On Using differentiated queuing to support Traffic Engineering

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***Abstract*—This paper presents a Traffic Engineering (TE) model where (1) a network is modeled as a set of parallel paths computed between ingress-egress pairs (2) the ingress-egress pairs are modeled as sets of queues and (3) the traffic allocation on the ingress-egress pairs is formulated as a dynamic flow optimization problem which is solved using *Pontryagin Minimum Principle (PmP)*. We show through simulation that the *PmP* solution may lead to different network configurations depending on how the ingress-egress pairs are modeled. We apply the *PmP* solution to find optimal network configurations for the traffic offered to a 14-node test network. Preliminary results reveal the relevance of using differentiated queuing compared to modeling the set of parallel paths using the same queuing model.**

I. Introduction

Multi-protocol label switching (MPLS) [1] extends the IPv4 routing protocols to provide new and scalable routing capabilities. These include Traffic Engineering (TE) and Virtual Private Networks (VPNs) support. TE allows the traffic to be efficiently routed through the network by effecting QoS agreements between the available resources and the current and expected traffic. MPLS provides more scalable network operation by off-loading the network administrator from the task of monitoring the state of the network and executing routing and compensation mechanisms when problems arise.

Finding a set of paths from a source to a destination and distributing the offered traffic across network links is one of the main objectives of TE. It can be achieved in a multi-path setting by using either a reactive scheme where path identification and traffic distribution are computed simultaneously to achieve an optimal traffic flow allocation, or a pre-planned model where path identification and traffic distribution are performed separately.

As presented above, TE is a task that must be carried out carefully to avoid the performance degradation that could occur from an inefficient path identification and/or traffic distribution.

This paper presents a model of flow optimization in MPLS networks. We provide routing solutions to the following questions related to the optimal distribution of traffic flows among the pre-computed paths in a multipath setting:

- how is the set of paths computed, and
- how is the offered traffic distributed among the selected paths.

We present a TE model that uses traffic splitting to achieve routing optimization in IP networks. The model can be used to achieve for example routing for video over bandwidth-limited networks. It uses a two-step scheme consisting of (1) identifying a set of parallel paths in a network using the *K-Shortest Path (KSP)* [3] algorithm and (2) distributing the offered traffic to this set of paths based on the *Pontryagin Minimum Principle (PmP)* model.

The remainder of this paper is organized as follows. Section II presents the parallel path modeling scheme while section III discusses the path identification and traffic distribution methods. Section IV presents some experimental results and an application of the methods to a small illustrative network. Our conclusions are presented in section V.

II. Modeling a set of Parallel Paths

Assume a network $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ where $\mathcal{N}$ is the set of nodes and $\mathcal{L}$ set of links. Consider a given subset $\mathcal{P}_{s-d}$ of N parallel paths between source-destination pair with $\mathcal{P}_{s-d} = \{p_1, \cdots, p_N\}$ where each path capacity is denoted by $C_n = \min_{\ell \in p_n} C_\ell$ for all $n = 1 \cdots, N$. Let $\lambda(t)$ denote the flow arrival rate to the set of paths $\mathcal{P}_{s-d}$ and assume that each flow transmits packets at a fixed rate for random duration with rate μ_n^{-1} along the path p_n it is assigned to. The offered load or the amount of traffic on that path at time t, denoted $x_n(t)$, is the sum of the total number of flows currently routed across it. It is known from the optimal control theory that the time evolution of mean quantities within a dynamic flow system can be expressed by the first order differential equations

$$\dot{x}_n(t) = -\mu_n G_n[x_n(t)] + \lambda_n(t) \quad n = 1, \cdots, N \tag{1}$$

where the function $\mu_n G_n[x_n(t)]$ approximates the intensity of outgoing traffic while $\lambda_n(t)$ represents the incoming traffic. In a multipath setting, the traffic offered to the source-destination pair (s,d) is splitted among the L paths to achieve load balancing. This load balancing process is conditioned by the feasibility constraints expressed by

$$\sum_{n=1}^{N} \lambda_n(t) = \lambda(t) \quad and \quad 0 \le \lambda_n(t) \le \lambda(t) \tag{2}$$

For each $n = 1, \cdots, N$, we thus seek to find the proportion of traffic $\alpha_n(t) = \lambda_n(t)/\lambda$ routed to each path n. The flow

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This work is supported by grant numbers 2047362 and 2677 from the South African National Research Foundation, Siemens Telecommunications and Telkom SA Limited.

pattern achieved is given by $\hat{\lambda}(t) = (\lambda_1(t), \lambda_2(t), \cdots, \lambda_N(t))$. It is said to belong to the set of feasible flow patterns $\mathcal{F}$ if it satisfies the feasibility constraints (2).

The functions G_n are determined by the stochastic properties of the arrival and service processes. However, all flows arriving at a given path are formed from one input process by random selection. Thus, for the Poisson process they have the same stochastic properties as the input process itself [4]. Therefore, $G_n = G$ and the model of the parallel set system is described by the equations

$$\dot{x}_n(t) = -\mu_n G[x_n(t)] + \lambda_n(t), \quad n = 1, \cdots, N. \tag{3}$$

The cost functional which is the total waiting time of all entities in the system during time $\langle 0, T)$ is given by

$$\tau = \int_0^T \sum_{n=1}^{N} x_n(t) dt \tag{4}$$

Equation (4) expresses the fact that the waiting cost in the system is proportional to the system's total traffic load: a heavily loaded network will keep entities longer in the network while a lightly loaded network will release these entities quicker. Having the model and the criterion τ , our objective is to assign flow $\lambda(t)$ within the system described by equations (3) so as to satisfy feasibility constraints (2) and minimize criterion τ (4).

A. The Pontryagin Minimum Principle (PmP) solution

From Pontryagin Minimum Principle [7], an optimal flow pattern $\lambda_n^*(t), n = 1, \cdots, N$ that solves the problem considered must minimize, at each time t, the Hamiltonian function over all flow patterns satisfying the feasibility constraints (2), i.e.,

$$H[x^*, q^*, \lambda^*] = \min_{\lambda \in \mathcal{F}} H[x^*, q^*, \lambda]. \tag{5}$$

where

$$H[x, q, \lambda] = \sum_{n=1}^{N} q_n \lambda_n(t) + \sum_{n=1}^{N} x_n(t) - \sum_{n=1}^{N} q_n \mu_n G[x_n(t)]$$

and $\dot{q}_n(t) = -\dfrac{\partial H}{\partial x_n}, \quad n = 1, \cdots, N$

which leads to the following problem

$$\min_{\lambda \in \mathcal{F}} \sum_{n=1}^{N} q_n \lambda_n(t)$$

subject to

$$\sum_{n=1}^{N} \lambda_n(t) = \lambda(t).$$

Solving the last problem yield the following equalities

$$\mu_n \frac{dG(x_n)}{dx_n} = \mu_{n+1} \frac{dG(x_{n+1})}{dx_{n+1}}, \quad n = 1, \cdots, L-1. \tag{6}$$

where L is the number of paths used by $\mathcal{P}_{s-d}$ to forward traffic to the destination. The quantity $\delta_n(x_n) = \mu_n \frac{dG(x_n)}{dx_n}$ represents the incremental increase in the output of the n^{th} path due to a small change in the traffic to be forwarded and awaiting service. Equations (6) state that these quantities should be equal for active paths. To specify the flow pattern, it is necessary to know when each path should be used and which quantities of total inflow should be directed to it.

Computing the switching times

When the traffic become less heavy it may be worthwhile to switch off one of the paths with a small capacity because the delay in the path with large capacity is shorter. For two paths with same capacity, their sequence make no difference. By assuming that the traffic load is always increasing, we expect it to not exceed some maximum, this means that function $G(x)$, which approximates the total traffic load must be concave. Now assume that the system starts an operation from the empty state, $x_n(0) = 0, n = 1, \cdots, N$, and the paths are numbered in decreasing capacity order, so that at the beginning all the inflow is directed to path 1 with the highest capacity. By doing so we increase x_1 and consequently, owing to the concavity of G, decrease $\frac{dG(x_1)}{dx_1}$. If the load is sufficiently large, after some time t_1 , $\delta_1(x_1)$ may reach $\delta_2(0)$. When $\delta_1(x_1)$ first becomes equal to $\delta_2(0)$, according to the necessary conditions for optimality, path 2 is switched on. If the load still continues to increase, inflows in the paths 1 and 2 grow and $\delta_1(x_1) = \delta_2(x_2)$ may become so small that they reach $\delta_3(0)$. Then the path 3 is switched on. That reasoning, and the argument that a path with larger capacity is switched on before the path with smaller capacity, suggest that we define the supremum $\hat{\delta}(t) = \max_{1 \leq n \leq N}\{\delta_n(x_n)\}$. Path n is switched on when $\delta_n(x_n)$ first becomes equal to $\hat{\delta}(t)$.

Computing the flow intensities

We shall consider the assignment of traffic to L paths which we know are to be used. Differentiating (6) with respect to time and substituting from path state equations (3) for $\dot{x}_n$ and $\dot{x}_{n+1}$, we find that flow intensities satisfy the equations:

$$\begin{aligned} &-\mu_n^2 \frac{d^2G(x_n)}{dx_n^2} G(x_n) + \mu_n \frac{d^2G(x_n)}{dx_n^2} \lambda_n = \\ &-\mu_{n+1}^2 \frac{d^2G(x_{n+1})}{dx_{n+1}^2} G(x_{n+1}) + \mu_{n+1} \frac{d^2G(x_{n+1})}{dx_{n+1}^2} \lambda_{n+1}. \end{aligned} \tag{7}$$

Thus, we have $L-1$ independent equations which are linear with respect to flow intensities. Using the flow conservation condition given by

$$\lambda_1(t) + \lambda_2(t) + \cdots + \lambda_L(t) = \lambda(t) \tag{8}$$

we now have a system of L linear equations and L unknown variables. The flow intensities $\lambda_n(t), n = 1, \cdots, L$, are found by solving this system of linear equations.

B. Modeling path sets using different Queuing models

We consider a single-queue model having identical channels and the incoming flow is dynamically forwarded over paths by computing switching times and flow intensities for each path.

- For **M/M/1** queuing, the function $G(x)$ which approximates the instantaneous system utilization factors is given by $G(x) \equiv$

$\rho = x/(1+x)$ according to the fact that the traffic flow x in the system is $x = \rho/(1-\rho)$ with $0 \leq \rho < 1$ [2].
- For **M/M/s** and **M/M/s/K** queuing with $s > 1$, the explicit expression of ρ cannot be obtained [2]. We then make use of a polynomial approximation to find a polynomial which approximates $G(x)$. According to the form of expression which gives the traffic on queue waiting to be forwarded to the destination it appears to be sufficient to represent the shape of the original curve over the range of offered loads by a polynomial whose degree is $s+1$. Since the Chebychev interpolation points, which are the zeros of the Chebychev polynomials given by

$$x_k^* = \cos\frac{2k+1}{2(s+1)}\pi, \quad k = 0, \cdots, s \tag{9}$$

make the best interpolation points [5], our technique consists of finding the points of our data which are closest to the Chebychev interpolation points.

Theorem. *The switching times increase with the value of s. Therefore using M/M/s queuing leads to longer switching times compared to M/M/1 queuing and the switching times achieved using the M/M/s/K queuing model are longer than those achieved by the M/M/s model.*

The theorem above guarantees that using differentiated queuing to model different set of parallel paths can lead to more efficient use of the network resources by reducing the impact of the competition on bottleneck links through switching time differentiation. Using this approach to manage a network can increase its robustness by minimizing the packet loss due to the interference among competing flows on links and increasing the network throughput to each destination. This leads to improved overall network performance as illustrated in section IV.

III. Algorithmic solutions

This section presents an algorithmic solution to the *PmP* problem and its application to traffic distribution in an MPLS setting.

A. The PmP solution

Given a set of parallel paths $\mathcal{P}_{s-d}$ and the traffic offered to this set λ_{s-d}, we use Pontryagin minimum Principle to compute the optimal quantities of total incoming flow which must be forwarded over each path $p \in \mathcal{P}_{s-d}$ and their switching times using the following five steps

step 1. Compute the quantities $\delta_n(x_n)$ for each path p_n and find the supremum $\hat{\delta}(t)$;
step 2. The path p_n is to be used if $\delta_n(x_n) = \hat{\delta}(t)$;
step 3. Find the feasible flow intensities over each path by solving the system of equations (7) and (8);
step 4. Integrate state paths equation (3);
step 5. Go to step 1 if $t < T$.

B. The TE application

Given a network, we consider the routing of the traffic offered to this network using a two-step model consisting of (1) finding sets of parallel paths for each source-destination pair and defining the bandwidth share of each pair on the links and (2) using the *PmP* algorithm above to distribute traffic to the network. This TE model may be applied to support Virtual Private networks (VPNs) in emerging MPLS networks using a preplanned model where a set of precomputed LSPs is dimensioned based on a-priori estimation of a traffic matrix. The algorithm executes the following four steps

Step 1. Implementation of Edge-Vertex-Disjoint Paths and the interference on links:
- Initialization of the interference on all links by setting $I_\ell = 0$ for all $\ell \in \mathcal{L}$;
- For each s-d pair $\mathcal{P}_{s-d}$ under consideration
  (1) Initialization of length L_ℓ of all links $\ell \in \mathcal{L}$ by setting $L_\ell = 1$.
  (2) Path finding. For each neighbor of node s
  - Run Dijkstra algorithm to find the path p_s^* with minimum length;
  - Update the interference I_ℓ by setting $I_\ell = I_\ell + 1$ for each link $\ell \in p_s^*$;
  - Prune the network to discard all links $\ell \in p_s^*$ by setting $L_\ell = \infty$.

Step 2. Set up the link bandwidth sharing: Set $B_\ell = C_\ell / I_\ell$ for all $l \in p$ such that $p \in \cup\mathcal{P}_{s-d}$, where C_ℓ is the maximum bandwidth of a link $\ell \in \mathcal{L}$ and I_ℓ is the interference on the shared link ℓ expressed by

$$I_\ell = \sum_{p \in \cup\mathcal{P}_{s-d}} \delta_{\ell,p} \tag{10}$$

where

$$\delta_{\ell p} = \begin{cases} 1 & \ell \in p \\ 0 & otherwise. \end{cases} \tag{11}$$

Step 3. Path dimensioning: For each source-destination pair $\mathcal{P}_{s-d}$, set $C_p = \min_{\ell \in p} B_\ell$.
Step 4. Optimal flow distribution: Given the demand offered λ_{s-d} to a source-destination pair $\mathcal{P}_{s-d}$, run the **PmP** algorithm described above to find the optimal distribution of traffic on the $s-d$ pair.

IV. Experimental results

This section presents simulation results which were performed when applying the PmP algorithm to distribute traffic on a set of parallel paths and numerical results obtained from applying the TE algorithm to engineer a 14-node test network. The parameter setting for the test network illustrated by Figure 1 are as follows:

Traffic is offered to 3 source-destination pairs. The maximum link capacity is set to $C = 30$ bandwidth units. For each source-destination pair, the traffic flows are queued using the $M/M/1$ and $M/M/2$, models. The flow bandwidth requests are uniformly distributed in range $[D_1, D_2]$ where $D_2 =$

$\sum_{p \in \mathcal{P}_{s-d}} C_p$ with C_p the capacity of a given path $p \in \mathcal{P}_{s-d}$, and $D_1 = D_2 - D_m/2$ with $D_m = \min_{p \in \mathcal{P}_{s-d}} C_p$. The duration T of our simulation is given by $T = \max_{s-d} |\mathcal{P}_{s-d}|$, and it is assumed that the traffic flows λ_{Si-Di} have higher priority over the path set $Si - Di$. To meet the feasibility constraint, the traffic flows which are not within the link capacity limits are lost.

We evaluated the efficiency of the network when using differentiated queuing model and ”same” queuing model for all parallel paths sets.

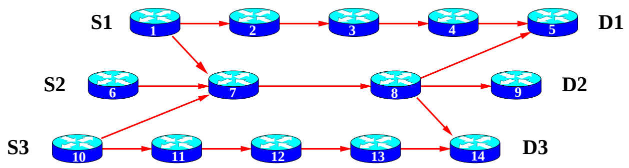


Fig. 1. Network test

Cap		Load	MM1		MM2		M/M/2/10	
μ_1	μ_2	λ	S-T	F-D	S-T	F-D	S-T	F-D
4	1	4	0.375	3.33 0.67	2	4.0 0.0	2	4.0 0.0
4	1	8	0.1485	5.9981 2.0019	0.3555	5.3585 2.6417	3.378	5.5439 2.4561
4	1	9	0.129	6.6609 2.3391	0.2925	5.819 3.181	0.3105	5.7979 3.2021
4	2	9	0.0495	5.7496 3.2504	0.165	5.5159 3.4841	0.168	5.6442 3.3558
4	2	10	0.0435	6.3015 3.6985	0.144	5.8742 4.1258	0.147	6.0267 3.9733
4	2	12	0.036	7.4773 4.5227	0.114	6.5774 5.4226	0.1155	6.757 5.2428
6	2	12	0.062	8.4916 3.5084	0.198	8.0151 3.9849	0.207	8.2545 3.7455

TABLE I

ANALYTICAL RESULTS

The performance parameters used are (1) the percentage flow acceptance referred to as ACC, which is the percentage of flows which have been successfully forwarded to the destination (2) the average link utilization referred to as $UTIL$ which defines the average link load and determines the potential for the network to support traffic growth and (3) the percentage of flow lost referred to as PFL, which is the percentage of flows which has been rejected by the link.

A. *Modeling a set of parallel paths*

We conducted a first set of experiments to assess the behavior of the different queuing models when applied to two parallel path sets using different offered loads and different path capacities. The simulation results depicted by Table I and Figure 2 agree with the theorem presented earlier by showing that (1) the switching time increase with s and (2) decreases with the difference between the path capacities. The impact of these findings is evaluated in the following section where these results are used to achieve different routing configurations.

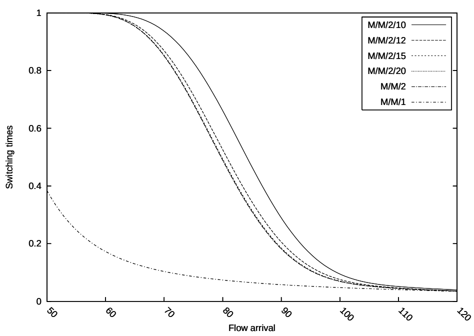


Fig. 2. *Switching times variations*

B. *Modeling a network*

We conducted another set of simulation experiments to evaluate the performance achieved by the test network when modeling the set of parallel paths using the *”same queuing model”* and *”differentiated queuing model”*. Preliminary results depicted respectively by figures (3) and (4) show that using *”differentiated queuing”* leads to better performance compared to using the *”same queuing model”*.

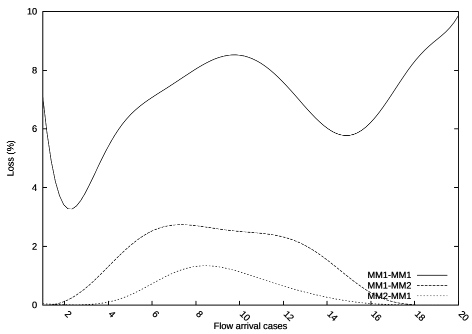
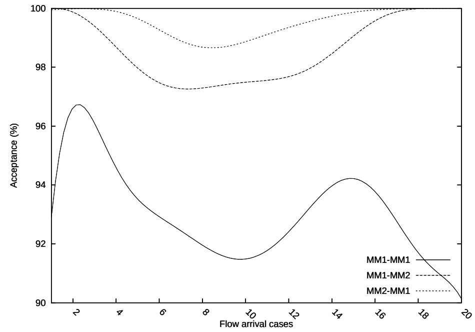


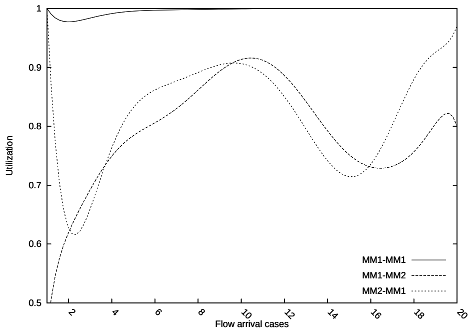
Fig. 3. *Flow lost*

V. CONCLUSION

This paper has presented a TE model where a network is modeled as a set of parallel paths where the traffic offered is distributed among the existing paths using Pontryagin Minimum Principle. We modeled the set of parallel paths using different queuing models. We illustrated the use of this TE model in a network by modeling the set of parallel paths using *same queuing model* and a hybrid model using *differentiated queuing* for different path sets. Preliminary simulation results revealed the efficiency of using *differentiated queuing* compared to the *same queuing* model.



(a) Flow acceptance



(b) Shared link utilization

Fig. 4. *Optimality parameters*

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