SLA Adaptation for Service Overlay Networks

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Abstract. Virtual Network Operators lease bandwidth from different data carriers to offer well managed Virtual Private Networks. By using proprietary algorithms and leased resource diversity they can offer Quality of Service, at competitive prices, which is difficult to attain from traditional data network operators. Since maximizing the profit is a key objective for virtual network operators, in this paper we describe a novel resource management approach, based on an economic model that allows continuous optimizing of the network profit, while keeping network blocking constraints. The approach integrates leased link capacity adaptations with connection admission control and routing policies by using concepts derived from Markov Decision Process theory. Our numerical analysis validates the approach and shows that the profit can be maximized under varying network conditions.

Keywords: Service Overlay Network, Economic Model, Resource Management, Quality of Service, Markov Decision Process.

1 Introduction

With the continuing increase in popularity of the Internet, more and more applications are offered. However, since the Internet is formed by numerous interconnected Autonomous Systems (AS) operating independently, real time applications such as Voice over Internet (VoIP), Streaming Multimedia and Interactive Games are often unable to get their required end-to-end Quality of Service (QoS) guarantee. One possible approach to overcome the problem is to use global Service Overlay Networks (SON) [1], [2], where a set of overlay routers (or overlay nodes, ON), owned and controlled by one Virtual Network Operator (VNO), is interconnected by virtual overlay links (OL) realized by leasing bandwidth from the AS's via Service Level Agreements (SLA) [3].

In general there are two approaches to provide QoS in Service Overlay Networks. In the first approach, the VNO that manages the SON leases the best effort access to the AS's. In this case, to ensure availability of required bandwidth and QoS, the SON has to monitor continuously its OL's established over *best effort* Internet and react fast in case of some OL quality deterioration, e.g., by rerouting the connections on the paths with acceptable QoS. In the second approach the VNO leases the overlay links with appropriate bandwidth and QoS guarantees (e.g., based on the MPLS-TE technology). In this case user end-to-end QoS connections are realized through the SON admission control and routing policy. Obviously the VNO can use both types of leased bandwidth in a flexible and controlled way in order to reduce cost since best effort bandwidth is less expensive.

The above arguments indicate that Virtual Network Operators can potentially offer well managed QoS Virtual Private Network (VPN) at competitive prices, by using economically-sound SONs that can be managed by sophisticated proprietary control mechanisms adaptable towards the needs of particular clients. At the same time the VNOs can lease bandwidth from several different operators that removes the geographical barriers and also offers much better architecture for reliability and failure protection. These advantages led to creation of several VNOs like Internap (internap.com), Mnet (mnet.co.uk), Sirocom (sirocom.com), Vanco (vanco.co.uk), Virtela [4] (virtela.net), Vanguard (vanguardms.com), Netscalibur (netscalibur.com).

In this paper, we focus on resource management in SONs based on leased bandwidth with QoS guarantees (e.g., based on the MPLS-Traffic Engineering technology). In particular, we describe a novel framework, based on an economic model, which allows continuous network profit optimization. The approach integrates leased link capacity adaptations (to traffic and SLAs variations) with connection admission control and routing policies by using concepts derived from Markov decision process theory.

The paper is organized as follows. The framework for the SON economic model is described in Section 2. In Section 3, we present the resource adaptation model that constitutes the main element of the economic model. Numerical analysis validating the proposed approach is given in Section 4.

2 SON economic framework

In general, the cost of establishing and operating a SON can be divided into three parts: the initial cost of installing ON's and the maintenance center, the ongoing costs of the leased bandwidth according to SLA, and the ongoing maintenance costs. These costs should be covered by the revenue achieved from connection charges. The monetary and provided goods flows between the users, SON and AS's are illustrated in Fig. 1.

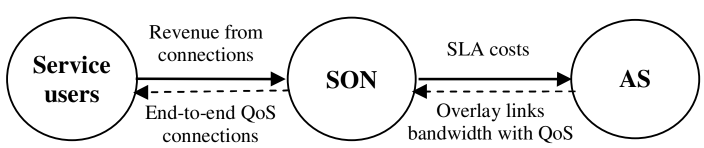

Fig. 1. SON economic framework.

To simplify presentation, assuming that the maintenance cost is proportional to SLA's cost, we can integrate them together in the total SON operation cost expressed as a sum of overlay link costs C_s (expressed as a cost per time unit). Further we assume that this total cost should be covered from the operating profit $\hat{P}$ and that the objective of the virtual operator of SON is to maximize this profit expressed as:

$$\hat{P} = \hat{R} - \sum_{s\in S} C_s = \sum_{j\in J} \overline{\lambda}_j \hat{r}_j - \sum_{s\in S} C_s \qquad \textbf{(1)}$$

where: $\hat{R}$: SON average revenue rate,

$\overline{\lambda}_j$: average rate of admitted class *j* connections,

$\hat{r}_j$: average revenue (price) for class *j* connections,

S : set of overlay links,

J : set of user connection classes.

In this formulation the maximization of the *revenue profit* can be achieved by leased bandwidth adaptation that influences the admission rate $\overline{\lambda}_j$ and cost C_s, and by adjusting the service prices $\hat{r}_j$. Note that a change of service price can influence the service demand [5] expressed in our model as the average rate of connection arrivals λ_j. The profit maximization should be done in such a way that the connection blocking probabilities B_j of all classes do not exceed the constraints B_j^c.

In general, the demand for SON services is variable due to factors like periodic variability in scale of a day, week, month, year, and variability caused by trends of increasing (decreasing) demand for certain services. Also bandwidth prices in SLA can fluctuate due to competition and market trends. Since the leased bandwidth amount within SLA can be adapted from time to time or even dynamically (on line), it is natural that the VNO needs a mechanism that can indicate when and how to adapt the SLA's to maximize profit while respecting the required blocking constraints. In this paper we describe a framework for such an approach.

The proposed framework is based on integration of a model for SLA adaptation with a model for CAC (call admission control) and routing that is based on Markov decision process. As it will be explained in Section 3, this integration provides two key advantages. First, the CAC and routing algorithm takes into account the costs of SLA and therefore the resource utilization is maximized taking into account their cost. Second, some statistics of CAC and routing parameters provide information indicating which SLAs should be adapted in order to maximize the profit.

It is important to emphasize that, as described in [6], in the proposed framework, besides the concept of revenue from connections, $\hat{r}_j$, we also use very similar concept of reward from connections, r_j. In general the reward from connections is a more general concept since it does not have to have monetary meaning and it can be treated as a control parameter. In our framework we first use the reward concept to maximize the *reward profit* from the network expressed as:

$$P = R - \sum_{s\in S} C_s = \sum_{j\in J} \overline{\lambda}_j r_j - \sum_{s\in S} C_s \qquad \textbf{(2)}$$

Then we determine $\hat{r}_j$ as a function of r_j. The reason for this dual approach is that it allows decomposition of the original problem (1) into two sub-problems. The first is optimal link bandwidth allocation for given connection arrival rates λ_j and blocking constraints B_j^c, that is solved by using the reward formulation (2). The outcome of resolving this sub-problem is a set of link bandwidth allocations and a set of connection reward parameters. The second sub-problem is to optimize $\hat{r}_j$ as a function of r_j. In the simplest case, one can assume that $\hat{r}_j = r_j$. Nevertheless the demand for services (λ_j) can be influenced by the choice of $\hat{r}_j$. In particular if the demand is significantly reduced for $\hat{r}_j = r_j$, one may need to reduce the revenue parameters in order to maximize the revenue profit (1). An approach to solve the second sub-problem is discussed in [6]. In the balance of this paper we concentrate on a solution of the first sub-problem. In particular we present a basic model for bandwidth adaptation assuming that connection reward parameters are given.

3 Resource Adaptation

In this section we describe a model for resource adaptation for given connection arrival rates. In Section 3.1 the applied CAC and routing policy based on Markov decision theory is presented. In Section 3.2 the mechanism for bandwidth adaptation is described for given reward parameters. Finally, in Section 3.3 we discuss the issue of adaptation of reward parameters in order to achieve the required blocking constraints. While the proposed framework is applicable to multi-class services with different bandwidth requirements, in this paper we will consider a network with homogeneous connections where all classes have the same bandwidth requirement and the same mean service time.

3.1 CAC and Routing Policy

For a network with given links dimensions and reward parameters, optimizing profit is realized with efficient use of available resources, through a CAC and routing policy which admits the connections on the most profitable routes. The policy used is a state dependent CAC and routing based on Markov Decision Process (MDP) theory [7]. In addition to dynamic link costs, defined in [7] as shadow prices, we integrated the costs of the SON physical overlay links, C_s, in the model.

As shown in [7, 8], for given reward profit rate, one can find an optimal CAC and routing policy that maximizes the average profit by using one of the standard MDP solution algorithms. In this paper, this exact approach is called the *MDP CAC and routing model*.

In the MDP model, the network state space is usually too large in realistic network examples. To overcome this problem, a decomposition technique, called *MDPD*, described in [7, 8], is applied. The technique uses a link independence assumption to decompose the network reward process into separable link reward processes. The decomposed process is described separately for each link s by the link state

$X=(x_j:j=1,2,\ldots)$ (where x_j is the number of class j connections admitted on the link), the link arrival and service rates λ_j^s, μ_j, and the link connection reward parameters r_j^s. In this paper, this approach is called the *MDPD CAC and routing model*. In this model, to integrate monetary link costs into the CAC and routing policy, we propose to divide connection reward into link connection rewards proportionally to the used resources cost:

$$r_j^s = r_j.(C_s/N_s)/(\textstyle\sum_{o\in S^k} C_o/N_o) \qquad \textbf{(3)}$$

where N_s : link s capacity (max number of connections)

S^k : set of links on path k

Then, analogously to.(2) the link expected profit is:

$$\overline{P}_s = \overline{R}_s - C_s = \textstyle\sum_{j\in J} \overline{\lambda}_j^s r_j^s - C_s \qquad \textbf{(4)}$$

where $\overline{\lambda}_j^s$ is the rate of admitted class j link connections.

In the MDPD model, a link net gain $g_j^s(X)$ is defined as the expected link reward increase from accepting an additional connection of class j. A state dependent link shadow price is then defined as the difference between the link reward and net gain. It represents the cost of accepting the class j call on link s in state X:

$$p_j^s(X) = r_j^s - g_j^s(X) \qquad \textbf{(5)}$$

During network operation, the link shadow prices can be calculated based on measurement of link connection arrival rates [7], [8]. Then the optimal CAC and routing policy will choose the connection path with the maximum positive net gain:

$$g_{\max} = \max_{k\in W_j}[r_j - \textstyle\sum_{s\in S^k} p_j^s(X)] \qquad \textbf{(6)}$$

If no path produces a positive gain, the connection is rejected.

3.2 Link Bandwidth Adaptation for Given Reward Parameters

With changing network conditions, such as traffic level or leased bandwidth cost, SON parameters should be adapted to continuously realize the reward profit maximization objective. As mentioned, the SON operator can control overlay links capacities (by modifying the SLAs) and reward parameters r_j. In this section, we concentrate on overlay link capacity adaptation with given reward parameters.

Profit Sensitivity to Link Capacity. In the MDPD model the network profit sensitivity to a link capacity can be approximated by the link profit sensitivity to the link capacity. Following equation (4) we have:

$$\partial\overline{P}_s/\partial N_s = (\partial\overline{R}_s/\partial N_s) - (\partial C_s/\partial N_s) \qquad \textbf{(7)}$$

It has been shown in [8] that the average reward sensitivity to link capacity can be approximated by the average link shadow price of a connection class with unit bandwidth requirement, $(\partial \overline{R}_s / \partial N_s) \cong \overline{p}_s(N_s)$. The value of the average link shadow price can be calculated or measured during execution of the CAC and routing algorithm. In the second term of (7), assuming that C_s is a linear function of N_s, we have $C_s = cN_s$ where c is the bandwidth unit cost. Substituting in (7), the link profit is maximized when $\partial \overline{P}_s / \partial N_s = 0$, i.e. at the solution for the following equation, which constitutes the base for the capacity adaptation procedure:

$$\overline{p}^s(N_s) - c = 0 \tag{8}$$

Bandwidth Adaptation Model. An iterative procedure is used to converge to the solution for (8), giving the optimized link capacity. In our case, we use Newton's successive linear approximations, in which the capacity new value N_{n+1} at each iteration step n is given by (link index s is omitted to simplify the notation):

$$N_{n+1} = N_n - \frac{\overline{p}_n - c}{[\partial(\overline{p}(N) - c)/\partial N]} \tag{9}$$

Approximating the derivative in equation (9) at iteration n:

$$\partial(\overline{p}(N) - c)/\partial N = \partial \overline{p}(N)/\partial N \cong (\overline{p}_n - \overline{p}_{n-1})/(N_n - N_{n-1}) \tag{10}$$

and substituting (10) in (9), the new capacity will be:

$$N_{n+1} = N_n - (N_n - N_{n-1})[(\overline{p}_n - c)/(\overline{p}_n - \overline{p}_{n-1})] \tag{11}$$

Link capacity adaptation is then realized by executing periodically the following steps for each link:

a. Estimate new average link shadow price $\overline{p}_n$ based on CAC and routing algorithm link shadow prices.
b. Calculate new value of link bandwidth:

$$N'_{n+1} = N_n + \alpha(N_{n+1} - N_n) \tag{12}$$

where N_{n+1} is from (11) and α is a damping factor used to improve convergence.
c. Round N'_{n+1} to the nearest value available from SLA and, if $N'_{n+1} - N_n$ exceeds the threshold of importance, use it as the new link capacity.

It is important to underline that the bandwidth adaptation procedure and the CAC and routing procedure (section 3.1) are integrated by the fact that link shadow prices obtained in the latter procedure are used in the capacity adaptations. In turn, CAC and routing policies adapt to changes in link capacities and in bandwidth unit costs.

3.3 Reward Parameter Adaptation to Meet the Blocking Constraints

The CAC algorithm rejects connection requests when bandwidth is not available or the connection is not profitable. The resulting blocking probabilities can be defined for each connection class j as:

$$B_j = (\lambda_j - \overline{\lambda}_j)/\lambda_j = 1 - (\overline{\lambda}_j/\lambda_j) \tag{13}$$

We define the network average blocking probability as:

$$B_T = \sum_j (\lambda_j - \bar{\lambda}_j) \Big/ \sum_j \lambda_j = \sum_j \lambda_j B_j \Big/ \sum_j \lambda_j = 1 - \left(\sum_j \bar{\lambda}_j \Big/ \sum_j \lambda_j\right) \quad \textbf{(14)}$$

As mentioned in Section 2, blocking probabilities should not exceed the network and/or class blocking constraints B_T^c and B_j^c . To achieve this objective we propose an adaptation of reward parameters, since in general the increase of r_j will cause decrease of B_j and B_T, and vice versa. Note that a change of r_j may influence the optimal solution for link bandwidth allocation. Therefore the adaptation of a reward parameter should be integrated with adaptation of link bandwidths. One possible relatively simple solution is to apply the two adaptation algorithms iteratively, as illustrated in Fig. 2. Network blocking constraint can be met by multiplying all class reward parameters *{r_j}* by a common factor *γ*.

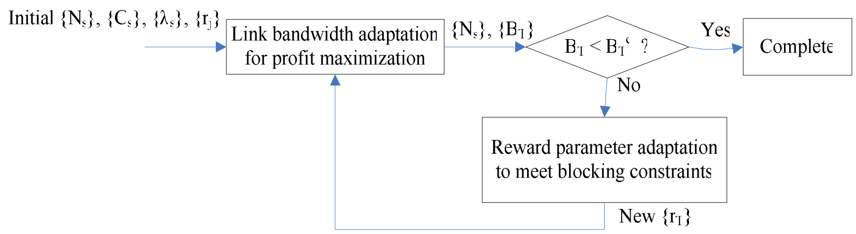

Fig. 2. SON adaptation algorithm

Once network constraint has been met, class blocking probabilities can be readjusted, as required to meet class constraints, by varying relatively the class reward parameters between them (while preserving the average network reward parameter). In this paper, we only consider meeting the network blocking constraint.

Let $r_T = \sum_j \bar{\lambda}_j r_j \Big/ \sum_j \bar{\lambda}_j$ and $r_s = \sum_j \bar{\lambda}_j^s r_j^s \Big/ \sum_j \bar{\lambda}_j^s = \sum_j \bar{\lambda}_j^s r_j^s \Big/ \bar{\lambda}_s$ be the current average network and link reward parameters. To achieve equality $B_T(r_T) = B_T^c$, one can apply Newton's iterations with an approximation for the derivative $\partial B_T / \partial r_T$.

At each iteration *n*, the new network reward parameter will be:

$$r_T^{n+1} = r_T^n + \frac{B_T^c - B_T^n}{(\partial B_T^n / \partial r_T^n)} \quad \textbf{(15)}$$

Since adaptation multiplies all class reward parameters by the same factor *γ*, all reward parameter relative differentials will be equal:

$$\partial r_j / r_j = \partial r_T / r_T = \partial r_s / r_s \quad \textbf{(16)}$$

Using (16) in the differentiation of (14) gives:

$$\frac{\partial B_T}{\partial r_T} = \frac{1}{\sum_j \lambda_j} \sum_j \left(\lambda_j \frac{r_j}{r_T} \frac{\partial B_j}{\partial r_j}\right) \quad \textbf{(17)}$$

To simplify calculation for $\partial B_j / \partial r_j$, we use the one moment performance model based on the link independence assumption, where link blocking probability B_s applies to all connection classes on the link. Then, connection path *k* and class *j* blocking probabilities are:

$$B^k = 1 - \mathbf{\Pi}_{s \in S^k} (1 - B_s) \qquad \textbf{(18)}$$

$$B_j = \Pi_{k \in W_j} B^k = \Pi_{k \in W_j} [1 - \Pi_{s \in S^k} (1 - B_s)] \qquad \textbf{(19)}$$

Differentiation of class blocking probability (19) gives:

$$\frac{\partial B_j}{\partial r_j} = \sum_{k \in W_j} \{[\mathbf{\Pi}_{o \in W_j \setminus \{k\}} (1 - \mathbf{\Pi}_{s \in S^o} (1 - B_s))] * \sum_{s \in S^k} \left[(\mathbf{\Pi}_{t \in S^k \setminus \{s\}} (1 - B_t)) * \frac{r_s}{r_j} \frac{\partial B_s}{\partial r_s} \right] \} \qquad \textbf{(20)}$$

To find link *s* blocking probability derivative $\partial B_s / \partial r_s$, we can use the formulation of the link average shadow price given in [8], which at optimal network profit (8) equals the bandwidth unit cost *c*:

$$\overline{p}_s = c = (\lambda_s / \overline{\lambda}_s)[E(\lambda_s, N_s - 1) - E(\lambda_s, N_s)] \sum_{j \in J^s} \overline{\lambda}_j^k r_j^s \qquad \textbf{(21)}$$

where *E(λ, N)* is the Erlang B formula. Based on (21), for a given *c*, differential δN_s required to maintain optimal profit condition corresponding to differential δr_s, is determined using the following:

$$E(\lambda_s, N_s + \partial N_s - 1) - E(\lambda_s, N_s + \partial N_s) = \frac{[E(\lambda_s, N_s - 1) - E(\lambda_s, N_s)] r_s}{r_s + \partial r_s} \qquad \textbf{(22)}$$

Using δN_s, link *s* blocking probability derivative is then approximated as:

$$\partial B_s / \partial r_s = [E(\lambda_s, N_s + \partial N_s) - E(\lambda_s, N_s)] / \partial r_s \qquad \textbf{(23)}$$

The adapted network reward parameter (15), obtained using (17), (20), (23), allows for determination of multiplier γ to be used for class reward parameters.

4 Numerical Analysis

In this section, we present numerical results for our resource adaptation model. Adaptation results are obtained based on each of the two cases of CAC and routing models (section 3.1): MDP and MDPD. The MDPD case allows for adaptations in realistic size networks, while the MDP case provides exact solutions which can be used to verify the approximate MDPD case. In both cases, the network performance evaluation (class blocking probabilities and flow distribution among the paths) is based on an exact model with exact network state. The advantage of using this exact performance model is that we can concentrate on key issues of profit optimization without being affected by the noise of an event-driven statistical simulation. The obvious limitation is that the network examples size is quite small due to the number of network states. In the future, we will present results based on event driven simulations that can handle realistic size examples.

In this analysis, we focus on the two important profit optimization process issues:

a. Link bandwidth adaptation to maximize profit, both in the MDPD model and the exact MDP model.
b. Reward parameter adaptation to meet the blocking constraints.

4.1 Analyzed Network Examples

To be able to process the exact analytical model, we limit network state space by using two simple network examples called *3L* and *5L*, where links capacities are also limited. Each network has three connection classes, each connecting a pair of nodes over direct or indirect paths. Connection classes arrival rates are $\lambda_1, \lambda_2, \lambda_3$, all have the same bandwidth requirement (1 unit), service rate (*μ=1)* and reward rate ($r_j=r=1$). Bandwidth unit costs are *0.2* in network *3L* and *0.1* in network *5L*. The networks are represented in Fig. 3 and 4, with connection class *1* shown. In network *3L*, connection classes *2* and *3* similarly connect respectively *ON2-ON3* and *ON3-ON1*. In network *4L*, connection classes *2* and *3* connect *ON0-ON2* and *ON0-ON3*.

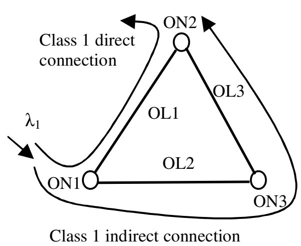

Fig. 3. Network 3L

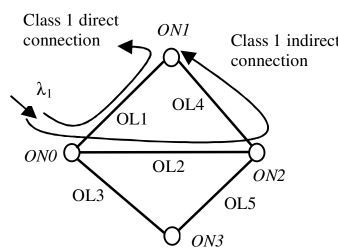

Fig. 4. Network 5L

4.2 Link Bandwidth Adaptation for Given Reward Parameters

Link Bandwidth Adaptation Convergence. To illustrate the convergence we use network 3L with initial link bandwidth set to $N_1 = N_2 = N_3 = 3$ and connection arrival rates set to $\lambda_1 = \lambda_2 = \lambda_3 = 3$. The link bandwidth adaptation procedure (with the damping factor set to one) is performed to obtain maximized network profit. The results are shown in Fig. 5. For both models, MDPD and MDP, the convergence to optimal links capacities of 6 is reached very fast after two iterations. Then we change arrival rates to $\lambda_1 = 4, \lambda_2 = 3, \lambda_3 = 2$ and the adaptation is performed again. The results are shown in Fig. 6 and 7 for MDPD and MDP models respectively. Both models converge to the same optimal values (N_1=7, N_2=6, N_3=4).

Numerical results for example network 5L, shown in Fig. 8, confirm the good convergence of the model to the optimal network profit.

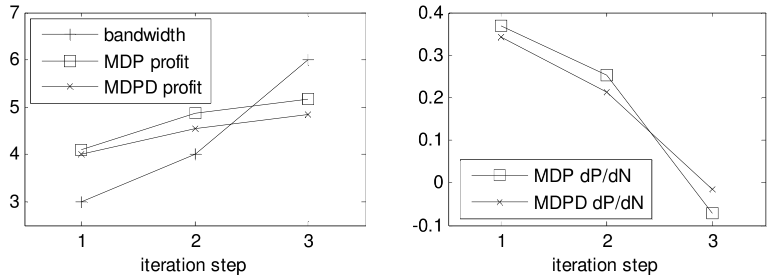

Fig. 5. Network 3L bandwidth adaptation, $\lambda_1 = \lambda_2 = \lambda_3 = 3$

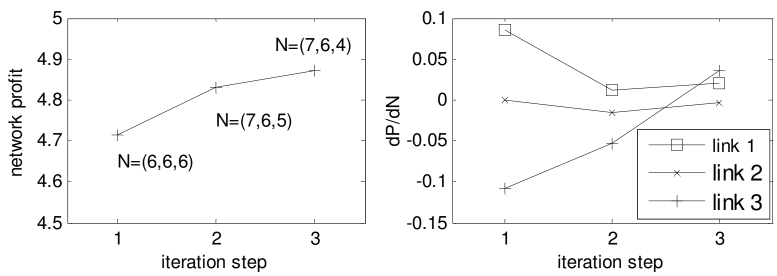

Fig. 6. Network 3L adaptation, MDPD, $\lambda_1 = 4, \lambda_2 = 3, \lambda_3 = 2$

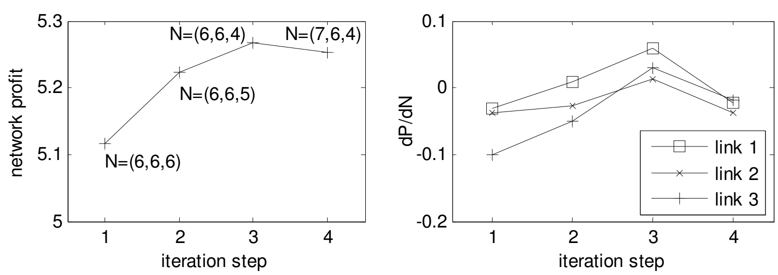

Fig. 7. Network 3L adaptation, MDP, $\lambda_1 = 4, \lambda_2 = 3, \lambda_3 = 2$

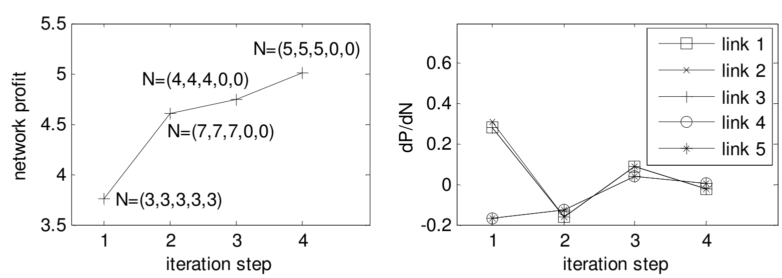

Fig. 8. Network 5L adaptation, MDP, $\lambda_1 = \lambda_2 = \lambda_3 = 3$

The presented results indicate good convergence of the proposed model. Also it is important that the approximate MDPD model converges to the same solution as exact MDP model with comparable convergence speed.

Convergence Improvement. Based on the shape of the profit sensitivity curve $\partial\overline{P}/\partial N_s\,(N_s)$, we noticed that, to improve convergence speed, the damping factor for positive derivative should be > 1, and the one for negative derivative should be < 1. More profound analysis of this issue will be given in a future publication, with experiments based on event driven simulation of larger network examples.

4.3 Reward Parameter Adaptation to Meet the Blocking Constraints

In this section, analysis results for using reward parameter adaptation to control network blocking probability are given. In the derivatives computation, we used simple linear interpolation to estimate fractional link capacities blocking probability. The adaptation algorithm is applied to network 3L with class arrivals *λ={4, 3, 2}*. For blocking constraint set at *2%*, results are represented in Fig. 9 while Fig. 10 shows the case when blocking constraint is set at *1%*.

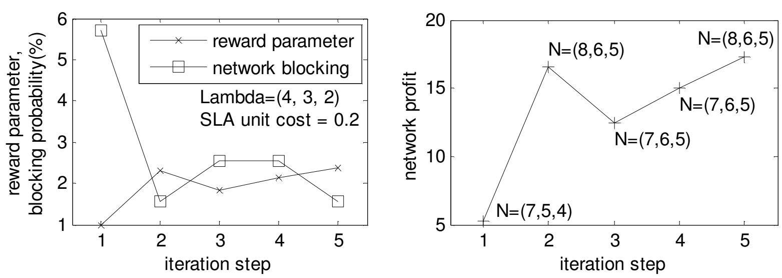

Fig. 9. Network 3L reward parameter adaptation, block constraint=2%

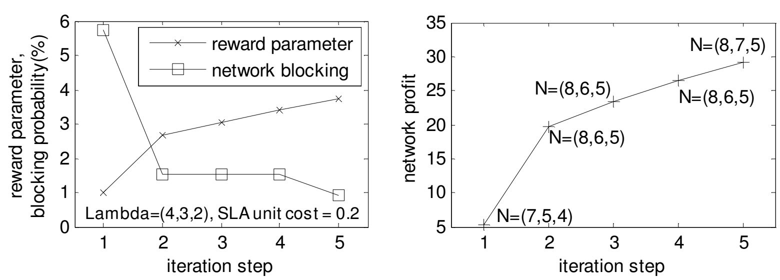

Fig. 10. Network 3L reward parameter adaptation, block constraint=1%

These results show that the adaptation algorithm can fulfill the blocking constraints in a few iterations.

5 Conclusions

In this paper, we proposed an economic framework for operating Service Overlay Networks with the objective of network profit maximization subject to blocking constraints. The framework uses Markov decision theory for integration of the CAC and routing model with the link bandwidth and reward parameter adaptation models. The key element of this integration is the concept of link shadow price that provides consistent economical framework for the whole problem. Preliminary numerical results validate the proposed approach by showing good convergence, although network examples are of limited size due to the exact analytical model used for network performance evaluation. Therefore, in a forthcoming publication, we will present a study based on event driven simulations using realistic size networks. In this case the measurements and predictions will be used to feed the MDPD based models. We will also study reward parameter adaptation to meet individual class blocking constraints.

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