University of Würzburg
Institute of Computer Science
Research Report Series

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Report No. 363   June 2005

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Abstract

In this paper, we consider configurable capacity tunnels. *Static bandwidth allocation* (SBA) assigns the network capacity to the tunnels according to the busy hours of their traffic aggregates. At secondary times, their capacity is underutilized and can not be used to accommodate excess traffic of other tunnels. The contribution of this paper is twofold. Firstly, we propose two mechanisms for *adaptive bandwidth allocation* (ABA) for the tunnels: *complete capacity reassignment* (CCR) and *selective capacity reassignment* (SCR). They both adapt the tunnel capacities to the current traffic demands but differ in their implementation, signaling, and configuration complexity. Secondly, we asses the bandwidth savings of ABA vs. SBA in wide area networks where the transfer rates of traffic aggregates fluctuate over time according to busy hours. Our results show that the capacity savings strongly depend on the traffic model and that they may be increased by time-aware routing.

1 Introduction

Configurable capacity tunnels are a popular means for traffic engineering in today's Internet. In MPLS, label switched paths (LSPs) are established through a network and associated with a guaranteed bandwidth [1]. Another area of application is network admission control (NAC). So-called border-to-border (b2b) budgets (BBBs) provide virtual capacity tunnels through a network. From now on, we use BBBs and capacity tunnels as synonyms. In contrast to a single LSP, a BBB can consist of a multi-path between border nodes. Per-flow admission control (AC) is then performed only at the ingress routers based on the capacity of the BBBs [2]. In the following, we explain the considered problem, give an overview of related work, and comment the structure of this work.

Static bandwidth allocation (SBA) assigns the network capacity to the capacity tunnels according to the busy hours of their traffic aggregates. At secondary times, the capacity is underutilized and can not be used to accommodate excess traffic of other tunnels. In local area networks (LANs), the busy hours of all traffic aggregates coincide. Therefore, it is not likely that one capacity tunnel is overloaded while another tunnel is underutilized. This is different in wide area networks (WANs) because the busy hours of the aggregates depend on the time zones of their border routers. Here, SBA seems to be too inflexible and adaptive bandwidth allocation (ABA) should be applied, i.e., the tunnel capacities are adapted to the current demands of their traffic aggregates. In this paper, we suggest two mechanisms for ABA. Complete capacity reassignment (CCR) reoptimizes and reconfigures all capacity tunnels based on a trigger. Selective capacity reassignment (SCR) reoptimizes and reconfigures the capacity of only those tunnels whose current traffic aggregates deviate significantly from planned values. CCR is easier to implement but SCR reduces the signaling and configuration efforts. In addition, we assess the bandwidth savings of ABA vs. SBA in WANs by comparing the overall required network capacity with either approach. We achieve a fair comparison by considering an AC application. We dimension the capacities for both allocation schemes in such a way that admission-controlled flows face the same blocking probabilities.

The general network design problem (NDP) [3] covers traffic estimation [4], (virtual) network topology design [5, 6, 7], capacity dimensioning [8] and routing [9]. Bandwidth allocation [10, 11] is part of that problem. Therefore, many issues of the NDP have been studied intensively in the context of various technologies. The efficiency of AC methods combined with different bandwidth allocation strategies has been compared in many studies. Typically, the network topology, link capacities, and the traffic matrix are given. The resulting flow blocking probabilities are simulated or analyzed based on a common traffic model and serve for a performance comparison. This performance evaluation approach has often been applied in the context of call blocking analysis in multi-service ATM networks [6, 12, 13] and multi-layer architectures [14].

In contrast, our performance analysis rather quantifies bandwidth savings. The network topology, the traffic matrix, and a target flow blocking probability are given and the required network capacity is calculated in our experiments. To the best of our knowledge this is the first paper opposing bandwidth allocation methods in such a manner. From our perspective, this kind of comparison leads to more significant results in practice regarding the economy of the compared systems than the above comparison methodology.

This paper is structured as follows: In Section 2, we briefly review our used NAC scheme and explain SBA for BBBs. Section 3 introduces two mechanisms for ABA. In Section 4, we propose several traffic models that capture the busy hours of aggregates with border routers in different time zones and compare the required capacity for ABA vs. SBA in a wide area test network. Finally, Section 5 summarizes this work.
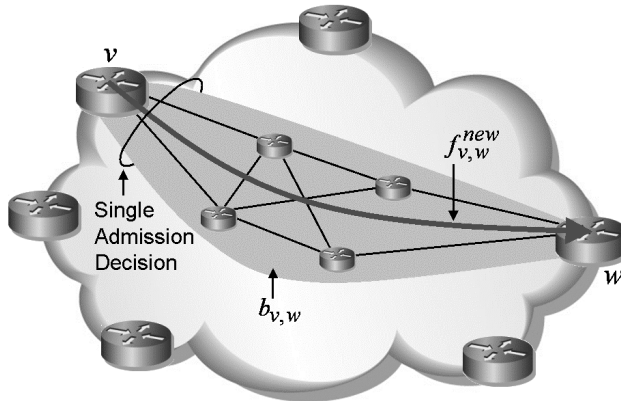
Figure 1: BBB NAC Architecure

2 Border-to-Border Budget Based Network Admission Control (BBB NAC)

We briefly review the BBB NAC architecture and explain how network capacity is assigned to the BBBs. This directly corresponds to static bandwidth allocation (SBA) but is also the base for adaptive bandwidth allocation (ABA, cf. Sec. 3).

2.1 BBB NAC Architecture

Admission control (AC) is a means to guarantee QoS in terms of limited packet loss and delay. It admits flow requests if sufficient resources, e.g. link capacity, are available to carry the new flow and the already admitted flows without significant packet loss and delay; otherwise, the flow is blocked. When the scope of AC is extended from a single link to an entire network, several fundamental network admission control (NAC) approaches [2] can be categorized. One of them is the BBB NAC which proved to be very resource-efficient. Due to its technical simplicity and economical superiority, the BBB NAC was implemented successfully in the testbed of the KING project (Key components for the Internet of the Next Generation) [15]. The BBB NAC is implemented in various forms. A first example are label switched paths (LSPs) in MPLS with guaranteed bandwidth. They constitute tunnels through the network that correspond to BBBs. This system conforms to BBB NAC if the ingress routers perform AC for their LSPs. In KING, the network architecture was purely IP-based. In contrast to LSPs, the traffic is carried on multi-paths in this implementation and the BBB NAC proved to be perfectly suitable for that purpose.

In a KING network, BBBs $b_{v,w}$ are defined between each two border routers v and w (cf. Fig. 1). BBB NAC entities are located at the network egde. They admit flows from v to w recording their requested rates and reject flows if their requested rates

exceed the remaining free capacity of $b_{v,w}$. An advantage of the BBB NAC is that it does not induce states inside the core of the network. This is desired due to scalability and resilience reasons. The network capacity assigned to $b_{v,w}$ is exclusively dedicated to the corresponding b2b aggregate $g_{v,w}$ and can not be used for traffic with different ingress or egress router. Figure 1 illustrates that a new flow $f_{v,w}^{new}$ passes only a single AC procedure at the network edge for a specific BBB $b_{v,w}$.

2.2 Dimensioning BBBs with Static Bandwidth Allocation (SBA)

The BBBs require enough capacity to carry the expected traffic with sufficiently low flow blocking. For the sake of simplicity, the concepts for appropriate BBB capacity assignment presented in this paper do not consider resilience but they can be extended for that purpose [2].

In the planning phase of a network, link capacities are not fixed, yet. Therefore, the required capacity for BBB $b_{v,w}$ is calculated to carry the expected offered load $a_{v,w}$ with a sufficiently low blocking probability. We assume a Poisson model for the flow arrivals and a generally distributed holding time. We work with rate requests of different size which increases the variance in our traffic model. These are realistic assumptions for a multi-rate real-time multimedia Internet [16, 17]. The well-known Kaufman-Roberts algorithm [18] computes the blocking probability given the offered load and the link capacity. Our capacity dimensioning algorithm for AC inverts this formulae in an efficient way such that we can determine the required capacity for all BBBs. The required link capacities are calculated by summing up the capacities of the budgets whose aggregates are transported over the specific link, i.e., the routing information comes into play.

When the link capacities of a network are already given, the BBBs must be configured in such a way that the admissible traffic rate never exceeds the link capacity and that the blocking of all b2b aggregates is as low as possible.

In practice, the sum of all required link capacities is easier to compare than effective blocking probabilities for all b2b aggregates. Therefore, we use the network dimensioning approach to compare the efficiency of SBA and ABA in Sec. 4. In addition, this performance measure tells about the capacity savings potential of these methods.

3 Adaptive Bandwidth Allocation (ABA)

If the traffic matrix is static, the BBBs need to be dimensioned only once which is static bandwidth allocation (SBA). As a result, we can calculate blocking probabilities for all b2b aggregates, which we call the planned values. However, if the traffic matrix changes, the b2b-specific flow blocking probabilities may deviate from these planned values. As a result, blocking probabilities can become very large for some aggregates and very low for some others meaning that their BBB capacity is underutilized. Adaptive bandwidth allocation (ABA) solves this problem by adapting the BBB capacities to the changed load conditions. We propose two concepts for ABA: (1) complete capacity reassignment (CCR) which reoptimizes and reconfigures the entire network; (2) selective capacity

reassignment (SCR) which adapts and reconfigures only those budgets that deviate significantly from their planned blocking probabilities.

First, we explain the architectural requirements for the network to perform ABA. Then we develop the two ABA concepts.

3.1 Network Requirements

To trigger an ABA mechanism, we need a qualified feedback from the network about the current traffic load and the corresponding flow blocking probabilities. Basically, both can be acquired through measurements. However, there are two reasons why we do not measure the blocking probabilities directly. First, blocking probabilities are usually in the order of 10^{-3} or below and a relatively long time is required to get a good estimate. Secondly, we want to detect situations with high blocking probabilities before they actually occur in order to avoid them.

Instead of observing the blocking probabilities directly, we rather observe the time-variant traffic matrix. Traffic matrix estimation is a difficult problem [4] but LDP statistics can provide sufficient support to derive an appropriate estimate of the current traffic matrix [19]. In our case, we use the counters of the BBB NAC entities. We then calculate the blocking probabilities by means of the Kaufman-Roberts algorithm based on the time-variant traffic matrix and a reasonable estimate of the request rate distribution obtained from the BBB NAC entities, as well.

An intelligent entity is required to gather all the network monitoring information and to calculate thereon the BBBs. This entity might also be used to remotely (re-)configure the BBBs in the network. In contrast to , e.g. a bandwidth broker, the entity might be implemented such that it is not vital to normal network operation. If so, the BBB capacity assignment can be performed offline.

3.2 Concepts for Adaptive Bandwidth Allocation

3.2.1 Complete Capacity Reassignment (CCR)

If triggered, the CCR method recalculates and reconfigures all BBBs in the network. There are two options to define a trigger. The most intuitive is to iterate the CCR in regular time intervals and is therefore independent of the current network state. A small interval requires much computation power and causes high signaling and configuration costs while a long interval leads to large response times and unnecessary blocking. Both extremes must be avoided.

Another method is to explicitly trigger the CCR whenever the flow blocking probability of one or more BBBs leaves a predefined tolerance interval (TI). Each BBB has a TI that provides an upper and lower bound for the corresponding flow blocking probability. CCR is triggered only if the current blocking probability changes significantly, i.e., if it leaves its TI. The TIs may be be defined as $TI = [p \cdot exp(-c), p \cdot exp(c)]$ where p is the planned flow blocking probability from the last CCR and c is a deviation parameter which controls the mean time between consecutive CCRs. The trigger for CCR can therefore be a capacity under- or overprovisioning in the BBBs.

3.2.2 Selective Capacity Reassignment (SCR)

The SCR also uses TIs and is based on the following idea. When the capacity assignment process is applied for the first time to initialize all BBBs, a fraction of all link capacities remains unassigned and is retained in a free resource pool (FRP). The flow blocking probabilities resulting from this initial process are considered as the planned values. If some flow blocking probabilities leave their TIs by the time, only the capacity of the affected BBBs is adapted by acquiring more capacity from the FRP or by returning excessive capacity to the FRP. This reduces the overall computation and configuration effort drastically. If the capacity in the FRP is depleted, all budgets are reinitialized. This leads to new planned values for the flow blocking probabilities and a fraction of all link capacities is again retained in the FRP.

4 Performance Evaluation of ABA vs. SBA

The benefit of ABA consists of potential bandwidth savings that increase with the temporal variability of the traffic matrix. With SBA, the bandwidth of each BBB must be dimensioned for its respective busy hour. In general, a link carries the traffic of various aggregates. If the busy hours of different aggregates occur at different times, less capacity may be required on a link if the BBBs adapt to their current demands. In this section we quantify the bandwidth savings potential of ABA.

4.1 Experiment Design

Figure 2 shows our test network. The nodes are located in different time zones and the population of the associated cities and surroundings are given. In the following, we briefly describe the traffic demand models for our experiments. First, we construct static traffic matrices. Then we make these traffic matrices time-dependent such that the busy hours between border nodes occur accoring to their associated time zones.

4.1.1 Static Traffic Matrices

Based on the average offered b2b load a_{b2b} in Erlang and the number of border nodes $|\mathcal{V}|$, we define the overall offered network load as $a_{tot} = a_{b2b} \cdot |\mathcal{V}| \cdot (|\mathcal{V}| - 1)$. For each pair of ingress/egress nodes v and w, the offered load $a_{v,w}$ is obtained

$$a_{v,w} = \begin{cases} \frac{a_{tot} \cdot \pi(v) \cdot \pi(w)}{\sum_{x,y \in \mathcal{V}, x \neq y} \pi(x) \cdot \pi(y)} & \text{if } v \neq w \\ 0 & \text{if } v = w \end{cases} \tag{1}$$

where $\pi(v)$ is the population of city $v \in \mathcal{V}$. We can control the value $a_{v,w}$ by setting a_{b2b} and use it in the following as a peak load for a time-dependent offered load.
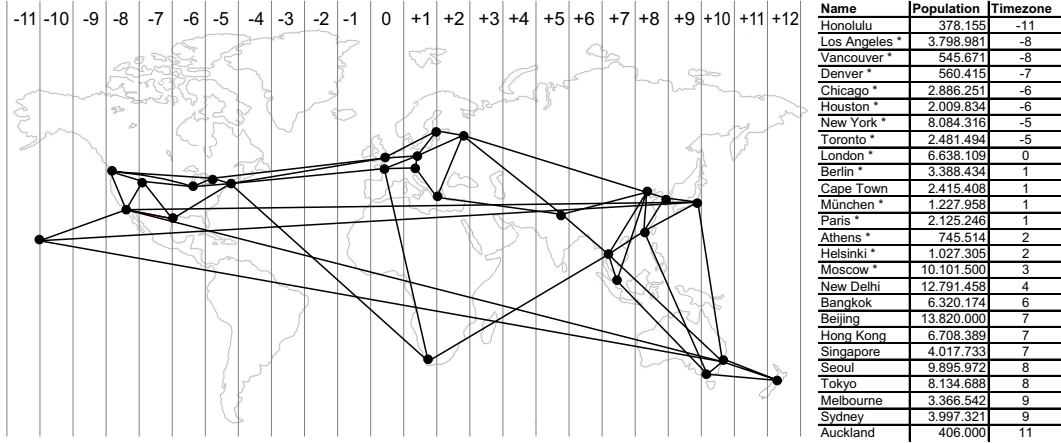
Name	Population	Timezone
Honolulu	378.155	-11
Los Angeles *	3.798.981	-8
Vancouver *	545.671	-8
Denver *	560.415	-7
Chicago *	2.886.251	-6
Houston *	2.009.834	-6
New York *	8.084.316	-5
Toronto *	2.481.494	-5
London *	6.638.109	0
Berlin *	3.388.434	1
Cape Town	2.415.408	1
München *	1.227.958	1
Paris *	2.125.246	1
Athens *	745.514	2
Helsinki *	1.027.305	2
Moscow *	10.101.500	3
New Delhi	12.791.458	4
Bangkok	6.320.174	6
Beijing	13.820.000	7
Hong Kong	6.708.389	7
Singapore	4.017.733	7
Seoul	9.895.972	8
Tokyo	8.134.688	8
Melbourne	3.366.542	9
Sydney	3.997.321	9
Auckland	406.000	11

Figure 2: Topology and population of our test network

4.1.2 Dynamic Traffic Matrices

For the construction of time-dependent variable traffic matrices, we define for each node $v \in \mathcal{V}$ an activity function that depends on the coordinated universal time (UTC) t and the time zone of v:

$$\text{active}(v,t) = \begin{cases} 0.1 & \text{if localtime}(v,t) \in [0{:}00; 6{:}00) \\ 1 - 0.9 \cdot \left(\cos \left(\frac{(\text{localtime}(v,t) - 6h)\pi}{18h} \right) \right)^{10} & \text{if localtime}(v,t) \in [6{:}00; 24{:}00) \end{cases} \tag{2}$$

The function $localtime(v,t) = (t + \tau(v) + 24) \bmod 24 \; \forall t \in [0{:}00; 24{:}00)$ defines the local time at node $v \in \mathcal{V}$ at UTC t with $\tau(v)$ being the time zone offset. The activity function is illustrated in Figure 3 and may be interpreted as the percentage of active population in the region of border router v.

We identify three simple options for the time dependency of the traffic load $a_{v,w}(t)$ between any two border routers:

Linearity to provider activity (LPA) With LPA the offered load is proportional to the provider activity: $a_{v,w}(t) = a_{v,w} \cdot active(v,t)$. LPA traffic may be caused by client-server applications, where the clients are triggered by human beings and push content to a server, e.g. for backup purposes.

Linearity to consumer activity (LCA) With LCA the offered load is proportional to the consumer activity: $a_{v,w}(t) = a_{v,w} \cdot active(w,t)$. LCA traffic may be caused by client-server applications, where the clients are triggered by human beings and pull content from a server, e.g. with web surfing. LPA and LCA provide similar traffic matrices. From our perspective, the LCA model is more realistic than LPA. Hence, we consider only LCA and LPCA in the following.
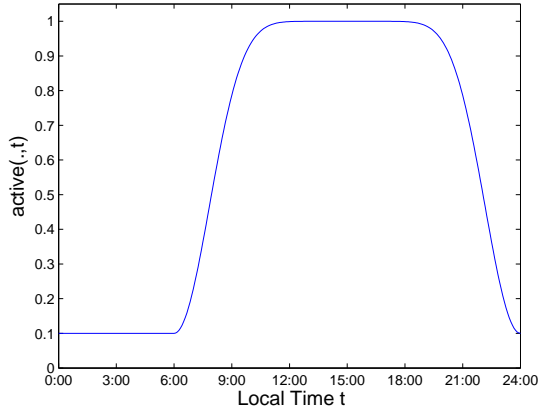
Figure 3: Node activity over 24h

Linearity to provider and consumer activity (LPCA) With LPCA the offered load is proportional to the provider and the consumer activity: $a_{v,w}(t) = a_{v,w} \cdot active(v,t) \cdot active(w,t)$. LPCA traffic may be caused by peer-to-peer applications, where content is exchanged among peers that are controlled by human beings. The peers may request and offer contents at the same time.

4.2 Capacity Dimensioning

ABA and SBA may be combined with BBB NAC. In the following we explain the calculation of the required link capacities for both methods. A flow blocking probability of at most 10^{-3} must be guaranteed with either approach.

4.2.1 Capacity Dimensioning for SBA

The traffic matrix $A_{max} = [max_t(a_{v,w}(t))]_{v,w \in \mathcal{V}}$ contains for each b2b aggregate its maximum offered load over all times t. These values have to be supported by the BBBs with staticaly assigned capacity. The capacity c_l of link l is then calculated as the sum of capacities of those BBBs whose aggregates are carried on l. In our experiments we use single-path routing. With multi-path routing the fraction of the aggregate on the links must be respected. Finally, we calculate the sum $\mathcal{C}_{tot}^{SBA}$ of the maximum link capacities c_l.

4.2.2 Capacity Dimensioning for ABA

We reoptimize the network every 5 minutes during a 24 hours day cycle. More precisely, we dimension the links based on the time-dependent traffic matrices $A(t = i \cdot 5 \text{ min})$, which yields time-dependent link capacities $c_l(t)$. The actually required link capacity $c_l = max_t(c_l(t))$ is the maximum of all link capacities at any possible time t. Finally, we calculate the sum $\mathcal{C}_{tot}^{ABA}$ of the maximum link capacities c_l.
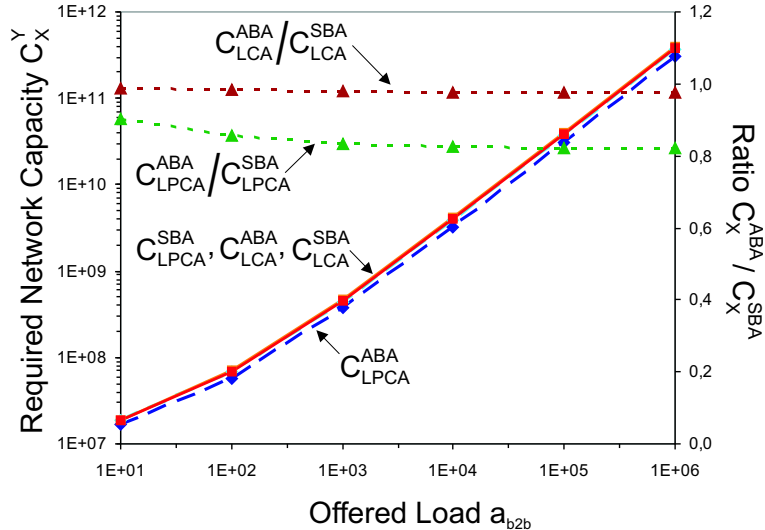
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Figure 4: Bandwidth savings with ABA for different traffic demand models

4.3 Numerical Results

The performance measure in our study is the overall required network capacity $\mathcal{C}_X^Y$. We calculate it for all combinations of traffic model $X \in \{LCA, LPCA\}$ and bandwidth allocation method $Y \in \{SBA, ABA\}$. Fig. 4 shows the required network capacity $\mathcal{C}_X^Y$ for a flow blocking probability of 10^{-3} depending on the offered b2b load a_{b2b}.

It is obvious that the required network capacity scales with a rising offered load. The capacity curves for $\mathcal{C}_{LCA}^{SBA}$, $\mathcal{C}_{LCA}^{ABA}$, and $\mathcal{C}_{LPCA}^{SBA}$ almost coincide and only $\mathcal{C}_{LPCA}^{SBA}$ is clearly visible as a separate line. The ratio $\mathcal{C}_{LCA}^{ABA}/\mathcal{C}_{LCA}^{SBA}$ depicted on a linear scale by the upper curve shows that almost no bandwidth savings ($\approx 2\%$) can be achieved with ABA if we consider the LCA model. In contrast, if we take the LPCA model into account, more significant bandwidth savings of about 18% can be obtained as illustrated by the curve labeled $\mathcal{C}_{LPCA}^{ABA}/\mathcal{C}_{LPCA}^{SBA}$ in Figure 4. The achievable capacity savings depend on the offered load a_{b2b} and siginificant savings can only be realized for sufficiently high values $a_{b2b} \geq 10^4$ Erlang. The figure also shows that the bandwidth savings stabilize with increasing offered load.

To understand this phenomenon, we study the link capacity requirements for both traffic models over 24 hours. Figure 5 (a) shows them for the link Seoul $\rightarrow$ Tokyo and Fig. 5 (b) for the link Bangkok $\rightarrow$ Beijing. The curves result for a blocking probability of 10^{-3} and a b2b offered load $a_{b2b} = 10^4$. In both cases, the maximum required link capacity is about the same for SBA and ABA in the presence of the LCA model (slashed lines). For LCA, the maximum link capacity for ABA is also required over a longer period of time than for LPCA. The LPCA traffic model allows for a bandwidth savings of 50% on the link Seoul $\rightarrow$ Tokyo when ABA is used instead of SBA. This is not possible on the link Bangkok $\rightarrow$ Beijing.
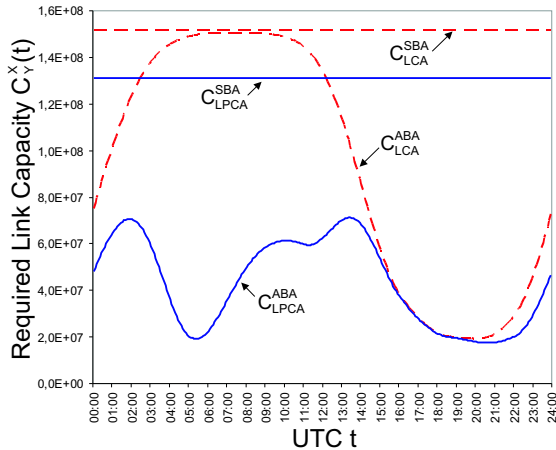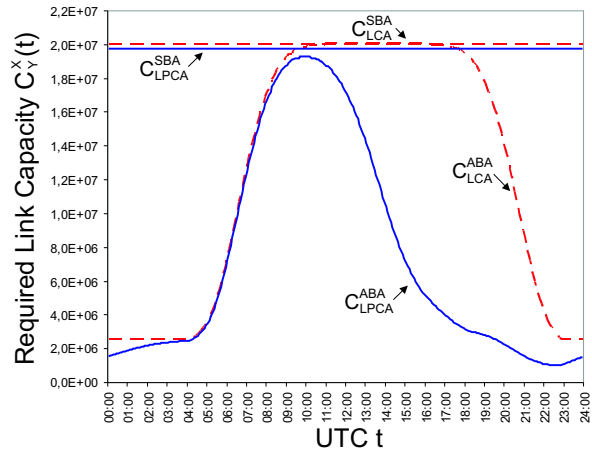
(a) Link Seoul → Tokyo   (b) Link Bangkok → Beijing

Figure 5: Impact of traffic demand models on required link capacities

We can explain these effects by further analyzing the traffic composed by sets of b2b aggregates on both links. Each aggregate has its own time-dependent capacity requirements and they are superposed on a single link. The LCA leads to a longer busy period of $a_{v,w}(t)$ than LPCA and this propagates to the time-dependent capacity requirements on a specific link. If the busy periods become shorter with LPCA compared to LCA, they are likely to occur temporally displaced. The reduced overlapping of busy periods decreases the maximum required link capacity for ABA. This is observed on the link Seoul → Tokyo that carries 30 different b2b aggregates which have border routers in different time zones. In contrast, the link Bangkok → Beijing supports only 22 different b2b aggregates whose border routers are not distant enough to achieve overlap-free busy periods for the LPCA traffic demand model.

Hence, ABA achieves significant capacity savings only if the busy periods of the traffic aggregates on a link do not overlap. Therefore, the savings potential of ABA vs. SBA may be increased by time-aware routing. This strategy is pursued in the KING project.

5 Conclusion

In this paper we considered adaptive bandwidth allocation (ABA) for virtual capacity tunnels – so-called border-to-border budgets – in wide are networks. We thereby investigated the impact of different traffic demand models on the bandwidth savings potential of ABA. Static bandwidth allocation (SBA) assigns the network capacity to the budgets according to the busy hours of their corresponding traffic aggregates. If the traffic matrix is highly variable, this leads to underutilization of some budgets and increased blocking probabilities at others. Adaptive bandwidth allocation (ABA) avoids this problem by adapting the capacity assigned to the budgets according to the current

traffic demand. We have presented two different ABA mechanisms named complete and selective capacity reassignment (CCR/SCR). The first approach tunes the network to the optimal point of operation whereas the second one changes only budgets with significantly underutilized capacity or severely increased blocking probabilities. Please note that the presented concepts for ABA could equally fit into a (G)MPLS environment, as they apply for the adaptation of configurable capacity tunnels in general.

We quantified the advantage of ABA over SBA by calculating the overal required network capacity with either method for a wide area test network. We constructed traffic matrices proportionally to the user activity at the network nodes and considered two different traffic demand models: linearity to consumer activity (LCA) and linearity to provider and consumer activity (LPCA) which have a major impact on the bandwidth savings potential. Capacity savings were hardly achievable with LCA ($\approx 2\%$), whereas more significant savings ($\approx 18\%$) could be obtained with the LPCA model.

The analysis of the utilization of individual links showed that the capacity savings can be increased if the routing compiles the traffic on a link in such a way that the busy hours of the participating border-to-border traffic aggregates occur at different times. This gives room to further optimization by time-dependent routing.

Acknowledgements

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