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Back Propagation Model for Estimating Communications Network Reliability

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ABSTRACT

This is the method for using neural network models to estimate the reliability of telecommunications networks with link reliabilities. Neural estimation is computationally speedy. The neural network is trained by back propagation algorithm. Two significant drawbacks of previous approaches to using neural networks to model system reliability are the long vector length of the inputs required to represent the network link architecture, and the specificity of the neural network model to a certain system size. This method overcomes both of these drawbacks with a compact, general set of inputs that adequately describe the likely network reliability. Here computationally demonstrate both the precision of the neural network estimate of reliability, and the ability of the neural network model to generalize to a variety of network sizes.

KEY WORDS: Propagation, reliability, communications.

1. INTRODUCTION

The design of communications networks, reliability has been defined in a number of ways. All terminal reliability is the probability that a set of operational edges provides communication paths between every pair of nodes. A communications network is typically modelled as a graph with N nodes, and Ledges; nodes represent sites (computers), and edges represent communication links. Each node, and each edge has an associated probability of failure, and the reliability of the network is the probability that the network is operational. The definition of reliability thus depends on which components are operational. The researchers have made the following assumptions:

i) Nodes are completely reliable; failure of links is the only cause of network failure.
ii) Link failure probabilities are independent.
iii) Link failures are equally probable. This assumption is often made because no detailed information about link failures is available, whereas information about the average failure is available

2. EXPERIMENTAL PROCEDURE

The identified compact, easily calculated measures of network connectivity and reliability as the candidate set of inputs: ND (of each node, 0 if the node is not present), minimum node degree of the network, median node degree of the network, maximum node degree of the network, link reliability (LR), number of links (NL), link connectivity (C), and a network reliability upper bound (UB). Five input configurations were studied.

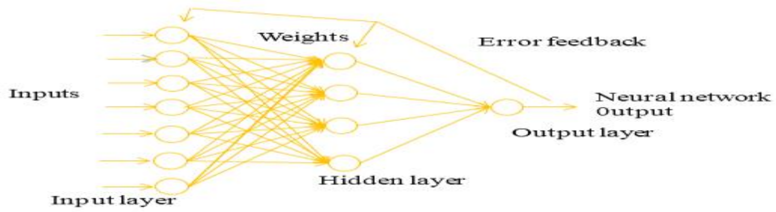

Fig.1.Structure of ANN

i) ND, LR, UB
ii) ND, NL, LR, UB
iii) ND, C, LR, UB
iv) ND, NL, C, LR, UB
v) ND min, ND med, ND max, NL, C, LR, UB.

We now show the method for a General ANN for design of networks from 10 to 20 nodes. Twenty input neurons are reserved for node degrees (to accommodate networks up to 20 nodes). For example, when data are sampled from a network with 10 nodes, node degrees are assigned to the first 10 input neurons, and the remaining 10 input neurons are set to zero. There are 22 input neurons for the first configuration, 23 for the second and third configurations, 24 for the fourth configuration, and 7 for the fifth configuration. While this topology representation uses up to 24 input neurons for a network with 20 nodes, the representation previously employed in the literature would use 190 input neurons just to represent the links for the same network. .The output of the ANN is the estimation of all-terminal network reliability (one real valued neuron). The target network reliability of each network is estimated using a Monte Carlo simulation method. This is one of the probability method.

2.1. Performance of the General ANN: We examined the performance of the General ANN for networks with node sizes from 10 to 20 not used in the training set (that is, other than 10, 15, and 20 nodes). The aim of this evaluation is to see how well our model can extend to network sizes unseen in training.

Table.1.RMSE and Mean Absolute Deviation (MAD) values for networks nodes between 10 and

Number of nodes	General ANN		Upper Bound	
	RMSE	MAD		RMSE
1	0.01844	0.01481	0.02870	0.01627
2	0.01663	0.01272	0.03216	0.01859
3	0.01485	0.01567	0.04432	0.03597
4	0.03007	0.02724	0.03635	0.03174
5	0.02294	0.02816	0.06473	0.09133

The test set had 100 randomly generated instances of each network size. Table.1 gives the RMSE, and MAD values for the General ANN, and the UB. We see no systematic error patterns in terms of network size. Therefore, it appears that the General ANN can be used to estimate all-terminal network reliability for any network size from 10 to 20 nodes with similar estimation error.

3. RESULTS AND DISCUSSION

Root mean square error and actual output for various iterations shown in the two various subplots. Here I used sample inputs to the ANN.The General ANN developed expressly for performed very well, better than both the UB, and the Specific ANN. In design optimization, one might use the General ANN for screening many designs to gauge the trade-off between system reliability and cost. An exact method or computationally laborious Monte Carlo simulation should be used on the final few candidate network designs to ascertain the precise system reliability.

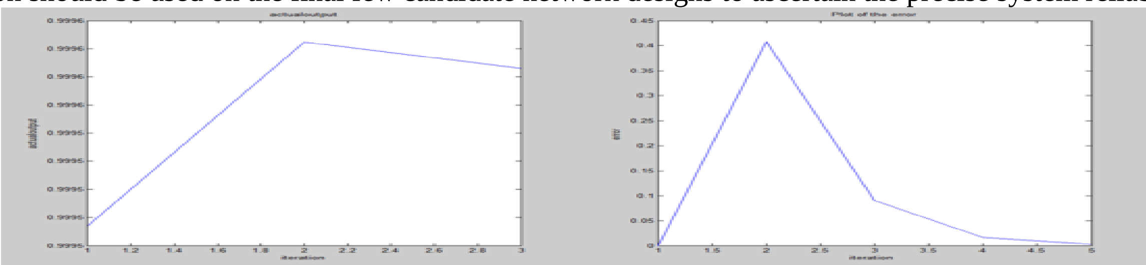

Fig.2.Simulation output

4. CONCLUSION

This is represented a novel method of communications networks for ANN that accommodates networks of varying node and link sizes. The inputs are compact and easily calculated. By using such an ANN that is manageable in size, and flexible for many network design problems, can be trained & validated. This contrasts with previous work in neural network estimation of network reliability where the encoding was lengthy, and the resulting ANN could only be used for a single node size network. Simulation results reveal that the good trained ANN. Thus The ANN is perfectly trained by the back propagation algorithm.

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