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Multi-objective Optimization of Bandwidth Broker with Evolutionary Algorithm

G. Lauks
Faculty of Electronics and Telecommunications, Riga Technical University,
Azene str. 12, Riga, Latvia, LV10-48, E-mail: lauks@rsf.rtu.lv

Introduction

The bandwidth allocation and reconfiguration of topology in optical transport networks (OTN) with DWDM and lambda switching is a process of rearranging a virtual topology to meet traffic demands that change over a period of time. The bandwidth on demand (BoD) concept stands urgent in liberalized market, when provision of Network layer services will be a separate undertaking.

Good overviews of the robust bandwidth allocation strategies and decision making under uncertainty are given in [1]. The optimization of network topology using genetic algorithm (GA) can be found in [2], [4] and others. In [6] are studied the reconfiguration procedures of Network as a markovian decision procedure (MDP).

An overview of evolutionary algorithms for multi-objective optimization is presented in [7]. The impact of self-similar traffic and reducing packet loss using neural networks in self-similar teletraffic patterns are studied in [5]. Modelling and multi-objective optimization of MPLS Networks including evolutionary approach are presented in [8].

The objective of this paper is to study the efficiency of bandwidth utilization procedures using Bandwidth Broker (BB). The following models are used: evolutionary decision making process, self-similar traffic, decision making under uncertainty, traffic forecasting with learning using neural networks (NN), optimization procedure based on multi-objective model with Pareto ranking and GA. The measure of effective bandwidth allocation is based on the well known concept of Pareto optimality from cooperative games theory. Altogether it should be consider as an attempt of modelling the system adaptation paradigm as a realization of evolutionary process with learning.

Problem statement

The notations used in the problem statement are: $T := \{t_1, t_2, ..., t_n, ...\}$ - set of decision making epochs; $N := \{N_i, i \in I\}$ - set of Network nodes; $L := \{L_{ij}, i, j \in I\}$ -set of links between the network nodes; $PATH := \{path_k, k \in K\}$ -set of predetermined paths, connecting source and destination nodes; $G = G(N, L, W)$ - graph, represented the Network model, where W – set of appropriate matrices of weights; $W := \{B, INCOME, COST\}$, where

- $B := \{b_{ij}, i, j \in I\}$ - matrix of bandwidth;
- $INCOME := \{income_k, k \in K\}$ - matrix of revenue;
- $COST := \{\cos t_{ij}, i, j \in I\}$ - matrix of costs;

$R := \{R_m^k, m \in M_k\}$ -set of possible routes for each path; $ACTION := \{action_n^r, r \in BBA\}$ -set of BB actions at t_n, where BBA – set of possible BB actions.

The following input parameters are assumed:

- N - set of nodes;
- B- set of available bandwidth on physical layer;
- PATH - set of paths as set of source-destination node pairs (S,D)
- BA –set of available bandwidth;
- Traffic_In -set of input traffic for each path.

As variables of model are:

- $R := \{R_m^k, m \in M_k\}$ -set of routes for each path;
- B -matrices of bandwidth;
- BBA - set of BB Actions.

The objective of the bandwidth allocation problem is to find the set of the Pareto optimal solutions, and from this set to select the optimum solution as a decision at t_n. Generally the bandwidth allocation as a multi-objective optimization problem can be written as:

$$\text{Min/max } f_m(X), m = 1,2,...,M \quad (1)$$

Subject to constraint

$$g_k(X) \le c_k, k = 1,2,...,K, \quad (2)$$

where $X = (x_1, x_2, ..., x_N)$ is an N- tipple vector of variables; $F = (f_1, f_2, ..., f_M)$ is an M-tipple vector of objectives.

For modelling and testing purposes there are assumed only two objective functions:

1. to maximize profit of undertaking;
2. to minimize traffic losses.

The following constraints are assumed:

1. HN - hop number or number of nodes per route (for modelling example $HN \le 3$),
2. For each link,

$$\sum_{i \in PATH} b_{link} \le B_{PHY} . \quad (3)$$

Traffic model

A superposition of many ON/OFF sources with heavy-tailed ON or OF durations has been suggested as traffic model that captures the long-range dependence effects of network traffic [5].

For self-similar traffic modelling G. Kramer self-similar traffic generator [3] is used, which generates self-similar traffic by aggregating multiple sources of Pareto-distributed ON/OFF periods. Input variables of traffic generator are: number of traffic sources, path rate in Mbps and mean value of load per path as utilization measure. Modelling of trends in traffic can be simulated by variation of input parameters.

To provide expected quality of services under dynamically changed demand BB needs to predict its future traffic volume. There are two types of solution of prediction problems: long term prediction (e.g. , in months or years) are useful for capacity planning, while short term prediction (e.g., seconds or minutes) are useful for overload prevention. In this paper an identification of traffic pattern and losses is based on regression techniques using NN. The data series of traffic observations within the given epoch takes the form of sets of pairs:

$$\{(\mathbf{x}^1, y^1), \ldots, (\mathbf{x}^N, y^N)\},$$

where $\mathbf{x} = (x_1^i, \ldots, x_n^i, b)$ - measure of input traffic with path bandwidth b; y- traffic loss with path bandwidth b.

The regression was modelled with NN. The training results are illustrated in Table 1.

Table 1. NN Training results (example)

Type	Error	Inputs	Hidden	Performance
Linear	19.11657	1	0	0.3223036
MLP	19.1107	1	1	0.2263361
MLP	19.10906	1	4	0.340517
Linear	19.10088	2	0	0.3216298
MLP	19.09996	1	1	0.2158548
MLP	19.09545	1	1	0.2310665
RBF	8.97502	1	1	0.1008614
RBF	8.973999	1	2	0.07066
RBF	8.94445	1	4	0.0251595
RBF	8.94445	1	8	0.005445

For training and testing the windowing method was used. Regression statistics for last network in Table 1 are illustrated in Table 2.

A statistics of losses was collected as follows[see Fig.1]:

$$y^{(n)} = \begin{cases} \sum_{k=1}^{N} (x_k - b_i)\tau_k , & \text{if } (x_k > b_i) , \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

where τ_k - time interval of k – input.

Table 2. Regression statistics

Statistics	Training	Verification
Data Mean	0.5465	0.5511
Data S.D.	3.937149	3.31554
Error Mean	-2.25E-11	-0.01508
Error S.D.	0.0214374	0.022145
Abs E. Mean	0.01099	0.01508
S.D. Ratio	0.005445	0.0042
Correlation	0.9999852	0.99

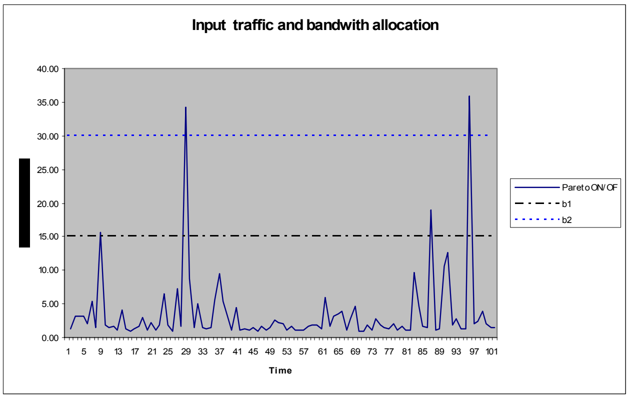

Fig. 1. Relationships between input traffic and bandwidth allocation

Cost model

In this paper the following cost model is used. For each epoch:

$$\text{PROFIT} = \text{INCOME} - \text{COST}; \quad (5)$$

$$INCOME = \sum_{k \in PATH} traffic\_out_k * \Pr ice_k \; ; \quad (6)$$

where $traffic\_out_k$ - outgoing traffic from k-path and $\Pr ice_k$ - service tariff for path k;

$$COST = \sum_{ij \in L} b_{ij} * Cost_{ij} \; ; \quad (7)$$

where $Cost_{ij}$ - cost of allocated bandwidth.

Decision making model

Traditionally, the decision process is modelled with Markovian model (MDP) [6]. For MDP the problematic condition is calculation of the state transition probabilities, which depends only on the current state (Markov property). Any more, in dynamically changed demand environment with long range dependencies the reducing of decision making process to Markovian is very sophisticated task. In this paper the evolutionary decision process are used with following sets:

1. A set of decision epochs: For self-similar traffic there are assumed the timescale of minutes or tens of minutes and that the time between transitions is constant.

For example, the SONET/SDH demand matrices are modified weekly so the decision is made in every week.

***2. A set of Network states*:** A Network state reflects the shape and position of Pareto front in the next transition. The set of Network states is the result of optimization procedure of bandwidth allocation at t_n.

3. A set of actions: An action defines how to perform the allocation process or how to pick the solution on the Pareto front. The following Bandwidth Utilization procedure is studied:

Step 1. For a given node pair, the node first sets up the PATH on the available Network layer bandwidth that connects the node pair.

Step 2. If the sets up of the PATH are not possible, then sets up the PATH on the available pool of bandwidth.

Step 3. If there is an available bandwidth, then the requested bandwidth is allocated to the Network layer bandwidth and used to set up the PATH. .

Step 4. If there is no available bandwidth, then Link layer bandwidth might be dynamically increased by the bandwidth broker from physical layer bandwidth,
and then bandwidth allocated to the Network layer and finally set up the PATH.

Step 5. If bandwidth is not available then traffic demand is lost.

The underutilization procedure is inverse.

Optimization procedure

The following GA is used for optimization of bandwidth allocation.

Table 3. Genetic Algorithm parameters

Item	**Value/Type**
Population Size	50
Maximum generations	1500
Selection	Roulette Wheel selection
Crossover	1 point
Crossover probability	0.8
Mutation probability	0.2

Decision space was specified by variables. The Pareto ranking and fitness calculation is similar to [2].

Experimental Results

To validate the correctness and effectiveness of proposed approach a simulative comparison is used to assess the bandwidth utilization procedure. The simulated Network parameters are shown in Table 4.

Table 4. Parameters of simulated Network

Item	**Value/Type**
Number of Nodes	10
Number of Paths	5
Number of traffic sources per Path	40

The results of simulations in compliance with objectives of this research are presented in Table 4, Table 5, Fig. 2 and Fig.3. The efficiency of BB for given traffic parameters are shown Table 4.

Table 5. Mean value of bandwidth utilization

Class	Traffic parameters		Bandwidth allocation	
	Mean	Variance	Without BB	With BB
A	2	2.5	~30%	~55%
B	2	1	~44%	~58%

Table 6. Performance improvement with prediction

Traffic trends	Packet losses [% of transmitted]	
	Without BB	With BB
Constant within the epoch	~1%	0.05%
Increasing by 10% within the epoch	~1,4%	0.06%
Decreasing by 10% within the epoch	~0.3%	0.02%

Training of NN in real time allows improving the efficiency of BB actions.

There are three conflicting variables: traffic losses, offered traffic and bandwidth utilization. Dependency of revenues from mean utilization of bandwidth is shown in Fig.2.

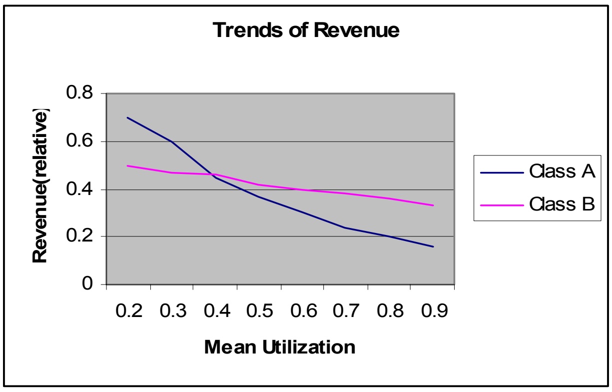

Fig. 2. Trends of revenue vs. mean utilization

For each epoch the optimal Pareto front is found.

Convergence to a Pareto front is achieved in some runs, by less than 50 iterations. (See Fig. 3).

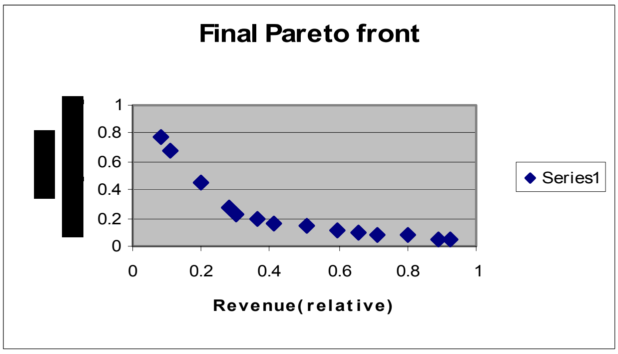

Fig. 3. Example of final Pareto front

Conclusion

This paper has presented a BB mechanism and its impact investigation on the network performance under self similar traffic. The simulation shows the high efficiency of BB actions to smooth the bursts of self-similar traffic. A multi-objective GA approach was used to the bandwidth allocation optimization problem The simulation results have demonstrated that GA-based multi-objective optimization method for BB is suitable mechanism, because guaranties the robust bandwidth allocation. The simulation results show that efficiency of BB actions depends very much on the traffic model and parameters. The degree of predictive accuracy is varied from epoch to epoch. However, generally a standard deviation ratio of 0.1 or lower indicates very good regression performance.

The dependence of bandwidth utilization efficiency on the realistic model of self-similar (or other) traffic with long range dependence needs future study

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Pateikta spaudai 2005 03 15

G. Lauks. Daugiafunkcinė juostos paskirstytojo optimizacija evoliucinio algoritmo pagalba // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2005. – Nr. 3(59). – P. 14–17.

Optiniuose tinkluose su dinaminiu maršrutu tikslinga perskirstyti perdavimo greitį ir paklausos priklausomybę tikrajame laiko dydyje. Šiame straipsnyje pateiktas daugiafunkcinės juostos paskirstytojo optimizacijos evoliucinio algoritmo pagalba būdas. Juostos paskirstytojas pateiktas kaip evoliucinis procesas dinamiškai besikeičiantis paklausos aplinkoje. Pateikta daugiafunkcinio evoliucinio algoritmo schema. Optimalūs sprendimai pagal Pareto randami atitinkamų genetinių operatorių pagalba. Pateikti eksperimentų rezultatai, parodantys galimybę gauti gerus kompromisinius rezultatus. Il. 3, bibl. 8 (anglų kalba; santraukos lietuvių, anglų ir rusų k.).

G. Lauks. Multi-objective Optimization of Bandwidth Broker with Evolutionary Algorithm // Electronics and Electrical Engineering. – Kaunas: Technologija, 2005. – No. 3(59). – P. 14–17.

The Optical Transport Networks with dynamic transport routing capability enable rearrangement of the logical link capacities on demand in real time. In this paper an evolutionary algorithm based approach for multi-objective optimization of Bandwidth Broker (BB) is presented. BB is represented as evolutionary process in dynamically changed traffic demand environment. Multi-objective Evolutionary algorithm scheme for bandwidth allocation is described. The suitability of Evolutionary algorithm approach is investigated. The Pareto optimal solutions are ensured by the underlying genetic operators. There are carried out a few experiments and the test results illustrate the trade-off between objectives and ability of this approach to produce many good compromise solutions. Ill.3, bibl.8 (in English; summaries in Lithuanian, English and Russian).

Г. Лаукс. Многоцелевая оптимизация распределителя полосы с помощью эволюционного алгоритма // Электроника и электротехника. – Каунас: Технология, 2005. – № 3(59). – P. 14–17.

В оптических сетях с динамической маршрутизацией целесообразно перераспределять скорости передачи и соответствии с запросом в реальном масштабе времени. В этой статье представлен подход многоцелевой оптимизации распределителя полосы с помощью эволюционного алгоритма. Распределитель полосы представлен как эволюционный процесс в динамически изменяющегося среде спроса. Представлена схема многоцелевого эволюционного алгоритма. Оптимальные решения по Парето находятся с помощью соответствующих генетических операторов. Приведены экспериментальные результаты, показывающие возможности получить хорошие компромиссные результаты. Ил.3, библ.8 (на английском языке; рефераты на литовском, английском и русском яз.).

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