Intelligent Routing using Machine Learning

Navpreet Chana[1], Chandra Prakash[2]
[1]Research Scholar, Department of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab, India
[2] Asst. Prof, Department of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjan, India,
[1]chana.navpreet@gmail.com, [2]chandra.14666@lpu.co.in

Abstract- **In this paper, a hybrid approach for intelligent routing using machine learning is being addressed. With the growing demand for networking in more and more computer applications, there arises the need for efficient and quality of service-based (QoS-based) transmission of data from one system to another, in the network. To achieve the above mentioned goal, intelligent routing algorithm has to be devised which can determine the best route through the network. For determining the best route, the intelligent algorithm must obtain information regarding the devices present in the network and the links to reach other nodes. The collected information is of imprecise in nature, hence requiring some mechanism of converting the imprecise information into the crisp values, which can further be used to determine the best route for the data transmission. The imprecise nature suggests the use of fuzzy reasoning, which is being used in combination with neural networks to make the networking adaptable.**

Keywords- **Intelligent routing, adaptive routing, neuro-fuzzy, OSPF.**

I. INTRODUCTION

With the automation of vast number of applications in various domains like business, education, research, e-commerce and many more, computer networks are becoming the need of the hour. However, internet's huge popularity since last decade is making ever-increasing demand for good communication network services to meet the current requirements of the users, placing packet routing as an important matter in the field of computer networks. This is largely due to the fact that the original infrastructure was developed for a limited set of services with static traffic behavior. The current as well as future network traffic will be more dynamic in nature and hence will face numerous challenges. At the same time, it must be ensured that the infrastructure networks are able to cope with these changes by means of efficient delivery of services through the core networks. In the classical solutions for routing such as Bellman-Ford algorithm and Dijkstra's algorithm, the main focus is to route the packet via the shortest path, without considering factor like traffic control and load balancing. Routing is a process of transferring packets from source node to the destination node. In order to make judicious choice for the route selection, it is imperative that there is some information about the network state, eg. Congestion, node or link failure, traffic load. Therefore, for designing any routing approach, two key questions are needed to be addressed: 1) how to obtain knowledge about network state and 2) given the knowledge, how to select an optimal path for routing the packet? The work presented through this paper suggests approach for transition from the static form of routing to the adaptive routing, incorporating fuzzy reasoning to deal with the imprecise data and neural network to find the optimal link to the next node as it provides the ability to learn and adapt in dynamic situations, making the network adaptable/dynamic. When the network load shifts from its original state, the current network routing methods begin to lose their effectiveness. The solution to the problem is the presented approach which accesses the network state and based upon which, it continues to use open shortest path first protocol when the network state is stable and hybrid approach when the state become unstable. Fuzzy systems are suitable for uncertain or approximate reasoning, especially for the system with a mathematical model that is difficult to derive. Fuzzy logic allows decision making with estimated values under incomplete or uncertain information. The most important advantage of neural network is its adaptability. Neural networks can automatically adjust its weights to optimize their behavior as decision makers, system controllers, predictors, etc. Adaptability allows the neural network to perform well even when the environment or the system being controlled varies over time.

II. METHODOLOGY

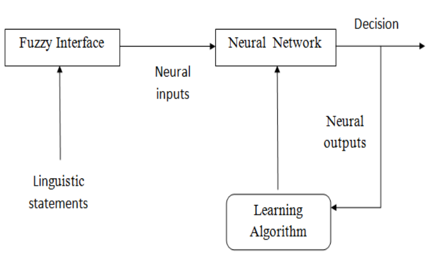

Fig. 1 Neuro-Fuzzy System

Every intelligent technique has particular computational properties (e.g. ability to learn) that make them suitable for particular problems and not for others. For example, neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions while fuzzy reasoning systems can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions. These limitations have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques. Since, in general, knowledge acquisition is difficult and also the universe of discourse of each input variable needs to be divided into several intervals, applications of fuzzy systems are restricted to the fields where expert knowledge is available and to the smaller number of input variables. To overcome the problem of knowledge acquisition, neural networks are extended to automatically extract fuzzy rules from numerical data. The approach starts with the development of a ”fuzzy neuron” which is the processing element of the hybrid network, followed by learning mechanisms, leading to the following steps

- Development of fuzzy neural model.
- Modeling of synaptic connections which incorporate fuzziness into neural network.
- Development of learning algorithm.

In response to the linguistic statements, fuzzy interface block provides an input vector to a multi-layer neural network which can be trained to yield desired outputs or decisions. All the inputs, outputs and weights are real numbers ranging between [0,1].

A. Steps in Fuzzy Inference System

The steps involved in the fuzzy inference system design are as follows:

Step 1: Fuzzy Inputs

This step obtains inputs and normalize them in the range of 0, 1 and then determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.

Step 2: Apply Fuzzy Operator

This step determines the degree to which the input satisfies for each rule. If the input of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result for that rule. This number will then be applied to the output function. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The method used may be either AND or OR operation, and the output is a single value.

Step 3: Apply Implication Method

Before applying implication proper weights are assigned to each rule. The input for the implication process is a single number and the output is a fuzzy set.

Step 4: Aggregate All Outputs

Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Aggregation occurs once for each output value and this happens before defuzzification. The output of the aggregation process is one fuzzy set for each output variable.

Step 5: Defuzzify

The input for the defuzzification process is a fuzzy set and the output
is a single number.

B. Fuzzy Inference System

The FIS used is a mamdani type system with two inputs and one output. The system inputs are route (or link) delay and route utilization. Both inputs are characterized by the fuzzy membership functions as shown in Figures 2 and 3. The membership functions for the fuzzy sets of inputs are chosen to be triangular. Both input variables (route delay and utilization) have five membership functions, which are entitled VL, L, M, H, and VH, which stand for very low, low, medium, high, and very high respectively.

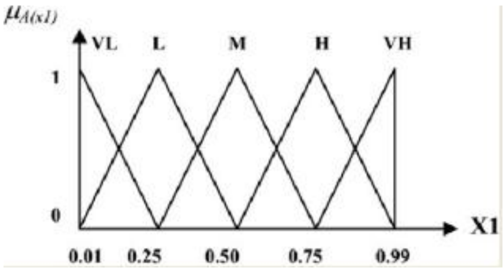

Fig. 2 Membership functions for route delay (X1)

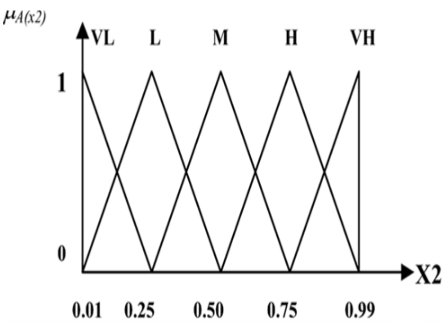

Fig. 3 Membership functions for route utilization (X2)

In total, there are 25 rules have been defined for this system. For example, if delay is VL and route utilization is VL, and then congestion is LL. After the aggregation process, there is fuzzy set for output variable. The outputs LL, LM, LH, ML, MM, MH, HL, HM and HH indicate low low, low medium, low high, medium low, medium medium, medium high, high low, high medium and high respectively. All the membership for the fuzzy sets are chosed to be triangular for its easy of computation.

Table I
Fuzzy Rules (Determining Congestion Rate)

Route Delay (ms)	Utilization				
	VL	**L**	**M**	**H**	**VH**
VL	LL	LM	LH	ML	MM
L	LM	LH	ML	MM	MH
M	LH	ML	MM	MH	HL
H	ML	MM	MH	HL	HM
VH	MM	MH	HL	HM	HH

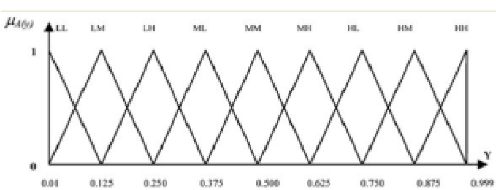

Fig. 4 Membership functions for output Y

The total delay from the current node *n* to the destination node *d* via some neighboring node *j* , is given by

$$D^{n}_{j,d} = \sum_{i=1}^{s} delay_i$$

where s is the total number of links in the route traversed by a packet. The utilization of each buffer on the route is calculated as

$$u_i = q_i / Q$$

$$B = \sum_{i=1}^{s} u_i$$

Each node has an incoming packet buffer with maximum capacity Q. The sum of these utilization measures is used to get a weighted measure λ for each buffer i. Finally, the estimated path utilization U from the current node n to the destination node d, via some neighboring node j, is calculated by multiplying the number of packets in each buffer by its corresponding weight factor λ, given by equation 6.

$$U^{n}_{j,d} = \sum_{i=1}^{s} \lambda_{ui} u_i$$

Using D and U, path congestion is calculated

$$P^{n}_{j,d} = \frac{\sum_{i=1}^{M} Y(\mu_{A_{i1}} \cdot \mu_{A_{i2}})}{\sum_{i=1}^{M} (\mu_{A_{i1}} \cdot \mu_{A_{i2}})}$$

where i is the node from which the packet is coming, j is the destination node, M is the number of fuzzy rules used, Y is the mean value of each membership function in fuzzy set μ_{a1} is the amount of membership function for delay and μ_{a2} is the amount of membership functions for path utilization.
This information is used to train the multilayer neural network.

III. RESULTS AND DISCUSSION

The new approach has been designed to outperform the OSPF, by considering number of additional parameters - link utilization, failure, delay and congestion. The results show, that the proposed approach when implemented, performs better in case of congestion, node/link failure resulting in higher throughput and reduced delay.

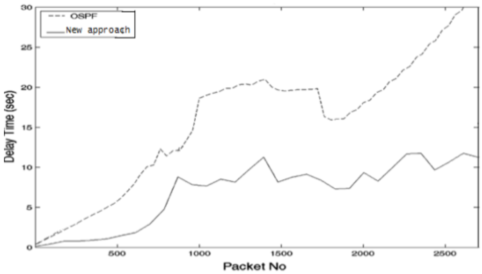

Fig. 5 End-to-end delay (in case of link failure)

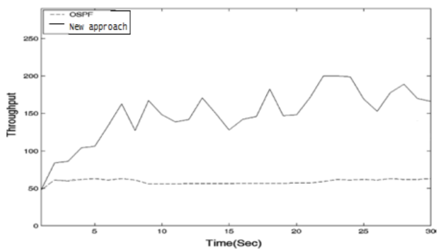

Fig. 6 Throughput

Table 2
Experimental results obtained from 25 simulations, competing the two algorithms

Standard Criteria	**Routing Algorithm**	
	New Approach	OSPF
Avg. end-to-end delay (ms)	*15.3*	32.20
Avg. throughput (packet/sec)	250	82
Overhead (%)	8	8

REFERENCES

[1] M. Baglietto, G.Battistelli, R. Bolla, R. Bruschi, F. Davoli, R. Zoppoli, "A neural network solution of QoS-IP team-optimal dynamic routing", 44'th IEEE Conference and the European Control Conference Dec 2005.

[2] Julia K.Brande, "Computer network routing with a fuzzy neural network", Virginia Polytechnic Institute and State University, Nov 1997.

[3] Md. Abdur Rahman, Reza GhasemAghaei, Abdulmotaleb El Saddik, Wail Gueaieb, "M-IAR: Biologically inspired routing protocol for wireless multimedia sensor networks", IEEE 2008.

[4] S.S.Iyengar, Hsiao-Chun W, N. Balakrishana, Shih Yu chang, "Biologically inspired cooperative routing for wireless mobile sensor networks", IEEE Systems Journals, vol. 1, Sep 2007.

[5] Rakesh Kumar, Mahesh Kumar, "Reliable and efficient routing using adaptive genetic algorithms in packet switched networks", IJCSI vol.9, issue 1, Jan 2012.

[6] M. Baglietto, G.Battistelli, R. Bolla, R. Bruschi, F. Davoli, R. Zoppoli, "A neural network solution of QoS-IP team-optimal dynamic routing", 44'th IEEE Conference and the European Control Conference Dec 2005.

[7] C.Casetti, R. Lo Cigno, M. Mellia, M. Munafo, Z. Zsoka, "A new class of Qos routing strategies based on network graph reduction", Elsevier Science B.V. 2002.

[8] Behzad Mahjour Shafiei, mohammad Amin Saeed, Farshid Iranmanesh, Fariborz Iranmanesh, "Computer network routing with fuzzy neural network", Advances in Environmental Biology 2012.

[9] Runtong Zhang and Jian Ma, "Fuzzy QoS management in diff-serv networks-systems, man and cybernetics," IEEE International Conference 2000, vol. 5, p. 3752-757.

[10] A.Vasilakos, C.Ricudis, K.Anagnostakis, W.Pedrycz, "Evolutionary fuzzy prediction for strategic Qos routing in broadband networks", IEEE 1998.

[11] Alandjani, G.; Johnson, E.E., “Fuzzy routing in ad hoc networks” Performance, Computing, and Communications Conference, 2003, 9-11 April 2003, Pages 525 – 530.