Improving Experience-Based Admission Control through Traffic Type Awareness

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Abstract— **Experience-based admission control (EBAC) is a hybrid approach combining the classical parameter-based and measurement-based admission control. EBAC calculates an appropriate overbooking factor used to overbook link capacities with resource reservations in packet-switched networks. This overbooking factor correlates with the average peak-to-mean rate ratio of all admitted traffic flows on the link. So far, a single overbooking factor is calculated for the entire traffic aggregate. In this paper, we propose type-specific EBAC which provides a compound overbooking factor considering different types of traffic that subsume flows with similar peak-to-mean rate ratios. The concept can be well implemented since it does not require measurements of type-specific traffic aggregates. We give a proof of concept for this extension and compare it with the conventional EBAC approach. We show that EBAC with type-specific overbooking leads to better resource utilization under normal conditions and to faster response times for changing traffic mixes.**

Index Terms— **admission control, reservation overbooking, quality of service, resource & traffic management**

I. INTRODUCTION

Internet service providers operating next generation networks (NGNs) are supposed to offer quality of service (QoS) to their customers. As the packet-based Internet protocol (IP) technology becomes more and more the basis of these networks, QoS in terms of limited packet loss, packet delay, and jitter is required to support real-time services. There are two fundamentally different methods to implement QoS: capacity overprovisioning (CO) and admission control (AC). With CO the network has so much capacity that congestion becomes very unlikely [1], [2], but this also implies that its utilization is very low even in the busy hour. Although CO is basically simple, it requires traffic forecasts and capacity provisioning must be done on a medium or long time scale.

In contrast, AC works on a smaller time scale. It grants access to flows with QoS requirements if the network load is sufficiently low and rejects excessive flow requests to shelter the network from overload before critical situations occur. QoS is thus realized by flow blocking during overload situations. Compared to CO, AC requires less capacity and yields better resource utilization at the expense of more signaling, coordination and state management [3]–[5] especially in the context of a network-wide AC [6].

A. Conventional Link Admission Control

In this work, we focus on link-based AC, i.e., on AC methods that protect a single link against overload. These methods are usually extended for application in networks on, e.g., a link-by-link basis. AC approaches can coarsely be classified into parameter-based AC (PBAC), measurement-based AC (MBAC), and derivatives thereof.

1) Parameter-Based Admission Control: PBAC, also known as (a priori) traffic-descriptor-based AC, is an approach appropriate for guaranteed network services [7], i.e., for traffic with imperative QoS requirements. It relies solely on traffic descriptors that are signaled by sources or applications and that describe the traffic characteristics of a flow, e.g. its mean and peak rate together with token bucket parameters. If an admission request succeeds, bandwidth is reserved and guaranteed to the new flow. PBAC is often inefficient regarding its resource utilization since the traffic descriptors usually overestimate the actual rate to avoid packet delay and loss due to spacing or policing. With PBAC, traffic is limited either by deterministic worst case considerations like network calculus [8], [9] or by stochastic approaches such as effective bandwidth [10]. In addition, PBAC calculations for heterogeneous traffic mixes can be very complex.

2) Measurement-Based Admission Control: MBAC, in contrast, is an AC method adequate for controlled load network services [11], i.e. for traffic with less stringent QoS requirements. It measures the current link or network load in real-time and takes a rate estimate of the new flow to make the admission decision. The determination of the traffic characteristics is thus shifted from the source or application to the network, and the specified traffic descriptor, e.g. the peak rate, can be very simple. MBAC can be classified into different approaches.

- *Aggregate-oriented MBAC (A-MBAC)* Most MBAC approaches measure the traffic properties of the entire traffic aggregate admitted to the link. The effective bandwidths of a flow is only required for the initial admission decision when the requested bandwidth is compared to the available link capacity.

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For that purpose, the rate of the admitted traffic aggregate is sufficient. A-MBAC has two advantages. The traffic measurement is simple since no per flow measurement states have to be managed and the statistical properties of a stationary traffic aggregate are more stable than those of individual traffic flows. On the other hand, the admission of new flows and the termination of others make the traffic aggregate a non-stationary process which must be carefully observed [12]. Comparisons of different A-MBAC approaches can be found in [13]–[19].

- *Flow-oriented MBAC (F-MBAC)* Some MBAC approaches use flow-specific measurements to assess the bandwidth consumption of each traffic flow individually. The initial effective bandwidth of a new flow is calculated based on its declared traffic descriptor. As soon as the confidence in the measurements of an admitted flow is high enough, its initial bandwidth is substituted by a calculated update based on the measured traffic parameters. Examples of F-MBAC methods are given in [20]–[23].

All previously addressed MBAC methods use real-time measurements and admit traffic as long as enough capacity is available. The downside of MBAC is its sensitivity to measurement accuracy and its susceptibility to traffic prediction errors which can occur, e.g., during QoS attacks, i.e., when admitted traffic flows are temporarily "silent" to provoke an underestimation of the admitted traffic rate and congest the link later by simultaneously sending at high bitrate.

B. Experience-Based Admission Control

To the best of our knowledege, experience-based AC (EBAC) is the first hybrid AC approach that takes advantage of traffic measurements without real-time requirements. It uses information about previously admitted traffic and past measurements to make current admission decisions.

The concept of EBAC is introduced in [24]. Its details are described in [25] and can be summarized as follows: with EBAC, a new flow is admitted to a link at time t if its peak rate together with the peak rates of already admitted flows does not exceed the link capacity multiplied by an overbooking factor $\varphi(t)$. The overbooking factor is calculated based on the reservation utilization of the admitted flows in the past. Hence, this method relies on experience. EBAC also requires traffic measurements to compute the reservation utilization, but these measurements do not have real-time requirements and thus influence the admission decision only indirectly. The proof of concept for EBAC is given in [25] by simulations and corresponding waiting time analyses of the admitted traffic. In particular, the steady state performance of EBAC is investigated for traffic with static characteristics. Since MBAC methods are sensitive to traffic variability, we investigate the behavior of EBAC in the presence of traffic changes in [26], [27]. Those changes may be due to variations on the packet and/or the flow scale level of the traffic. In [26], traffic changes on the packet scale level are investigated with regard to the performance of EBAC. A single overbooking factor is calculated based on the traffic characteristics of the entire admitted traffic aggregate. This article is based on the results of [27] and focuses on traffic changes on the flow scale level. We extend EBAC towards type-specific overbooking (TSOB), i.e., we make the EBAC mechanism aware of different traffic types and use additional information about the individual characteristics of these traffic types and about the composition of the admitted traffic mix to calculate a compound overbooking factor $\varphi_c(t)$. We therefore consider different types of traffic subsuming flows with similar peak-to-mean rate ratio and also their share in the currently admitted traffic mix. The TSOB extension of EBAC can be well implemented since it does not require type-specific measurements. We give a proof of concept for EBAC with TSOB and compare it with the conventional EBAC approach. We show that EBAC with TSOB leads to better resource utilization under normal traffic conditions and to faster response times in case of changing traffic mixes. Unlike conventional EBAC, the extension completely prevents congestion due to overreservation if the fraction of flows with high reservation utilizations increases in the traffic mix, i.e., if the traffic intensity increases due to a changing composition of the admitted traffic mix.

The remainder of this article is organized as follows. In Section II, we review the EBAC concept. Section III describes our simulation design and the applied traffic model. Section IV proposes the extension of EBAC towards type-specifc overbooking (TSOB). The simulation results in Section V show the superiority of EBAC with TSOB over conventional EBAC. Further work on EBAC is briefly presented in Section VI. Section VII finally summarizes this work and gives a conclusion.

II. FUNDAMENTALS OF EXPERIENCE-BASED ADMISSION CONTROL (EBAC)

Experience-based AC (EBAC) is a hybrid approach combining functional elements of PBAC and MBAC in a novel AC concept. It therefore implements link admission control, but can be easily extended to a network-wide scope. EBAC relies on peak rate traffic descriptors which may be significantly overestimated in the signaled flow requests. The utilization of the overall reserved capacity gives an estimate for the peak-to-mean rate ratio (PMRR) of the traffic aggregate and allows for the calculation of a factor to overbook the link capacity. The idea is simple, but safety margins are required to provide sufficient QoS and questions arise regarding its robustness against traffic flows with varying rates and burstiness. In this section, we elaborate the EBAC concept and describe its basic functional components.

A. Admission Decision on a Single Link

EBAC makes an admission decision as follows. An AC entity limits the access to a link l with capacity c_l and records the admitted flows $\mathcal{F}(t)$ at any time t together with their requested peak rates $\{r_f : f \in \mathcal{F}(t)\}$. When a new flow f_{new} arrives, it requests for a peak rate $r_{f_{new}}$. If

$$r_{f_{new}} + \sum_{f\in\mathcal{F}(t)} r_f \leq c_l \cdot \varphi(t) \cdot \rho_{max} \tag{1}$$

holds, admission is granted and f_{new} joins $\mathcal{F}(t)$. Otherwise, the new flow request is rejected. Flows are removed from $\mathcal{F}(t)$ on termination. The experience-based overbooking factor $\varphi(t)$ is calculated by statistical analysis and indicates how much more bandwidth than c_l can be safely allocated for reservations. The maximum link utilization threshold ρ_{max} limits the traffic admission such that the expected packet delay W exceeds an upper threshold W_{max} only with probability p_W.

B. Calculation of the Maximum Link Utilization Threshold

The value of ρ_{max} depends significantly on the traffic characteristics and the capacity c_l of the EBAC-controlled link. Simple solutions are based on the $M/M/1-\infty$ and the $N{\cdot}D/D/1-\infty$ queuing system. Real-time traffic produced from, e.g., voice or video applications has a rather constant output rate that can be controlled by a spacer such that a maximum flow rate is enforced. Therefore, we calculate the threshold ρ_{max} based on the $N{\cdot}D/D/1-\infty$ approach, which assumes N homogeneous traffic flows in $\mathcal{F}$, each sending packets of constant size B (in bits) and with constant packet inter-arrival times A (in seconds). An analysis method for this queueing system is presented Section 15.2.4 of [10]. More details on the computation of ρ_{max} can be found in [25]. For the ease of simulation of changing traffic, we set the maximum link utilization to a conservative and constant value of $\rho_{max} = 0.95$.

C. Calculation of the Overbooking Factor

The overbooking factor $\varphi(t)$ depends on the admitted traffic $\mathcal{F}(t)$ which, in turn, depends on time t because new flows are admitted and existing ones terminate. For the computation of $\varphi(t)$, we define $R(t) = \sum_{f\in\mathcal{F}(t)} r_f$ as the reserved bandwidth of all admitted flows at time t and $C(t)$ denotes their unknown cumulated mean rate. EBAC measures the consumed link bandwidth $M(t)$ of the overall reservation $R(t)$. To obtain $M(t)$, we use measurements based on equidistant, disjoint intervals such that for an interval $I(t_i) = [t_i, t_i + \Delta]$ with length Δ, the measured rate $M(t_i) = \frac{\Gamma(t_i)}{\Delta}$ is determined by metering the traffic volume $\Gamma(t_i)$ sent during $I(t_i)$. For the rates $R(t)$ and $M(t)$, a time statistic for the reservation utilization $U(t) = \frac{M(t)}{R(t)}$ is collected. The values $U(t)$ are sampled in constant time intervals and are stored as hits in bins for a time-dependent histogram $P(t, U)$. From this histogram, the time-dependent p_u-percentile $U_p(t)$ of the empirical distribution of $U(t)$ can be derived by

$$U_p(t) = \min_u\{u : P(t, U \leq u) \geq p_u\}. \tag{2}$$

Since traffic characteristics change over time, the reservation utilization statistic must forget obsolete data to reflect the properties of the new traffic conditions. Therefore, we record new samples of $U(t)$ by incrementing the corresponding histogram bin by one and devaluate the contents of all histogram bins in regular devaluation intervals I_d by a constant devaluation factor f_d. The devaluation process determines the memory of EBAC. The reciprocal of the reservation utilization percentile is the overbooking factor

$$\varphi(t) = \frac{1}{U_p(t)} \tag{3}$$

which is computed each time a new value $U(t)$ is recorded in the histogram. To obtain a meaningful value for $U_p(t)$, enough statistical data must be collected before Equation (3) yields a reliable overbooking factor.

D. Peak-to-Mean Rate Ratio (PMRR)

The intrinsic idea of EBAC is the exploitation of the peak-to-mean rate ratio (PMRR) of the traffic aggregate admitted to the link. With EBAC, the signaled peak rate r_f of an admitted flow f is enforced by a traffic shaper. In contrast to reality, the mean rate c_f of a flow is known a priori in our simulations. We define the PMRR of a flow by $k_f = \frac{r_f}{c_f}$. Analogously, $K(t) = \frac{R(t)}{C(t)}$ denotes the PMRR of the entire traffic aggregate admitted to the link at time t. $K(t)$ is an upper limit for the achievable overbooking factor $\varphi(t)$.

E. Memory of EBAC

1) Implementation as Simple Histogram: The histogram $P(t, U)$, i.e. the collection and the aging of the reservation utilization statistic, implements the memory of EBAC. This memory correlates successive flow admission decisions and consequently influences the adaptation of the overbooking factor $\varphi(t)$ to changing traffic conditions on the link. The statistic aging process, characterized by the devaluation interval I_d and the devaluation factor f_d, makes this memory forget about reservation utilizations in the past. The parameter pairs (I_d, f_d) yield typical half-life periods T_H after which collected values $U(t)$ have lost half of their importance in the histogram. Therefore, we have $\frac{1}{2} = f_d^{T_H/I_d}$ and define the EBAC memory based on its half-life period

$$T_H(I_d, f_d) = I_d \cdot \frac{-ln(2)}{ln(f_d)}. \tag{4}$$

With Equation (4), different combinations of devaluation parameters (I_d, f_d) and $(I_{d'}, f_{d'})$ yield equal half-life periods if either $I_{d'} = ln(f_{d'})/ln(f_d^{(1/I_d)})$ or $f_{d'} = f_d^{(I_{d'}/I_d)}$ holds. However, these equations guarantee only that the two resulting histograms are identical at times $t = LCM(I_d, I_{d'})$, where LCM denotes the least common multiple. The reservation utilizations obtained in the intervals I_d and $I_{d'}$ are devaluated differently for the two parameter sets due to the length of the devaluation interval and the different devaluation factors. This leads to intermediate deviations between the two histograms and consequently to different overbooking factors.

2) Implementation as Time Exponentially-Weighted Moving Histogram: To express the performance of the EBAC memory by only its characteristic half-life period, we introduce the method of a time exponentially-weighted moving histogram (TEWMH) [28] which also improves the timeliness of the overbooking factor calculation. This method follows the principle of time exponentially-weighted moving average (TEWMA) [29] used to improve the timeliness of rate measurements, and it logically extends TEWMA for application to statistical histograms.

Based on the EBAC memory defined in Equation (4), we define the aging rate $a = \frac{ln(f_x)}{I_x}, x \in \{d, d'\}$. Rate a is constant for two parameter sets (I_d, f_d) and $(I_{d'}, f_{d'})$ if they yield the same half-life period T_H. Instead of incrementing the histogram bins by one, we weight the reservation utilization hits in the time interval $[t_i, t_i + I_x]$ exponentially by the weight factor $\frac{1}{e^{at}}$ and use the result as an increment for the bins. Parameter $t \in [0, I_x - 1]$ thereby denotes the time offset of the sampled reservation utilization in seconds since the last devaluation. This way, newer values $U(t)$ experienced in the interval $[t_i, t_i + I_x]$ become more important than older values and, as a consequence, all reservation utilizations gathered in this interval are evenly devaluated at its end. In addition, the histograms of both parameter sets are comparable at any time and always lead to identical overbooking factors depending only on the half-life period T_H.

III. EBAC PERFORMANCE SIMULATION

In this section, we first present the simulation design of EBAC on a single link and then describe the traffic model we used on the flow and packet scale level.

A. Simulation Design

We evaluate the performance of EBAC on a single link by discrete event simulation. The simulator is implemented in Java^{TM} and based on a simulation library called *JSimLib* which has been developed at the Chair of Distributed Systems of the University of Würzburg in the past years. The design of the simulation is shown in Figure 1. Different types of traffic *source generators* produce flow requests that are admitted or rejected by the *admission control* entity. The flows request reservations of different bandwidths which leads to different request-dependent blocking probabilities on a heavily loaded link. To avoid this, we apply trunk reservation [30], i.e., a flow is admitted only if a flow request with maximum reservation size could also be accepted. For an admission decision, the AC entity takes the overbooking factor $\varphi(t)$ into account and admits a flow if Equation (3) holds. In turn, the AC entity provides information regarding the reservations $R(t)$ to the *EBAC system* and yields flow blocking probabilities $p_b(t)$. For each admitted source, a *traffic generator* is instantiated to produce a packet flow that is shaped to its contractually defined peak rate. Traffic flows leaving the *traffic shapers* are then multiplexed on the buffered *link* l with capacity c_l. The link provides information regarding the measured traffic $M(t)$ to the EBAC system and yields packet delay probabilities $p_d(t)$, packet loss probabilities $p_l(t)$, and the packet waiting time $W(t)$. In the presence of traffic changes, an important performance measure for the EBAC mechanism is the overall response time $T_R(t)$, i.e., the time span required by the EBAC system to fully adapt the overbooking factor $\varphi(t)$ to a new traffic situation.

B. Traffic Model

In our simulations, the traffic controlled by EBAC is modelled on two levels, i.e. the flow scale level and the packet scale level. While the flow level controls the inter-arrival times of flow requests and the holding times of admitted traffic flows, the packet level defines the inter-arrival times and the sizes of packets of individual flows.

1) Flow Level Model: On the flow level, we distinguish different traffic source types, each associated with a characteristic peak-to-mean rate ratio (PMRR) and corresponding to a source generator type in Figure 1. The inter-arrival time of flow requests and the holding time of admitted flows both follow a Poisson model [31], i.e., new flows arrive with rate λ_f and the duration of a flow is controlled by rate μ_f. The mean of the flow inter-arrival time is given by $1/\lambda_f$ and the holding time of a flow is exponentially distributed with a mean of $1/\mu_f$. Provided that no blocking occurs, the overall offered load $a_f = \frac{\lambda_f}{\mu_f}$ is the average number of simultaneously active flows measured in Erlang. To saturate an EBAC-controlled link with traffic, the load is set to $a_f \geq 1.0$. The latter assumption allows for an evaluation of the EBAC performance under heavy traffic load such that some flow requests are rejected.

2) Packet Level Model: On the packet level, we abstract from the wide diversity of packet characteristics induced by the application of different transmission layer protocols. Since we are interested in the basic understanding of the behavior of EBAC, we abstain from real traffic patterns and define a flow of consecutive data packets simply by a packet size distribution and a packet inter-arrival time distribution. Both contribute to the rate variability within a flow that is produced by a traffic generator in Figure 1. To keep things simple, we assume a fixed packet size per flow and use a Poisson arrival process to model a packet inter-arrival time ditribution with rate λ_p. We are aware of the fact that Poisson is not a suitable model to simulate Internet traffic on the packet level [32]. We therefore generate Poisson packet streams and subsequentially police the individual flows with peak-rate traffic shapers (cf. Figure 1). The properties of the flows are significantly influenced by the configuration of these shapers. In practice, the peak rate r_f of a flow f is limited by an application or a network element and the mean rate c_f is often unknown. In our simulations, however, the mean rate is known a priori and, therefore, we can control the rate of flow f by its peak-to-mean rate ration (PMRR) $k_f = \frac{r_f}{c_f}$.

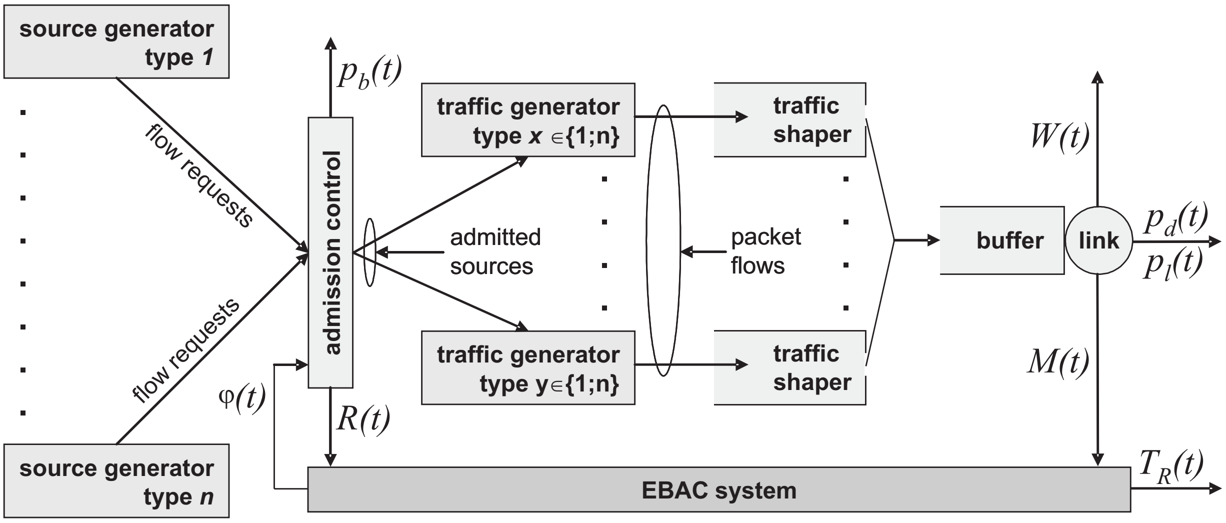

Figure 1. Simulation design for EBAC performance evaluation.

3) Traffic Variations: Traffic variations may be due to changes of traffic characteristics on the packet and/or the flow scale level. Variations on the packet level are caused by individual traffic sources that change their sending behavior. Variations on the flow level signify a change of the traffic mix. This article studies the performance of EBAC for traffic changes on the flow scale level. In the corresponding simulations, the traffic mix comprising flows with different characteristic PMRRs k_f varies over time which directly impacts the traffic load on the link. Hence, we investigate the transient behavior of EBAC through simulation of traffic changes which are caused by variations of the traffic mix and characterized by either a decrease or increase of the traffic intensity. In practice, applications know and signal the peak rates r_f of their corresponding traffic flows. The type of an application can be determined, e.g., by a signaled protocol number. We use only these limited information in our simulations. The mean rates c_f of the flows are not known to the EBAC measurement process, they are just model parameters for the packet flow generation and thus serve for controlling the rate of flow f by its PMRR $k_f = \frac{r_f}{c_f}$.

IV. EBAC WITH TYPE-SPECIFIC OVERBOOKING

In this section, we present type-specific overbooking (TSOB) as a concept extending EBAC. So far, we only consider the traffic characteristics of the entire aggregate of admitted traffic flows and calculate a single factor to overbook the link capacity. We now include additional information about the characteristics of individual traffic types and their share in the currently admitted traffic mix to calculate a compound type-specific overbooking factor. First, we describe the system extension and then we show how the compound overbooking factor for EBAC with TSOB can be estimated without type-specific traffic measurements. Finally, we present some simulation results showing the advantage of EBAC with TSOB over conventional EBAC.

A. EBAC System Extension

In general, the traffic aggregate on a link is composed of flows of different traffic types i for which the peak-to-mean rate ratios (PMRRs) K_i remain rather constant over time. Parameter i then denotes a traffic type subsuming flows of different applications but with similar PMRRs K_i. For admission, each flow is supposed to register at the AC entity with its peak rate and its traffic type. This yields type-specific aggregate reservations $R_i(t)$ for which $\sum_{i=0}^{n} R_i(t) = R(t)$ holds. On arrival of a new flow f_i^{new}, $R_i(t)$ is increased by the peak rate $r_{f_i^{new}}$ of the flow and it is decreased by the same rate when the flow terminates. The value $\alpha_i(t) = R_i(t)/R(t)$ then reflects the share of a traffic type i in the mix and the entire traffic composition consisting of n different traffic types is given by vector

$$\alpha(t) = \begin{pmatrix} \alpha_1(t) \\ \vdots \\ \alpha_n(t) \end{pmatrix}, \ \sum_{i=1}^{n} \alpha_i(t) = 1. \tag{5}$$

EBAC with TSOB uses information about the PMRRs K_i and the time-dependent traffic composition $\alpha(t)$ to determine type-specific reservation utilizations $U_i(t)$. In Section IV-B, we explain how the values $U_i(t)$ can be estimated without type-specific traffic measurements. The values $U_i(t)$ are stored as hits in bins of separate histograms $P_i(t, U)$ which yield type-specific reservation utilization percentiles $U_{p,i}(t)$. The EBAC admission decision for a new flow f_i^{new} of type i is then extended to

$$r_{f_i^{new}} \cdot U_{p,i}(t) + \sum_{f \in \mathcal{F}(t)} r_f \cdot U_{p,type(f)}(t) \leq c_l \cdot \rho_{max}. \tag{6}$$

We weight these percentiles $U_{p,i}(t)$ by their corresponding shares $\alpha_i(t)$ and finally calculate the compound overbooking factor for EBAC with TSOB as

$$\varphi_c(t) = \frac{1}{\sum_i \alpha_i(t) \cdot U_{p,i}(t)}. \tag{7}$$

B. Estimation of Type-Specific Reservation Utilizations

A crucial issue for the performance of EBAC with TSOB is the estimation of the type-specific reservation utilizations $U_i(t)$. Making type-specific measurements $M_i(t)$ would yield exact values for $U_i(t) = M_i(t)/R_i(t)$. For a reduced number of traffic classes, type-specific measurements seem feasible if we consider new network technologies such as differentiated services (DiffServ) [33] for traffic differentiation and multiprotocol label switching (MPLS) [34] for the collection of traffic statistics. However, current routers mostly do not provide type-specific traffic measurements and, therefore, we have to use the available parameters $M(t)$, $R(t)$, $R_i(t)$, and $\alpha(t)$ to estimate the values $U_i(t)$. In the following, we develop two methods to obtain estimates for the type-specific reservation utilizations.

1) Estimation with Linear Equation Systems (LES): The first method calculates the type-specific reservation utilizations $U_i(t)$ as results of a linear program and uses the equation $U(t) = \sum_i \alpha_i(t) \cdot U_i(t)$ setting up a linear equation system (LES, cf. e.g. [35]) of the form

$$\begin{pmatrix} U(t_{j-n}) \\ \vdots \\ U(t_j) \end{pmatrix} = \begin{pmatrix} \alpha_1(t_{j-n}) \dots \alpha_n(t_{j-n}) \\ \vdots \qquad\qquad \vdots \\ \alpha_1(t_j) \quad \dots \quad \alpha_n(t_j) \end{pmatrix} \begin{pmatrix} U_1(t_j) \\ \vdots \\ U_n(t_j) \end{pmatrix}, \tag{8}$$

where n is the number of traffic types and j denotes a time index. Let $\mathcal{A}(t_j)$ denote the matrix of column vectors $(\alpha_i(t_{j-x}))_{1 \leq i \leq n}$ in Equation (8), then we have $\mathcal{U}(t_j) = \mathcal{A}(t_j) \cdot \mathcal{U}_i(t_j)$. Hence, a unique solution of the LES requires probes of $U(t)$ and $\alpha(t)$ for $t \in [t_{j-n}, t_j]$ and n linearly independent columns in $\mathcal{A}(t_j)$, i.e. $\det(\mathcal{A}(t_j)) \neq 0$. We calculate a new solution of the LES every time the vector $\alpha(t)$ changes significantly, i.e., $\exists k : \frac{|a_k(t_i) - a_k(t_{i-1})|}{a_k(t_i)} > \epsilon$. A problem of estimating type-specific reservation utilizations with the LES method is that the linear independence of the matrix columns in $\mathcal{A}(t_j)$ is not guaranteed at any time t_j when the traffic composition changes. In this case, a unique solution for the equation system does not exist and the values $U_i(t_j)$ cannot be included in the histogram $P_i(t, U)$. Therefore, we simply insert the utilizations $U_i(t_{j-x})$ of the last feasible LES until a new linearly independent LES is found.

Algorithm 1 illustrates the computation of matrix $\mathcal{A}(t_j)$ with linearly independent column vectors. It takes the current traffic composition vector $\alpha(t_j)$, the previous matrix $\mathcal{A}(t_{j-1})$, and a set $\mathcal{L}$ of unused α-vectors as input parameters and returns a linearly independent matrix $\mathcal{A}(t_j)$ with $1 \leq i \leq n$ columns. The first call of this algorithm returns the transposed column vector $\alpha(t_i)$ to an $n \times 1$ matrix. For any further call, vector $\tilde{\alpha}(t_j)$ is initialized with $\alpha(t_j)$. If there are recent α-vectors not yet considered in $\mathcal{A}(t_{j-1})$, i.e. $\mathcal{L} \neq \emptyset$, then $\alpha(t_j)$ joins $\mathcal{L}$ and $\tilde{\alpha}(t_j)$ is set as an exponentially-weighted moving average (EWMA) [29] of all yet unconsidered α-vectors in $\mathcal{L}$. The EWMA is calculated over vector elements α_i such that

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Input:   traffic composition vector $\alpha(t_j)$,
         previous matrix $\mathcal{A}(t_{j-1})$,
         set $\mathcal{L}$ of unused vectors $\alpha(t)$

  if $\mathcal{A}(t_{j-1}) = NULL$ then
    $\mathcal{A}(t_j) := \alpha(t_j)^T$    {first call}
    RETURN($\mathcal{A}(t_j)$)
  else
    $\tilde{\alpha}(t_j) := \alpha(t_j)$
    if $\mathcal{L} \neq \emptyset$ then
      $\mathcal{L} := \mathcal{L} \cup \alpha(t_j)$
      $\tilde{\alpha}(t_j) :=$ BUILDEWMAVECTOR($\mathcal{L}$)
      NORMALIZE($\tilde{\alpha}(t_j)$)
    end if
    $\mathcal{A}(t_j) := \mathcal{A}(t_{j-1})$
    $n :=$ NUMBEROFELEMENTS($\alpha(t_j)$)
    if rank($\mathcal{A}(t_j)$) $= n$ then
      REMOVEFIRSTCOLUMN($\mathcal{A}(t_j)$)
    end if
    APPENDLASTCOLUMN($\mathcal{A}(t_j), \tilde{\alpha}(t_j)^T$)
    if $\det(\mathcal{A}(t_j)) \neq 0$ then
      $\mathcal{L} := \emptyset$
      RETURN($\mathcal{A}(t_j)$)
    else
      RETURN($\mathcal{A}(t_{j-1})$)
    end if
  end if

Output:  matrix $\mathcal{A}(t_j)$
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Algorithm 1: GENERATESHAREMATRIX: computation of linearly independent matrix column vectors.

$$\tilde{\alpha}_i(t_x) = \begin{cases} \alpha_i(t_{min}) \text{ if } t_{min} \text{ is earliest time index in } \mathcal{L} \\ \beta \cdot \tilde{\alpha}_i(t_{x-1}) + (1-\beta) \cdot \alpha_i(t_x) \text{ else.} \end{cases} \tag{9}$$

In Equation (9), the devaluation parameter $\beta \in [0, 1]$ controls the influence of older values $\tilde{\alpha}_i(t_x)$ whose impact decays exponentially with β. The computation of $\tilde{\alpha}(t_j) = (\tilde{\alpha}_1(t_j), \dots, \tilde{\alpha}_n(t_j))$ can lead to $\sum_{i=1}^{n} \tilde{\alpha}_i(t_j) \neq 1$ and, therefore, vector $\tilde{\alpha}(t_j)$ must be normalized after the application of the EWMA algorithm.

Finally, we construct a new matrix $\mathcal{A}(t_j)$ from the matrix $\mathcal{A}(t_{j-1})$ by removing the oldest α-vector from $\mathcal{A}(t_{j-1})$ and appending the transposed vector $\tilde{\alpha}(t_j)$ to it. However, if the input matrix $\mathcal{A}(t_{j-1})$ is not of size $n \times n$, a column is appended and none is removed. The constructed matrix $\mathcal{A}(t_j)$ is then tested for linear independency and, if $\det(A) \neq 0$, it is returned by the algorithm which also empties the set $\mathcal{L}$ of unconsidered α-vectors. Otherwise, the previous matrix $\mathcal{A}(t_{j-1})$ is returned.

Algorithm 1 requires at least n calls before it can provide a matrix with linearly independent column vectors as necessary for a unique solution of Equation (8). Since linear independency cannot be guaranteed for each new vector $\alpha(t)$, the continuous computation of current type-specific reservation utilizations by the LES method is not guaranteed. Therefore, this method must be considered as approximation of the type-specific reservation utilizations $U_i(t)$.

2) Estimation with Least Squares Approximation (LSA): The second approach estimates the type-specific reservation utilizations $U_i(t)$ using a least squares approximation (LSA, cf. e.g. [36]). For the ease of understanding, we illustrate this method, without loss of generality, for two different traffic types $i \in \{1, 2\}$. The variables $U_1(t)$ and $U_2(t)$ denote their type-specific reservation utilizations. The global reservation utilization is calculated as $U(t) = \alpha_1(t) \cdot U_1(t) + \alpha_2(t) \cdot U_2(t)$ and with $\alpha_1(t) + \alpha_2(t) = 1$ we get

$$U(t) = \alpha_1(t) \cdot (U_1(t) - U_2(t)) + U_2(t). \tag{10}$$

We substitute $a_j = U_1(t_j) - U_2(t_j)$ and $b_j = U_2(t_j)$ and obtain the least squares error ε for parameters $U_1(t)$ and $U_2(t)$ if we minimize the term

$$\varepsilon = \min_{a_m, b_m} \sum_{j=1}^{m} [U(t_j) - (\alpha_1(t_j) \cdot a_m + b_m)]^2. \tag{11}$$

The time index j thereby covers all values $U(t_j)$ and $\alpha(t_j)$ from the first probe ($j = 1$) to the last ($j = m$) ever determined by the EBAC system. We find the minimum of ε where the first derivatives of Equation (11) yield zero, i.e., we set $\frac{\partial\varepsilon}{\partial a} \overset{!}{=} 0$ und $\frac{\partial\varepsilon}{\partial b} \overset{!}{=} 0$ and resolve these equations to parameters a_m and b_m which yields

$$a_m = \frac{m \cdot \sum_j \alpha_1(t_j) U(t_j) - \sum_j \alpha_1(t_j) \cdot \sum_j U(t_j)}{m \cdot \sum_j \alpha_1(t_j)^2 - \left(\sum_j \alpha_1(t_j)\right)^2} \tag{12a}$$

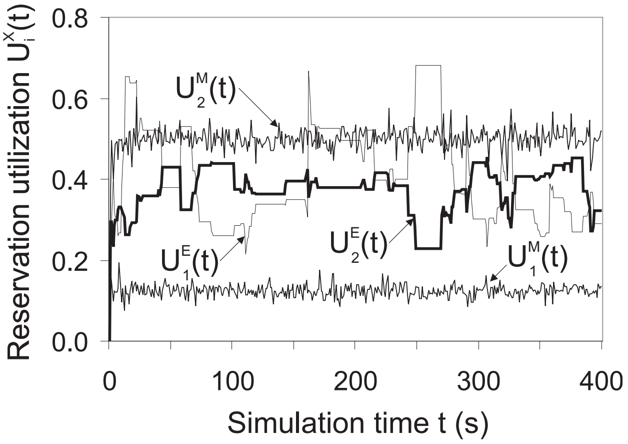
$$b_m = \frac{\sum_j U(t_j) \cdot \sum_j \alpha_1(t_j)^2 - \sum_j \alpha_1(t_j) \cdot \sum_j \alpha_1(t_j) U(t_j)}{m \cdot \sum_j \alpha_1(t_j)^2 - \left(\sum_j \alpha_1(t_j)\right)^2} \tag{12b}$$

for $1 \leq j \leq m$. The sums in Equations (12a) and (12b) can be computed iteratively which helps to cope with the large set of parameter values observed over all times t_j. To limit the effect of short-time fluctuations, we apply the TEWMA algorithm to these sums. Let $\mathcal{S}_m$ denote any of the sums in Equations (12a) and (12b) at time t_m, then the TEWMA at time t_{m+1} is

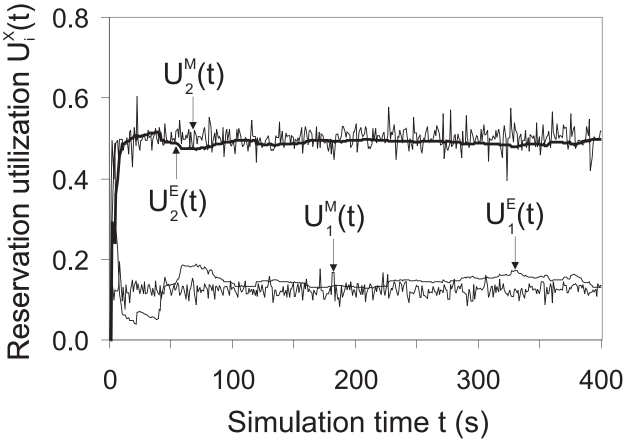
$$\mathcal{S}(t_{m+1}) = \mathcal{S}(t_m) \cdot e^{-\gamma \cdot (t_{m+1} - t_m)} + x(t_{m+1}). \tag{13}$$

In Equation (13), the devaluation factor $\gamma \in [0, 1]$ leads to an exponential decay of older values $x(t_{j \leq m})$ in the sum $\mathcal{S}$. This incremental implementation of the LSA method is efficient and enables its application to more than two different traffic types. With the calculated parameters a_m and b_m, the estimates for the type-specific reservation utilizations are finally obtained as $U_1(t_m) = a_m + b_m$ and $U_2(t_m) = b_m$.

3) Comparison of Measured and Estimated Type-Specific Reservation Utilizations: We perform simulations with both previously described methods estimating the type-specific reservation utilizations. For the sake of clarity, we simulate with only two different traffic types $i \in \{1, 2\}$. Type 1 has a mean PMRR of $E[K_1] = 2$ and an initial mean share of $E[\alpha_1] = 0.2$ in the traffic mix. Traffic type 2 is characterized by $E[K_2] = 8$ and $E[\alpha_2] = 0.8$. All simulations use the same seed for the random number generator to exclude effects of different statistical characteristics of the simulated traffic. This guarantees a fair comparison of the results.



(a) Estimation with linear equation systems



(b) Estimation with least squares approximation

Figure 2. Comparison of measured and estimated type-specific reservation utilizations.

Figure 2(a) shows a comparison of the measured type-specific reservation utilizations $U_i^M(t)$ and their corresponding estimates $U_i^{LES}(t)$ obtained by the LES method. Figure 2(b) compares the values $U_i^M(t)$ to their approximations $U_i^{LSA}(t)$ achieved with the LSA method. The measured and the type-specific reservation utilizations are determined every second. On the packet scale level of the traffic, we have Poisson distributed inter-arrival times which lead to short-time fluctuations for the measured values $U_i^M(t)$. These fluctuations are clearly damped by the TEWMA algorithm used for the estimated values $U_i^{LES}(t)$ and $U_i^{LSA}(t)$. Obvioulsy, the LES method is not feasible for the approximation of type-specific reservation utilizations since the resulting estimates deviate strongly from the exact measurements. The reason is that, in many cases, the linear equation system in Equation (8) does not yield a unique solution. In contrast, the LSA method provides good estimates for the corresponding measured utilizations. Hence, this approach enables EBAC with TSOB without type-specific traffic measurements and is used for the following performance comparisons.

V. PERFORMANCE COMPARISON OF CONVENTIONAL EBAC AND EBAC WITH TSOB

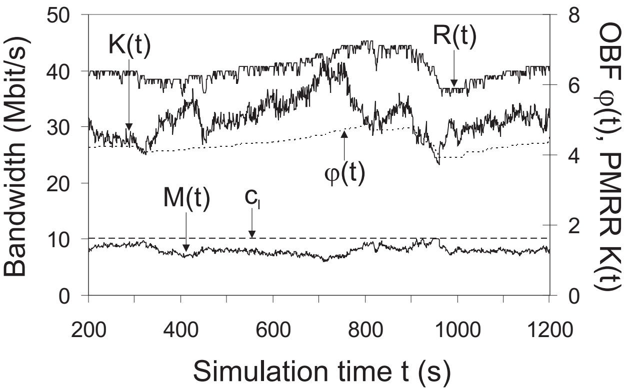
To investigate EBAC with TSOB, we perform a number of simulations each associated with a different traffic situation. For all simulations, we use a link capacity of $c_l = 10$ Mbit/s and simulate with two traffic types $i \in \{1, 2\}$ with characteristic peak-to-mean rate ratios (PMRRs) $E[K_1] = 2$ and $E[K_2] = 8$. A flow f_i of any type i reserves bandwidth with a peak rate $r_{f_i} = 768$ Kbit/s and has a mean holding time of $1/\mu_f = 90$ s. The mean interarrival time of flow requests is set to $1/\lambda_f = 750$ ms such that the link is saturated with traffic, i.e., some flow requests are rejected. For conventional EBAC we use the overbooking factor $\varphi(t)$ according to Equation (3) and for EBAC with TSOB, we calculate the factor $\varphi_c(t)$ according to Equation (7). We first investigate EBAC with TSOB for a rather constant traffic mix and then study its behavior for a suddenly changing traffic composition $\alpha(t)$.

A. Simulation with Constant Traffic Mix

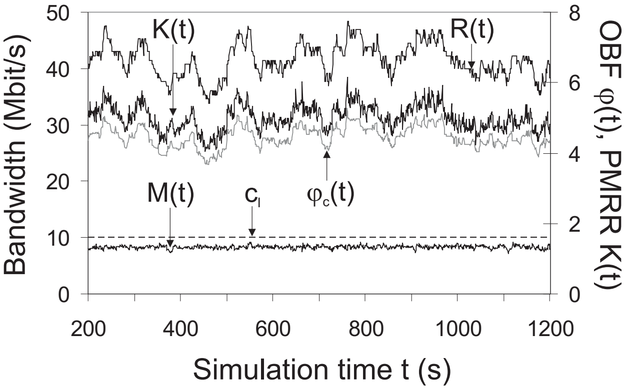
The first experiment simulates traffic with rather constant traffic shares $\alpha_i(t)$, i.e., the composition of the traffic mix remains constant except for statistical fluctuations. The results of a single simulation run are shown in Figure 3(a) for conventional EBAC and in Figure 3(b) for EBAC with TSOB. The mean shares of the traffic types in the aggregate are set to $E[\alpha_1] = 0.2$ and $E[\alpha_2] = 0.8$. We repeated this experiment 50 times to obtain reliable confidence intervals which proved to be very small. However, the illustration of a single simulation run shows more clearly the advantage of EBAC with TSOB over conventional EBAC. For EBAC with TSOB (cf. Figure 3(b)), the decreases of the PMRR $K(t)$ due to statistical fluctuations of $\alpha(t)$ lead to a significant decrease of the overbooking factor (OBF) $\varphi(t)$. The increases of $K(t)$ due to changing $\alpha(t)$ lead to a significant increase of $\varphi(t)$. For conventional EBAC (cf. Figure 3(a)), these changes happen rather slow and, therefore, the QoS may be at risk or the link capacity may be underutilized. In contrast, EBAC with TSOB adjusts its compound overbooking factor $\varphi_c(t)$ very quickly to the modifications of $\alpha(t)$ and, therefore, it is able to keep the measured rate $M(t)$ on a clearly more stable level than conventional EBAC. This, in turn, leads to better QoS and also improves the resource utilization.

B. Simulation with Changing Traffic Mix

In the following two simulation experiments, we focus on the reaction of EBAC with and without TSOB after a decrease or an increase of the traffic intensity. We consider sudden changes of the traffic composition $\alpha(t)$ to have worst case scenarios and to obtain upper bounds on the EBAC response times.



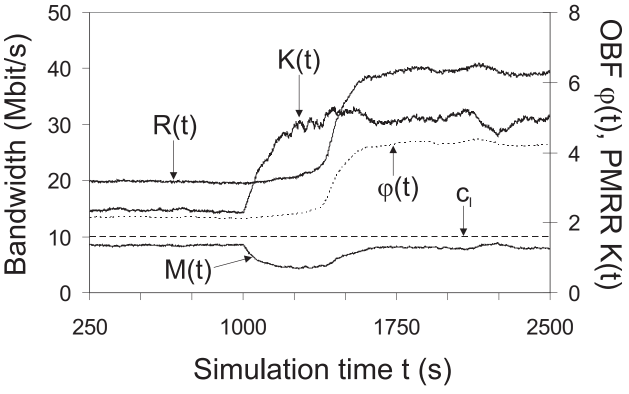
(a) Conventional EBAC



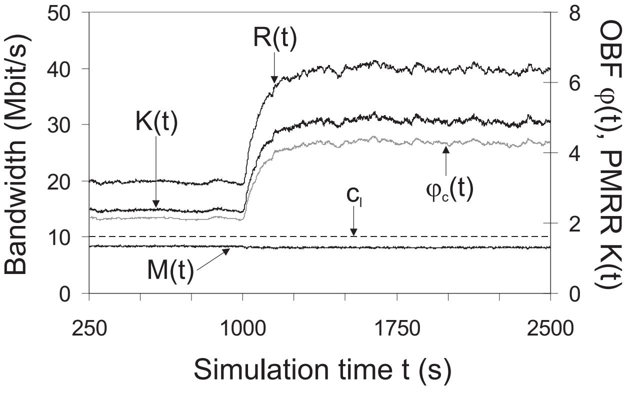
(b) EBAC with TSOB

Figure 3. Conventional EBAC vs. EBAC with TSOB for a constant traffic mix.

1) Simulation with Decreasing Traffic Intensity: We investigate the change of the traffic intensity from a high to a low value. Figure 4 shows the average results over 50 simulation runs. We use the same two traffic types with their characteristic PMRRs as before. However, we start with mean traffic shares $E[\alpha_1] = 0.8$ and $E[\alpha_2] = 0.2$. At simulation time $t_0 = 1000$ s, the mean shares of both traffic types are swapped to $E[\alpha_1] = 0.2$ and $E[\alpha_2] = 0.8$ by changing the type-specific request arrival rates, i.e., the traffic intensity of the entire aggregate decreases due to a change in the traffic mix $\alpha(t)$. This leads to a sudden increase of the PMRR $K(t)$ which results in an immediate decrease of the measured traffic $M(t)$ for conventional EBAC (cf. Figure 4(a)). With observable delay, the conventional EBAC system adapts its overbooking factor $\varphi(t)$ as a result of the slowly decreasing p_u-percentile $U_p(t)$ in the histogram $P(t, U)$. From other simulations [26] we know that this delay strongly depends on the EBAC memory defined by the half-life period T_H in Equation (4). In contrast, EBAC with TSOB (cf. Figure 4(b)) increases its overbooking factor $\varphi_c(t)$ almost at once since the p_u-percentiles of the type-specific histograms $P_i(t, U)$ remain rather constant.

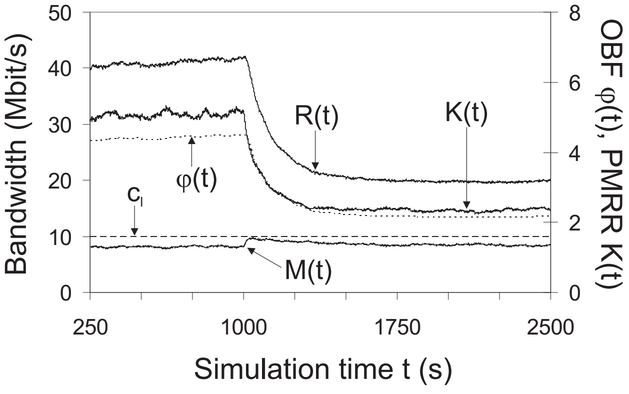


(a) Conventional EBAC

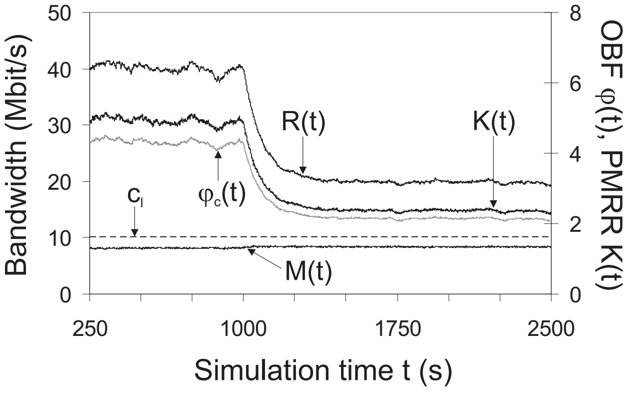


(b) EBAC with TSOB

Figure 4. Conventional EBAC vs. EBAC with TSOB during a decrease of the traffic intensity.



(a) Conventional EBAC



(b) EBAC with TSOB

Figure 5. Conventional EBAC vs. EBAC with TSOB during an increase of the traffic intensity.

Since only the shares of the traffic types in the mix have changed, the compound overbooking factor $\varphi_c(t)$ is immediately adapted. As a consequence, the faster reaction of EBAC with TSOB leads to a higher and more stable link utilization.

2) Simulation with Increasing Traffic Intensity: We now change the traffic intensity from a low to a high value which leads to a decrease of the PMRR $K(t)$ of the traffic aggregate. The simulation results are shown in Figure 5. Using the same two traffic types as before, we start with mean traffic shares $E[\alpha_1]=0.2$ and $E[\alpha_2]=0.8$ and swap them at simulation time $t_0=1000$ s to $E[\alpha_1]=0.8$ and $E[\alpha_2]=0.2$ by changing the type-specific request arrival rates. This increases the traffic intensity of the aggregate due to a change in the traffic mix $\alpha(t)$. In this simulation experiment, the QoS is at risk because flows with low traffic intensity are successively replaced by flows with high intensity and, therefore, the load on the link is rising. Conventional EBAC (cf. Figure 5(a)) reacts again slower than EBAC with TSOB (cf. Figure 5(b)) although this time, their speed of adapting the overbooking factor differs less. From other simulations [26] we know that the response time of conventional EBAC is independent of the EBAC memory in case of a sudden traffic increase. Our simluation results show that conventional EBAC yields a slightly higher link utilization compared to EBAC with TSOB. However, this high utilization comes at the expense of a violation of QoS guarantees as the measured traffic $M(t)$ consumes the entire link capacity c_l for a short period of time (cf. Figure 5(a)). As a consequence, the packet delay probability $p_d = P(\text{Packet delay} \geq 50\,\text{ms})$ increases, rising from $p_d = 0$ for EBAC with TSOB to a maximum of $p_d \approx 0.3$ for conventional EBAC in this experiment. This obviously favours the extension of EBAC towards type-specific overbooking.

VI. FURTHER WORK ON EBAC

This section briefly presents further work on experience-based admission control (EBAC). We illustrate the performance of EBAC in steady state and in the presence of traffic changes on the packet scale level. We also present a feasible application of EBAC in a network-wide scope.

A. EBAC in Steady State

The intrinsic idea of EBAC is the exploitation of the peak-to-mean rate ratio $K(t)$ of the traffic aggregate admitted to the link. In [25], we simulated EBAC on a single link with regard to its behavior in steady state, i.e., when the properties of the traffic aggregate are rather static. These simulations provided a first proof of concept for

EBAC. We showed for different peak-to-mean rate ratios that EBAC achieves a high degree of resource utilization through overbooking while packet loss and packet delay are well limited. Further simulation results allowed us to give recommendations for the EBAC parameters such as measurement interval length and reservation utilization percentile to obtain appropriate overbooking factors $\varphi(t)$. They furthermore showed that the EBAC mechanism is robust against traffic variability in terms of packet size and inter-arrival time distribution as well as against correlations thereof.

B. EBAC in the Presence of Traffic Changes

In [26], we investigated the transient behavior of conventional EBAC after sudden traffic changes on the packet scale level of admitted traffic flows. We analyzed the EBAC response time $T_R(t)$ and the QoS performance in terms of packet loss $p_l(t)$ and packet dealy $p_d(t)$ (cf. Figure 1) which are potentially compromised in case of traffic increases. As EBAC partly relies on traffic measurements, it is susceptible to changes of the traffic characteristics of admitted flows. There are certain influencing parameters coupled with this problem. One of them is the length of the EBAC memory which has been defined by its half-life period T_H (cf. Equation (4)). We evaluated the impact of the EBAC memory on a sudden decrease and increase of the traffic intensity expressed by changes of the peak-to-mean rate ratios of the simulated traffic flows. For a changing traffic intensity, the response time T_R required to adapt the overbooking factor to the new traffic situation depends linearly on the half-life period T_H. For decreasing traffic intensity, the QoS of the traffic is not at risk. For a suddenly increasing traffic intensity, however, it is compromised for a certain time span T_R^Q. The corresponding experiments used an unlimited link buffer and illustrate the performance of EBAC under extreme traffic conditions corresponding to a collaborative and simultaneous QoS attack by all traffic sources.

C. Application of EBAC in a Network Scope

The performance of EBAC has intensively been studied by simulations on a single link. A simple deployment of EBAC in a network-wide scope is the link-by-link application of the concept. However, this method requires a lot of signaling which may lead to scalability problems. Another option is to perform admission control only at the network border by using separate instances of EBAC at all network ingress routers. This approach guarantees scalability, but requires further investigation of the resulting distributed network admission control (NAC) system.

A prototype applying EBAC at the network border exists for the purely IP-based network architecture of the KING (Key components for the Internet of the Next Generation) project [37], [38]. Its implementation requires the collection, synchronization, and correlation of many distributed network information about, e.g., resource reservations of flows admitted at the ingress routers, traffic measurements on the links, routing and load balancing in the network. As a consequence, the network-wide admission decisions cannot be made independently of each other since they have a correlated impact on the link loads in the network.

However, if a network architecture fulfills certain requirements, the application of EBAC in the scope of a network is well feasible. The border-to-border (b2b) budget-based network admission control presented in [6] is a feasible approach which implements admission control at the border of a network and uses directed b2b tunnels with pre-determined capacities. For a simple deployment of EBAC in a network, these tunnel capacities can be overbooked by the EBAC mechanism like physical link capacities, i.e., the tunnels are considered as virtual links. This approach requires separate EBAC instances for all capacity tunnels and, hence, the complexity of the problem is now reduced to appropriate tunnel dimensioning and to b2b aggregate-specific traffic measurements. If the network is based on, e.g. the (generalized) multiprotocol label switching ((G)MPLS) architecture [34], [39], tunnels can be implemented as label switched paths (LSPs) between label edge routers (LERs) and traffic can be easily measured per tunnel. Traffic matrices determined with help of the label distribution protocol (LDP) [40] provide the necessary traffic measurements per LSP.

VII. CONCLUSION

Experience-based admission control (EBAC) is a new link admission control paradigm [24] representing a hybrid solution between parameter-based and measurement-based admission control. In this article, we gave a general overview of EBAC and, in particular, presented its extension towards type-specific overbooking (TSOB) which improves the original EBAC concept. We briefly reviewed the EBAC system and explained the simulation design and the traffic model used for the analyses of the performance of EBAC with and without TSOB. We simulated EBAC under changing traffic conditions on the flow scale level and presented the corresponding simulation results as the main contribution of this article. Finally, we summarized further work on EBAC regarding its steady state behavior [25], its behavior in the presence of traffic changes on the packet scale level [26], and its application in a network-wide scope.

The extension of EBAC towards TSOB [27] yields a compound overbooking factor which considers different traffic types subsuming flows with similar peak-to-mean rate ratios. A major challenge regarding this extension is the determination of type-specific reservation utilizations required to calculate the compound overbooking factor. In general, the traffic cannot be measured for type-specific aggregates and, as a consquence, the type-specific reservation utilizations cannot be obtained directly. Therefore, we proposed two different methods to estimate them. Only one method, based on a least squares approximation of the type-specific reservation utilizations, proved to be sufficiently accurate and was thus used for the further performance investigations. For the comparison between conventional EBAC and EBAC with TSOB, we simulated sudden changes on the flow scale level of the traffic mix to have worst case scenarios and to obtain upper bounds on the EBAC response times. To that aim, the share of flows with highly utilized reservations, i.e. the traffic intensity, was either suddenly decreased or increased. As a result, we found that if the traffic intensity decreases, EBAC with TSOB adapts faster than conventional EBAC and leads to a significantly better resource utilization during the adaptation phase. If the traffic intensity increases, the advantage of EBAC with TSOB over conventional EBAC becomes even more obvious. While EBAC with TSOB can prevent overload situations due to even extreme changes in the traffic mix, conventional EBAC has no appropriate means to avoid them.

This article provided a proof of concept for EBAC with TSOB but many technical details must be clarified before it can be deployed in practice. E.g., a reliable network-wide measurement system needs to be installed, an appropriate number of different traffic types for TSOB must be found, and applications with similar peak-to-mean rate ratios have to be identified and classified. These issues must certainly be solved. However, we already had a prototype of the conventional EBAC running in a real network testbed which showed the feasability to implement the concept.

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