BANDWIDTH ALLOCATION FOR VIRTUAL PATHS USING GENETIC ALGORITHMS (GA-BAVP)

Andreas Pitsillides*, Costas Pattichis*, A. Sekercioglu**, Thanos Vassilakos***
*Department of Computer Science, University of Cyprus, Nicosia, Cyprus
email: {cspitsil}{pattichis}@turing.cs.ucy.ac.cy
** School of Computer Science and Software Engineering, Swinburne University of Technology, Melbourne, Australia, email: ASekerci@swin.edu.au
***Institute of Computer Science, Foundation for Research and Technology-Hellas, (FORTH), Crete, Greece, e-mail: vasilako@csi.forth.gr

Abstract: The suitability of genetic algorithms (GAs) in Bandwidth Allocation for Virtual Paths (GA-BAVP) is investigated. Results for a simple network topology are compared with those obtained using a classical unconstrained optimisation technique. Our preliminary results suggest it is worthwhile to obtain further insight into the reported strength of GA-BAVP.

1. Introduction

BISDN's will support various classes of multimedia traffic with different bit rates and quality of service requirements, thus traffic control and resource management are crucial in order to guarantee the desired grade of service. Several mechanisms will exist in a BISDN to allocate resources and control traffic, such as bandwidth allocation, buffer management, call admission control, input rate regulation, routing, and queue scheduling. It has been suggested that these controls will be applied at different levels in the network such as cell level, burst level , connection (i.e. call) level, Virtual Path (VP) level, and the network level. In this paper we will focus on the bandwidth allocation problem for VPs, aimed at the VP and network levels.
The suitability of genetic algorithms (GAs) in Bandwidth Allocation for Virtual Paths (GABAVP) is investigated, and the results for a simple network topology are compared with those obtained using a classical unconstrained optimisation technique in [1]. The motivation behind the use of GAs compared to more traditional optimization techniques lies in their robustness and efficiency which is based on the following [2]: (i) GAs work with a coding of the parameter set, not the parameters themselves, (ii) GAs search from a population of paints, not a single paint, (iii) GAs use payoff (objective function) information, not derivatives of functions or other auxiliary knowledge, and (iv) GAs use probabilistic transition rules, not deterministic rules.
In section 2 we present the problem formulation and solution approaches, in section 3 we present our preliminary results for a simple topology, and compare with the solution obtained using a classical technique. Finally, in section 4 we offer our conclusions.

2. Problem formulation and solution approaches

GA-BAVP aims to supply optimal bandwidth (capacity, service-rate) assignment to VPs, taking into account global network considerations. It is located at the higher levels of the control structure; the VP and network levels. It is therefore associated with a "slow" time scale in terms of minutes or tens of minutes. Gerla et al [3] developed a M/M/1 queuing model (assuming independence between the queues) for Bandwidth Allocation for Virtual Paths (BAVP) aimed at minimising total expected delays. Hui et al [4] formulate BAVP as a Non-Linear Programming model which minimises the total usage cost. Herzberg and Pitsillides [5] propose an alternative model for BAVP which uses a network carrier viewpoint and maximises total network throughput (proposed earlier by Herzberg in [6]). Note that other criteria of optimisation can be incorporated to formulate a multiobjective optimisation problem [7], that can also be hierarchically organised [8]. Also game theoretic concepts may be used to deal with other issues, such as conflicting objectives, or introducing fairness into the VP allocations.
Here we firstly present an extension of the objective function used in [5] to provide the bandwidth allocation problem with fairness among the VPs and then propose genetic algorithms to solve the multiobjective optimisation problem.

Multiobjective BAVP model

Consider a (virtual) network consisting of N nodes representing ATM switches, and L transmission links connecting the nodes. For given: network topology; expected OD traffic loads; and link capacities, we try to find an optimal VP bandwidth assignment which maximises the total expected network throughput. We seek to provide for "fair" allocations of

bandwidth among all VPs (note that different VPs can have different performance objectives). The measure of fairness employed here is based on the concept of Pareto optimality from games theory [9] (also known as efficient, noninferior and nondominated optimality) which applies to cooperative game situations (rather than Nash optimality which applies to non cooperative).

We define:

C_i^{link} - Available bandwidth of link *i*, *i=1,..,L* for VP assignment.

N_p - Number of network unidirectional OD pairs, indexed $j = 1,\ldots, N_p \le N(N-1)$.

P_j - Number of predetermined possible paths connecting OD pair *j* (allows for multiple VPs between an OD pair).

$U_{j,p}$ - Bandwidth assigned to OD pair *j* through path *p*, $j = 1,\ldots, N_p$, $p = 1,\ldots, P_j$.

U_j - Bandwidth assigned to OD pair *j*. Clearly $U_j = \sum_{p=1}^{P_j} U_{j,p}$, $j = 1,\ldots, N_p$.

U^* - Pareto optimal solution, $U^* = [U_1^*,\ldots,U_{j_p}^*]$.

$D_j(U_j)$ - Expected throughput of OD pair *j* when it utilises bandwidth assignment of size U_j (typically a concave non-decreasing function).

$T_j^{\min}$ ($T_j^{\max}$) - Minimal (maximal) bandwidth assigned by the user to OD pair *j* (e.g. $T_j^{\min}$ can be set to meet minimum performance objectives and $T_j^{\max}$ for fairness).

$d_{j,p}^i$ - a (0,1) indicator variable which takes the value of 1 if path *p* of OD pair *j* uses link *i*.

$F_j(U_j)$ ($f_j(u)$) - probability (density) function for bandwidth demand.

Observe that the $U_{j,p}$ are the references to be provided to the lower levels.

The mathematical formulation for such a model is:

$$\max_U \left\{ D_1(U_1),\ldots,D_j(U_j) \right\} \qquad (1)$$

subject to the constraints

$$\sum_{j=1}^{N_p}\sum_{p=1}^{P_j} d_{j,p}^i U_{j,p} \le C_i^{link}, \qquad i = 1,\ldots,L$$

$$T_j^{\min} \ge U_j = \sum_{p=1}^{P_j} U_{j,p} \ge T_j^{\max} \qquad j = 1,\ldots,N_p$$

$$U_{j,p} \ge 0 \qquad j = 1,\ldots,N_p \qquad p = 1,\ldots,P_j.$$

Note that $U^* \in U$ the set of all Pareto optimal solutions if and only if $D_j(U_j) \le D_j(U_j^*)$, *j*=1,...,N_p, with strict inequality for at least one *j*.

To solve the above model, statistical characteristics of the functions $D_j(U_j)$, $j = 1,\ldots,N_p$ should be known. We assume that each function $D_j(U_j)$ is derived from an appropriate probability function $F_j(U_j)$ for bandwidth demand and a corresponding probability density function $f_j(u)$. By considering the throughput as a "fluid flow", the function $D_j(U_j)$ can be obtained [5]:

$$D_j(U_j) = \int_0^{U_j} u f_j(u)du + U_j \int_{U_j}^{\infty} f_j(u)du = \\ = \int_0^{U_j} u f_j(u)du + U_j[1 - F_j(U_j)] \qquad (2)$$

The first term in equation (2) is the expected throughput for bandwidth demand below the assigned bandwidth of U_j, and the second term is for demand above the assigned bandwidth of U_j. In [5], we show that the expected throughput decreases, as variance of bandwidth demand (derived from normal probability) increases. Figure 1 presents a family of $D_j(U_j)$ functions derived from Normal Probability Functions having an average bandwidth demand of 150 Mbit/s and different variance values σ. For illustrative purposes an assigned value of $U_j = 200$ Mbit/sec is shown by the dotted vertical line.

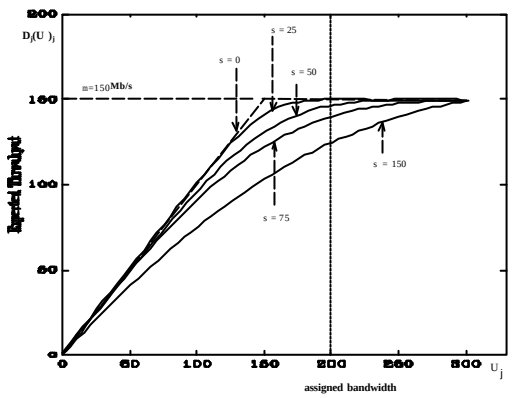

Figure 1. Typical throughput functions $D_j(U_j)$.

The above problem belongs to the general class of multiobjective non-linear constrained optimisation problems. We want to find the set of the Pareto optimal solutions, and from this set select the optimum (or preferred) solution; defined as any preferred Pareto optimal solution that belongs to the indifference band (a subset of the Pareto optimal set where the improvement of one objective function is equivalent–in the mind of the decision maker–to the degradation of another [10]).

<u>solution approaches</u>

Among the many methods that generate the set of feasible solutions [10], [11] are: i) The weighted sum of the objective functions [7] (weighting method, parametric method). For example, Herzberg et al [6] converts the multiobjective non linear problem to a single objective LP problem (hence only generates one solution among the infinitely many). ii) The ε-constrained method [10] which can produce the set of noninferior solutions and (in conjunction with the Surrogate Worth Tradeoff (SWT) [10] method) generate the relative tradeoffs between the objective functions. Hence it allows a quantitative comparison of the objective (even noncommensurate) functions (e.g. [1]). iii) Hierarchical multiobjective analysis that exploits the general concept of decomposition-coordination; it provides computational tractability, and possibly decentralisation of computations [10]. and iv) Optimisation based on GAs [2] (we explore here for the single objective case).

Genetic algorithms

…..

3 Preliminary results

In [1], using a 3-node network we compare the optimal bandwidth solution, for two single objective formulations (sum and product of individual objective functions) and the Pareto optimum set. It is shown that there are pronounced differences in the optimum bandwidth allocations of the two schemes, and that the single objective formulations are particular solutions of the Pareto optimum set. Therefore the choice of the optimum solution based on either of the two single optimisation objectives, is not clear cut. However equipped with the Pareto optimum set one can select the "best" compromise solution, in the eyes of the decision maker (e.g. using the SWT method).
In this study, as discussed earlier, we want to exploit the reported strength of genetic algorithms to gain further insight into the problem of multiobjective BAVP, initially starting with single objective optimisation.

A few words about the method/coding/etc…

Results

We consider a 3-node network (N=3) with 2 OD pairs, both destined for node 3. Two VPs are established for each OD pair (N_p=4, P_j=2, j=1,2).

The link capacities are set equal to 100 Mbit/sec ($C_i^{link} = 100$, i=1,2,3).

The network topology is shown in figure 2, and the traffic characteristics (assuming a normally distributed probability function for bandwidth demand) are tabulated below.

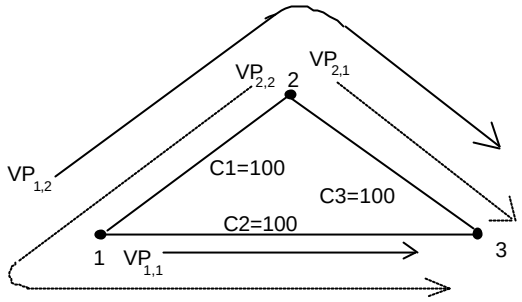

Figure 2. Three node network topology used for example 1.

			case i)	case ii)
OD pair	VP	μ	σ	σ
1-3	$VP_{1,1}$ link 1,3 $VP_{1,2}$ link 1,2,3	110	55	55
2-3	$VP_{2,1}$ link 2,3 $VP_{2,2}$ link 2,1,3	50	25	100

Table 1. Traffic characteristics for example 1.

For each of the two optimisation techniques considered here (classical constrained optimisation[#1] and genetic[#2] based optimisation), two cases are considered (see Table 1). The first depicts traffic with low variance for both OD pairs ("smooth" traffic). In the second case OD pair 2-3 has a high variance to depict "bursty" traffic. For ease of comparison the results are tabulated below. Table 2 considers the sum of the objective functions and Table 3 the product of the objective function

[#1] Using MATLAB function constr.m for constrained non linear optimisation; uses a Sequential Quadratic Programming method.
[#2] Using custom written C code and the program supplied by ….

	sum of the objective functions, $Max\{D_1(U_1)+D_2(U_2)\}$			
	classical		**genetic**	
	bandwidth allocations	objective function	bandwidth allocations	objective function
case i	U_1=133 U_2=67	$D_1(U_1)$ = 99 $D_2(U_2)$ =50	U_1= U_2=	$D_1(U_1)$ = $D_2(U_2)$ =
case ii	U_1=121 U_2=79	$D_1(U_1)$ =95 $D_2(U_2)$ =44	U_1= U_2=	$D_1(U_1)$ = $D_2(U_2)$

Table 2. Bandwidth allocations for example 1 for the sum of the objective function using.classical optimisatron techniques in comparison to genetic based optimisation techniques.

	product of the objective functions $Max\{D_1(U_1)\times D_2(U_2)\}$			
	classical		**genetic**	
	bandwidth allocations	objective function	bandwidth allocations	objective function
case i	U_1=125 U_2=75	$D_1(U_1)$ = 96 $D_2(U_2)$ =52	U_1= U_2=	$D_1(U_1)$ = $D_2(U_2)$ =
case ii	U_1=102 U_2=98	$D_1(U_1)$ =86 $D_2(U_2)$ =51	U_1= U_2=	$D_1(U_1)$ = $D_2(U_2)$ =

Table 3. Bandwidth allocations for example 1 for the product forms of the objective function using.classical optimisation techniques in comparison to genetic based optimisation techniques.

Conclusions

In the problem investigated, preliminary findings suggest that using genetic algorithms a satisfactory solution to the allocation of bandwidth for Virtual Paths can be obtained. However, further work is currently in progress to explore completely the capacity of GAs., not only for single objective optimisation, but also for the multiobjective case.

References

[1] A.Pitsillides, "Control structures and techniques for Broadband-ISDN communication systems", Ph.D. Thesis, Swinburne University of Technology, 1993

[2] D.E. Goldberg, Genetic Algorithms in Search, Optimization & Machine Learning Addison-Welsey, Reading, MA 1989.

[3] M. Gerla, J. A. S. Monteiro, R. Pazos, "Topology Design and Bandwidth Allocation in ATM nets", IEEE JSAC, Vol. 7, No. 8, pp. 1253-1262, Oct. 1989.

[4] J. Y. Hui, M. B. Gursoy, N. Moayeri, R. D. Yates, "A layered broadband switching architecture with physical or virtual path configurations", IEEE Journal of Selected Areas in Communications, Vol. 9, No. 9, pp. 1416-1426, December 1991.

[5] M. Herzberg, A. Pitsillides, "A hierarchical approach for the bandwidth allocation, management and control in B-ISDN", IEEE International Conference on Communications, ICC'93, Geneva, May 1993.

[6] M. Herzberg, "A linear programming model for virtual path allocation and management in B-ISDN", ABSSS' 92, Melbourne, July 1992.

[7] L. A. Zadeh, "Optimality and non-scalar-valued performance criteria", IEEE Aut. Control, AC-8, 1963.

[8] A. Pitsillides, J. Lambert, D. Tipper, “An illustrative hierarchical structure for the allocation of bandwidth to virtual paths”, ATNAC94, Australian Telecommunication Networks and Applications Conference, Melbourne, 5-7 Dec. 1994

[9] J. Von Neumann, O. Morgenstern, "Theory of games and economic behaviour", Princeton Uni., 1953.

[10] Y. Y. Haimes, K. Tarvainen, T. Shima, J. Thadathil, "Hierarchical Multiobjective Analysis of Large-Scale Systems", Hemisphere Publishing, 1990.

[11] J. G. Lin, "Three methods for determining Pareto-optimal solutions of multiple-objective problems", Directions in Large-Scale Systems, Y-C. Ho, S. K. Mitter (editors), Plenum Press, 1975.