not moveable, the main design decisions are the following:

– Flow of network.
– Cost of the network.
– Prior fix the location of network.
– Consider that all nodes are reliable.
– Selection of routing edges (links).
– Predefine the cost of each links and its reliability
– Links cost and reliability are fixed
– Only used bi-directional link.
– Redundant links are not permeable.
– Only two stages of links in a network either operational or failed.
– Network is non reparable.
– Treat network as an undirected graph (G (V, E)).
– Links failure probability is P_o.
– Links failures are Independent.

Our proposed approach improves reliability by reducing cost C(x) by a factor α in comparison to the existing methods. The proposed algorithm works on complex network and randomly we can add or remove n nodes in a network and maximum allowed size of the network is upto 256 nodes. The complete paper is summarized into six different sections. Each section is having equal importance and weightage. The Introduction is defined in section I. Literature review and problem definition is well explained in section II and III. The methodology is explained in section IV of the paper and section V and VI is used for presenting results and conclusion.

II. LITERATURE SURVEY

Dengiz *et al*., (1999) states that reliability of any network is depends on nodes and the links between them. She uses genetic algorithm for the exact calculation of reliability in respect to all terminal network. Her design consideration is based on cost and reliability [3]. Srivaree-ratana *et al*., (2002), states that all-terminal network reliability problem is a type of NP-hard.NP-hard means in computational time efforts are growing exponentially means that no. of nodes and links in the network are of varying size. Normally we were examining the topologies while designing the optimal network. For optimal designing of network, he uses ANN techniques. Neural networks are raised up then trained and validated using the various topologies [4]. Lee *et al.,* (2010) use ANN model and Gaussian functions for predicting the reliability and explains how Gaussian functions has better stability [14]. Altiparmak *et al*., (2009), designs a new encoding technique for estimating the reliability of communication network. She uses network with identical link for estimating reliability. She proves that how neural estimation is speedy, cost effective and used for iterative algorithms [17]. Yano and Wadayama (2012), investigate the network failure probability. He uses simple random graph and lower and upper bounds that is related to graph. He finds that upper and lower bounds of graphs that displayed the working of network [23]. Petingi (2013) identified irrelevant edges by using some adequate conditions. He had defined the issues occurring during the identification of D-irrelevant edges and the complexity in graphs regarding diameter related problems [26]. Rebaiaia (2013) used minimal cuts and minimal paths with the help of BDD diagrams for reliability calculation. The approach reduces the space and time for identifying reliability of communication network of national radio. The computation consists of Data Transformation, Data Reduction, and Data Filtration [25]. Zhang *et al*., (2014) had given a network performance-reliability-preserving reduction method. He had defined the concept of network performance reliability using performance indicators. These indicators work with some parameters (loss rate, delay and throughput). The method proposed uses Monte Carlo simulation and network performance model [30]. Chatterjee (2017) has proposed ROBDD diagrams to identify analysis problem of network reliability for network. For traversing of the network, Breadth First search is been used and for reliability evaluation ROBDD based sift reordering technique is been presented [36]. Pérez-Rosés (2018) had focused on recent developments of reliability with the basic concepts. He examined deviation of the novel problem [37]. Zhang *et al*., (2019) proposed a novel approach for the designing of network that can meet the surging demand for emergency evacuation. The paper constructs a bilevel programming model. Method proposed by him is an iterative optimization method with a dynamic penalty function algorithm [38].

III. PROBLEM DEFINITION

The Problem definition section well explained the definition of reliability in terms of communication network and the problem how a fault tolerant and reliable network can be designed so that cost is improved in terms of designing as well as reliability of network. Our algorithm is dealing with Genetic as well as optimized neural network approach to calculate exact reliability of varying size network. The main objective of this paper is to be design a network so network reliability and cost of the network is optimized. The approach can provide a specific algorithm for network reliability estimation and predict a failure by using genetic approach and ANN method. The network optimized design with a minimum cost can be expressed by the formula that sees reliability requirements is given below

Minimize $Z(X) = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} c_{ij}\, x_{ij}$ (9)

Where N= No. of node in a network
(i,j)= Link between two nodes
c_{ij}= Cost between two links(i,j)
x_{ij}= Decision variable, either 0 or 1.

Presumption:

— Nodes are always operational.
— Nodes of the network are fixed.
— If a link is repaired once in life time it cannot be reusable.

Link Reliability is defined by $r(i,j) = r$. It states that $(X) \geq R_0$. X_{ij} is the network topology. The main design decision is to maximize the reliability between source and destination vertex under permissible

maximum cost($Cost_{(max)}$) condition. Before designing following assumptions must be considered:
— Nodes can be stop functioning any time.
— Links can be move to non-operation mode any time.
— Degree of each node $\deg(i, j) \geq 2$.
— No Articulation point is to be considered.

IV. PROPOSED METHODOLOGY

In this paper we proposed a new methodology, based on an advanced Artificial Neural Network to estimate network reliability for varying size network. The proposed methodology is termed as Optimized Artificial Neural Network (OANN). In previous study ANN is although used for estimating the reliability of a network [3-5, 10, 13-16, 33, 39]. Our proposed solution overcomes the difficulty of previously defined approach of network reliability estimation like Minimal Cut and Path, Particle Swarm Optimization (PSO) and MCS (Monte Carlo Simulation). The proposed algorithm is well graphically explained in Figs. 5 and 6. We follow the many type of network [30].
– Serial Network.
– Parallel Network.
– Serial-Parallel Network
– Mesh Network
The proposed algorithm is able to handle any kind of network either serial or parallel. The method proposed in this paper use a special encoding technique for estimating the reliability. Fig. 4 shows a simple network of 7 nodes and 8 modules for such kind of simple and static network reliability calculation is quite easy and is calculated by the simple method like:

$R(s) = (-\mathrm{A} + \mathrm{B} + \mathrm{C} + \mathrm{D} - \mathrm{E} + \mathrm{F} - \mathrm{G})$

Where

$A = \mathrm{R_a} * \mathrm{R_b} * \mathrm{R_c} * \mathrm{R_e} * \mathrm{R_f} * \mathrm{R_g} * \mathrm{R_h}$

$\mathrm{B} = \mathrm{R_a} * \mathrm{R_b} * \mathrm{R_c} * \mathrm{R_d} * \mathrm{R_e} * \mathrm{R_f} * \mathrm{R_g} * \mathrm{R_h}$

$\mathrm{C} = \mathrm{R_a} * \mathrm{R_b} * \mathrm{R_d} * \mathrm{R_h}$

$\mathrm{D} = \mathrm{R_e} * \mathrm{R_f} * \mathrm{R_g} * \mathrm{R_h}$

$\mathrm{E} = \mathrm{R_a} * \mathrm{R_b} * \mathrm{R_d} * \mathrm{R_e} * \mathrm{R_f} * \mathrm{R_g} * \mathrm{R_h}$

$\mathrm{F} = \mathrm{R_a} * \mathrm{R_b} * \mathrm{R_c} * \mathrm{R_h}$

$\mathrm{G} = \mathrm{R_a} * \mathrm{R_b} * \mathrm{R_c} * \mathrm{R_d} * \mathrm{R_h}$

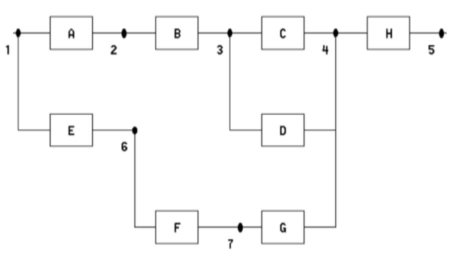


Fig. 4. Simple network with 7 nodes and 8 modules.

Assume the reliability of all the nodes are (0.851, 0.781, 0.831, 0.940, 0.851, 0.851, 0.851, 0.851)
$R(s) = 0.7372$
W. C. yeh proposed a method that can be used for calculating that predicted reliability [21]. $P\lfloor R_G^+ \rfloor$ is the predicted reliability and calculated by following equation

$$P\lfloor R_G^+ \rfloor = 1 * u(v_j) + 0 * w(v_j) = R(v) \quad (10)$$

The Eq. (11) is used for finding expected overall reliability of graph G (N, L, p) for given ***v*** links. The overall system reliability is obtained represented by $R_k^+(G)$ and obtained by the following formulate.

$$P\left[\sum_{j=1}^{k} \frac{R_k^+(G)}{k}\right] = \sum_{j=1}^{k} \frac{P\left[R_k^+(G)\right]}{k} \quad (11)$$

Equation 12 is obtained from equation 10 and 11 and is as follows.

$$P\left[\sum_{j=1}^{k} \frac{R_k^+(G)}{k}\right] = \sum_{j=1}^{k} \frac{R(v)}{k} = R(v) \quad (12)$$

The $R_k^+(G)$ must be balanced, asymptotically consistent estimator for $R(v)$ is calculated by using following formula given below:

$$A\_const\_Var\left[R_k^+(G)\right] = \sum_{j=1}^{T} \frac{R(v)[1 - R(v)]}{T} \quad (13)$$

For calculating exact reliability we require an algorithm that can be worked for static, as well as varying size network and that, can be meeting the optimal network design problem in optimal time. The main objective is to target for predicting reliability>=threshold (0.99) and fault-tolerant optimal design.
Prerequisite:
– *Consider a Transportation network if a network contains an articulation vertex then add a parallel link to make it Euler (every node should have even degree).*
– *Remove all the pendant nodes (deg(v_i)=1)*
– Let N be the set of working nodes except source node (S_n).
– Graph G = (V, E) with N nodes, where each link L_e is having its flow capacity c (e) > 0. Consider two nodes source and sink node (s ≠t).

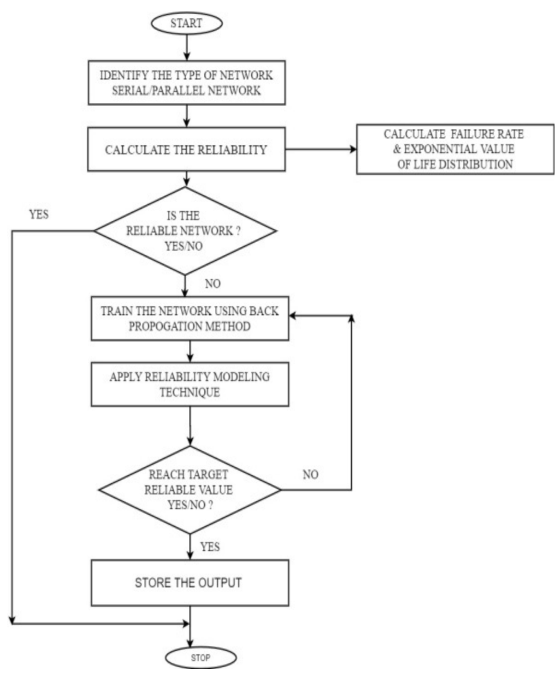


Fig. 5. Basic ANN approach for Reliability estimation.

The basic approach for Reliability estimation is well defined by a pictorial chart in Fig. 5 and extended OANN approach is well presented in Fig. 6 contains ten different stages.
Proposed approach is completed into four phases:

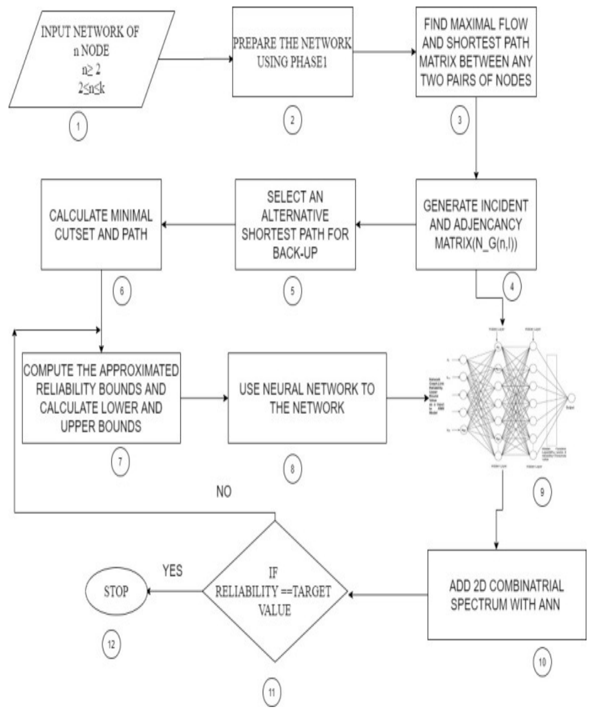


Fig. 6. OANN approach for Reliability estimation.

Phase 1(Network Identification Phase): This phase is completed into various steps.
— Check the network by mapping the first and second condition of perquisite. If the condition does not satisfy then make the network according to perquisite. .
— Partition the Links in the transportation network into k sets {K=0, 1, 2, 3} i.e. k=0 then no need to partitioned and quit from algorithm.
H = set of all links not incident to S_n
$I_{s,n}$ = set of all links incident to S_n and D_n.
$J_{s,!nt}$= set of all links incident to S_n and not to D_n.

Phase 2: Maximum flow
— Calculate maximum flow of the network.

$$F_{ij} \le C_{ij}$$

— Find all possible path between any two pair of nodes (there are no links in the common path but there exist a common node in the two paths).
General algorithm used for identifying path, flow and capacity are having no. of drawbacks like it is not suitable for dynamic size network or varying size network. When the network size is too large and varying size, then it becomes unproductive because lots of computations are need and recursively required.
The aforementioned problem can be solved by using a special kind of algorithms called Genetic algorithm. Genetic algorithm is a problem-solving method which is based on the perception of selection (natural selection technique) and genetics [11-12, 15, 18, 20, 22]. The concept of genetic algorithm for finding the shortest path in varying size network design is fast and accurate and its complexity is better than the above algorithms. Fitness function is follows:

$$Z(x) = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} 1 * c_{ij}x_{ij} + \delta(\mathrm{cMax}(\mathrm{R}(\mathrm{x}) - \mathrm{Ro}))2 \quad (14)$$

Algorithm for Shortest path is as follows
– Find the degree of each node and record associate links of each node. Example is shown in Table 2.
– Select the State Space or Search Space of Network
– Mark the fitness value of each possible solution.
– Identify the set of reproduction operators which are applied on Chromosome
– Select the two parents Chromosome from population.
– For the formation of two offspring, choose point to crossover between parents.
– Compute the fitness value of both new offspring .
– Compare the fitness of offspring & parent to identify the best fittest solution.
– If require replace the parent with offspring.
The overall complexity of above algorithm is O (V, E) time.

Table 2: Associated Link table of Fig. 5.

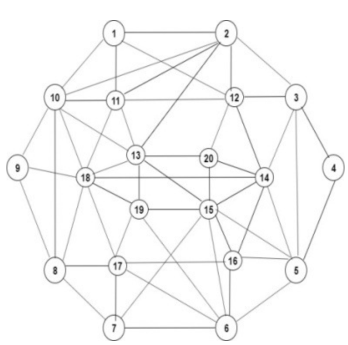
	Node No.	Degree of Node	Associated Links
 **Fig. 7.** Mesh Network.	1	4	2→10→11→12
	2	6	1→3→10→11→12→13
	3	5	2→4→5→12→14
	4	2	3→5
	5	6	3→4→6→14→15→16
	6	6	5→7→15→16→17→19
	7	4	6→8→15→17
	8	5	7→9→10→17→18
	9	3	8→10→18
	10	7	1→2→8→9→11→13→18
	11	6	1→2→10→12→13→18
	12	6	1→2→3→11→14→20
	13	7	2→10→11→15→18→19→20
	14	7	3→5→12→15→16→18→20
	15	8	5→6→7→13→14→16→19→20
	16	5	5→6→14→15→17
	17	6	6→7→8→16→18→19
	18	8	8→9→10→11→13→14→17→19
	19	5	6→13→15→17→18
	20	4	12→13→14→15
	Deg(G)	110	

Table 3 shows that ω value is too high or there is no direct link from that vertex. The value ω may be range from 2200 to 10000 and so on it is depending on the simulation we used.

Table 3: Associated Link matrix of Fig. 7.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	ω	L	ω	ω	ω	ω	ω	ω	ω	L	L	L	ω	ω	ω	ω	ω	ω	ω	ω
2	L	ω	L	ω	ω	ω	ω	ω	ω	L	L	L	L	ω	ω	ω	ω	ω	ω	ω
3	ω	L	ω	L	L	ω	ω	ω	ω	ω	ω	L	ω	L	ω	ω	ω	ω	ω	ω
4	ω	ω	L	ω	L	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω
5	ω	ω	L	L	ω	L	ω	ω	ω	ω	ω	ω	ω	L	L	L	ω	ω	ω	ω
6	ω	ω	ω	ω	L	ω	L	ω	ω	ω	ω	ω	ω	ω	L	L	L	ω	L	ω
7	ω	ω	ω	ω	ω	L	ω	L	ω	ω	ω	ω	ω	ω	L	ω	L	ω	ω	ω
8	ω	ω	ω	ω	ω	ω	L	ω	L	L	ω	ω	ω	ω	ω	ω	L	L	ω	ω
9	ω	ω	ω	ω	ω	ω	ω	L	ω	L	ω	ω	ω	ω	ω	ω	ω	L	ω	ω
10	L	L	ω	ω	ω	ω	ω	L	L	ω	L	ω	L	ω	ω	ω	ω	L	ω	ω
11	L	L	ω	ω	ω	ω	ω	ω	ω	L	ω	L	L	ω	ω	ω	ω	L	ω	ω
12	L	L	L	ω	ω	ω	ω	ω	ω	ω	L	ω	ω	L	ω	ω	ω	ω	ω	L
13	ω	L	ω	ω	ω	ω	ω	ω	ω	L	L	ω	ω	ω	L	ω	ω	L	L	L
14	ω	ω	L	ω	L	ω	ω	ω	ω	ω	ω	L	ω	ω	L	L	ω	L	ω	L
15	ω	ω	ω	ω	L	L	L	ω	ω	ω	ω	ω	L	L	ω	L	ω	ω	L	L
16	ω	ω	ω	ω	L	L	ω	ω	ω	ω	ω	ω	ω	L	L	ω	L	ω	ω	ω
17	ω	ω	ω	ω	ω	L	L	L	ω	ω	ω	ω	ω	ω	ω	L	ω	L	L	ω
18	ω	ω	ω	ω	ω	ω	ω	L	L	L	L	ω	L	L	ω	ω	L	ω	L	ω
19	ω	ω	ω	ω	ω	L	ω	ω	ω	ω	ω	ω	L	ω	L	ω	L	L	ω	ω
20	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	ω	L	L	L	L	ω	ω	ω	ω	ω

– Select shortest path from step no. 3 between any specified pair of nodes.
– Generate a Matrix [$S\_P_{i,j}$] from step no. 3 including Probability of failure of any link
– Generate Incident Matrix and Adjacency Matrix (I_M & A_M) for the Graph traced by prerequisite.
– Record any second shortest path between any specified pair of nodes and set as an alternate path or protection path using DBPP method [29].

Phase 3(Minimal Cut Set Phase): This phase contains 5 major steps. The proper communication in the networks depends on whether or not there is a communication path between n_s node and n_t node. Failures in the network is of three type
– Networks with node failures
– Networks with link failures
– Networks with both node and link failures

In our approach, we consider minimum cutset if there exist network with link failure, where each link is represented by an unordered pair of nodes. For a node pair n_i and n_j are said to be adjacent to each other if their exist a path between specified pair of vertices. Our main aim is to eliminate some links from the G such that after removing the links, there is no path from source to terminal node and cost of diminishing is equal to its capacity C (L_{link}).The number of minimal path for varying size network is 2^{M-N+2} and minimal cuts for the same is given as 2^{N-2} (Where N=nodes and M= links) [8]. Estimation of network reliability through cut set enumeration is by Max-Flow Min-Cut theorem [27, 32, 34].

— If flow of the network is less than the desired flow then traverse the complete network with the probability failure (Pf_i) of each link.
— Evaluate minimal cutset (MC_s) of the network when a link failure occurs in a network.
– Consider a graph N_G(V,E) from step 2 of phase 1.
– Pick a random edge (v_i, v_j) into a single vertex.
– Remove all self-loops.
– Return MC_s , W represented by two vertices.
— (MC_s ,$F_{i,j}$) ←E_ MC_s with respect to total traffic, I_M & A_M of Graph G with N nodes.
— Compare the result of step 3 with all minimal cutset and generate an matrix C_ MC_s(Compared Minimal Cut set) on the basis of minimal cutset with same capacity and varying capacity.
— Evaluate all cuts and subsets cut for required capacities.
— Remove all the redundant rows from the matrix C_ MC_s.

Phase 4 (Optimized Neural network method for maximizing reliability): MCS and PSO approaches require more effort and time to calculate reliability [21]. For estimating reliability of dynamic sized networks, we require a dynamic method which helps for providing optimal network design solution. The main aim of this is to design maximal reliable and fault-tolerant network topology. The inputs parameter of OANN algorithm models are as follows and algorithm is fully implemented in python 3.6 for reliability estimation.

Input:
— The network graph G(V,E) with N nodes achieved by after proper cutset which are indicated by the value of X_i and having a string on length n*(n-1)/2. (In the form of Matrix).
— The estimated upper and lower bound of network.
— Pre calculated bias value with weight function.
— Pre-Estimated reliability for comparing the results.
— The link reliability (0.81, 0.85, 0.95, 0.99, 0.99 or 0.99) (Same link Probability as stated in our previous paper [30])

Proposed Algorithm:
1. Assign random weight and learning rate to all the links to initiate the algorithm.
2. Using the input X_i and the ($X_i \rightarrow N_h$) linkages and assign X_i to N_h and record the A_R of N_h in the separate array.
3. By applying A_R of N_h and linkages to output. Each $H_r$sums its weighted input signals to calculate net input (where r = 1 to k, H_r-Hidden unit and N_h-Hidden Nodes)

$$H_{inr} = V_{or} + \sum_{i=1}^{n} X_i V_{ir} \quad (15)$$

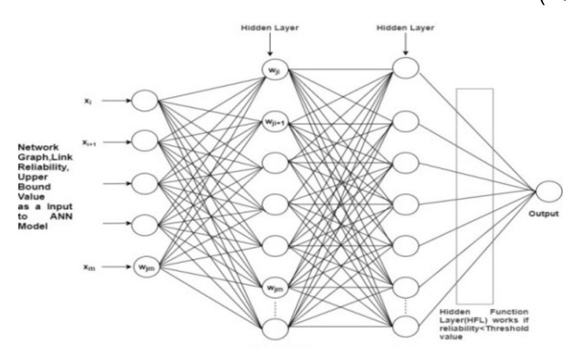


Fig. 8. Proposed Neural Network Model.

Find the A_R of output nodes. Compute output of the H_r by applying A_f_function.

$$H_r = f_a(H_{inr}) \tag{16}$$

and feed the output signal from the H_r to the output unit.

— For each O/P unit O_k, we compute the net input again by using the following formula:

$$O_{ins} = W_{os} + \sum_{r=1}^{k} H_r W_{rk} \tag{17}$$

where k=1 to m

— Apply the A_f_function to obtain the O/P(activation function is denoted by f_a)

$$O_s = f_a(Y_{ins})$$

— Find the *Err-rate* at the O/P node and readjust all the links within H_r and O_k. For each O_k receives pattern corresponding to input training pattern. These patterns help us for computing the error correction term Δ_k :

$$\Delta_k = (t_k - O_k) f'(O_{ink}) \tag{18}$$

Note: We can use δ in place of Δ but our assumption is that change will occur in dataset not in a value.

– Weight and bias modification is based on error value and if required then change the weight and bias. Change in weight $\Delta W_{rk} = \alpha \Delta_k Z_j$ change in bias $\Delta W_{ok} = \alpha \delta_k$ forward δ_k to hidden layer.

– Arrange the errors in cascade form using W_i(weights) and *Err*(error) and deliver to hidden node on ANN

– Each hidden unit H_r, sums its delta inputs from output

$$\delta_{inr} = \sum_{k=1}^{m} \delta_k W_{rk} \tag{19}$$

We can use δ in place of Δ because change in a value only.

– Update the weights values between hidden nodes and input nodes until the desired result will not received.

– Using the final linkage weights score the A_R of the output nodes.

The above algorithm is used for calculating errors by back propagating it to the n^{th} layer.

V. RESULTS

— Iteration 1 with a sigmoid value the weight are randomly initialized to the range (-1, 1) say x_1=1 and x_2=1.

— Hidden layer value calculation with a weight w is as follows

$$a_1^{(2)} = \sigma(w_{11}^{(2)} x_1 + w_{21}^{(2)} x_2) \tag{20}$$

Calculate all the values in the same fashion.

— Calculate the cost by the formula

$$\text{Cost} = \frac{1}{2}(y - a_1^2)^{2^2} \tag{21}$$

— Perform backpropagation stage on the result and test until the desired level is not achieved.

— Calculate the Error in output layer

$$\delta_1^{(3)} = (y - a_1^{(3)})^1 a_1^{(3)} (1 - a_1^{(3)})^1 \tag{22}$$

— Calculate the error in the hidden layer.

— Calculate the error with respect to weight between hidden and output layer (Layer 1).

— Calculate the error with respect to weight between hidden and output layer (Layer 2).

— Calculate the error with respect to weight between input layer and hidden layer.

— Update the weight between hidden and output layer (Layer 1).

— Update the weight between hidden and output layer (Layer 2).

— If Results are below expected threshold value Hidden function layer works automatically.

Complete algorithm steps are well implemented in python and comparison results of our approach is shown in various tables. We implement our algorithm in 6 tracks and it was effectively test on n=1 to 256 vertices graph. Fig. 10 shows the simulation screenshot of code (implemented in python). Table 4 shows the Minimal Path and Minimal Cut on n node network.

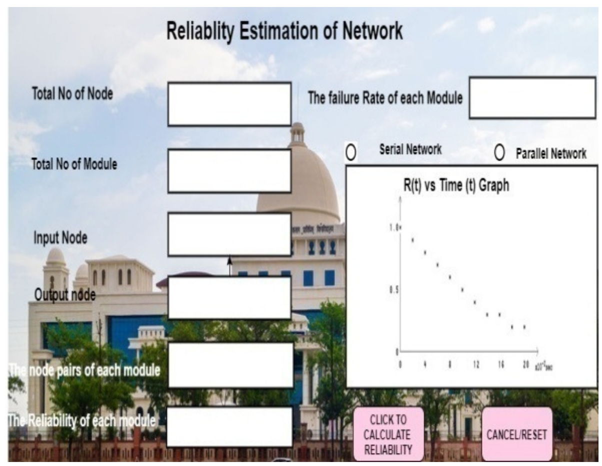


Fig. 9. Simulation Environment for Reliability Calculation.

Table 4: Number of MPs and MCs.

Simulation Track	#MP's	# MC's	Time(S)
1	7	12	00.85591
2	16	110	00.282727
3	110	79	313.17000
4	29	68	1129.0000
5	10	219	818.80000
6	28	28	0.708676

Here, we discuss some of the computational results for costs, reliabilities, and search effort required for topologies for identical and varying link reliabilities. Table 5 gives the results of actual reliability (A_R(x)) and estimation reliability (E_R(x)) for identical and varying links.

Table 5: Shows Actual Reliability and Estimation of Reliability.

S.No.	N	L	p	R_0	A_R(x)	E_R(x)
1.	5	10	0.8	0.9	0.916	0.9175
2.	5	10	0.9	0.95	0.9575	0.9561
3.	7	22	0.9	0.9	0.9031	0.9034
4.	7	22	0.9	0.95	0.9513	0.9516
5.	7	22	0.91	0.95	0.9578	0.9582
6.	8	28	0.9	0.9	0.9078	0.9125
7.	8	28	0.9	0.95	0.9614	0.9624
8.	9	36	0.9	0.95	0.9669	0.9670
9.	9	36	0.9	0.95	0.9567	0.9569
10.	9	36	0.9	0.95	0.9031	0.9034
11.	10	45	0.9	0.95	0.9513	0.9493
12.	10	45	0.9	0.95	0.9614	0.9614
13.	10	45	0.9	0.95	0.9078	0.9125
14.	15	105	0.9	0.94	0.9414	0.9414
15.	15	190	0.9	0.95	0.9578	0.9582
16.	25	300	0.9	0.95	0.9178	0.9325
17.	9	36	0.9	0.95	0.9514	0.9624

Errors in general neural network with identical link reliability is presented in Table 6.

Table 6: Errors estimation for neural network with identical link reliability.

Set No.	Training	Testing Set	ANN UB Value	OANN UB value
1	0.03196	0.06234	0.10064	0.01324
2	0.03567	0.04297	0.08268	0.01375
3	0.03246	0.06896	0.08422	0.00907
4	0.03296	0.06361	0.09910	0.01568
5	0.03315	0.06296	0.09422	0.09427
6	0.03325	0.06261	0.09912	0.09919

The simulation results of network under certain conditions of MCS and PSO algorithm is shown in Table 7.

Table 7: MCS-PSO table at $\mathrm{R(X)} = 0.9349$ and $\mathrm{R(X)} = 0.9748$.

	MCS-PSO(0.9349)		MCS-PSO (0.9748)	
Set No.	R_v	H_v	R_v	H_v
1	1199.6981	1171.5900	1208.9600	1176.885
2	1199.7862	1171.1900	1204.6500	1179.775
3	1207.6685	1170.9600	1201.2700	1181.085
4	1205.5602	1170.9500	1200.6800	1187.756
5	1215.7808	1171.7801	1214.6500	1189.665
6	1213.3404	1171.6502	1215.2500	1173.665

The simulation results of network under certain conditions of MCS- PSO algorithm Vs ANN algorithm is shown in Table 8.

Table 8: MCS-PSO table at $\mathrm{R(X)} = 0.9749$ and $\mathrm{ANN(R(X)} = 0.97)$

	MCS-PSO(0.9749)		ANN(0.97)	
Set No.	R_v	H_v	R_v	H_v
1	1202.3756	1177.8856	1217.1825	1209.1265
2	1202.7756	1180.7756	1216.9965	1209.1015
3	1206.7756	1181.0856	1218.4995	1208.5475
4	1204.5756	1188.5756	1217.6955	1208.7745
5	1203.5756	1189.8656	1221.0865	1208.1965
6	1204.6656	1193.6656	1220.4885	1208.7205

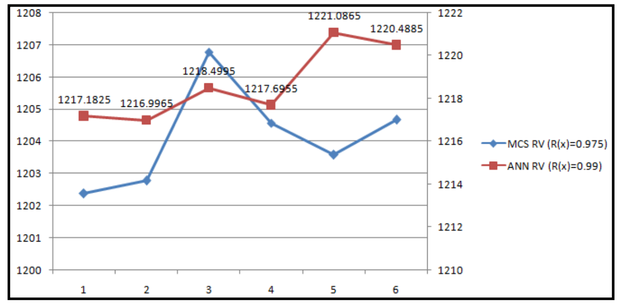


Fig. 10. MCS(R(x)=0.99) Vs OANN(R(x)=0.99).

Table 9: MCS-PSO table at *ANN* (*R*(*X*) = 0.99) and Proposed OANN.

	ANN(0.99)		OANN (R(X)=0.99)	
Set No.	R_v	H_v	R_v	H_v
1	1217.1825	1209.1265	1218.0001	1210.1230
2	1216.9965	1209.1015	1217.4950	1211.0248
3	1218.4995	1208.5475	1219.3420	1211.0250
4	1217.6955	1208.7745	1217.1940	1211.0250
5	1221.0865	1208.1965	1218.1210	1212.1240
6	1220.4885	1208.7205	1221.9951	1211.8970

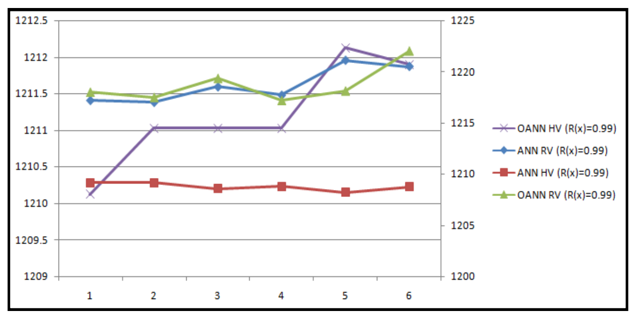


Fig. 11. ANN(R(x)=0.99) Vs OANN(R(x)=0.99).

Table 10: Difference between Estimated R(x) and Actual R(x) for six simulation tracks.

Simulation Track	R_0	Actual R(X)	Estimated R(X)	Difference In %
S1	0.91	0.9513	0.958	0.704%
S2	0.95	0.9538	0.9538	0.000%
S3	0.9	0.9032	0.9032	0.000%
S4	0.95	0.9611	0.9591	-0.208%
S5	0.95	0.9579	0.9605	0.261%
S6	0.90	0.90664	0.90694	0.033%

VI. RESULT SUMMARY

This paper provides novel reliability technique for the network of varying size. The proposed algorithm of is completed into various phases of estimating all shortest path, minimal cut set and reliability estimation. The Simulation is performed in Python 3.0 and in NS2. ANN technique is used for finding the overall system reliability. System reliability is calculated which is based on probabilities of failure of components and node. The first phase of the solution is used to remove various articulation vertex and insert node and edges wherever is required. It little bit increase the complexity of network. Second phase is based on genetic algorithm for finding various shortest paths between two specified pair of vertices. Third phase is used for MC in a graph and fourth and last important phase is OANN technique for exact estimating the reliability of given network. The main aim of this paper is to exact estimation of reliability of complex and varying size network. The comparison results analysis of various our algorithm and traditional algorithm is shown in Tables 6, 7 and 8.

VII. CONCLUSION

The main strength of the paper is how proposed algorithm overcomes the difficulties of existing algorithm. Algorithm proposed in this paper uses network reduction technique and advance algorithm for finding all shortest path and flow among the network. Proposed optimized ANN is used for exact estimation for reliability of computer network. The complexity of the proposed algorithm is far better than the existing algorithm and it speed up reliability estimation of varying size communication networks. The OANN approach and precise backtracking algorithm are used for network design using simulated hardening methods for optimization and can be predict that the OANN approach gives better design results at terrain conditions with manageable cost.

VIII. CURRENT AND FUTURE DEVELOPMENTS

With recent growth in technology and communication industry, maximizing overall reliability for an optimal design of networks is a challenging task. Main consideration of design is that overall fault of the networks and cost of design should be minimum is one the key issues. Many systems and models which requires reliability calculations for finding an optimal solution or solving decision problems has already stated and discussed thoroughly in the thesis. Such systems are as follows:

– Network reliability analysis
– Transportation network and vehicle reliability performance
– Oil and gas production systems
– Water Distribution systems
– Distributed system reliability
– Model selection with cross validation
– Modeling and analysis in correlated software system
– Uncertainty in reliability in software model
– Reliability modeling and performance of tree-structured grid system

Change in technology and networking are transforming the networking infrastructure into a highly heterogeneous large scale highly increasing growing and variable sized entity. Thus, presenting new challenges and captivating much interest in reliable and operational systems in such networking environment.

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