Heuristic algorithm for optimal LSP set up policy in MPLS Networks.

J.Jeļinskis [1]

[1]Riga Technical University, Faculty of Electronics and Telecommunications

Riga, Āzenes str. 12, E-Mail: jans.jelinskis@etf.rtu.lv

Abstract - In present time there is very active research in the field of multiprotocol label switching (MPLS), and lots of networks are supporting MPLS.

In this paper, we verify a possibility of a heuristic LSP setup policy algorithm, which uses optimization procedure based on multi-objective model with Pareto ranking and Genetic Algorithm. Adaptation to variable and bursty traffic is achieved by using Neural Network learning capabilities, and decision making under uncertainty is made up with Fuzzy Logical approach.

This algorithm functions in two phases – learning and operating, which are accomplished consecutive.

In this paper algorithm is described and depicted. Experimental data are depicted and future research subjects are pointed.

Keywords: traffic engineering; MPL; LSP establishment

I. INTRODUCTION.

In present days research in the field of multiprotocol label switching (MPLS) is very active, and as a result lots of networks support MPLS and number of such networks is growing all the time. MPLS is a switching technology to forward packets based on a short, fixed length identifier called label. MPLS uses indexing instead of long address matching, and achieves fast forwarding. MPLS network consists of label switched paths (LSPs) and edge/core label switched routers (LSRs). LSPs are virtual unidirectional paths established from the sender to the receiver [5]. One of the most notable applications of MPLS is traffic engineering (TE) [6], since LSPs can be considered as virtual traffic trunks that carry flow aggregates generated by packet classification.

Network design methods, which use off-line approach – that is - hypothetical knowledge of traffic demand, are not suitable for MPLS networks [8] because of the high unpredictability of the internet traffic. A fully connected MPLS network, where direct LSPs link every pair of LSRs, is very inefficient [7] because of very high signaling cost and the management of a huge number of LSPs. The signaling cost if of the order of N^2, where N is the total number of routers in network.

There are two different approaches for MPLS network design - traffic driven and topology-driven. In the traffic driven approach, the LSP is established on demand according to a request for a flow, traffic trunk or bandwidth reservation. The LSP is released when the request becomes inactive. In the topology driven approach, the LSP is established in advance according to the routing protocol information. The LSP is maintained as long as the corresponding routing entry exists, and it is released when the routing entry is deleted. The advantage of the traffic - driven approach is that only the required LSPs are setup, while in the topology-driven approach, the LSPs are established in advance, even if no data flow occurs.

LSP setup policies that are based on traffic driven approach, in which an LSP is established whenever the number of bytes forwarded within specified time boundaries exceeds a threshold, are simple, but not suitable because of very high signaling costs and high control efforts for variable and bursty traffic [1]. There is need of new traffic-driven approaches that are usable with variable and bursty traffic requests, because internet traffic has been found to exhibit significant amounts of self similarity and long range dependence [3, 9] do to an extremely high variability of duration of burst.

In present paper, we verify a possibility of a new LSP setup policy algorithm, which uses optimization procedure based on multi-objective model with Pareto ranking and Genetic Algorithm. Adaptation to variable and bursty traffic is achieved by using Neural Network (NN) learning capabilities, and decision making under uncertainty is made up with Fuzzy Logical (FL) approach.

II. LSP SETUP PROBLEM.

When a bandwidth request arrives between two nodes in a network that are not connected by a direct LSP, the decision about to establish such a LSP arises.

Decision of establishing LSP is based on lots of arguments, who can be presented as vector (1):

$$D_a = (a_1, a_2, a_3 \ldots . a_i); \quad (1)$$

There is no one strict state of argument vector D_a, which for certain define objective of setting up LSP. In this case large number of objectives is suitable [2], and to find them, an Evolutionary Multiobjective Search is proposed with Genetic Algorithm.

Multiobjective optimization problem can be expressed as:

$$\text{“minimize”}\ f(x)=(f1(x), \ldots, fk(x)) \\ \text{subject to } x \in X \quad (2)$$

where x represents a solution, and X is a finite set of feasible solutions. We can`t use term “minimize” just so, because in general, there does not exist a single solution, that is minimal to all objectives. That means, we can try to find a set of solutions $X^* \subseteq X$, called the Pareto optimal set, with the property that:

$$\forall x^* \in X^* \ \nexists\, x \in X \text{ such that } x \succ x^* \quad (3)$$

$$\text{where } x \succ x^* \text{ iff } \forall i \in \{1, ..., k\}$$
$$f(x_i) \le f(x_i^*) \;\wedge\; \exists i \in \{1, ..., k\} : f(x_i) < f(x_i^*)$$,

where $x \succ x^*$ is read as x dominates x*, and solutions in the Pareto optimal set are also known as admissible solutions [4].

GA with following pseudocode was used:

a) Choose initial population randomly ;
b) Evaluate the fitness function of each individual in the given population;
c) Do {

- Select best-ranking individuals to reproduce;
- Breed new generation through crossover and mutation (genetic operations) - make offspring;
- Evaluate the individual fitness of the new offspring;
- Replace worst ranked part of given population with offspring;

Until <terminating condition>}

To model a chromosome only two arguments were used - utilization and losses, as functions of available bandwidth and requested traffic.

In this research for traffic generation Glen Kramer self similar traffic generator [11] was used. In this generator, the resulting self-similar traffic is obtained by aggregating multiple sub-streams, each consisting of alternating Pareto-distributed on/off periods.

The load generated by one sub-stream is measured as *λ=E[on]/(E[on]+E[off])*, where *E[on]* and *E[off]* are expected lengths of on and off periods respectively [11]. The total load generated by the traffic generator is equal the sum of loads generated by all sub-streams.

As a result Pareto front of admissible states of network parameters was found, which are shown in Fig. 1:

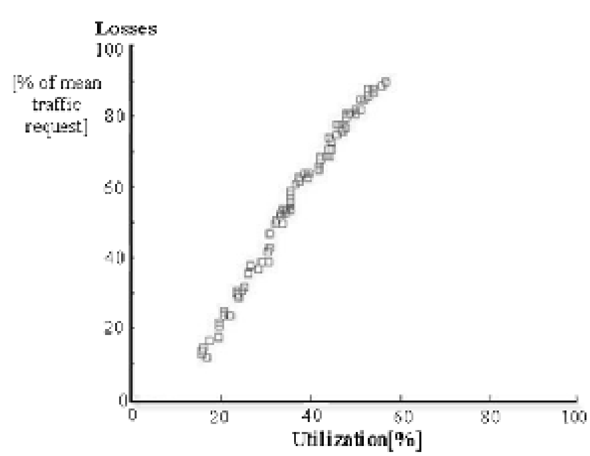

Fig. 1. Pareto front of admissible network states.

III. PROBLEM OF DECISION PROCESS.

Most frequently the decision process is modeled with Markovian Model (MDP) [10]. The most problematic condition for MDP is calculation of the state transition probabilities, which depends only on the current state. In dynamically changed demand environment with long range dependencies the reducing of decision making process to Markovian is very complicated task.

In this paper Neural Network learning capabilities and Fuzzy Logic ability to make decisions under uncertainty are used.

The Neural Network was designed with subsequent parameters, which are shown in Table 1.

TABLE 1
PARAMETERS OF DESIGNED NEURAL NETWORK

Item	Value/Type
Type of Neural Network	RBF Multilayer
Number of input neurons	2
Number of hidden neurons	8
Number of output neurons	6
Learning algorithm	Kohonen

As input parameters of Neural Network were used values from obtained Pareto front. Output values for data set were calculated as membership function values for Fuzzy Logic system.

Neural networks are prone to "overlearning" - they tend to learn so much about a database, including the random error and noise, that when you present a new set of data with different random error characteristics, the network has trouble providing accurate predictions.

There is a problem – we have not to allow neural network to overlearn, because of danger of corrupting accurate predicting results.

Data base of fuzzy rules is generated depending on earlier obtained Pareto front of suitable states of network parameters.

Each fuzzy set is described by a symmetric Gaussian membership function (4).

$$f(x_i) = e^{\frac{-|x_i - m|}{s^2}} \quad (4)$$

When trained neural network receive actual state of network parameters, it generates values of membership functions for Fuzzy Logic system, which considering fuzzy rules from generated database, after defuzzification, convert Neural Network given values into strict decision about LSP control actions.

IV. LEARNING AND OPERATING PHASES.

LSP setup control algorithm, which is presented in this paper provide following learning and operating manner.

Activities are divided into learning phase and operating phases. Initially only learning phase is active, but after operating phase activation, both, learning and activating phases are present.

1) Learning phase.

During this phase statistical data are collected persistently; based on them, with Genetic Algorithm means the Pareto admissible solutions are found. Data file with Pareto solutions and correspondent membership function values is generated. Neural Network training is performed.

2) Operating phase.

Operating phase is performed together with learning phase, which in this case is performed in background, to provide data for Neural Network regular training. In operating phase, network parameters and traffic request are obtained directly from network, and Neural Network learning capabilities allow generating admissible membership function values for Fuzzy Logic operating block. Fuzzy Logic as output gives us strict decisions, made under uncertainty, which allows system to act with network states, which are more or less close to admissible ones.

Learning and operating phase lengths or ratio of these two phases was not subject of this research, and this issue is supposed to be objective of future research.

In sum, algorithm proposed in this paper can be depictured as follows in Fig. 3:

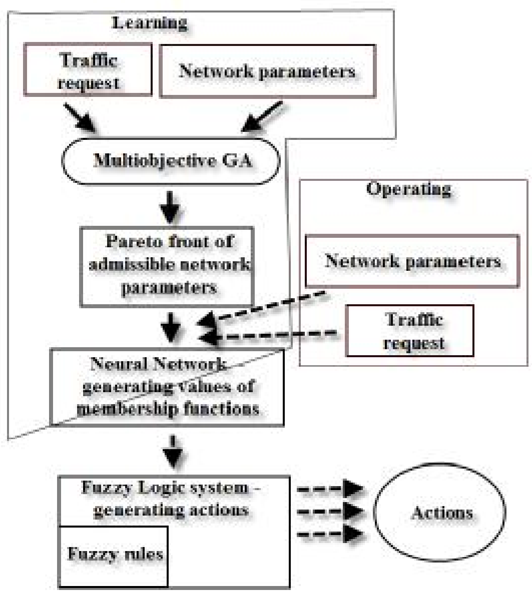

Fig. 3. LSP setup optimal control algorithm.

V. ADAPTATION TO CHANGE OF SELF-SIMILAR TRAFFIC AMPLITUDE.

During amplitude of self similar traffic changes of in the course of time, boundaries of data which are sent to Neural Network changes too. If operating data are out of boundaries of NN training data, increase of NN operation error is expected.

Adaptation time is dependent on lengths and ratio of learning and operating phases. It is vitally important, that final decision making error is not exceeding certain determined threshold.

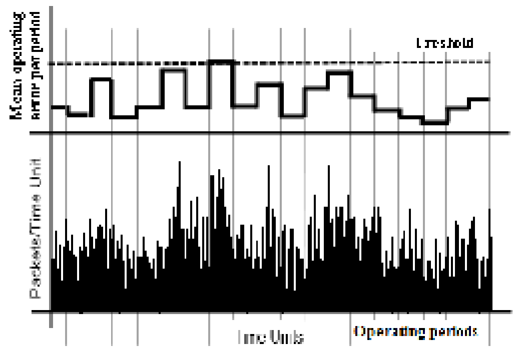

Fig. 4. Mean operating error per operating period, depending on self-similar traffic amplitude variation.

To validate the correctness of proposed approach simulation of algorithm was made. Neural Network was trained with different data sets, and then data sets with exceeding boundaries (obtained from self-similar network traffic simulator) were given to NN to operate with. Operating error was traced as deviation from permissible space from admissible solution of Pareto front, which was found with previous learning data.

Nearest exploration of adaptation to change of self-similar traffic amplitude is considered to be subject of future research.

VI. CONCLUSION AND FUTURE RESEARCH.

In this paper we present possible LSP setup optimal control algorithm, which uses optimization procedure based on multi-objective model with Pareto ranking and Genetic Algorithm. With Neural Network learning capabilities and Fuzzy Logic potential, algorithm allows operating with bursty traffic and gives a possibility to make a decision under uncertainty.

For Neural Network we should acquire more training cases, which may lead to improved performance and make the results more reliable. But on the other hand, acquiring large number of cases leads to bigger computing time and requires longer periods between learning and operating phases.

Non-optimal learning data set selection can increase NN operating error.

A self-similar traffic change in length of time is also mentioned as possible reason of increase of NN operating error, but no considerable research is made in this field.

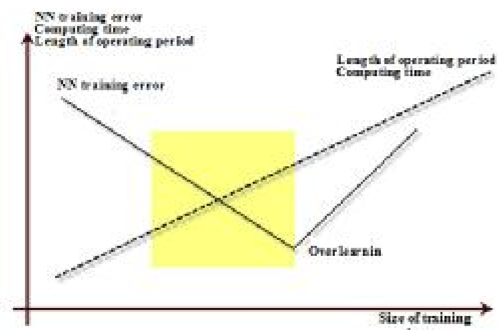

Fig. 5. Computing time, Length of operating period and Neural Network training error depending on size of Neural Network training data set.

The objective of future research is search for optimal training data set for Neural Network, and optimal ratio between learning and operating phases as well as active time of both phases, depending on amplitude changes of Self-similar traffic in time scale, with intention to optimize these parameters for effective operating of proposed algorithm.

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