Cost Analysis of Optical Networks with Dynamic Setup and Release of λ-channels

Cheng-Shang Chang, Hsin-Yi Lee

Abstract— **We consider a threshold type control mechanism for dynamic setup/release of λ-channels in optical networks. There are two types of costs for the control mechanism: the setup/release cost and the operation cost. For such a control mechanism, there is a corresponding Markov model with high complexity. By state aggregation, we are able to identify a semi-Markov process that is simpler to analyze. Based on the semi-Markov process, we derive the average cost formula for the threshold type control mechanism and carry out several numerical examples to find the optimal thresholds that minimize the average cost.**

Keywords— **lightpath, Semi-Markov process.**

I. Introduction

The trend in the network infrastructure is moving toward high-speed routers interconnected by intelligent core optical networks. The basic transportation method is to provision wavelength circuits called lightpaths. The intelligence in optical networks allows the control on wavelengths. In this paper, we mention about the control plane issue.

First, we give a brief introduction to the layered infrastructure of optical networks[6],[1]. The three layers are the fiber layer, the optical layer, and the logical layer (see Figure 1)[7]. The fiber layer constitutes the layout of physical infrastructure of the optical network. Note that when we mention one single link between nodes or stations, it may consist of pairs of fibers.

The optical layer contains two sublayers: the λ-channel sublayer and the transmission channel sublayer[7]. The function of the λ-channel sublayer is to manage the allocation of λ-channels for point-to-point optical links. The end-to-end lightpath is a sequence of optical links(or nodes) that may use the same or different wavelengths[5]. The lightpaths are established through the coordinated actions of optical nodes along the route.

The function of the transmission channel sublayer is to convert the logical signals into the optical signals. Many logical connection requests are from logically routed network(LRN), taking the forms like synchronous digital hierarchy(SDH) path signals, asynchronous transfer mode virtual paths(ATM VP's), or plesiochronous digital hierarchy(PDH) path signals[4]. Those logically routed networks are thus in the logical layer.

Lightpaths that are in the form of the λ-channels may be dynamically set up or released in response to the change of connection requests from LRNs. A mechanism is required for dynamic connection management[2] to determine the lightpath routing before the connection is setup. On the contrary, connection release may be initiated by a signal from any node along the path and then the control mechanism decides if it is necessary to signal all the participating network elements to release the lightpath.

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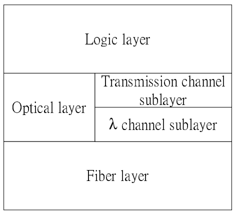

Fig. 1. The layered architecture of the optical network

In general, there are two types of costs for the λ-channels: the setup/release cost and the operation cost. The setup/release cost is the cost involving a sequence of steps to make optical connections. The operation cost includes the cost that involved the maintenance or repair fee of the system.

One of the main objectives of this paper is to investigate the tradeoff between the setup/release cost and the operation cost. In Section II, we consider a threshold type of control mechanism for dynamic setup or release of λ-channels. A Markov model is proposed in Section II-A to analyze such a control mechanism. As the complexity of the Markov model is high, a semi-Markov process that uses the technique of state aggregations is derived in Section II-B. We then also derive the average cost in Section II-B. Various numerical examples are computed to find the optimal thresholds for dynamic setup or release of λ-channels.

II. Modelling for dynamic setup and release of λ-channels

In this section, we consider an optical network that implements a control mechanism for dynamic setup and release of λ-channels. For the optical network, we assume there are K λ-channels. Once being set up, one λ-channel provides M logical channels and each logical channel can accommodate one connection request. Throughout the paper, we call M the capacity of one λ-channel. Also, a λ-channel is said to be active after being set up, and idle after being released.

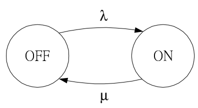

Fig. 2. The ON-OFF model

We assume there are N independent sources of connection requests and each source is modelled by a continuous-time two-state Markov chain (see Figure 2). In the OFF state, the source is idle and it will generate a connection request according to an exponentially distributed time with mean $1/\lambda$ and then is switched to the ON state. In the ON state, the source occupies a logical channel for an exponentially distributed time with mean $1/\mu$ and then is back to the OFF state. Let the number of λ-channels K is not less than $\lceil \frac{N}{M} \rceil$ so that none of the connection requests are blocked.

The control mechanism is as follows: let $N(t)$ be the number of ON sources at time t and $I(t)$ being the number of active λ-channels at time t. Then an additional λ-channel is set up at time t when there is a connection request at time t and $N(t^-) = MI(t^-)$. By setting up a λ-channel for the connection request at time t, we have $N(t) = N(t^-)+1$ and $I(t) = I(t^-)+1$. The release of a λ-channel is based on the concept of the average utilization, which is defined to be $N(t)/MI(t)$. A λ-channel is released at time t when a connection request is released at time t and $N(t^-) - 1 = rM(I(t^-) - 1)$. When this occurs, we have $N(t) = N(t^-) - 1$ and $I(t) = I(t^-) - 1$. The release threshold r is between 0 and 1 and it is chosen so that rM is an integer. The optimal value of the release threshold r will be chosen to minimize the average system cost discussed in Section III. For such a control mechanism, we have that

$$rM(I(t) - 1) < N(t) \leq MI(t), \quad \text{for all } t.$$

A. Markov model

Now we introduce an additional indicator random variable $J(t)$ to further distinguish the previous change of $I(t)$. The indicator variable $J(t)$ is 1 if the previous change of $I(t)$ is to increase $I(t)$ by 1, and $J(t)$ is 2 if the previous change of $I(t)$ is to decrease $I(t)$ by 1.

Consider the trivariate stochastic process $Z(t) = (N(t), I(t), J(t))$. Since $N(t)$ is from multiplexing the N i.i.d ON-OFF sources, it is well known that $N(t)$ is a continuous-time Markov process with the transition diagram in Figure 3. As both $I(t)$ and $J(t)$ are simply functions of the state change of $N(t)$, the stochastic process $Z(t)$ is also a a continuous-time Markov process. In Figure 4, we show the transition diagram of process $Z(t)$ with each state denoted by (n, i, j). The number in each state indicates the number of active ON sources, n. The states within each dotted circle have the same number of active λ-channels, i. The upper states have j equal 1 and the lower states have j equal 2.

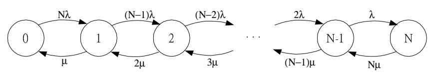

Fig. 3. The state transition diagram of $N(t)$

Let $q((n_1, i_1, j_1), (n_2, i_2, j_2))$ be the transition rate of $Z(t)$ from the state (n_1, i_1, j_1) to the state (n_2, i_2, j_2). In general, we can classify the transitions of $Z(t)$ in Figure 4

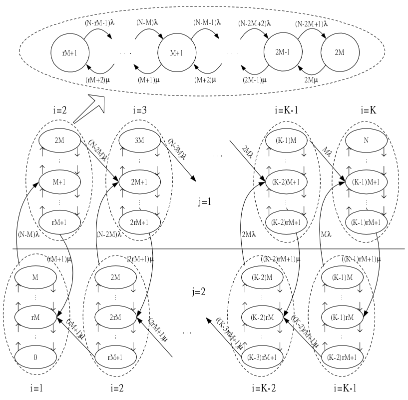

Fig. 4. The state transition diagram of $Z(t)$

into two classes: (i) internal transitions where $I(t)$ is not changed, and (ii) external transitions where $I(t)$ is changed. Refer to Figure 3 and we have

$$q((n, i, j), (n+1, i, j)) = (N-n)\lambda, \ \forall\, i, j, (i-1)rM+1 \leq n < iM,$$

$$q((n, i, j), (n-1, i, j)) = n\mu, \ \forall\, i, j, (i-1)rM+1 < n \leq iM.$$

The external transitions can be further divided into two types: (i) the upward transition and (ii) the downward transition. The upward transition corresponds to the setup of a λ-channel and it has the transition rate

$$q((n, i, j), (n + 1, i + 1, 1)) = (N - n)\lambda, \ \forall\, i, j, \text{and } n = iM.$$

The downward transition corresponds to the release of a λ-channel and it has the transition rate

$$q((n, i, j), (n-1, i-1, 2)) = n\mu, \ \forall\, i, j, \text{and } n = (i-1)rM+1.$$

B. Semi-Markov process by state aggregation

To simplify the trivariate stochastic process, we consider the bivariate stochastic process $W(t) = (I(t), J(t))$.It is obtained by aggregating the states in $Z(t)$ with the same value of $I(t)$ and $J(t)$ (see Figure 5).

We claim that $W(t)$ is a semi-Markov process (see e.g., [3]). For this claim, we need to identify an embedded Markov chain of the semi-Markov process $W(t)$. Note from Figure 5 that all the transitions in $W(t)$ are the external transitions in $Z(t)$ Also, there is exactly *one entry state* for every aggregated state in Figure 5 (this is the reason why we introduce the indicator variable $J(t)$). Let τ_k be the epoch immediately after the k^{th} external transition of $Z(t)$. Consider the stochastic sequence $W_k \equiv \{W(\tau_k), k \geq 1\}$. Since there is exactly one entry state for every aggregated state, it is easy to see that conditioning on $W_k = (i, 1)$ is equivalent to conditioning on $Z(\tau_k) = ((i-1)M+1, i, 1)$. Similarly, conditioning on $W_k = (i, 2)$ is equivalent to conditioning on $Z(\tau_k) = (irM, i, 2)$. Thus, the Markov property of $\{W_k, k \geq 1\}$ then follows directly from the Markov property of $Z(t)$.

B.1 Transition probabilities of the embedded chain

Parallel to the two types of external transitions in $Z(t)$, the embedded chain $\{W_k, \geq 1\}$ also has the following two

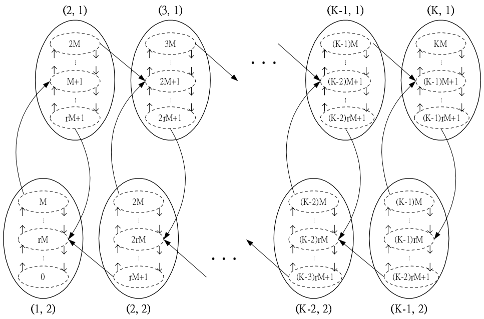

Fig. 5. The aggregated states of the process $W(t)$

types of transitions: the upward transitions and the downward transitions. For these, we define

$$p^u_{i,j} = P(\ W_{k+1} = (i+1, 1) \mid W_k = (i, j)\ ),\ \forall\ i, j,$$

and

$$p^d_{i,j} = P(\ W_{k+1} = (i-1, 2) \mid W_k = (i, j)\ ),\ \forall\ i, j.$$

The transition diagram of the embedded Markov chain is shown in Figure 6.

The transition probability $p^u_{i,1}$ is the conditional probability that the Markov process $Z(t)$ reaches the state $(iM+1, i+1, 1)$ before the state $((i-1)rM, i-1, 2)$ given that $Z(0) = ((i-1)M+1, i, 1)$. Similarly, $p^d_{i,1}$ is the the conditional probability that the Markov process $Z(t)$ reaches the state $((i-1)rM, i-1, 2)$ before the state $(iM+1, i+1, 1)$ given that $Z(0) = ((i-1)M+1, i, 1)$. Note that $p^u_{i,1} + p^d_{i,1} = 1$. To compute such conditional probabilities, we further define $p^u_{n,i,1}$ to be the conditional probability that $Z(t)$ reaches the state $(iM+1, i+1, 1)$ before the state $((i-1)rM, i-1, 2)$ conditioning on $Z(0) = (n, i, 1)$.

Conditioning on whether the first internal transition is an arrival of a connection request or a release of a connection request, we have the following recursive equations

$$p^u_{n,i,1} = \frac{(N-n)\lambda}{(N-n)\lambda + n\mu} p^u_{n+1,i,1} + \frac{n\mu}{(N-n)\lambda + n\mu} p^u_{n-1,i,1},$$
$$n = (i-1)rM+1, (i-1)rM+2, \ldots, iM.$$

We can then solve $p^u_{n,i,1}$'s in (1) with the obvious boundary conditions $p^u_{iM+1,i,1} = 1$ and $p^u_{(i-1)rM,i,1} = 0$. We then obtain $p^u_{i,1} = p^u_{(i-1)M+1,i,1}$ and $p^d_{i,1} = 1 - p^u_{i,1}$. The transition probabilities $p^u_{i,2}$ and $p^d_{i,2}$ can be computed similarly.

Let $\pi^e_{i,j}$ (with the superscript e denoting the embedded chain) be the stationary probability for the embedded Markov chain $\{W_k, k \geq 1\}$ to be in the aggregated state (i, j). Also let

$$\boldsymbol{\pi^e} = (\pi^e_{1,2}, \pi^e_{2,1}, \pi^e_{2,2}, \ldots, \pi^e_{K-1,1}, \pi^e_{K-1,2}, \pi^e_{K,1}).$$

Then one can easily derive from Figure 6 the corresponding transition probability matrix P of the embedded chain as follows:

$$P = \begin{bmatrix} 0 & 1 & 0 & 0 & \ldots & 0 & 0 & 0 \\ p^d_{2,1} & 0 & 0 & p^u_{2,1} & \ldots & 0 & 0 & 0 \\ p^d_{2,2} & 0 & 0 & p^u_{2,2} & \ldots & 0 & 0 & 0 \\ 0 & 0 & p^d_{3,1} & 0 & \ldots & 0 & 0 & 0 \\ 0 & 0 & p^d_{3,2} & 0 & \ldots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & p^u_{K-2,2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \ldots & 0 & 0 & p^u_{K-1,1} \\ 0 & 0 & 0 & 0 & \ldots & 0 & 0 & p^u_{K-1,2} \\ 0 & 0 & 0 & 0 & \ldots & 0 & 1 & 0 \end{bmatrix}. \quad (2)$$

One can then solve the stationary probabilities by the global balance equation

$$\boldsymbol{\pi^e} = \boldsymbol{\pi^e} P \quad (3)$$

and

$$\boldsymbol{\pi^e}\mathbf{e} = 1, \quad (4)$$

where $\mathbf{e}$ is the column vector of 1's with an appropriate dimension.

B.2 The holding time of the embedded chain

In this section, we derive the holding time distribution of the embedded chain $\{W_k, k \geq 1\}$. The holding time for the state $(i, 1)$ ($(i, 2)$) is simply the first exit time of the Markov process $Z(t)$ to either the state $((i-1)rM, i-1, 2)$ ($(((i-1)rM, i-1, 2))$) or the state $(iM+1, i+1, 1)$ ($((iM+1, i+1, 1))$) given that $Z(0) = ((i-1)M+1, i, 1)$ ($(Z(0) = (irM, i, 2))$.

The first exit time of a Markov chain is known to have a phase distribution (see e.g. [3]) and it can be modelled by a transient Markov process with an absorbing state. In Figure 7, we show the transition diagram for the holding time of the aggregated state (i, j). Note that there are n_i states in the aggregated state (i, j) , where $n_i = iM -$

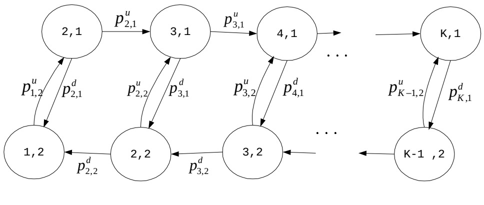

Fig. 6. The state transition diagram for the embedded Markov chain W_k

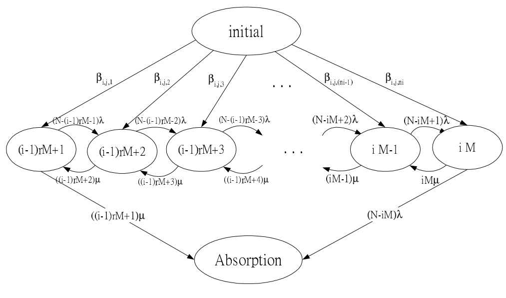

Fig. 7. The transition diagram for the holding time of the aggregated state (i, j)

$(i-1)rM$. We number the state $((i-1)rM+1,i,j)$ as the first state of the n_i states in Figure 7 and the state (iM,i,j) as the last state of the n_i states. In addition to these n_i states, we add an absorbing state in the transition diagram in Figure 7. Let $\boldsymbol{\beta_{i,j}} \equiv (\beta_{i,j,1}, \beta_{i,j,2}, \ldots, \beta_{i,j,n_i})$, be the initial probability vector, i.e., with probability $\beta_{i,j,\ell}$ the initial state is the ℓ^{th} state. We have

$$\beta_{i,1,\ell} = \begin{cases} 1 & \text{if } \ell = (i-1)M + 1 - (i-1)rM \\ 0 & \text{elsewhere} \end{cases},$$

and

$$\beta_{i,2,\ell} = \begin{cases} 1 & \text{if } \ell = irM - (i-1)rM \\ 0 & \text{elsewhere} \end{cases}.$$

Let $\mathbf{Q}_{i,j}$ be the $n_i \times n_i$ transition rate matrix for the n_i states. In Figure 8, we show the transition rate matrix $\mathbf{Q}_{i,j}$ and the transition rates are simply the *internal* transition rates of $Z(t)$.

$$Q_{i,j} = \begin{pmatrix} -\begin{pmatrix}(N-(i-1)rM-1)\lambda \\ +((i-1)rM+1)\mu\end{pmatrix} & (N-(i-1)rM-1)\lambda & 0 & \cdots & 0 & 0 & 0 \\ ((i-1)rM+2)\mu & -\begin{pmatrix}(N-(i-1)rM-2)\lambda \\ +((i-1)rM+2)\mu\end{pmatrix} & (N-(i-1)rM-2)\lambda & 0 & \cdots & 0 & 0 \\ 0 & ((i-1)rM+3)\mu & -\begin{pmatrix}(N-(i-1)rM-3)\lambda \\ +((i-1)rM+3)\mu\end{pmatrix} & (N-(i-1)rM-3)\lambda & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & (iM-2)\mu & -\begin{pmatrix}(N-iM+2)\lambda \\ +(iM-2)\mu\end{pmatrix} & (N-iM+2)\lambda & \\ 0 & 0 & \cdots & 0 & (iM-1)\mu & -\begin{pmatrix}(N-iM+1)\lambda \\ +(iM-1)\mu\end{pmatrix} & (N-iM+1)\lambda \\ 0 & 0 & 0 & \cdots & 0 & iM\mu & -\begin{pmatrix}(N-iM)\lambda \\ +iM\mu\end{pmatrix} \end{pmatrix}$$

Fig. 8. The transition rate matrix

Let $H_{i,j}$ be the holding time of the aggregated state (i,j) and $F_{H_{i,j}}$ be its cumulative distribution. From the well known results for the phase distribution (see e.g., [3]), it follows that

$$F_{H_{i,j}}(x) = 1 - \boldsymbol{\beta_{i,j}} e^{\boldsymbol{Q_{i,j}}x}\mathbf{e}$$

and that

$$E[H_{i,j}] = -\boldsymbol{\beta_{i,j}}\mathbf{Q}^{-1}\mathbf{e} \tag{5}$$

III. Minimizing the average cost

In this chapter, we formulate the problem of choosing the appropriate release threshold r as a cost minimization problem. We assume there are two types of costs: the setup cost and the operation cost. Let β be the setup cost of a λ-channel. Without loss of generality. Let α be the operation cost for running an active λ-channel per unit of time.

Let $G(m)$ be the total cost after m *upward* transitions of the embedded chain $\{W_k, k \geq 1\}$. The setup cost after m *upward* transitions is simply βm. To compute the operation cost, let $N_{i,j}(m)$ be the number of visits to the aggregated state (i,j) and $L_{i,j}(k)$ be the holding time in the aggregated state (i,j) during the k^{th} visit to that state. Then the operation cost after m *upward* transitions is $\sum_{i=1}^{K} i\ \alpha \sum_{j=1}^{2} \sum_{k=1}^{N_{i,j}(m)} L_{i,j}(k)$. Thus,

$$\begin{aligned} G(m) &= \sum_{i=1}^{K} i\ \alpha \sum_{j=1}^{2} \sum_{k=1}^{N_{i,j}(m)} L_{i,j}(k) + \beta\ m \\ &= m\ \Big(\ \sum_{i=1}^{K} i\ \alpha \sum_{j=1}^{2} \frac{N_{i,j}(m)}{m} \sum_{k=1}^{N_{i,j}(m)} \frac{L_{i,j}(k)}{N_{i,j}(m)} + \beta\ \Big) \end{aligned} \tag{6}$$

On the other hand, let $T(m)$ be the time it takes for the m upward transitions. Note that

$$\begin{aligned} T(m) &= \sum_{i=1}^{K} \sum_{j=1}^{2} \sum_{k=1}^{N_{i,j}(m)} L_{i,j}(k) \\ &= m\Big(\sum_{i=1}^{K} \sum_{j=1}^{2} \frac{N_{i,j}(m)}{m} \sum_{k=1}^{N_{i,j}(m)} \frac{L_{i,j}(k)}{N_{i,j}(m)}\Big). \end{aligned}$$

Since the embedded Markov chain is positive recurrent, we have $N_{i,j}(m) \to \infty$ as $m \to \infty$. It follows from the strong laws of large numbers for the semi-Markov process $W(t)$ that

$$\lim_{m\to\infty} \sum_{k=1}^{N_{i,j}(m)} \frac{L_{i,j}(k)}{N_{i,j}(m)} = E[H_{i,j}], \quad a.s.,$$

and that

$$\lim_{m\to\infty} \frac{N_{i,j}(m)}{m} = \pi_{i,j}^{e}, \quad a.s.$$

Thus, we can define the average cost per unit of time g as follows:

$$\begin{aligned} g &= \lim_{m\to\infty} \frac{G(m)}{T(m)} \\ &= \frac{\sum_{i=1}^{K} i\ \alpha \sum_{j=1}^{2} \pi_{i,j}^{e} E[H_{i,j}] + \beta}{\sum_{i=1}^{K} \sum_{j=1}^{2} \pi_{i,j}^{e} E[H_{i,j}]} \end{aligned} \tag{7}$$

Choosing the release threshold r can then be formulated as the minimization problem for the average cost per unit of time g. In all our numerical examples, the capacity of one λ-channel M is 20, the number of sources N is 180, and the number of λ-channels K is 9. Also, note that the optimal release threshold r^* depends on the ratio β/α. To identify the optimal release threshold r, we also plot the numerical results in these two tables in Figure 9 and Figure 10. Since the setup cost is the dominant factor for large β/α, one can see from these figures that one should choose a lower release threshold r as the ratio β/α becomes larger.

Note also that the rates of an ON-OFF source altering between two states influence the number of setup/release actions, we consider $(\mu+\lambda)$ altogether. To be precise, we fix π_{on} to obtain the same uniformized Markov processes and the same stationary distribution of the embedded Markov chain. Then different rates only change the holding time of each state in the embedded Markov chain W_k and we have $E[H_{i,j}] = \frac{1}{\mu+\lambda} f(i,j)$. In Figure 11, we show the optimal release thresholds r^* with different $(\mu+\lambda)$ and β/α, but with the same $\pi_{\text{on}} = 0.4$. One can see from the figure that with larger $(\mu + \lambda)$, one should choose smaller r^*. To explain the result, note that the effect of $(\mu + \lambda)$ on the holding time in g shift to β' in a new average cost $g' = \frac{\sum_{i=1}^{K} i\ \alpha \sum_{j=1}^{2} \pi^e_{i,j} E[H_{i,j}] + \beta'}{\sum_{i=1}^{K} \sum_{j=1}^{2} \pi^e_{i,j} E[H_{i,j}]}$ with $\beta' = \beta(\mu + \lambda)$. As $(\mu + \lambda)$ becomes larger, it is equivalent to a larger β/α in g, so we choose a lower release threshold.

IV. Conclusions

Motivated by the trend for supporting cost-effective resource usage for data transmission, we considered a threshold type control mechanism for dynamic setup/release of λ-channels in optical networks. There are two types of costs for the control mechanism: the setup/release cost and the operation cost. For such a control mechanism, we proposed a Markov model with ON-OFF sources. However, solving such a Markov model directly is in general difficult. By state aggregation, we were able to identify a semi-Markov process that is simpler to analyze.

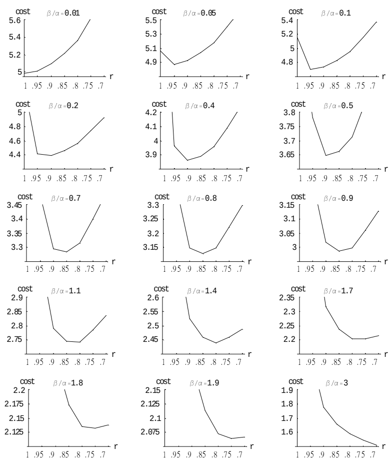

Fig. 9. Minimization point in fixed traffic $\lambda = 0.99$ and $\mu = 1$ and variant $\frac{\beta}{\alpha}$

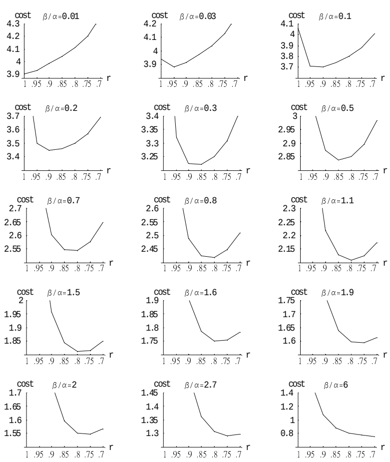

Fig. 10. Minimization point in fixed traffic $\lambda = 0.6$ and $\mu = 1$ and variant $\frac{\beta}{\alpha}$

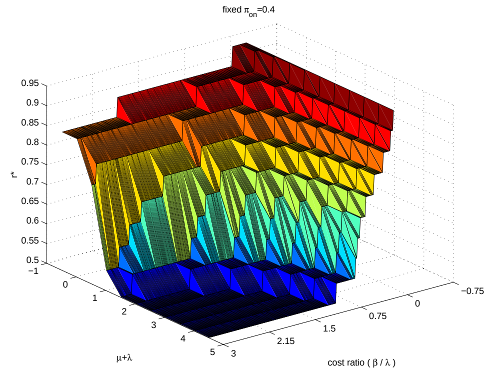

Fig. 11. Minimized release threshold for fixed $\pi_{on} = 0.4$ with variant $\frac{\beta}{\alpha}$ and $\mu + \lambda$

For this semi-Markov process, we derived detailed approaches to compute the transition probabilities and the expected holding times of the embedded Markov chain. Based on these, we derived a formula for the average cost and formulated the problem of finding the appropriate thresholds as a minimization problem for the average cost.

From Equation (7), the average cost g is affected by the ratio of β/α. Several numerical examples are carried out to find the optimal thresholds that minimize the average cost. Intuitively, the results show that as β/α increases, the optimal release threshold r^* decreases. To examine how μ and λ affect r^*, we fix π_{on}. Because fixed π_{on} ensures the same uniformized Markov processes and then μ and λ only affect the holding time at any state. To explain the result in Figure 11, note that the effect of $(\mu + \lambda)$ on the holding time in g shift to β' in a new average cost $g' = \frac{\sum_{i=1}^{K} i\ \alpha \sum_{j=1}^{2} \pi^e_{i,j} E[H_{i,j}] + \beta'}{\sum_{i=1}^{K} \sum_{j=1}^{2} \pi^e_{i,j} E[H_{i,j}]}$ with $\beta' = \beta(\mu + \lambda)$. As $(\mu + \lambda)$ becomes larger, it is equivalent to a larger β/α in g, so we choose a lower release threshold.

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