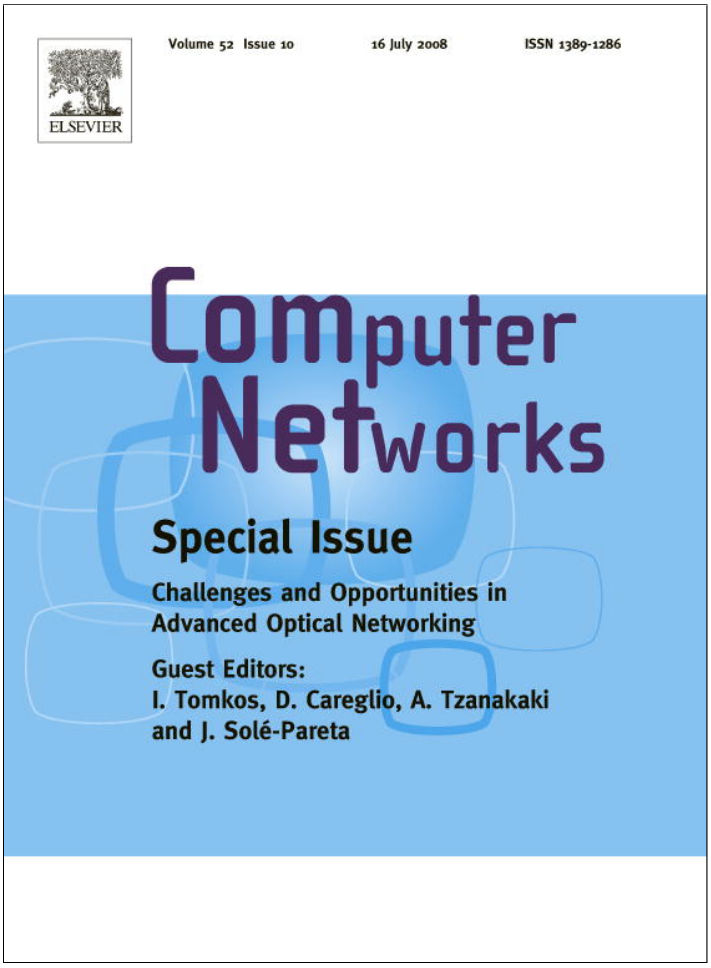
Volume 52 Issue 10
16 July 2008
ISSN 1389-1286
ELSEVIER
Computer Networks
Special Issue
Challenges and Opportunities in Advanced Optical Networking
Guest Editors:
I. Tomkos, D. Careglio, A. Tzanakaki and J. Solé-Pareta

Computer Networks 52 (2008) 1916–1926

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

A Bayesian decision theory approach for the techno-economic analysis of an all-optical router (extended version)

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ARTICLE INFO

Article history:
Received 10 July 2007
Received in revised form 12 February 2008
Accepted 18 February 2008
Available online 16 March 2008

Keywords:
Multilayer router
Bayesian decision theory
Techno-economic trade-off
IP over WDM

ABSTRACT

Typically, core networks are provided with both optical and electronic physical layers. However, the interaction between the two layers is at present limited, since most of the traditional transport functionalities, such as traffic engineering, switching and restoration, are carried in the IP/MPLS layer. In the light of this, the research community has paid little attention to the potential benefits of the interaction between layers, multilayer capabilities, on attempts to improve quality of service control.

This paper shows when to move incoming label switched paths (LSPs) between layers based on a multilayer mechanism that trades off a QoS metric, such as end-to-end delay, and techno-economic aspects. Such a mechanism follows the Bayesian decision theory, and is tested with a set of representative case scenarios.

1. Introduction

Core networks are typically equipped with both electronic and optical resources. This means that incoming traffic can be routed in either the optical or electrical domain. Essentially, electronic routing has the well-known advantages of statistical multiplexing and granularity, but is a hard-computational process for high-speed networks and it further introduces queuing delay to packets. On the other hand, data packets switched in the optical domain only experience propagation delay. However, optical resources provide a granularity which is too coarse for typical Internet streams, even if they come from the multiplex of many users.

In this IP over WDM scenario new challenges appear, since it is necessary to manage two layers, which can provide some functionalities to both of them. This is the case of routing, traffic engineering, quality of service, resilience techniques, resources optimization, etc. which could be carried out in either the IP or the WDM layer. Over the few years, a considerable effort has been dedicated to the development of automatic switched optical network (ASON) and generalized multiprotocol label switching (GMPLS). Thanks to this development, a standardized control plane has been defined, which allows a framework to propose solutions to the previous problems: traffic engineering [1], routing [2,3] or grooming [3,4].

In conclusion from previous papers in this area [4–7], it is highly desirable to efficiently combine the benefits of both optical and electronic domains to solve previously cited problems. With this aim, architectures to build multilayer-capable routers have been defined [5,8]. In this situation, incoming label switched paths (LSPs) traverse the multilayer-capable router, which has to decide whether to perform optical or electronic switching (Fig. 1). If an incoming LSP is routed in the electronic domain, it suffers hop-by-hop opto-electronic conversion (with subsequent delay), otherwise the router provides an optical bypass. The choice of electronic or optical switching is based upon a set of previously-defined rules in the multilayer-capable router. However, these rules

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doi:10.1016/j.comnet.2008.02.018

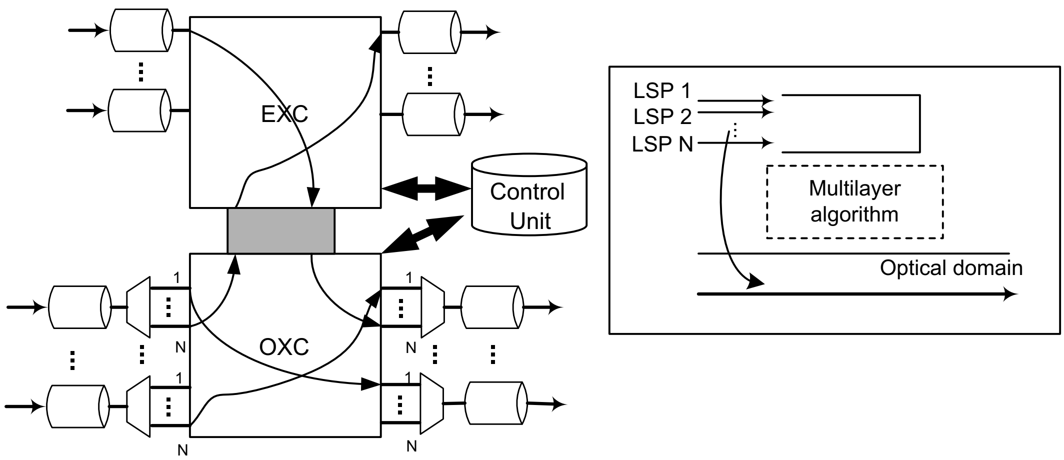

Fig. 1. Multilayer-capable router scenario.

are still open. The authors in [9] address the multilayer traffic engineering problem, proposing a cost model based on the link occupation. Depending on the link occupation, the router is able to decide the number of LSPs switched through each lightpath. Nevertheless, no QoS evaluation, in terms of end-to-end delay, is performed, while the paper is more focused on load balancing issues. In [1], the authors propose an ILP optimization algorithm to minimize the load in the electronic domain using cut-through lightpaths, subject to the network equipment restrictions.

In this paper, we propose a techno-economic model to help routers take the decision of optical or electronic switching of their LSPs. Such an approach makes use of Bayesian decision theory, and takes into account several aspects concerning the quality of service perceived by packets, by means of queuing delay, and also techno-economic aspects such as the relative cost associated to switching LSPs in either the optical or the electronic domain. The algorithm's computational cost is low and only have to be computed when a new LSP arrives at the router or any of the input parameters of the algorithm vary. This multilayer algorithm could be easily implemented in the control unit of the multilayer-capable router (Fig. 1).

In the light of this, the remainder of this work is organized as follows: Section 2 covers the mathematical foundations for such techno-economic analysis with a Bayesian decisor. In this section, a set of experiments and numerical examples is also provided to show how to reach an optimal decision. Section 3 studies the behavior of the bayesian decisor in a dynamic environment, with its analytical definition and experiments. Finally, Section 4 outlines a summary of the results obtained and further lines of investigation.

2. Analysis

2.1. Problem statement

As previously stated, the aim is to define a mathematically rigorous set of rules that helps such multilayer-capable core routers decide whether to switch a given LSP in the optical domain or in the electronic domain.

At a given time, a multilayer router handles a number of LSPs. Typically, due to QoS constraints, optical switching is preferred due to the lack of queuing delay. In principle, many LSPs can be multiplexed in the electronic domain, whereas the lightpath bandwidth may be underutilized if LSPs are switched in the optical domain. This can be seen as a capacity planning problem. Given a set of input LSPs, the question is to derive the number of LSPs that should be switched in the electronic domain and the amount of LSPs to be switched in the optical domain, in an attempt to maximize utility. It is preferred to switch in the electronic domain because the availability of buffering in core nodes allows for a higher utilization, and the remaining optical bandwidth can be used for newly arriving LSPs.

Thus, the router must trade-off these two parameters: queuing delay versus the cost associated to optical switching (a techno-economic trade-off). Moreover, it needs to have a set of predefined rules to make a decision on how many LSPs should be switched in the optical domain and how many in the electronic domain.

To do so, let N refer to the number of LSPs handled at a given random time by the multilayer router, and let $L(d_i,x)$ refer to the loss function. The loss function $L(d_i,x)$ denotes the cost or loss of switching i LSPs in the electronic domain (thus, $N-i$ LSPs in the optical domain) with subsequent queuing delay experienced by the packets of the electronically switched LSPs, which is denoted by x (for simplicity, the optically switched LSPs have been assumed to experience zero delay). The term d_i denotes the "decision" of routing i LSPs out of a total of N in the electronic domain, and is defined for some decision space $\Omega = \{d_1, \ldots, d_N\}$. In the light of this, $L(d_i,x)$ is given by:

$$L(d_i, x) = (C_e(i) + C_o(N-i)) - U(x), \quad i = 1, \ldots, N, \quad x > 0 \tag{1}$$

where $C_e(i)$ and $C_o(N-i)$ refer to the cost associated to routing i LSPs in the electronic domain and $N-i$ in the optical domain, respectively; and $U(x)$ refers to the utility associated to a queuing delay of x units of time, experienced by the electronically switched LSPs.

Following [10], the Bayes risk, which is essentially the expectation of the loss function with respect to x, equals:

$$R(d_i) = \mathbb{E}_x L(d_i, x) = (C_e(i) + C_o(N-i)) - \mathbb{E}_x U(x),\quad i = 1,\ldots,N \tag{2}$$

The goal is to obtain the optimal decision d_N^* such that the Bayes risk $R(d_N^*)$ is minimum. In other words:

Find d_N^* such that $R(d_N^*) = \min_{d_i, i=1,\ldots,N} R(d_i)$

The next section proposes a set of utility functions, $U(x)$, that measure the QoS experienced (in terms of queuing delay) by the electronically switched packets, and also introduces a metric for quantifying the relative cost of optical switching with respect to electronic switching.

2.2. The utility function U(x)

As previously stated, the utility function $U(x)$ is defined over the random variable x, which represents the queuing delay experienced by the packets of electronically switched LSPs. The queuing delay shall be assumed to be Weibull distributed, since this has been shown to accurately capture the queuing delay behavior of a router with self-similar input traffic [11–13]. In the light of this, the delay probability density function is given by [11]:

$$p(x) = (2-2H)C\frac{(C-m)^{2H}}{2K(H)^2 am}(Cx)^{1-2H} \times \exp\left(-\frac{(C-m)^{2H}}{2K(H)^2 am}(Cx)^{2-2H}\right),\quad x > 0 \tag{3}$$

where C is the lightpath capacity, m is the average input traffic and a is a variance coefficient such that $am = \sigma^2$ (with σ^2 being the input traffic variance) and H is the Hurst parameter.

Once $p(x)$ has been defined, the next step is to define a measure of the “utility” associated to routing LSPs in the electronic domain.

2.2.1. Delay based utility

In its simplest form, we can easily evaluate the utility based on the observed delay, that is, $U_{\text{mean}}(x) = -x$. The utility function is thus opposite to the queuing delay x, since more utility occurs for smaller delays. Thus, computing the Bayes risk defined in Eq. (2) yields:

$$\mathbb{E}_x[U_{\text{mean}}(x)] = \mathbb{E}_x[-x] = -\int_0^\infty xp(x)\mathrm{d}x \tag{4}$$

which equals the average queuing delay experienced by the electronically switched packets. Such a value takes the following analytical expression:

$$\mathbb{E}_x[U_{\text{mean}}(x)] = -\frac{1}{C}\left(\frac{2K(H)^2 ami}{(C-mi)^{2H}}\right)^{1/(2-2H)}\Gamma\left(\frac{3-2H}{2-2H}\right) \tag{5}$$

However, the average delay is not always a useful (or at least, representative) metric in the evaluation of the quality of service experienced by certain applications, especially when quantifying the relative QoS experienced by real-time applications. The following considers two other utility functions used in the literature for hard real time and elastic applications [14,15].

2.2.2. Hard real-time utility

Hard real-time applications are those which tolerate a delay of up to a certain value, say $T_{\max}$, but their performance degrades very significantly when the delay they experience exceed such value. Examples of these are: online gaming, back-up services and grid applications. The parameter $T_{\max}$ denotes the tolerated delay threshold for each particular application. The ITU-T recommendation Y.1541 [16] and the 3GPP recommendation S.R0035 [17] define service classes based on thresholds.

Thus, hard real-time utility can be modeled by a step function as shown in Fig. 2 left, and takes the expression:

$$U_{\text{step}}(x) = \begin{cases} 1, & \text{if } x < T_{\max} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

The Bayes risk requires to compute the average utility

$$\mathbb{E}_x[U_{\text{step}}(x)] = \int_0^{T_{\max}} p(x)\mathrm{d}x = 1 - \int_{T_{\max}}^\infty p(x)\mathrm{d}x = 1 - P(x > T_{\max}) \tag{7}$$

which, according to Eq. (3), leads to

$$\mathbb{E}_x[U_{\text{step}}(x)] = 1 - \exp\left(-\frac{(C-mi)^{2H}}{2K(H)^2 ami}(CT_{\max})^{2-2H}\right),\quad T_{\max} > 0 \tag{8}$$

2.2.3. Elastic utility

Other services consider a more flexible QoS function, since the service is degraded little by little (Fig. 2 right). These services consider zero delay as the maximum possible utility, but the utility slowly reduces with increasing delay. For instance, the ITU-T recommendation G.107 defines the “E model” [18], which explains in detail the voice service degradation as perceived by humans. In other utility function analyses, the exponential function has been used to describe the degradation of elastic services [15].

Thus, the elastic utility function is modeled as:

$$U_{\exp}(x) = \lambda e^{-\lambda x},\quad x > 0 \tag{9}$$

where λ refers to decay ratio of the exponential function. Following the definition of $T_{\max}$ above, the value of λ has been chosen such that 90% of the utility lies before $T_{\max}$. That is

$$\lambda = \frac{1}{T_{\max}\log(1-0.9)} \tag{10}$$

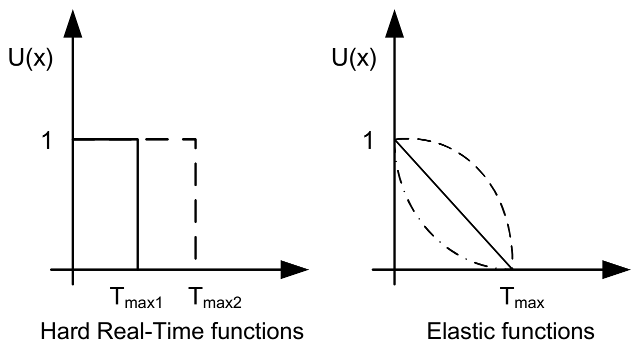

Fig. 2. Utility functions: hard real-time (left) and elastic (right).

Finally, the average elastic utility follows

$$\mathbb{E}_x[U_{\exp}(x)] = \int_0^\infty \lambda e^{-\lambda x} p(x) dx \tag{11}$$

which has no analytical form. However, we can use the Taylor expansion to approximate it, since

$$\mathbb{E}[f(x)] \approx \int_0^\infty p(x) \Big(f(\mathbb{E}[x]) + f'(\mathbb{E}[x])(x - \mathbb{E}[x]) + \frac{1}{2} f''(\mathbb{E}[x])(\mathbb{E}[x] - x)^2 \Big) dx = f(\mathbb{E}[x]) + \frac{1}{2} f''(\mathbb{E}[x]) \sigma_x^2 \tag{12}$$

Thus

$$\mathbb{E}_x[U_{\exp}(x)] \approx U_{\exp}(\mathbb{E}_x[x]) + \frac{1}{2} U''_{\exp}(\mathbb{E}_x[x]) \sigma_x^2 \approx \lambda e^{-\lambda \mathbb{E}_x[x]} + \frac{1}{2} \lambda^3 e^{-\lambda \mathbb{E}_x[x]} \sigma_x^2 \tag{13}$$

where $\mathbb{E}_x[x]$ is given by Eq. (5), and the variance σ_x^2 can be easily derived from Eq. (3):

$$\sigma_x^2 = \frac{1}{C^2} \left(\frac{2K(H)^2 ami}{(C - mi)^{2H}} \right)^{1/(1-H)} \left(\Gamma\left(\frac{2-H}{1-H}\right) + \Gamma^2\left(\frac{3-2H}{2-2H}\right) \right) \tag{14}$$

2.3. The economic cost of electronic and optical switching

As previously stated, the values of $C_e(i)$ and $C_o(N-i)$ in Eq. (1) represent the cost associated to switching i LSPs in the electronic domain and $N-i$ in the optical domain. As previously stated, optical resources should be penalized more than the electronic ones in order to maximize link utilization. For simplicity purposes, we have considered a *linear* cost approach, at which electronic switching is penalized as $C_e(i) = Ki$ for some $K > 0$, and the cost of optical switching is $C_o(N-i) = R_{\text{cost}} K(N-i)$. The value of R_{cost} (generally $R_{\text{cost}} > 1$) denotes the relative optical-electronic cost, that is, the ratio at which the optical cost increases with respect to the electronic cost.

2.4. Scenario definition

A few numerical examples applied to real case scenarios are shown as follows. The aim is to show practical cases where the implemented algorithm, at a given core multilayer switch, decides the number of optically switched LSPs that should be transmitted according to three sets of parameters: (1) QoS parameters, essentially the $T_{\max}$ value introduced above; (2) the relative cost R_{cost} which provides a measure of the economic cost of switching LSPs in the optical domain with respect to the electronic switching; and, (3) the self-similar characteristics of the incoming flows, represented by the Hurst parameter H. Furthermore, the impact of the LSPs mean and variance modification are studied.

The simulation scenario assumes a 2.5 Gbps core network, which carries a number of $N = 60$ standard VC-3 LSPs (typically 34.358 Mbps each). The values of m, σ and H, which represent the characteristics of the traffic flows, i.e. average traffic load, variability and Hurst parameter, have been chosen as $H = 0.6$ (according to [19]) and m and σ such that $\frac{\sigma}{m} = 0.3$.

Finally, the value of K has been chosen as $K = \frac{1}{N}$, in order to get the electrical cost normalized, i.e. within the range [0,1].

2.5. Study of threshold T_{max}

This experiment shows the influence of the choice of $T_{\max}$ in the decision to be made by the multilayer router with relative optical-electronic cost set to $R_{\text{cost}} = 2$. Fig. 3 shows this case for several values of $T_{\max}$ assuming the step or hard real-time utility function (left) and the exponential utility function (right). The values of $T_{\max}$ have been chosen to cover a wide range from 1 ms to 100 ms. Clearly, the number of optically switched LSPs should increase with decreasing values of $T_{\max}$, since high QoS constraints require small delays in the packet transmission (thus larger number of optically switched LSPs to reduce latency).

Typically, most of the end-to-end delay suffered by applications occur in the access network, and it is widely accepted that the core network should be designed to introduce delay of no more than 1–10% of the total end-to-end delay. For hard real-time applications, which may demand a maximum end-to-end of 100 ms, the core delay is thus in the range of 1–10 ms. This would require a total number of electronically switched LSPs of $d_{60}^* = d_{43}$ (see □) and $d_{60}^* = d_{55}$ (see ○), respectively, of a total of $N = 60$ LSPs. For the same delay constraints, elastic applications impose a number of electronically switched LSPs of $d_{60}^* = d_{34}$ (see □) and $d_{60}^* = d_{44}$ (see ○), respectively.

2.6. Analysis with different R_{cost} values

This experiment shows the impact of R_{cost}, which refers to the relative cost of optical switching with respect to electronic switching, in the final decision d^*, to be taken by the multilayer router. Fig. 4 left shows where the optimal decision lies (minimum cost) for different R_{cost} values considering the case of linear utility function. As shown on the right, the more expensive optical switching is (large values of R_{cost}), the smaller is the number of LSPs switched optically. In other words, for high R_{cost} values, only a small portion of LSPs is switched in the optical domain. This becomes clear for $R_{\text{cost}} = 4$, where the first optical LSPs occurs after $i = 40$ electronically switched LSPs. Fig. 5 shows the evolution of the optimal number of electronically switched LSPs i with respect to N when for the exponential utility function. Its behavior is quite similar to the U_{mean} function with differences in the function slope.

Fig. 6 shows the evolution of the optimal number of electronically switched LSPs i with respect to N for the hard real-time utility function. Essentially, the functions U_{mean} and $U_{\exp}$, as defined in Section 2.2, show a smooth decrease with respect to delay, whereas U_{step} has an abrupt utility transition at the value $T_{\max}$. Such abrupt transition is further translated to the optimal decision, as shown in the figure.

To sum up, when optical switching becomes too expensive, the R_{cost} is critical in the optimal decision, thus

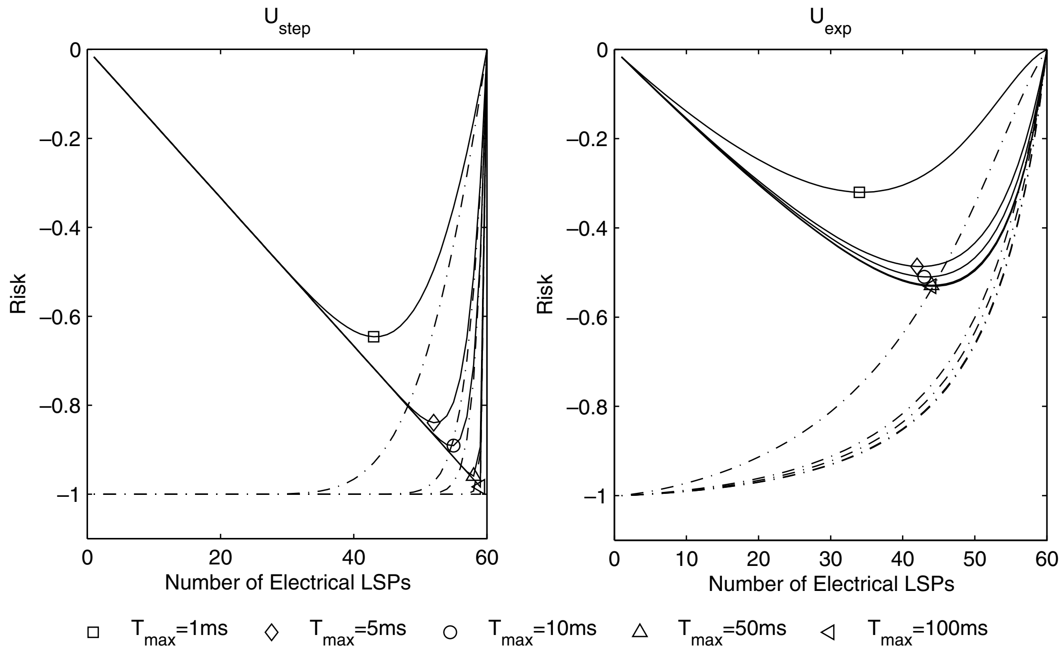

Fig. 3. Bayes risk curves and optimal decisions (minimum values of risk) for several $T_{\max}$ values assuming hard real-time utility (left) and elastic utility (right) functions. Dashed line = Utility.

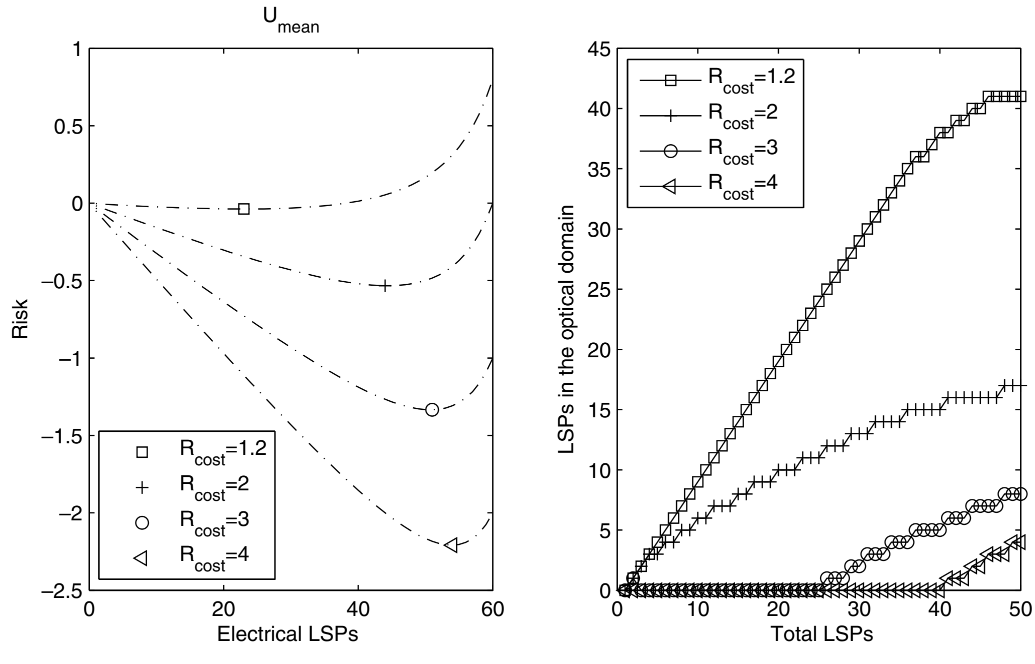

Fig. 4. Variation of relative cost (R_{cost}) for U_{mean}.

canceling any influence of the QoS parameter $T_{\max}$. In this light, the network operator has a means to decide where the optimal decision lies, trading off the R_{cost} parameter and the QoS values.

2.7. Influence of the Hurst parameter H

The previous two numerical examples have assumed a value of $H = 0.6$, as observed in real backbone traces [19]. However, other scenarios may show different values of H and it is interesting to study its impact on the bayesian decisor. In this light, Fig. 7 shows the influence (left) or no influence (right) of such parameter H in the optimal decision. In spite of the fact that long-range dependence degrades queuing performance generally, at high-delay values, the delay variability is smaller for high values of H (see [11], Fig. 7).

Thus, the characteristics of the incoming traffic have a higher or lower impact on the bayesian decisor, depending on the QoS parameters. When $T_{\max} \geqslant 10$ ms, there is little

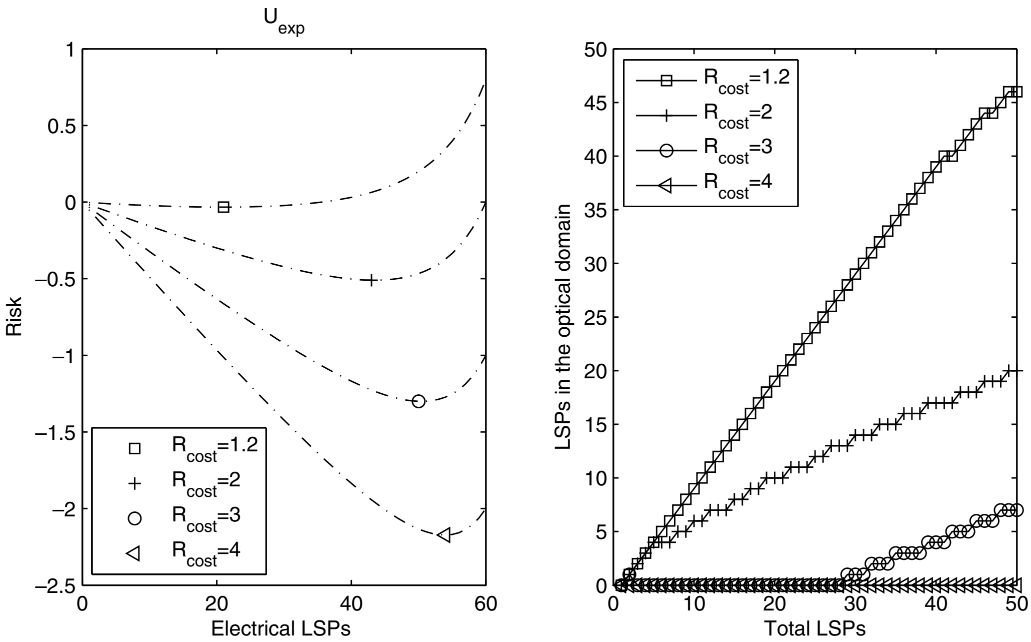

Fig. 5. Variation of relative cost (R_{cost}) for U_{exp}.

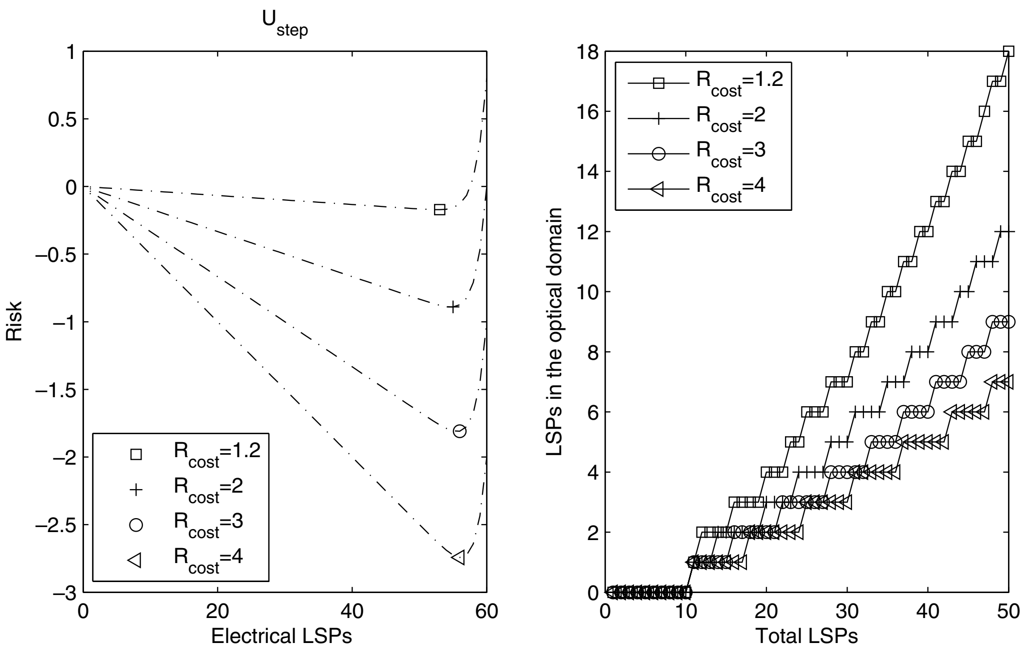

Fig. 6. Variation of relative cost (R_{cost}) for U_{step}.

influence of H (Fig. 7 right), but for T_{max} = 1 ms and smaller, the value of H is key since it moves the decision in a wide range of optimal values: from d_{29} in the case of H = 0.5 to d_{57} for H = 0.9 (Fig. 7 left).

The level curves shown in Fig. 8 show such behavior for the three utility functions (T_{max} = 10 ms). Each level curve corresponds to a different utility.

Fig. 8 middle (case of exponential utility function) and left (case of mean utility function) shows an influence with the H value. However, Fig. 8 right (case of step utility function) should read as having no influence with the Hurst parameter (i.e. parallel level curves = optimal decision independent of H value). It is important to remark that such independent behavior with parameter H does not occur if T_{max} = 1 ms is chosen.

2.8. Impact of the mean and variance of the LSPs

Typically, a network operator agrees a service level agreement with its customers, but it may well happen that less channel capacity is used or that the traffic variation changes. Accordingly, this experiment studies the decisor behavior when the LSPs' mean and variance (values m and σ^2) vary, for different utility functions, which are

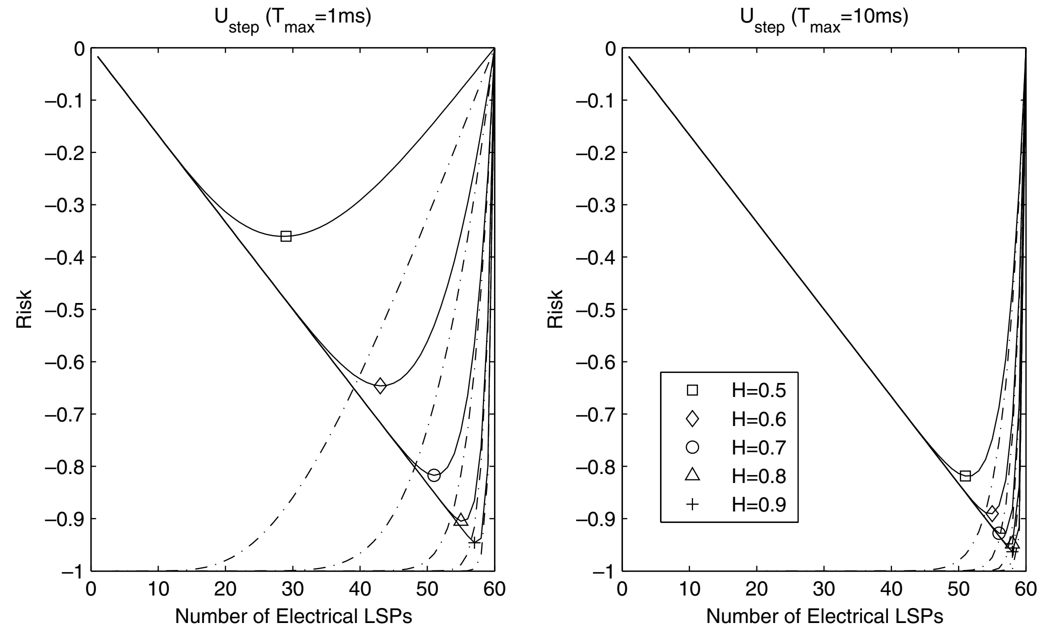

Fig. 7. Hurst parameter variation.

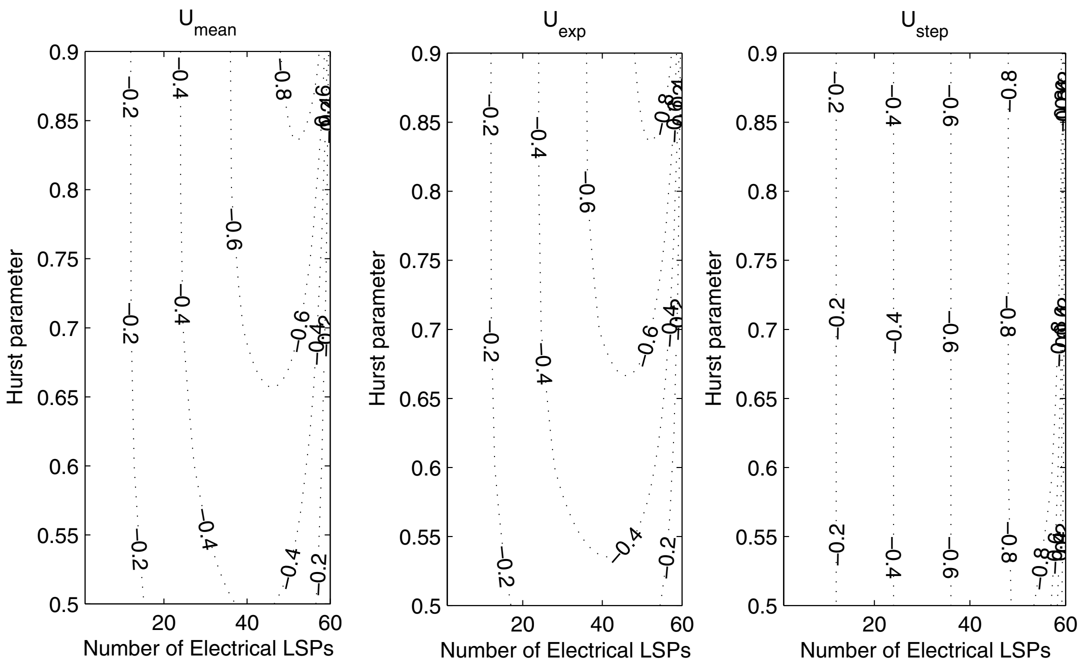

Fig. 8. Hurst parameter variation (risk level curves).

shown in Figs. 9 and 10, respectively. In the former, the original LSPs mean value is m = 34.358 Mbps (VC-3), depicted with $\triangle$. This value has been modified in the range from -10% (30.92 Mbps, depicted as $\square$) to + 1% (34.7 Mbps, as $\triangleleft$). This range aims to simulate the case of LSPs transmitting at a much lower ratio (-10% to +1%), but rarely exceed 1% of its nominal rate. As shown, there is little influence in the final decision d^*_{60}, especially in the case for the step utility function. Clearly, the change in the LSPs' transmission rate has an impact on the optimal decision, nevertheless this impact is much smaller than the impact of other system parameters: $T_{\max}$ (see Fig. 3), R_{cost} (see Fig. 4) and H (see Fig. 7).

Finally, for changes in parameter σ^2 (rate variance), the impact is negligible, as shown in Fig. 10.

3. Dynamic behavior of the risk process

3.1. Analysis

This section studies the dynamic behavior of the risk process in a multilayer router. Let us consider that LSPs

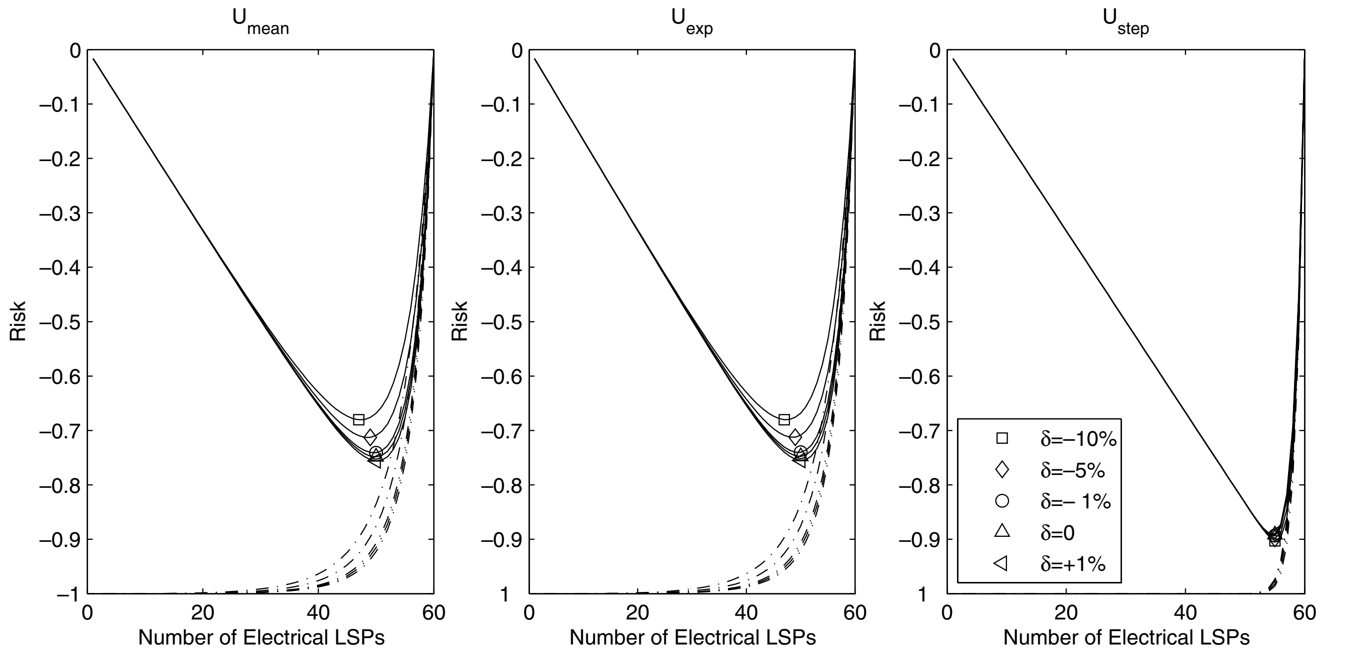

Fig. 9. Mean LSPs variation.

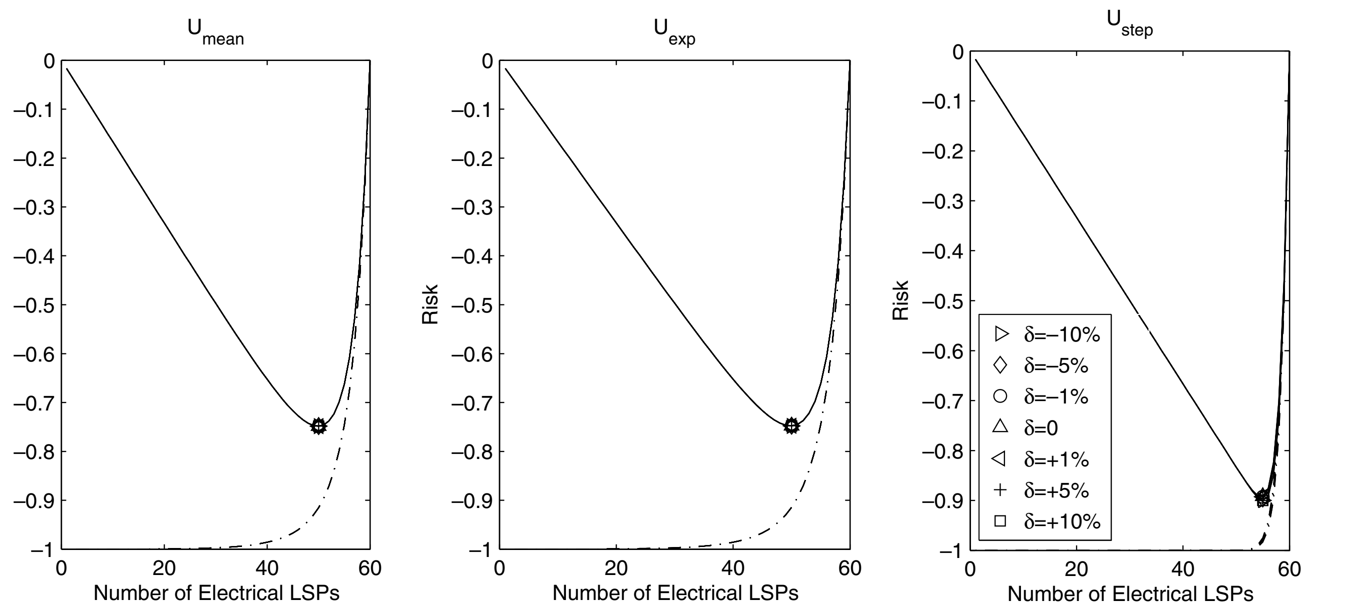

Fig. 10. Variance LSPs variation.

arrive following a Poisson process (rate λ) with exponentially distributed duration (mean $1/\eta$). The cost process can be formulated as a Continuous-Time Markov Chain. More specifically, let $\{X(t), t>0\}$ denote the chain that gives the *total* number of LSPs under service by a multilayer router at time t, out of which i LSPs are switched in the electronic domain and $X(t)-i$ are being switched in the optical domain. And let $N_{\max}$ denote the maximum number of LSPs supported by the multilayer router simultaneously.

For simplicity, let us consider discrete-time transitions between states of the chain, which we denote by $\{X(n), n=0,1,\ldots\}$. Then, the transition probabilities p_{jk} are given by

$$p_{j,j+1} = \frac{\lambda}{\lambda + j\eta} \qquad p_{j,j-1} = \frac{j\eta}{\lambda + j\eta} \tag{15}$$

for $j=1,\ldots,N_{\max}-1$ and $p_{01} = p_{N_{\max}(N_{\max}-1)} = 1$, while $p_{jk}=0$ for all other values of (j,k). We analyze the process $\{V_j(n), n=0,1,2,\ldots; j=0,1,\ldots,N_{\max}\}$ which refers to the accumulated cost in n steps of the chain $X(n)$, assuming it departed from state j. Let r_{jk} denote the cost associated to the transition from state j to state k. Let us define $r_{jk} = L(d_k^*, x)$, which corresponds to the decision policy of choosing the optimal decision according to Eq. (1) for a total number of k LSPs. Accordingly, it follows that

$$V_j(n) = \sum_{k=1}^{n} p_{jk}(r_{jk} + V_k(n-1))$$
$$j = 1, 2, \ldots, N_{\max} - 1; \quad n = 1, 2, \ldots; \tag{16}$$

and $V_j(0) = 0, V_0(1) = L(d_1^*, x), V_{(N_{\max})}(1) = L(d_{N_{\max}-1}^*, x)$, which follows directly from the one-step Chapman–Kolmogorov equations. Note that the accumulated cost in n steps from state j is equal to the cost of the one-step transition to state k plus the accumulated cost from such state k in $n-1$ steps. Now, we use Eq. (15) to obtain:

$$V_j(n) = p_{j(j+1)}(r_{j(j+1)} + V_{j+1}(n-1)) + p_{j(j-1)}(r_{j(j-1)} + V_{j-1}(n-1))$$
$$j = 1, 2, \ldots, N_{\max} - 1; \quad n = 1, 2, \ldots; \tag{17}$$
$$V_0(n) = r_{01} + V_1(n-1); \quad n = 1, 2, \ldots; \tag{18}$$
$$V_{N_{\max}}(n) = r_{N_{\max}(N_{\max}-1)} + V_{N_{\max}-1}(n-1); \quad n = 1, 2, \ldots; \tag{19}$$

and $V_j(0) = 0$. Finally, expanding the transition probabilities brings the final recursion formula:

$$V_j(n) = \frac{\lambda}{\lambda + j\eta}(r_{j(j+1)} + V_{j+1}(n-1)) + \frac{j\eta}{\lambda + j\eta}(r_{j(j-1)} + V_{j-1}(n-1)) \quad j = 1, 2, \ldots, N_{\max} - 1; \quad n = 1, 2, \ldots; \tag{20}$$

and $V_j(0) = 0$. It is worth noticing that the expression for $V_0(n)$ and $V_{N_{\max}}(n)$ remain the same. Taking expectations on both sides of the equation gives

$$\overline{V_j(n)} = \frac{\lambda}{\lambda + j\eta}(R(d_{j+1}^*) + \overline{V_{j+1}(n-1)}) + \frac{j\eta}{\lambda + j\eta}(R(d_{j-1}^*) + \overline{V_{j-1}(n-1)}) \; j = 1, 2, \ldots, N_{\max} - 1; \quad n = 1, 2, \ldots; \tag{21}$$
$$\overline{V_0(n)} = R(d_1^*) + \overline{V_1(n-1)}; \quad n = 1, 2, \ldots \tag{22}$$
$$\overline{V_{N_{\max}}(n)} = R(d_{N_{\max}-1}^*) + \overline{V_{N_{\max}-1}(n-1)}; \quad n = 1, 2, \ldots; \tag{23}$$

and $\overline{V_j(0)} = 0$ where $R(\cdot)$ is given by Eq. (2) and $\overline{V_j(n)} = \mathbb{E}(V_j(n))$.

Now, we explicitly calculate the first steps of the recursion formula ($n = 0,1$), and provide results for a generic $n = 1,2,\ldots,10$ in Section 3.2. For $n = 0$, as defined above:

$$\overline{V_j(0)} = 0 \qquad j = 0, 1, \ldots, N_{\max} \tag{24}$$

For $n = 1$, using the result for $n = 0$, it yields:

$$\overline{V_j(1)} = \frac{\lambda}{\lambda + j\eta}R(d_{j+1}^*) + \frac{j\eta}{\lambda + j\eta}R(d_{j-1}^*)$$
$$j = 1, \ldots N_{\max} - 1 \tag{25}$$

and $V_0(1) = R(d_1^*), V_{(N_{\max})}(1) = R(d_{N_{\max}-1}^*)$. Eq. (21) provides the dynamic behavior of the Bayes risk, as we move n steps forward from any state j.

3.2. Numerical example

Fig. 11 shows the risk curves of a multilayer router as a function of the total number of LSPs switched. Actually, each curve represents a different (increasing) number of LSPs. The optimal decisions are represented by the symbol □. In the figure, a total number of $j = 30$ LSPs gives an optimal decision of $d_{30}^* = d_{17}$ electronically switched LSPs. As shown, as the number of LSP arrivals increases, the optimal number of electronically switched LSPs i also increases, thus reducing the risk. For $j = 60$, the optimal number of LSPs switched in the electronic domain is $d_{60}^* = d_{44}$. Interestingly, in some cases, the optimal number of electronically switched LSPs remains the same regardless of a small increment in the number of incoming LSPs j (several squares along the same vertical line).

The accumulated risk function $V_j(n)$ as defined in the section above was analytically solved for $n = 0$ and $n = 1$ only. Fig. 12 shows the time evolution of $V_j(n)$ for a time horizon from $n = 1$ to $n = 10$, given different initial states ($j \in \{30,50,70\}$). The $\rho = \frac{\lambda}{\eta}$ value for the experiment was 50%, although the variation of this parameter was tested

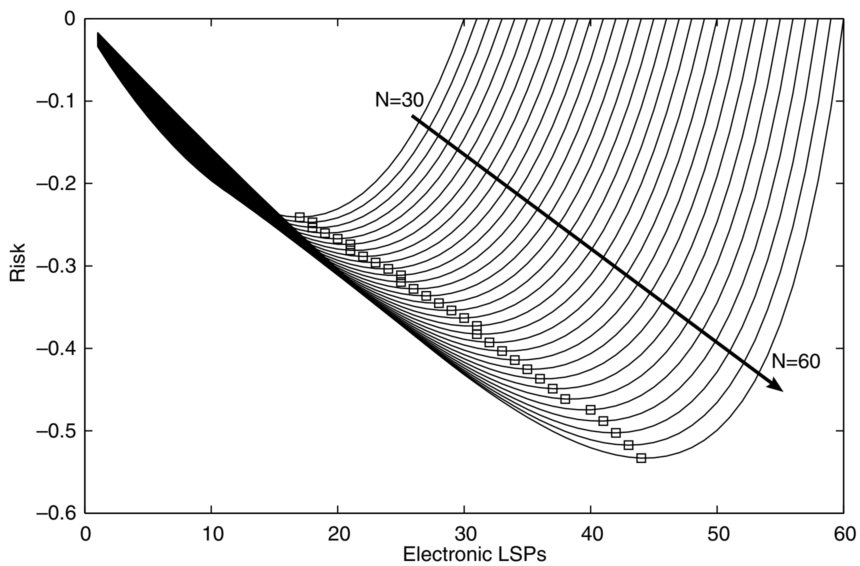

Fig. 11. Risk versus optimal number of electronic LSPs for a total number of LSPs in the range 30–60.

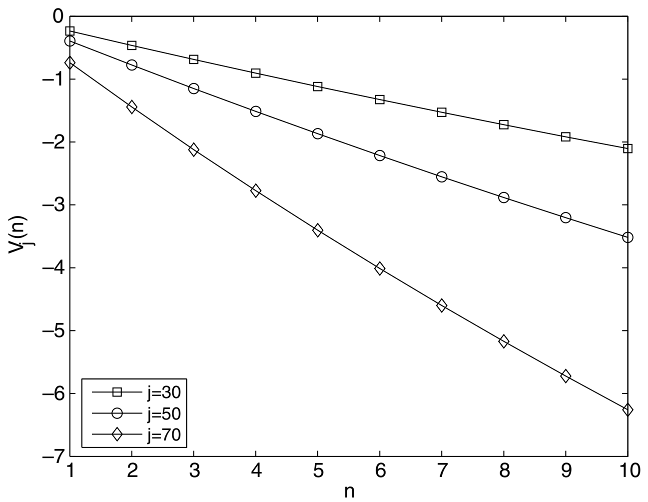

Fig. 12. Evolution of $V_j(n)$ from different states.

and it was not outstanding. $V_j(n)$ is a monotonically decreasing function, since as previous risk curves have shown (for instance Fig. 11), the risk of the optimal decision (d_j^*) is negative. Besides, as the decisor works with the loss function (Eq. (1)), it is reasonable that the function decreases. If the decisor had been defined with a profit function, $V_j(n)$ would have been a monotonically increasing function. In other words, a negative loss function implies that there is a (positive) revenue for the operator. The initial state for $V_j(n)$ determines the evolution of the accumulative risk function and its slope is determined by this point. Furthermore, it is noteworthy that there is a quasi-linear behavior for all curves.

4. Summary and conclusions

This paper's main contribution is two-fold: First, it presents a novel methodology, based on the Bayesian decision theory, that helps multilayer-capable routers to take the decision of either optical or electronic switching of incoming LSPs. Such decision is made based on technical aspects such as QoS constraints and long-range dependence characteristics of the incoming traffic, nonetheless it also considers the cost differences of optical and electrical switching. This way permits high flexibility to the network operator to trade-off both economic and technical aspects.

Secondly, this paper proposes the Bayesian decision theory as the mathematical framework for dealing with the decision of optical or electronic switching of LSPs. Such mathematical framework is of low complexity, and can easily adapt to changing conditions: QoS guarantees, traffic profiles, economic aspects and network operator preferences.

Finally, this algorithm can be implemented in a per node basis by using local and independent parameters (e.g delay thresholds and optical-electronic cost) in each node. However, in further extensions of this mechanism, the local QoS parameters used in each node will be based on information regarding end-to-end delay throughout the whole network.

Acknowledgements

This paper has been partly presented at the ONDM 2007 conference. The authors would like to thank the support from the IMDEA Mathematics Research Institute, the European Union VI Framework Programme e-Photon/ONe + Network of Excellence (FP6-IST-027497), the European Union VII Framework Programme BONE ("Building the Future Optical Network in Europe") Network of Excellence, and the IST Project NOBEL II (FP6-IST-027305).

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