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# Resource allocation in satellite networks: certainty equivalent approaches versus sensitivity estimation algorithms

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## SUMMARY

In this paper, we consider a resource allocation problem for a satellite network, where variations of fading conditions are added to those of traffic load. Since the capacity of the system is finite and divided in finite discrete portions, the resource allocation problem reveals to be a discrete stochastic programming one, which is typically *NP-hard*. We propose a new approach based on the minimization over a discrete constraint set using an estimation of the gradient, obtained through a '*relaxed continuous extension*' of the performance measure. The computation of the gradient estimation is based on the *infinitesimal perturbation analysis* technique, applied on a *stochastic fluid model* of the network. No closed-forms of the performance measure, nor additional feedback concerning the state of the system, and very mild assumptions on the probabilistic properties about the statistical processes involved in the problem are requested. Such optimization approach is compared with a *dynamic programming* algorithm that maintains a perfect knowledge about the state of the satellite network (traffic load statistics and fading levels). The comparison shows that the sensitivity estimation capability of the proposed algorithm allows to maintain the optimal resource allocation in dynamic conditions and it is able to provide even better performance than the one reached by employing the dynamic programming approach. 

KEY WORDS: satellite networks; resource allocation; optimization; sensitivity estimation; dynamic programming

## 1. INTRODUCTION

### 1.1. Optimization problems in telecommunication networks

In computer networks extending over large geographical areas and in multiservice packet switching communication networks, in the presence of limited resources (buffers, bandwidth, or

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processing capacity), several forms of control are exerted to maintain a desired level of performance for all users and traffic types. Especially nowadays, in the Internet community, research efforts are still evolving in order to establish optimization mechanisms able to support *quality of service* schemes in the *Internet* [1, 2].

Many optimization problems of telecommunication networks have a discrete stochastic programming nature: in a stochastic resource allocation scenario, the decision variables are non-negative integers and must be modified along time in order to optimize the system performance, for example, in terms of blocking probability of the connection requests, packet loss probability, mean delay or delay jitter of the packets. Such problems are *NP-hard* (see, References [3, 4] and references therein) and are often solved by means of centralized approaches, in which the control systems are strictly based on closed-form expressions for the performance measure (see, for example, References [5–9] and references therein, for what concerns *call admission* and *bandwidth control*, *routing* and *pricing* issues).

The main drawback of these approaches is due to the fact that conditions for the applicability of closed-form functional costs are difficult to implement in real-life contexts. Such optimization approaches act according to a *parameter adaptive certainty equivalent control* [10], namely, a mapping between the current statistical behaviour of the system and the parameters of the functional costs must be periodically performed on line, in order to maintain good performance of the resource allocation algorithms. Moreover, not only closed-forms for important performance measures (e.g. mean delay and delay jitter of the packets) are not always available (for example in the presence of self-similar traffic), but also '[…] *even under Markovian assumptions for processes of queueing systems, there are only limited cases where closed-form expressions can be obtained*' [11], and, in general, it is very difficult to assure that in a real application scenario some strict hypotheses are verified. Many of these techniques need also the application of *dynamic programming*, whose on-line implementation in a real context may become quite impractical due to the well-known '*curse of dimensionality*' problem (see, e.g. Reference [12] and references therein).

### *1.2. Certainty equivalent approaches versus sensitivity estimation algorithms*

The application of algorithms able to estimate the sensitivity of the performance measure could help in providing sub-optimal control decisions, without the adoption of closed-form functional costs and the application of such, computationally expensive, dynamic programming algorithms. If such sensitivity estimation algorithms are computationally light, they can be employed on line with a small computational effort (see, e.g. References [3, 4, 13–15]). The possibility of completely decentralizing the sensitivity estimation and the resource allocation strategies constitutes an attractive property, too, since the adoption of a centralized unit that periodically monitors all the components of the system cannot be implemented in a real context [16].

Sensitivity estimation algorithms can be based on the so-called *perturbation analysis* (PA) technique. PA is a sensitivity estimation technique for *discrete event systems* (DESs) [11, 17–19]. It is based on the observation of the sample paths followed by the stochastic processes of a DES and gives an estimation of the derivative of the performance index, allowing the application of a gradient-based algorithm, in order to optimize the system performance. Such optimization strategies are known in the literature as '*on-line surrogate optimization methodologies*', because they act on line, with a gradient-based algorithm, by applying a 'surrogate' relaxation of the discrete functional cost [3, 4].

 

In this work, our first aim is to present a novel solution for the bandwidth allocation in a satellite environment based on an on-line surrogate optimization methodology. Without loss in generality concerning the development of the optimization algorithm, we consider a resource allocation problem currently quite popular in the telecommunication community: the resource allocation in satellite networks. Such optimization problem is even more difficult than the typical problems of the terrestrial broadband environments, simply because channel degradation effects must be taken into account together with the traffic changes. However, as will be clear from the following, the model proposed can be easily generalized for other telecommunication application scenarios and functional costs.

Moreover, we shall investigate how such optimization approach can ameliorate the performance of a control strategy based on a closed-form expression of the performance index. This latter optimization technique, employed in previous works [8, 20], needs the so-called *certainty equivalence* assumption, namely a perfect knowledge about the statistical proprieties of the satellite system must be always in effect. In this way, each time a change in the statistical behaviour of the system is detected, a new call to a proper optimization procedure guarantees the maintenance of the optimal resource allocation among the components of the system. In fact, it is necessary to periodically perform on line a mapping between the current state of the network and the parameters of the employed closed-form functional cost. Two drawbacks can severely deteriorate the performance of such optimization strategy. The first one concerns the presence of errors over the measures performed in order to estimate the current state of the network. The second one regards the possibility that the current statistical behaviour of the system does not conform to the hypotheses assumed *a priori* to provide a particular closed-form expression of the performance index.

In this paper, we shall dwell on this subject, by investigating how much the adoption of an on-line surrogate methodology is able to face these drawbacks. We shall discover that the proposed optimization methodology shows a surprising 'self-learning' capability, guaranteeing dynamic reactions to the statistical changes of the system, without any feedback over the system's state and under very mild assumptions concerning the statistical behaviour of the traffic sources.

The remainder of the paper is organized as follows. In the next section we formulate the model of the satellite network together with the underlying discrete stochastic optimization problem; then, in Section 3, we illustrate our *certainty equivalent* approach and, in Section 4, the technique used to compute the performance derivative estimation. In Section 5, the application of an *on-line surrogate optimization* algorithm is addressed and, in Section 6, we summarize and compare the main features of the proposed optimization techniques. In Section 7 we deal with some simulation experiments; conclusions and future work are proposed in Section 8.

## 2. THE MODEL OF THE SATELLITE SYSTEM

*State of the art*: Many satellite systems (*Low Earth Orbit*, *Medium Earth Orbit* and *Geostationary* satellites) have been proposed to support multimedia services worldwide. Broadcast Satellites are standardized by *ETSI* to be based on *Digital Video Broadcasting* (*DVB*/*MPEG*-2) in the forward direction and *asynchronous transfer mode* (ATM) in the return link [21]. Many research issues are currently under investigation to improve the performance of multimedia satellite systems: integrated satellite architectures, beam scheduling, on board signal generation, adaptive modulation and coding, multiple access, flow control and resource allocation [8, 20, 22–29].

In satellite networks, the major concern is related to variable fading conditions over the channel that can heavily affect the transmission quality, especially when working in *Ka band*, where the effect of rain over the quality of transmission is more significant.

In the literature, it is possible to find optimal policies developed in the case of a finite quantity of transmission energy for satellite network devices. References [26, 30, 31] show a dynamic programming formulation of the problem that leads, for special cases, to a closed-form optimal policy, in order to find a trade-off between the minimization of the energy required to send a fixed amount of data and the maximization of the throughput over a fading channel. Power allocation for fading multi-user broadcast channels is a popular topic also in information theory (see, e.g. References [32–34]). Error recovery techniques, such as *automatic repeat request* (ARQ) and *forward error correction* (FEC), are employed in wireless environments to face adverse channel conditions. ARQ is usually deprecated, since real-time traffic requires stringent latency constraints. On the other hand, FEC mechanisms allow recovering erroneous packets, despite channel degradation, but they may cause further congestion and more packet loss in the network [22, 23, 35], owing to their overhead. Hence, a trade-off must be found out between the resource allocation and the redundancy introduced by the FEC algorithm.

In the aforementioned works, the problem is analysed and solved at the physical layer: a power allocation is performed in order to obtain reactions to variable fading conditions. In References [8, 15, 20] and in this work, a FEC mechanism is located at the physical layer and adaptive bandwidth allocation strategies are provided at the data link (or upper) layers to minimize the loss probability of the overall system.

Resource management schemes are usually considered for satellite systems with respect to the *call admission control* (CAC) issue (see, e.g. References [22, 23, 36–38] and references therein). The satellite system is managed at the call level, looking for movable boundary access techniques through dynamic reactions performed by the resource management agent to face variable system conditions.

In this work, we investigate bandwidth allocation strategies disregarding the CAC problem and exploiting the effect of variable traffic and fading level conditions, considering the network at the packet level. In this perspective, an on-line surrogate algorithm is investigated to counteract variable fading levels and traffic load conditions. The stochastic processes involved with fading are assumed to be non-stationary. Therefore, the optimization algorithm has to dynamically adjust the bandwidth allocation, by adaptively following the current behaviour of the stochastic processes and distributing the available channel capacity among the traffic stations.

*The system architecture*: The satellite environment under investigation consists of a fully meshed satellite network that uses bent-pipe geostationary satellite channels, joining $N$ traffic stations. This means that the satellite only performs the function of a repeater, without on-board processing of data. The system operates in MF-TDMA (*multi frequency-time division multiple access*) mode, which allows us to divide the system capacity $K$ into a number of channels, so that the traffic stations can be downsized with respect to a pure TDMA system. TDMA allows the transmission of digital data streams from many sources sequentially assigned to different time slots. Each earth station has to know when to transmit and it must be able to recover the carrier and the clock for each received burst in time to sort out all wanted channels; this can be accomplished through preambles at the beginning of each burst. $K$ represents the number of available bandwidth units, where a unit consists of the smallest quantity of bandwidth assignable to a station. TDMA is easy to reconfigure for changing traffic demands, it resists noise and interference and, in particular for satellite systems, it maximizes the downlink *carrier/noise power* ratio.

A master station is supposed to maintain the system synchronization and is responsible for the capacity allocation to the traffic stations. The master station performance is the same as the slave stations' one; thus, the role of master can be assumed by any station in the system. This assures that the master operates in clear sky conditions for almost all of the time, because when the current master's attenuation exceeds a given threshold, its role is assumed by another station that is in good conditions. In other settings, the satellite itself could be responsible of the allocation: in this case, it should be equipped with an *on-board processing unit*, in order to receive information periodically from the stations and calculate the next bandwidth allocation.

### 2.1. A stochastic fluid model of the network

We base our problem formulation on a *stochastic fluid model* (SFM) of the telecommunication network. SFMs have been proposed for modelling the workload flow in substitution of traditional packet-based queueing models. SFMs adopt a fluid-flow point of view rather than the transaction-flow point of view of traditional queuing models (see e.g. Reference [39] for an overview concerning this topic). In the recent years, SFMs have been recognized as suitable models for performance analysis of telecommunication networks designed to transport fixed-size data units, over high-speed transmission links in the order of gigabits per second [39, 40] (e.g. ATM or DVB).

We adopt a SFM for each single satellite station to formulate the optimization problem related to the satellite system under investigation and to take advantage of a derivative estimator of the performance index through *infinitesimal perturbation analysis* (IPA). As is shown in References [11, 17, 19], the IPA techniques for the optimization of performance parameters at the packet level are strictly based on a SFM of the system.

With a notation that slightly differs from Reference [17], each station has a finite-capacity buffer of fixed size $Q$ and a single server (Figure 1).

This buffer is aimed at receiving a variable bit rate traffic from different sources. The scheme above can be referred to as the 'basic' SFM: it consists of a 'fluidized queue', with a single class fluid source. The stochastic processes associated with this model and useful for our problem formulation are $\beta(t)$, the service rate process, namely, the maximal fluid discharge rate from the server; $\alpha(t)$, the input flow rate (*inflow*) process into the SFM; $x(t)$, the buffer workload process, namely, the fluid volume in the buffer; and $\gamma(t)$, the loss rate (*overflow*) process due to a full buffer.

Such SFM can be viewed as a dynamical system, whose evolution is determined by the inflow and service rate processes (the so-called 'defining processes' $\alpha(t), \beta(t)$), while the other two processes (called 'derived processes' $x(t), \gamma(t)$) can be derived as follows. At time $t$, if $x(t) = 0$ and

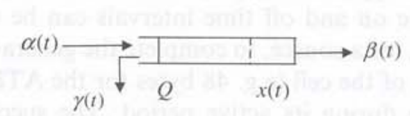


Figure 1. Model of the single satellite station.

$\alpha(t) - \beta(t) \leqslant 0$, or $x(t) = Q$ and $\alpha(t) - \beta(t) > 0$, then $\mathrm{d}x(t)/\mathrm{d}t = 0$, otherwise $\mathrm{d}x(t)/\mathrm{d}t = \alpha(t) - \beta(t)$. For the overflow rate process $\gamma(t)$, $\mathrm{d}\gamma(t)/\mathrm{d}t = \alpha(t) - \beta(t)$ if $x(t) = Q$, otherwise $\mathrm{d}\gamma(t)/\mathrm{d}t = 0$.

In the next section, following Reference [17], we shall put in evidence that, with only such 'ingredients', it is possible to establish a simple way to determine an estimate of the gradient of the cost function, in order to optimize the system performance.

### 2.2. *The traffic model*

*2.2.1. Self-similarity in wired and wireless networks.* Even if the on-line surrogate optimization methodology we are going to formulate is not related to a specific behaviour of the traffic sources, we shall adopt, in the simulation results, a specific traffic model in order to obtain a closed-form functional cost of the performance index. Hence, we now introduce the traffic model adopted for each inflow process $\alpha_i(t), i = 1, \ldots, N$.

In recent years, analyses of packet-based traffic have demonstrated that its main statistical characteristics have good affinity to *self-similar* processes. Intuitively, self-similar traffic is supposed to present the same statistical behaviour over large time intervals. Leland *et al.* analysed Ethernet traffic [41], highlighting its self-similar nature, as Paxson and Floyd [42] extended these observations to the TCP protocol over WANs. Besides, Garrett and Willinger [43] proposed this model also for video *variable bit rate* (VBR) traffic.

It is well known that the bandwidth of wireless interconnect techonology is very low compared to wired interconnect technology. Wired networks differ in a lot of other aspects from wireless ones (e.g. router size, buffer size, traffic load). As a result, extrapolating conclusions drawn on wired networks to wireless networks may not be a straightforward matter. However, self-similar traffic arises for wireless networks, too. The self-similarity nature of traffic is mostly related to users' behaviour than to the underlying technology. In References [27, 44] four types of traffic profiles have been proposed, on the basis of the most frequently used wireless applications: *e-mail, www, file transfer protocol,* and *telemetry traffic*: '*Heavy-tailed nature of on–off periods has more to do with basic properties on information storage and processing, it is not a result of the network protocols or user preference; therefore, changes in protocol processing and document display cannot remove the self similarity of the web traffic. Also, it is shown that both the user's thinking or reading times and the file size distributions are strongly heavy-tailed*' [27].

Therefore, we shall adopt a self-similar model for the traffic sources. We present a brief description of the main features of such type of traffic and how it has been implemented in our simulations.

*2.2.2. On–off self-similar traffic sources.* Suppose to have $M$ independent sources, each one generating a traffic flow at constant cell rate $R$ (cells/s) for a random time period $\tau$, at the end of which the source does not send any packet for a random time interval $\sigma$. Such types of sources are called in the literature '*on–off sources*' and they are aimed at modelling VBR traffic (e.g. real time or streaming audio–video applications) [45]. As in References [7, 8, 20, 46], we suppose that the cell dimension is fixed; the on and off time intervals can be expressed as multiples of $T_s$, where $T_s$ is the time necessary, for a source, to complete the generation of a new cell; $T_s = L/B_p$, where $L$ is the payload length of the cell (e.g. 48 bytes for the ATM cell) and $B_p$ is the peak bit rate, i.e. the source's bit rate during its active period. The succession of several periods, as mentioned above, creates a traffic pattern as depicted in Figure 2, where $\tau'$ and $\sigma'$ are two

 

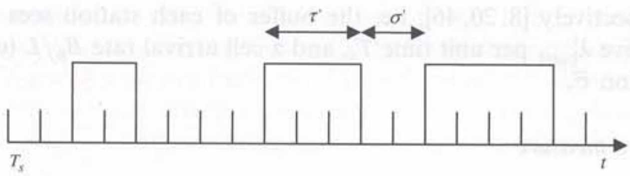


Figure 2. Typical sample path of an on–off source.

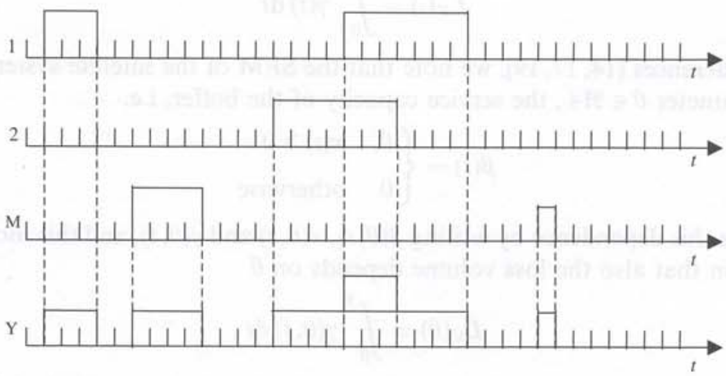


Figure 3. The aggregation of $M$ independent on–off sources.

possible realizations of the random variables $\tau$ and $\sigma$ that describe the statistical behaviour of the single on–off traffic source.

Let us suppose that $\tau$ follows a *heavy-tailed* distribution, for example the *Pareto* one

$$\Pr(\tau = t) = ct^{-(\alpha+1)}, \quad t = 1, 2, \ldots \tag{1}$$

where $c$ is a normalization constant such that

$$c = \frac{1}{\sum_{t=1}^{\infty} t^{-(\alpha+1)}} \tag{2}$$

From these equations, it follows that, for $1<\alpha<2$, $\tau$ has a finite average value

$$\bar{\tau} = E\{\tau\} = \sum_{t=1}^{\infty} ct^{-\alpha}$$

but infinite second moment $E\{\tau^2\}$ [45].

It is shown in Reference [46] that the aggregation of $M$ independent sources (the $Y$ process depicted in Figure 3) with such probability distribution over $\tau$ determines an aggregated flow with self-similar properties (asymptotically in $M$ and $\bar{\sigma}$), and this has a dramatic impact over the resources that must be reserved to such flow in order to guarantee cell-level QoS constraints (see, e.g. References [45, 46]).

We suppose that each inflow process $\alpha_i(t)$ is composed by the aggregation of $M$ independent on–off sources with Pareto-distributed on and off periods. The statistical parameters that describe each $\alpha_i(t)$ are, for each station $i$, the *peak bit rate* $B_{\text{p}}$ (bits/s) (supposed, for simplicity and without loss of generality, to be equal for each transmitting station) and the *burst arrival rate* $\lambda^i_{\text{burst}} = M^i/(\bar{\tau}^i + \bar{\sigma}^i)$, where $\bar{\tau}^i$ and $\bar{\sigma}^i$ are the mean time duration of the burst and of the silence periods, respectively [8, 20, 46]; i.e. the buffer of each station sees a mean number of bursts becoming active $\lambda^i_{\text{burst}}$ per unit time $T_s$, and a cell arrival rate $B_p/L$ (cells/s) in each burst of mean time duration $\bar{\tau}^i$.

### 2.3. *The performance measure*

The performance measure of interest is the *loss volume* $L_V(\cdot)$ over the interval $[0, T]$

$$L_V(\cdot) = \int_0^T \gamma(t)\, dt \tag{3}$$

Following References [14, 17, 19], we note that the SFM of the satellite system depends on a real-valued parameter $\theta \in \Re+$, the service capacity of the buffer, i.e.

$$\beta(t) = \begin{cases} \theta, & x(t) > 0 \\ 0 & \text{otherwise} \end{cases}$$

We now indicate this dependence by writing $\beta(\theta, t)$, $x(\theta, t)$ and $\gamma(\theta, t)$, and this modification leads to the conclusion that also the loss volume depends on $\theta$

$$L_V(\theta) = \int_0^T \gamma(\theta, t)\, dt \tag{4}$$

The satellite system is composed by $N$ stations, each of which is provided with a single buffer with capacity $Q_i$, service rate $\theta_i(t)$ and its specific inflow rate process $\alpha_i(t)$. The total loss volume becomes the sum of the contributions of each station (Figure 4)

$$L_V(\theta_1, \ldots, \theta_N) = \sum_{i=1}^{N} \int_0^T \gamma_i(\theta_i(t), t)\, dt \tag{5}$$

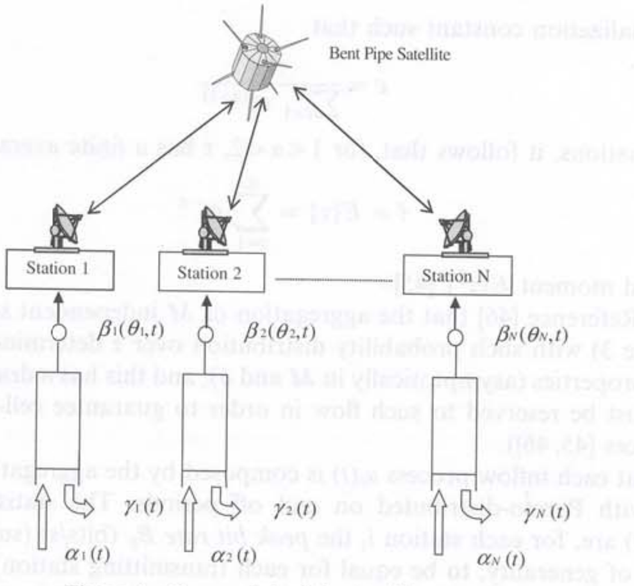


Figure 4. The model of the satellite system.

 

The total capacity of the satellite must be divided among the $N$ stations. Let $\boldsymbol{\theta}^{\mathrm{d}}(t) = [\theta_1^{\mathrm{d}}(t), \ldots, \theta_N^{\mathrm{d}}(t)]$ be the vector of the service capacities allocated to each station at time $t$. $\boldsymbol{\theta}^{\mathrm{d}}(t)$ must belong to the following constraint set:

$$\Theta_{\mathrm{d}} = \left\{ \boldsymbol{\theta}^{\mathrm{d}}(t) \in \mathbb{N}^N : \theta_i^{\mathrm{d}}(t) = h_i(t)\,\mathrm{MAU}, h_i(t) \in \mathbb{N}, \sum_{i=1}^{N} \theta_i^{\mathrm{d}}(t) = K \right\} \tag{6}$$

$\theta_i^{\mathrm{d}}(t)$ is a *discrete* parameter, in the sense that the allocated service rate for each station is a discrete number of *minimum allocation units* (MAUs), namely, the smallest portion of bandwidth that can be allocated to a station. $K$ is the total service capacity available for the satellite system.

## 2.4. The fading effect and problem formulation

The effect of fading, supposed, for the sake of simplicity, to be unique for each transmitting station (i.e. each station is supposed to transmit to destinations affected by the same fading levels [8, 20]), is modelled as a reduction in the bandwidth actually 'seen' by a traffic station. The fading effect is represented by a variable $\phi_i$, independent of $\theta_i^{\mathrm{d}}$, that shows how the bandwidth is reduced. For each station $i$, at time $t$, the '*real*' $\theta_i(t)$ is

$$\theta_i(t) = \phi_i(t)\theta_i^{\mathrm{d}}(t); \quad \phi_i(t) \in [0, 1]; \ i = 1, \ldots, N \tag{7}$$

$\phi_i(t) = 1$ corresponds to no fading effect over the links of station $i$ at time $t$, while $\phi_i(t) = 0$ corresponds to the so-called '*outage*' situation for station $i$, i.e. at time $t$, station $i$ sees a service rate process $\beta_i(t) = 0$, in spite of any possible allocation of the service capacity $\theta_i^{\mathrm{d}}(t)$.

*2.4.1. Adaptive forward error correction codes.* In our model, the fading effect involves a reduction of the bandwidth actually 'seen' by the station, or, equivalently, an increase in the bandwidth required by the traffic sources to maintain the same *bit error rate* (BER). We suppose the presence of fade countermeasures located at the physical layer, totally managed by the single earth station. It is expected to provide the desired BER through *forward error correction* (FEC) codes [8, 20, 22, 23, 25, 47]. Whenever the fading effect causes errors over the packets, an adaptive control can monitor the C/N (*carrier/noise power*) factor and, on the basis of this measure, increase the redundancy of the packets sent introduced by the FEC. In this way, for each station, the available bandwidth is reduced: since more bits are necessary to transmit a single packet (because of FEC coding), the outflow cell rate can be considered as modified by the fading effect. Clearly, heavier fading conditions will involve a more consistent decrease of the allocated bandwidth, because more coding protection of data will be necessary, and *vice versa*.

So, we are going to discuss the combination of a BER-related fade countermeasure technique with a resource allocation problem, where a master control station is supposed to be responsible of the reallocation of bandwidth, but not necessarily supposed to know the fading level of each station as, on the contrary, it is done in References [8, 20]. In this way, we reduce the centralization of the system, because the master only has to know the sensitivity estimation of each station, ignoring the information about the fading level.

*2.4.2. The discrete stochastic optimization problem.* Let $\boldsymbol{\varphi}(t)$ and $\boldsymbol{\theta}^{\mathrm{d}}(t)$ be the aggregate vectors of the fading levels $\phi_i(t)$ and the discrete bandwidth allocations, $\theta_i^{\mathrm{d}}(t), i = 1, \ldots, N$, respectively. The optimization problem can now be stated. It consists of finding out the optimal bandwidth allocation ${}^{\mathrm{Opt}}\boldsymbol{\theta}^{\mathrm{d}}(t)$, $t > 0$, in a such a way that the overall loss volume of the system is minimized

$$ {}^{\mathrm{Opt}}\boldsymbol{\theta}^{\mathrm{d}}(t) = \arg \min_{\boldsymbol{\theta}^{\mathrm{d}}(t)\in\Theta^{\mathrm{d}},\forall t>0} J[\boldsymbol{\theta}^{\mathrm{d}}(t)] \tag{8} $$

$$ J[\boldsymbol{\theta}^{\mathrm{d}}(t)] = \mathop{E}_{\omega_1,\ldots,\omega_N} L_{\mathrm{V}}(\boldsymbol{\varphi}(t), \boldsymbol{\theta}^{\mathrm{d}}(t)) = \mathop{E}_{\omega_1,\ldots,\omega_N} \left[ \sum_{i=1}^{N} \int_0^T \gamma_i(\phi_i(t)\theta_i^{\mathrm{d}}(t), t)\,\mathrm{d}t \right] \tag{9} $$

$\omega_i$ is the generic sample path for station $i$, namely, a realization of the stochastic processes that characterize the temporal evolution of station $i$: $\alpha_i(t), \beta_i(t), \phi_i(t), i = 1, \ldots, N$.

The expectation $E_{\omega_1,\ldots,\omega_N}[\cdot]$ is over all the feasible sample paths $\omega_i \in \Omega_i$ for each station $i$. Equation (8) expresses a discrete stochastic programming problem. Even when the setting is deterministic and the expectation is not requested, this class of problems is *NP-hard* (see e.g. References [3,4] and references therein). In some cases, depending upon the form of the objective function $J(\boldsymbol{\theta}^{\mathrm{d}})$ (e.g. separability, convexity), efficient algorithms based on *finite-stage dynamic programming* or *generalized Lagrange relaxation* methods are known (see, e.g. Reference [48]). Alternatively, if no *a priori* information is known about the structure of the problem, some forms of search algorithms is employed (e.g. *simulated annealing* [49], or *genetic algorithms* [50] techniques). When the system operates in a stochastic environment and no closed-form expression of the performance metric of interest $L_{\mathrm{V}}(\cdot)$ is possible, the situation is further complicated by the need of estimating $E_{\omega}[L_{\mathrm{V}}(\cdot)]$. This generally requires *Montecarlo* simulation approaches or direct measurements made on the system that are far from being realistic for real on-line optimization strategies.

In order to face such heavy drawbacks, following the theoretical framework of Gokbayrak and Cassandras [3,4], we shall formulate a new optimization algorithm, based on a sensitivity estimation procedure. We shall compare it with the optimization technique employed in References [8,20], based on a closed-form expression of the performance index and on the adoption of a dynamic programming algorithm.

## 3. THE OPTIMIZATION ALGORITHM BASED ON A *CERTAINTY EQUIVALENT* APPROACH

### *3.1. A closed-form formula for the loss probability*

Also in the presence of a self-similar behaviour of the traffic sources, it is possible to exploit analytical models for the computation of the loss probability [45,46]. Such closed-form expressions could be used in the aforementioned resource allocation framework in order to optimize the system performance (e.g. References [8,20]). Anyway, they need to assume a perfect knowledge of the system's state and a strong consumption of computing power, due to the continuous on-line minimization of a global cost through the adoption of a proper dynamic programming algorithm.

We now describe in some detail such optimization strategy. Following the model employed in References [8,20], we adopt the *Tsybakov–Georganas* formula for the cell loss probability

 

PLoss$_i$ of each station $i$

$$\mathrm{PLoss}_i(\theta_i^d) = \begin{cases} \min\left\{\dfrac{c\lambda^i R^\alpha}{\alpha(\alpha-1)(X_i - \lambda^i R\bar{\tau})}(Q_i)^{-\alpha+1}, 1\right\} & \text{if } X_i > \lambda^i R\bar{\tau} \\ 1 & \text{otherwise} \end{cases} \tag{10}$$

Some of the parameters appearing in (10) have been already defined in Section 2.2 ($\alpha$ and $c$ referring to the Pareto distribution over the burst and silence periods of the sources, denoted with $\tau$ and $\sigma$, respectively). The others are explained in the following. Let $T_s$, as defined in Section 2.2, be the reference time interval (*slot*), to which we shall refer all the relevant parameters of the cell queue of each station $i$. The slot also represents the minimum duration of a burst, and the burst length $\tau$ is expressed as an integer number of slots. Then, $R = \lceil T_s B_p / L \rceil$ is the number of cells generated by an active burst in a slot ($\lceil w \rceil$ being the smallest integer greater than or equal to $w$). Suppose that the number of new sources becoming active in each slot are i.i.d. *Poissonian* (which is true for the model of Section 2.2, asymptotically in the number of sources and in each $\bar{\sigma}_i$ [46]), with parameter $\lambda^i = \lambda^i_{\text{burst}} T_s$. If $H$ is the cell's header length in bits, then $X_i = \lfloor \theta_i^d \phi_i / (L+H) T_s \rfloor$ represents the bandwidth $\theta_i^d$, assigned to station $i$ and degraded according to the current value of fading $\phi_i$, expressed in cells per slot ($\lfloor w \rfloor$ being the largest integer less than or equal to $w$).

### 3.2. A dynamic programming algorithm

Once that a closed-form expression is available, and supposing to know perfectly, for each active station $i$, all the traffic parameters and the current fading levels necessary to correctly update Equation (10), it is possible to employ a proper dynamic programming algorithm, in order to optimally distribute the available channel capacity among the stations. The optimization problem formulated in Equations (8) and (9) has to be slightly modified by taking into account Equation (10), thus stating the problem of the minimization of the overall loss probability at each time instant $\kappa = 1, 2, \ldots$, where a new bandwidth reallocation is performed

$$^{\mathrm{Opt}}\boldsymbol{\theta}^{\mathrm{d}}(\kappa) = \arg \min_{\boldsymbol{\theta}^{\mathrm{d}}(\kappa) \in \Theta^{\mathrm{d}}} J[\boldsymbol{\theta}^{\mathrm{d}}(\kappa)] \tag{11}$$

$$J[\boldsymbol{\theta}^{\mathrm{d}}(\kappa)] = \sum_{i=1}^{N} \mathrm{PLoss}_i(\theta_i^{\mathrm{d}}(\kappa)), \quad \kappa = 1, 2, \ldots \tag{12}$$

The index $\kappa$ denotes the reallocation time instants at which a new solution of (11) is computed according to the current state of the network. The expectation operator $E_{\omega_1,\ldots,\omega_N}[\cdot]$, is now useless, because, in order to face the problem formulated by Equations (8) and (9), an assumption has been taken over the statistical behaviour of the traffic sources, thus leading to Equation (10) and then, an optimization procedure is employed to find the solution of (11) and (12) at the beginning of each reallocation time instant $\kappa = 1, 2, \ldots$. On the other hand, in the on-line optimization methodology that we are going to investigate, the adoption of an on-line gradient descent technique will allow us to spread the solution of (8) and (9) over time, instead of concentrating it at the beginning of each reallocation time instant.

 

### 3.3. The on-line computational effort

The minimization of (10) can be performed through a *dynamic programming* approach. Ross [51] shows how to employ a dynamic programming algorithm in order to solve the optimization of the overall blocking probability of a multiservice system at the call level, in the presence of a limited set of bandwidth resources.

Such algorithm is polynomial with respect to the number of stations and to the total number of available MAUs in the system. Hence, its computational burden seems to be not so heavy as expected. Unfortunately, the total number of available MAUs can be very large in the presence of a satellite link with a high capacity and with the adoption of small values in the MAU parameter (from 100 kbps down to lower values). So, if also the number of active stations is high, such optimization procedure might need several seconds to terminate successfully. This drawback can severely degrade its performance. As we shall also show in the simulation results, since the adoption of large MAU values is not recommendable (as it leads to poor performance of the optimization algorithm, too), if such dynamic programming algorithm has to be employed, a proper trade-off must be found, in order to limit its computational burden, without adopting too large MAU values.

Even if the on-line surrogate optimization methodology will reveal to be computationally lighter, we do not insist, in this paper, about its suitability due to its lower computational complexity, but we shall try to highlight how it is able, in virtue of its sensitivity estimation capability, to achieve better solutions than the ones obtained by employing the aforementioned dynamic programming algorithm.

In the next two sections, we develop the application of this optimization technique, based on a sequence of discrete reallocations, driven by an underlying gradient descent that follows the minimization of the overall loss volume of the system.

## 4. PERFORMANCE DERIVATIVE ESTIMATION THROUGH *PERTURBATION ANALYSIS*

In order to generate a gradient descent of bandwidth reallocations, it is necessary to obtain a derivative estimation of the performance index $J[\boldsymbol{\theta}^{d}(t)]$. Since our challenging task is to build an optimization technique able to manage any possible statistical behaviour of the traffic sources, we employ a derivative estimation technique that assumes very mild *a priori* hypotheses concerning the stochastic processes involved in the system.

### 4.1. The unbiasedness condition in perturbation analysis

We must note that the *infinitesimal perturbation analysis* (IPA) technique, proposed in References [14, 17] for SFMs of a telecommunication network, can be efficiently employed to satisfy our needs. In order to obtain gradients of performance metrics, IPA derives the effect on the system of a small (infinitesimal) perturbation on parameters that influence its evolution. One of the main advantages of IPA is that no *a priori* information on the form of the objective function is required, since the gradient estimates are computed directly from the current sample path $\omega$ of the system [11, 14, 17].

It has been demonstrated that IPA would yield an '*unbiased*' estimator for a large class of networks in a SFM setting [11, 14, 17]. The concept of *unbiasedness* is an essential property for the use of PA in an optimization framework and it can be explained as follows. $L_V(\cdot)$ is denoted in the remainder of the paper with $L(\cdot)$ to limit the notational burden.

Let $L(\theta)$ be a generic performance measure observed on a generic sample path (e.g. loss volume, cumulative workload, etc.), which is a function of the parameter of interest $\theta$ (e.g. service rate, buffer dimension). If $\Omega$ is the set of all feasible sample paths and $\omega$ a generic one, a PA estimator is defined to be *unbiased* if the derivative operator can be replaced with the expectation operator and *vice versa*:

$$\frac{\mathrm{d}}{\mathrm{d}\theta} \underset{\omega}{E}[L(\theta)] = \underset{\omega}{E}\left[\frac{\mathrm{d}L}{\mathrm{d}\theta}\right] \tag{13}$$

Interchanging the expectation with the limit of the incremental ratio is necessary to build an estimator of the performance derivative as a function of the current sample path $\omega$. This issue requires that $L(\theta)$ satisfy some particular characteristics. Much work has be conducted in the last few years in the operations research community to study which are the conditions for (13) when PA techniques are applied in the context of *discrete event systems* (DESes) (see, e.g. References [11, 14, 17, 19] and references therein). The two conditions that ensure the unbiasedness of IPA derivatives are [17]:

(1) for every $\theta \in \Theta$, $\partial L(\cdot)/\partial\theta$ exists, *with probability* 1 (w.p.1);
(2) the function $L(\cdot)$ is Lipschitz-continuous throughout $\Theta$ and the Lipschitz constant has a finite first moment, w.p.1.

It is worth noting that our choice of modelling the satellite system with a SFM leads to the applicability of an unbiased estimator through IPA. The aforementioned conditions are very general and do not limit the application of IPA estimators to a large set of DES of interest for telecommunication networks. In general, due to the discontinuities of $L(\theta)$ over $\Theta$ for several DES models, traditional queuing models give *biased* derivative estimators that do not satisfy Equation (13) (see, e.g. Reference [11] for an overview concerning this topic). On the contrary, adopting the SFM of Section 2.1, it is proved (e.g. in Reference [17]) that our performance function $L(\cdot)$ satisfies conditions 1 and 2 and a guaranteed unbiased PA estimator can be obtained.

### *4.2. Gradient estimation through infinitesimal perturbation analysis*

Once we have found out the right PA technique for gradient estimation applicable to our context (i.e. the IPA applied to a SFM of the network), the next step is to show the IPA formulas adopted.

Let $\hat{t}$ be a time period between two consecutive bandwidth reallocations. As we shall show later, the gradient estimation performed in the time interval $[(\kappa-1)\hat{t}, \kappa\hat{t}]$ drives the bandwidth reallocation carried out at time $\kappa\hat{t}, \kappa = 1, 2, \ldots$

To derive the employed IPA estimator, the following assumptions are needed [17]:

(1) the function $\alpha(t) - \beta(\theta, t)$ is piecewise continuously differentiable, w.p.1;
(2) no multiple events may occur simultaneously, w.p.1;
(3) the sample derivative $\partial L(\theta)/\partial\theta$ always exists, w.p.1;

These assumption are necessary to avoid the piecewise existence of the required IPA estimator (see, e.g. Reference [17] for further details). They pertain to the underlying SFM of the DES and do not affect our ability to derive sensitivity estimation as functions of measures collected over the real system, without supposing a specific behaviour of the inflow process.

 

Let these three mild assumptions be in effect, and let $B_k$ be an '*active*' period of the buffer (during the time interval $[(\kappa-1)\hat{t};\kappa\hat{t}]$), namely, a period of time in which the buffer is non-empty; we denote it with

$$B_k(\xi_k(\theta), \eta_k(\theta)) \tag{14}$$

where $\xi_k$ is the start point and $\eta_k$ the end point of $B_k$. We define the index set $\Gamma^k(\theta)$ as

$$\Gamma^k(\theta) = \{\text{All time instants in increasing order } [v_1^k, \ldots, v_{N_k}^k] \text{ during } B_k, \text{ when a loss occurs in the buffer}\}$$

Clearly, $\Gamma^k(\theta)$ strictly depends on the service rate of the buffer $\theta$. Let $v_{N_k}^k$ be the instant of time when the last loss occurs during $B_k$. Let $L^k(\theta)$ be the value of the loss volume in $B_k$. Then, for every $\theta \in \Theta$, it can be demonstrated that

$$\frac{\partial L^k(\theta)}{\partial \theta} = -(v_{N_k}^k - \xi_k(\theta)) \tag{15}$$

Namely, the contribution to the required derivative of each active period $B_k$, during which some loss occurred, is the length of the time interval from the start of $B_k$ until the last time point in $B_k$ at which the buffer is full (see Figure 5).

As to the proof of Equation (15) and its unbiasedness, the reader is referred to Reference [14] or [17].

Hence, at the time of bandwidth reallocation at station $i$, denoting by $N_{B_i}$ the number of active periods between two consecutive bandwidth reallocation time instants where at least one loss occurs, we can write an estimation of the gradient as

$$\frac{\partial L(\theta_i)}{\partial \theta_i} = \sum_{k=1}^{N_{B_i}} \frac{\partial L^k(\theta_i)}{\partial \theta_i}; \quad i = 1, \ldots, N \tag{16}$$

It is worth pointing out that $\partial L(\theta_i)/\partial \theta_i = \partial L(\phi_i \theta_i^{\mathrm{d}})/\partial \theta_i$ in virtue of (7), whereas gradient estimation is performed with respect to the 'real' service rate $\theta_i$, as defined in (7). This implies 'capturing' (within the duration of the busy periods) both effects of the previous bandwidth allocation $\theta_i^{\mathrm{d}}$ and of the realization of the stochastic process $\phi_i$ in each time interval $[(\kappa-1)\hat{t};\kappa\hat{t}], \kappa = 1, 2, \ldots$.

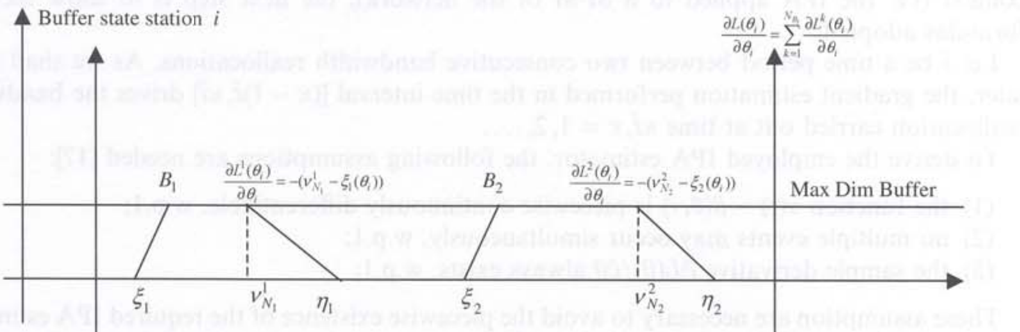


Figure 5. Gradient estimation looking only at the sample path of the buffer state at station $i$.

 

The IPA performance derivative obtained by Equations (15) and (16) is also known as '*non-parametric*', since it is computable directly from an observed sample path $\omega$, without any further knowledge concerning the probability distributions of the stochastic processes involved in the system [11, 14, 17]. '*The form of the IPA estimators is obtained by analyzing the system as a SFM, but the associated values are based on real data*' [14]. This fact implies that it is applicable not only in off-line simulation settings (aimed, for example, at the planning of the telecommunication network), but also in real on-line scenarios for practical network management and control [11, 13, 14, 17, 19, 52]. In the next section we shall proceed according to this last direction.

## 5. THE ON-LINE SURROGATE OPTIMIZATION METHODOLOGY

Since our aim is to apply the estimator for the derivative of the performance parameter $\partial L(\theta_i)/\partial\theta_i$ formulated in the previous section, it is necessary to '*relax*' the discrete constraint set $\Theta_d$ into a continuous one $\Theta_c$. The $\partial L(\theta_i)/\partial\theta_i$ is used to optimize a continuous bandwidth allocation $\boldsymbol{\theta}^c$ with the following constraints:

$$\boldsymbol{\theta}^c \in \Theta_c, \Theta_c = \left\{ \theta_i^c \in \Re^+;\ i = 1, \ldots, N;\ \sum_{i=1}^{N} \theta_i^c = K \right\} \tag{17}$$

As proposed in References [3, 4] the discrete functional cost defined over $\Theta_d$ is transformed into a '*surrogate*' one that works over $\Theta_c$. We construct an estimation of the gradient, according to the current measured sample path by Equations (15) and (16), and we apply a sequence of minimization steps until the optimum is reached.

The following scheme illustrates each step of the optimization algorithm, whose computation can be decentralized (Figure 6). Our on-line surrogate approach acts as follows. Initially, the bandwidth resources are equally distributed among the stations and, during the system evolution, for every $t = \kappa\hat{t}, \kappa = 1, 2, \ldots$, each station $i$ must

1. ***observe*** *the buffer temporal evolution during the time interval* $[(\kappa-1)\hat{t}, \kappa\hat{t}]$ *according to the current sample path* $\omega_i$ *and bandwidth allocation* $\theta_i^d[(\kappa-1)\hat{t}]$, $\boldsymbol{\theta}^d[(\kappa-1)\hat{t}] \in \Theta_d$;
2. ***compute*** *the derivative estimation* $\dfrac{\partial L(\theta_i[(\kappa-1)\hat{t}])}{\partial\theta_i}$ *according to Eqs. (15) and (16);*
3. ***adjust*** *the value of its "bandwidth allocation need" using the gradient method:*
 $\theta_i^c[\kappa\hat{t}] = \theta_i^d[(\kappa-1)\hat{t}] - \eta\,\dfrac{\partial L(\theta_i[(\kappa-1)\hat{t}])}{\partial\theta_i}$;
4. ***communicate*** *such* $\theta_i^c[\kappa\hat{t}]$ *to each master station;*
5. *(for any station that has the role of master station),*
 *by looking at the information received by the other stations (i.e.,* $\theta_\varsigma^c[(\kappa-1)\hat{t}]$, $\varsigma = 1, \ldots, N;\ \varsigma \neq i$*), and, on the basis of the local bandwidth need* $\theta_i^c[(\kappa-1)\hat{t}]$,
 ***convert*** $\boldsymbol{\theta}^c[(\kappa-1)\hat{t}]$ *to the nearest discrete feasible neighbor* $\boldsymbol{\theta}^d[\kappa\hat{t}]$ *in such a way that* $\boldsymbol{\theta}^d[\kappa\hat{t}] \in \Theta_d$;
 *such conversion defines the bandwidth allocation for the satellite system in the time interval* $[\kappa\hat{t}, (\kappa+1)\hat{t}]$.

Figure 6. The algorithm employed in each station $i$ to yield an optimal resource allocation for the overall system.

 

As is shown in Reference [4], the nearest feasible neighbour $\boldsymbol{\theta}^{d}[\kappa\hat{t}] \in \Theta_{d}$ of $\boldsymbol{\theta}^{c}[(\kappa-1)\hat{t}]$ can be determined, at step 5, by using an algorithm based on the *Simplex method*. However, it is possible to apply a simpler $O(N+1)$ algorithm based on the $N+1$ discrete neighbours of $\boldsymbol{\theta}^{c}[(\kappa-1)\hat{t}]$, not necessarily all feasible, and on the selection of one of them, which satisfies the discrete constraint set $\Theta_{d}$ (see Reference [3] for further details).

### *5.1. Decentralized sensitivity estimation versus centralized reallocations*

The gradient-descent algorithm of step 3 allows a decentralization of the optimization procedure. We suppose that a personal processor is assigned to each station $i$; in this way, the optimization procedure runs in parallel on each independent processor located in each station. Such distributed computation is a very attractive property, as it enables each station to compute its '*optimized bandwidth need*' locally on the basis of the temporal evolution of the stochastic processes. The temporal evolution of the optimization procedure is depicted in Figure 7. $\mathbf{I}_{i}[\kappa\hat{t}]$ denotes the information available for the (currently active) master station $i$ at the reallocation time instant $\kappa\hat{t}$, i.e.: $\theta^{c}_{\varsigma}[(\kappa-1)\hat{t}]$, $\varsigma = 1, \ldots, N$. $\mathbf{I}_{i}[\kappa\hat{t}]$ is necessary to perform the 'surrogate to discrete' mapping $\boldsymbol{\theta}^{c}[(\kappa-1)\hat{t}] \Rightarrow \boldsymbol{\theta}^{d}[\kappa\hat{t}]$ and to deploy the bandwidth allocation for the next time interval $[\kappa\hat{t}; (\kappa+1)\hat{t}]$.

### *5.2. Proof of convergence*

The theoretical framework of Gokbayrak and Cassandras [3, 4] assures that this surrogate optimization approach guarantees the convergence to the optimal resource allocation. We now briefly summarize the conditions requested for its convergence.

The employed gradient-based algorithm is a standard stochastic approximation scheme driven by the IPA gradient estimator of (15)–(16). Four technical conditions are required to establish convergence to a global optimum.

- The first one is related to a decreasing behaviour of the gradient stepsize $\eta$ and is discussed in Section 6.
- The second one involves unbiasedness and consistency of the employed IPA estimator. The unbiased condition has been investigated in Section 4.1. Consistency is related to the

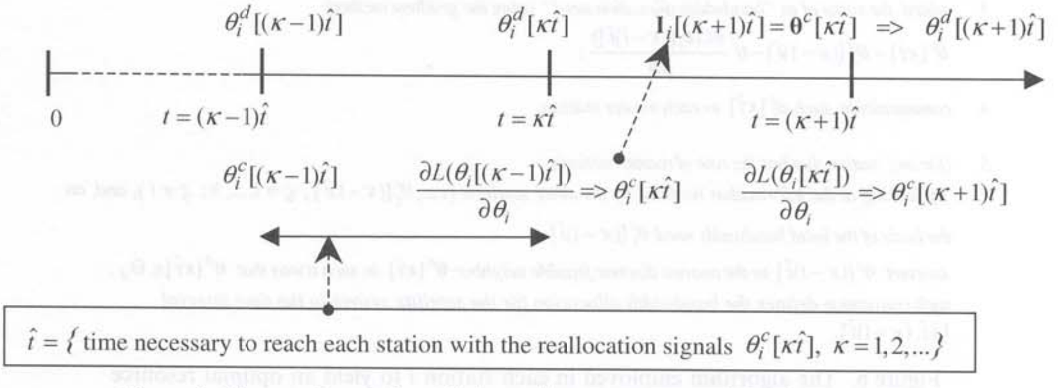


Figure 7. Temporal evolution of the on-line surrogate optimization approach.

 

convergence capability of the proposed estimator with respect to the 'real' (and unknown) gradient of the functional cost $\partial/\partial\theta_i E_{\omega_i} L(\theta_i), i = 1, \ldots, N$ [11]. Consistency requires that as the length of the observed sample path $\omega_i$ increases, the IPA estimator $\partial L(\theta_i)/\partial\theta_i$ converges to $\partial/\partial\theta_i E_{\omega_i} L(\theta_i)$ w.p.1. In practice, the hope is that as the number of observation increases, the accuracy of the estimator increases, too.

Consistency is related to the ergodicity of the stochastic processes involved in the system. In the setting we are considering, they are assumed to be non-stationary. Hence, it is hard to prove consistency. However, as also pointed out in Reference [14], '*we concentrate on obtaining reliable shorter-term sensitivity information tracking the behaviour of the network and seeking to continuously improve its performance*'. Thus, the need of consistent gradient estimators can be disregarded.

- A third condition pertains to the cost function to guarantee a unique global optimum. It is independent of the stochasticity of the system and it can be relaxed, thus leading to possible convergence to a local, rather than global, optimum. The regularity properties of the cost function are related to the resource allocation framework under investigation. For the problem investigated here, we argue that a unique global optimum exists for each possible combination of fading levels and traffic sources' state. The following simulation results confirm this conjecture.
- The final condition requires that $\sup_{\theta^c \in \Theta_c} \|\nabla L(\theta^c)\| < \infty$ (where $\|\cdot\|$ denotes the standard euclidean norm). Namely, the gradient estimation should be defined and limited in the surrogate domain $\Theta_c$. Looking at Figure 5, it is easily observable that for every buffer and service capacity allocation, the differences arising in IPA formula (15) are always bounded by the reallocation time period $\hat{t}$. Therefore, this final condition is satisfied.

In Reference [13], a similar approach is applied for the optimization of the *call admission control* in a circuit switched network, and, at the best of our knowledge, this is the first time that such technique is adopted to optimize the performance of a telecommunication network at the packet level.

### *5.3. Computational complexity*

The computational efforts required by both the gradient estimation procedures and the algorithm adopted in step 5 are linear in the state space, namely, the computational complexity of such optimization approach grows linearly with respect to the number of stations in the network. For this reason, and owing to the mild assumptions requested for the applicability of the adopted IPA technique, we could claim that the proposed optimization algorithm can be efficiently applied in real on-line scenarios, according to different channel degradations and statistical behaviours of the traffic sources.

### *5.4. The reallocation period*

The reallocation period $\hat{t}$ has been kept fixed at 1.0 s. One second between every bandwidth reallocation is a realistic value for a satellite network. In fact, the master control station has to get the sensitivity estimation of each earth station to compute the next reallocation (Figure 7), and, particularly with geostationary satellites, which are located at a distance of about 36 000 km from the earth with a *round trip time* close to 500–600 ms, it is necessary to take into account the relevance of the propagation delay for this information.

*5.5. System signalling*

If, at time $t = \kappa\hat{t}$, station $i$ generates its new '*bandwidth need*' $\theta_i^c[\kappa\hat{t}]$, such value becomes available for all other stations only at the time $t = (\kappa + 1)\hat{t}$ (see Figure 7). Such exchange of information phase (step 4) looks like the *link state* (LS) signalling protocol of the *QoS routing* in a *MPLS* environment (see, e.g. Reference [53]). In LS routing, network nodes should be aware of the state of the links, possibly located several hops away. This calls for a periodic flooding exchange of LS information, which contributes extra traffic to the network. Our model needs a flooded and periodic exchange of *node state* (NS) information concerning the local sensitivity estimation of the gradient of each satellite station. The proposed periodic and flooded exchange of NS information is feasible for the satellite system, because it is lighter than the LS signalling of QoS routing. It can be periodically activated according to the typical time constraints of the network under investigation. For example, with geostationary satellites, fixing the reallocation time period $\hat{t}$ at 1.0 s (as, for example, in References [8, 20]), we adopt a feasible lapse of time necessary for the '*reallocation signals*' to become available to each station in the system.

## 6. BANDWIDTH ALLOCATION STRATEGIES

We now summarize all the bandwidth allocation strategies employed in the following simulation results. At the end of each simulation, the final loss volume is computed in terms of the overall *Loss Probability* among the stations of the satellite system.

*CF&DP* (*Closed Form* functional cost with *Dynamic Programming* optimization approach): the certainty equivalent approach formulated in Section 3 is employed.

For all stations in the satellite system, a perfect knowledge on both the parameters of traffic sources and the fading levels is supposed to be always in effect for each time of bandwidth reallocation. The current fading state can be obtained on the basis of the FEC redundancy factor implemented by the physical layer of each station, according to the current degradation of the satellite channel.

The sensitivity of the solution obtained with the adoption of this technique will be investigated, with respect to possible estimation errors over the real traffic sources' state.

*SE&GD* (*Sensitivity Estimation* and *Gradient Descent* optimization approach): the IPA technique described in the previous section is adopted, and derivative estimations are computed. After that, the gradient algorithm illustrated in Section 5 is applied using a gradient stepsize $\eta_\kappa$:

$$\theta_i^c[\kappa\hat{t}] = \theta_i^d[(\kappa-1)\hat{t}] - \eta_\kappa \frac{\partial L(\theta_i[(\kappa-1)\hat{t}])}{\partial\theta_i} \tag{18}$$

where $\eta_k$ is modified at each step according to the following relationship:

$$\eta_\kappa = [(a \times 10^6) - \kappa(b \times 10^3)] \\ a = 12; \quad b = 200 \tag{19}$$

The rationale of this choice stems from the fact that, in stochastic optimization problems, the convergence of (18) is related to the decreasing behaviour of the stepsize $\eta_\kappa$ (see e.g. References [51, 54–56]). Of course, the function specifying how $\eta_\kappa$ has to decrease as the step $\kappa$ increases must be empirically evaluated in order to reach a 'good' level of optimality for the DES under investigation. The $a = 12; b = 200$ setting was found out by means of simulation analysis and the best combination of the parameters $a, b$ was obtained.

To better counteract non-stationary conditions (i.e. variable $\lambda_{\text{burst}}$ and fading levels), it is helpful to speed-up the algorithm convergence each time a new stationary condition is in effect. To do this, the gradient descent (18) is restarted with $\kappa = 0$ each time a large difference in one of the estimates $\partial L(\theta_i)/\partial\theta_i$ arises with respect to the previous samples of $\partial L(\theta_i)/\partial\theta_i$ (obtained in the last intervals of bandwidth reallocation). In this way, larger gradient stepsizes are provided in front of new stationary conditions and faster convergences to the corresponding optimal steady states are guaranteed. In practice, changes in the stochastic environment are derived heuristically through thresholds over the IPA gradient estimator. When a variation on the gradient estimation takes place (e.g. it exceeds a threshold in the difference between the current gradient estimation and the mean of the last 10 gradient estimations) a variation in the mean of the stochastic processes is supposed to have happened, so the gradient descent restarts from $\kappa = 0$ to speed up convergence.

It is also worth noting that no feedback about the state of the system (i.e. fading levels, traffic sources' state) is necessary to apply the optimization descent (18).

*Optimal* (*Optimal* bandwidth allocation): since the SE&GD technique is guaranteed to achieve the optimal resource allocation after the sub-optimal transient period introduced by the gradient descent (18), it is possible to calculate the optimum system performance by observing the optimal allocations reached in steady state. Then, in a second stage of simulation, it is possible to re-apply such optimal allocations and to measure the optimum system performance.

An ATM structure of the packets is employed in the following simulation results. No further difficulty is involved in the SE&GD strategy if a different packet structure is adopted (such as: DVB, IPv4 or IPv6).

In Table I, the main differences between the SE&GD and CF&DP techniques are summarized. To help the CF&DP in providing fast reallocations, the delay due to the computational burden introduced by dynamic programming is disregarded, fixing the reallocation time interval always to 1.0 s.

Table I. Differences between the proposed allocation strategies.

| | SE&GD | CF&DP |
|---|---|---|
| *A priori* assumptions on the traffic sources | None | Self-similarity |
| Knowledge of the traffic parameters | None | $\lambda_{\text{burst}}$ and peak bandwidth |
| *A priori* assumptions about the SFM of the network | See Section 4.2 for gradient estimation procedure (very mild hypotheses) | None |
| Feedback on the fading levels | None | Yes |

 

## 7. SIMULATION RESULTS

We now illustrate a comparison among the aforementioned optimization techniques. Different traffic scenarios of variable traffic load and fading levels are taken into account. An investigation about the sensitivity of the obtained solutions with respect to the system parameters (e.g. MAU dimension, reallocation time intervals) will be also discussed in Section 7.4.

We have developed a C++ simulator for the network of queues that models the satellite system (see Figure 4). Such satellite system is made by 2 earth stations. The number of stations has been intentionally kept to such low value, in order to better understand the behaviour of the various techniques compared under different traffic patterns and fading situations. Increasing the number of stations to simulate more complex scenarios would not substantially change the evaluation [57], but it would make the comparison not so immediate and easy.

The simulations performed fall in the category of the so-called '*finite time horizon*' or '*terminating*' simulations [58]. The *independent replications* technique for the analysis of stochastic simulation systems (i.e. the repetition of the same simulation with different pseudorandom number generators until a confidence interval is reached for the performance parameter) was applied. For all the results presented, the width of the confidence interval over the loss volume at the end of $T$ is less then 1% of the estimated value for 95% of the cases.

### 7.1. Traffic load changes

*7.1.1. Simulation parameters.* The time horizon of the following simulation scenario $T$ is fixed to 3.0 min and the channel capacity $K$ is fixed at 80.0 Mbps. We suppose no fading attenuations acting over the system (i.e. $\phi_i(t) = 1; i = 1, \ldots, N; \forall t \in [0, T]$). According to the self-similar traffic model introduced in Section 2, 100 on–off sources, with Pareto distributed burst periods of activity, generate a traffic stream, which is aggregated in a unique traffic flow. Such flow constitutes the inflow process of each buffer of the satellite system. Each source is supposed to transmit at a peak bit rate $B_p$ of 1.0 Mbps. During the simulation, the average values of active and silence periods (respectively, $\bar{\tau}$ and $\bar{\sigma}$) are changed, by following the scheme in the chart below:

| | Time interval | | | | | |
|---|---|---|---|---|---|---|
| | 0.0–60.0 s | | 60.0–120.0 s | | 120.0–240.0 s | |
| Activity period (s) | $\bar{\tau}$ | $\bar{\sigma}$ | $\bar{\tau}$ | $\bar{\sigma}$ | $\bar{\tau}$ | $\bar{\sigma}$ |
| Station 1 | 1.0 | 3.0 | 1.0 | 1.0 | 1.0 | 3.0 |
| Station 2 | 1.0 | 1.0 | 1.0 | 3.0 | 1.0 | 1.0 |

Since the number of on–off sources for each station is fixed at $M^i = 100$ for $i = 1, 2$, the station in high traffic conditions sees a burst arrival rate of $\lambda^i_{\text{burst}} = M^i/(\bar{\tau}^i + \bar{\sigma}^i) = 50$ bursts/s, $i = 1, 2$, while, for the one in low traffic conditions, the burst arrival rate is $\lambda^i_{\text{burst}} = 25$ bursts/s, $i = 1, 2$. Both stations are provided with a finite buffer of 100 cells, thus guaranteeing a reasonable bound for the mean delay and delay jitter. For instance, with an allocation of 25.0 Mbps (that is a lower bound of the following bandwidth allocations), such bound is around

 

1.7 ms for each ATM cell. The MAU of each station is 100 kbps. In the chart above it is shown that, every minute, traffic statistics have been changed, inverting the role of the heavy-traffic station and the low-traffic one. The gradient stepsize $\eta$ in (18) was fixed according to (19). To infer changes in the stochastic environment, the threshold in the difference between the current gradient estimation and the mean of the last 10 gradient estimations was set to 0.45.

*7.1.2. Bandwidth allocation comparison.* A sample path in the SE&GD's bandwidth allocations is depicted in Figure 8, where, for each station, the fraction of the total system's capacity assigned by the SE&GD technique is visualized. It is clear how the algorithm is able to react to traffic variations: in the first minute, Station 2 suffers of heavier traffic load, and a larger quantity of MAUs has been allocated to it. The situation is inverted in the second minute, and it is evident in this case how SE&GD provides more resources to Station 1. Finally, in the last minute, the situation is brought back to the one of the beginning. The optimal steady states in the bandwidth allocations are found by looking at the allocations performed by the SE&GD technique at the end of the transient periods of the employed gradient descent (18).

In Figure 9, the CF&DP's bandwidth allocations are depicted together with the ones obtained through the SE&GD technique. The CF&DP reveals to be a good heuristic for the bandwidth allocation, because it is able to follow the variable traffic conditions. However, it is not able to maintain the best resource allocation: the bandwidth allocation to the station in heavier traffic load is lower than the one obtained by applying the SE&GD technique (around 47.0 Mbps

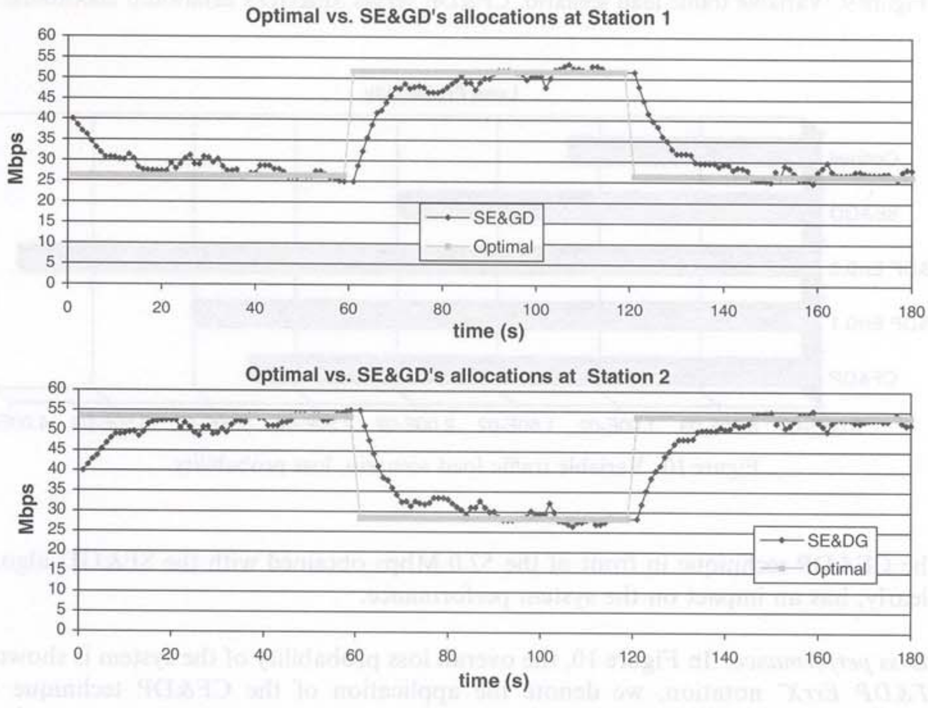


Figure 8. Variable traffic load scenario, Optimal versus SE&GD's bandwidth allocations.

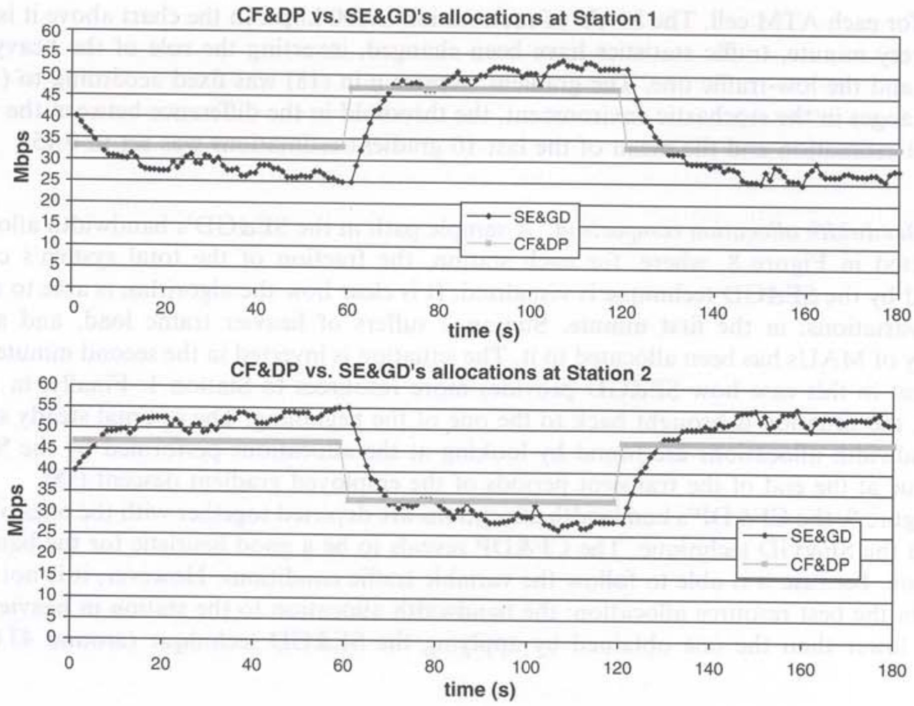


Figure 9. Variable traffic load scenario, CF&DP versus SE&GD's bandwidth allocations.

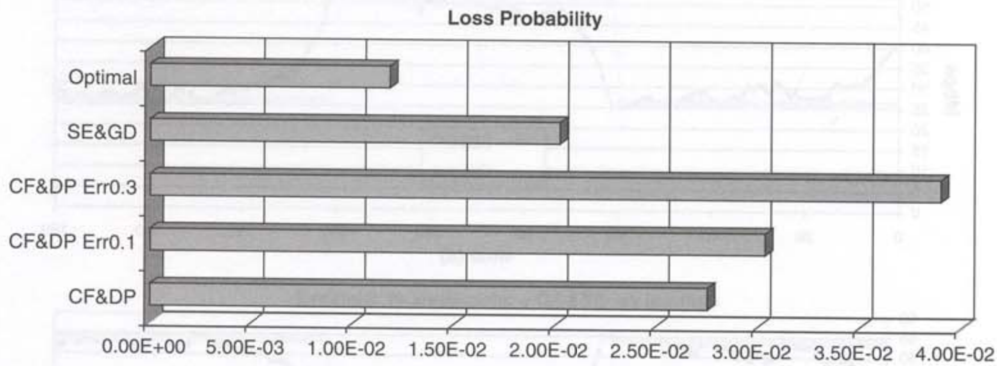


Figure 10. Variable traffic load scenario, loss probability.

using the CF&DP technique in front of the 52.0 Mbps obtained with the SE&GD algorithm). This, clearly, has an impact on the system performance.

*7.1.3. Loss performance.* In Figure 10, the overall loss probability of the system is shown. With the '*CF&DP ErrX*' notation, we denote the application of the CF&DP technique with a percentage error over the traffic load foreseen at station 1, e.g. with '*CF&DP ErrX*' we highlight the performance of the CF&DP technique in which the feedback over the state of the first station underestimates the real traffic load with a percentual error that amounts to $X\%$ over the real value. For example, with $X = 10\%$, a $\lambda_{\text{burst}}$ of 45 burst/s is employed in the functional cost (10) of the CF&DP technique, instead of the real value of 50 burst/s. Such estimation errors can severely decrease the CF&DP's performance, especially if they affect the feedback with a percentual error around 30%. On the other hand, with a perfect feedback on the system's state, the CF&DP technique reaches good performance, but only the application of the SE&GD technique guarantees the best approximation of the optimal solution.

*7.1.4. Remarks on the impact of traffic statistics.*

1. *Modelling other stochastic scenarios*. It is worth noting that the adoption of other $\lambda_{\text{burst}}$ and $B_p$ conditions to mimic specific applications (such as *ftp*, *www*, *e-mail* as in Reference [27, Chapters VI, VII]) does not change significantly the evaluation presented here. This was validated by experiments not reported here. Moreover, the adoption of other traffic models with short-range dependent characteristics such as *Markovian* traffic (e.g. *Poisson* or on–off *Markov Modulated Poisson Process*) implies a smaller variance on the mean rate of the sources. This has an impact over the SE&GD performance, since gradient estimation would be computed through more 'regular' traffic samples. However, variable traffic conditions (e.g. changing the mean rate of the sources) again produce the sub-optimal transient periods (due to the gradient descent) similar to the ones obtained for the self-similar traffic. Therefore, the differences in the performance presented in Figure 10 do not change significantly, even when a Markovian model of the traffic sources is employed.
2. '*Active learning*'. The SE&GD technique is able to learn the optimal equilibrium in the bandwidth allocation, thus guaranteeing better performance than the one reached by the certainty equivalent approach, even in the presence of a traffic load, whose statistical behaviour is very close to the assumptions adopted to provide a closed-form expression of the loss performance metric.

   The intuition behind such efficiency stems from the fact that, by means of its gradient descent, the SE&GD technique tries to follow the resource allocation that guarantees that all the components of the funtional cost and its gradient achieve the same values. In this way, the equilibrium point that corresponds to the minimum value of performance index is obtained. Moreover, since the gradient estimation procedure is continuously performed during the system evolution, such optimal equilibrium reveals to be adaptive to the current realization of the stochastic processes. As a result, without any direct feedback over the system's state (traffic load statistics and fading levels), such technique is able to learn the best resource allocation as function of the non-stationary behaviour of the stochastic processes.
3. *The failure of the CF&DP approach*. The CF&DP technique, even if it has a perfect knowledge over the system's state, is not able to catch the optimal resource allocation. In fact, the *PLoss* formula (10) holds asymptotically in the number of sources [46] (i.e. the number of sources in the aggregated flow $M$ should tend to infinity, as well as $\bar{\sigma}$). Hence, in a realistic scenario with a finite number of on–off sources, it can be seen as only a heuristic indication about the performance achieved by the system under the current state of the network. In the next section, we have a closer look into this topic,

 

highlighting how the *a priori* assumptions made over the traffic sources can reveal to be insufficient to catch their real statistical behaviour.

*7.2. A priori assumptions over the traffic sources versus their real statistical behaviour*

In order to employ the closed-form loss probability formula (10), the assumption of a self-similar behaviour of the inflow processes has been made *a priori*. As we have already mentioned in Section 2.2, a self-similar behaviour of a traffic flow means that it maintains a high variability in the rate produced by its inflow process. The *Tsybakov–Georganas* formula (10) assumes an *exact* self-similar behaviour, namely, such high variability can be always observed at every time scale we measure the bit rate produced by the traffic source. A traffic process composed by a group of on–off sources shows an *exact* self-similar behaviour only when the number of the sources tends to infinity (the so-called asymptotical self-similarity; see, e.g. Reference [46] for further details). In a real scenario, this hypothesis reveals to be quite unrealistic, since the number of traffic sources is always finite and, in practice, different asymptotical self-similar behaviours can be obtained by varying the number $M$ of on–off sources in the aggregate flow. In Figure 11, the temporal evolution of a self-similar flow is depicted with different values of $M$. With $M = 100$, the $\bar{\tau}$ and $\bar{\sigma}$ parameters are both fixed at 1.0 s and with $M = 300$, they are fixed at 1.0 and 5.0 s, respectively. In this way, the obtained $\lambda_{\text{burst}}$ is always 50 burst/s and the impact of the parameter $M$ on the traffic traces can be highlighted.

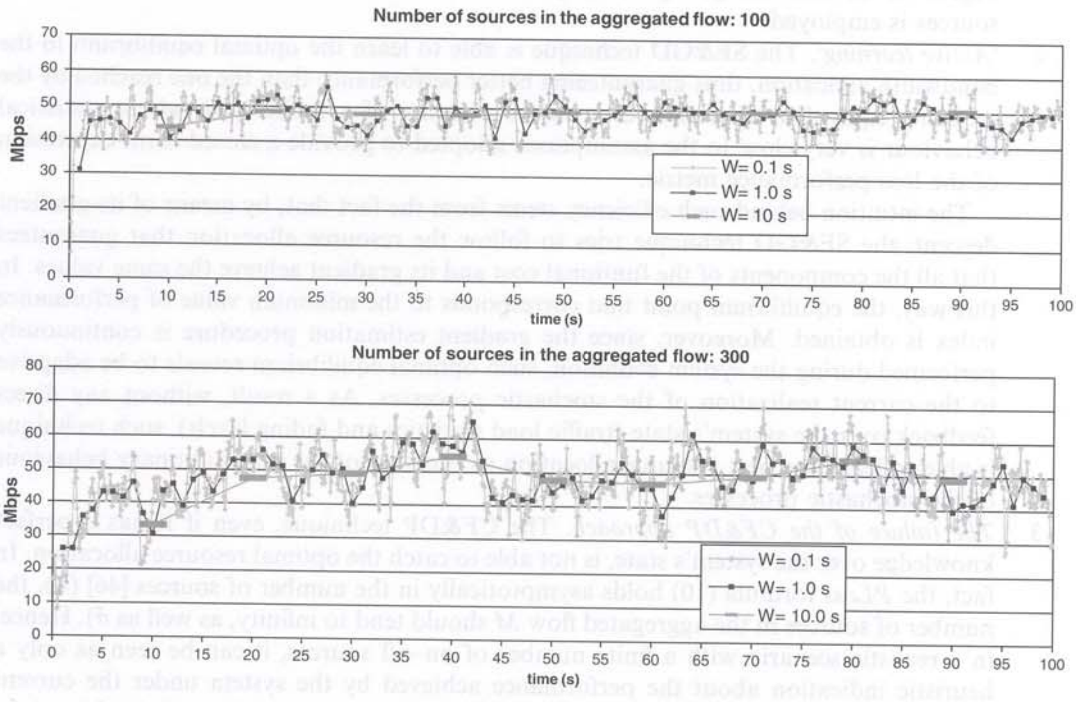


Figure 11. Traffic load scenario $\lambda_{\text{burst}} = 50.0$, $\bar{\tau} = 1.0$ s.

 

To show the self-similarity of a traffic flow, a sequence of measurements (about the bit rate produced by the inflow process during a finite observation period) must be performed over the inflow process (see, e.g. Reference [45]). An exact self-similar behaviour guarantees that, in spite of every possible dimension of such observation window, a large variance in the input rate is observed. On the other hand, in the presence of a more regular traffic process, such measures tend quite rapidly to the mean value of the process's input rate, as the dimension of the observation window increases. We denote with $W$ the dimension of such observation window. Three different values of $W$ are employed: 0.1, 1.0 and 10.0 s. As expected, with 100 sources in the aggregated flow, an observation window of $W = 10.0$ s always returns measures very close to the mean rate of the input process (around 48.0 Mbps). On the other hand, with 300 sources in the aggregated flow the measures performed every 10.0 s show a sensible variance over the mean rate of the inflow process. To better emphasize this difference, in Figure 12, the variance above the measures performed in the $W = 10.0$ case are shown. Clearly, with $M = 100$, the variance is always around zero, while in the $M = 300$ case, a higher variability arises over the performed measures.

As we have briefly shown, even with equal values of the $\lambda_{\text{burst}}$ parameter, an inflow process composed by a group of on–off sources, whose mean periods of activity $\bar{\tau}$ are Pareto distributed, can show, in practice, different self-similar behaviours. As a result, we could claim that the *a priori* assumptions about the traffic sources, even if necessary for the adoption of the closed-form formula (10), are only an approximation of the real behaviour of the inflow processes.

The CF&DP technique cannot react to such sensible differences. In fact, if the $\lambda_{\text{burst}}$ and the $\bar{\tau}$ parameters are maintained constant in updating Equation (10), it remains insensitive to any change in the number of sources in the aggregated flow and, as a consequence, to any possible different self-similar realization of the inflow processes. So, it can only guarantee an approximation of the optimal resource allocation, because it is not able to distinguish among traffic sources that can follow, in practice, sensible differences in their statistical behaviour.

Clearly, in order to take into account the real statistical behaviour of the traffic sources, it should be necessary to apply proper estimation algorithms over the inflow processes, and this can require the adoption of complex estimation techniques (see, e.g. References [22, 23]). The SE&GD algorithm developed in this paper, in virtue of its sensitivity estimation capability directly applied over the gradient of the chosen performance metric, reveals to be a very effective

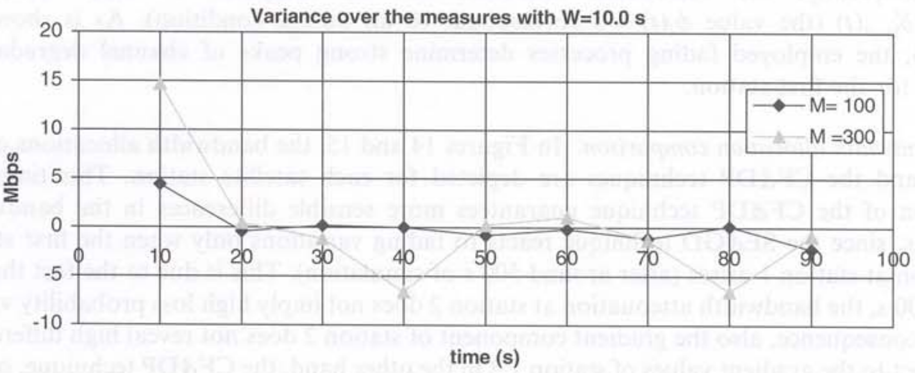


Figure 12. Variable traffic load scenario, variance of the measures performed with $W = 10.0$ s.

 

optimization approach, as it is able to 'learn' the real impact of statistical behaviour of the traffic sources over the system performance.

*7.3. Fading changes*

*7.3.1. Simulation parameters.* We consider now the effect of the fading phenomenon. The time horizon of the simulation scenario $T$ has been increased to 20.0 min and the channel capacity $K$ is fixed at 50.0 Mbps. Again, a group of on–off sources with Pareto distributed burst periods of activity constitutes the inflow process for each satellite station. The peak bit rate $B_p$, the mean burst $\bar{\tau}$ and silence period $\bar{\sigma}$ of such on–off sources are fixed to 1.0 Mbps, 1.0 and 1.0 s, respectively. The number of on–off sources for each station is fixed at $M^i = 10$, $i = 1, 2$. All of the other system's parameters (buffer dimensions, MAU values and reallocation time interval's length) are maintained the same as in the latter simulation scenario. This time, no traffic changes take place, namely, each inflow process generates a $\lambda^i_{\text{burst}} = 5$ bursts/s for each station $i$ of the satellite system, $i = 1, 2$. The gradient stepsize $\eta$ in (18) was fixed to $6 \times 10^6$, disregarding its decreasing behaviour (as mentioned in Section 6). However, this does not significantly affect the convergence of the gradient descent and guarantees a sensible speed up whenever fading changes take place.

The employed fading processes come from [8], where real-life fading attenuation samples are taken from a data set chosen from the results of experiments, in *Ka band*, carried out on the *Olympus* satellite by the CSTS (*Centro Studi sulle Telecomunicazioni Spaziali*) Institute, on behalf of the *Italian Space Agency*. The up-link (30 GHz) and down-link (20 GHz) samples considered were 1 s averages, expressed in dB, of the signal power attenuation with respect to clear sky conditions. The *carrier/noise power* ($C/N_0$) factor is monitored at each station and, on the basis of its values, different bit and coding rates are applied, in order to limit the BER below a chosen threshold of $10^{-7}$. Six different fading classes are defined, corresponding to combinations of channel bit rate and coding rate that give rise to redundancy factors $\delta^i_{\text{level}}$, $i = 1, 2$, level $= 1, \ldots, 6$ ($\delta^i_{\text{level}} \geqslant 1.0$). $\delta^i_{\text{level}}$ represents the ratio between the *information bit rate* (IBR) in clear sky and the IBR in the specific working condition. This gives rise to corresponding bandwidth reduction factors $\phi_i(t) = 1/\delta^i_{\text{level}}(t)$. With the data adopted in Reference [8] we have

$$\phi_i(t) \in \{0.0, 0.15625, 0.3125, 0.625, 0.8333, 1.0\}, \quad i = 1, 2$$

and, consequently, the bandwidth reduction can be computed as $\theta_i(t) = \phi_i(t)\theta^d_i(t)$; $\phi_i(t) = 1/\delta^i_{\text{level}}(t)$ (the value $\phi_i(t) = 0$ corresponds to an outage condition). As is shown in Figure 13, the employed fading processes determine strong peaks of channel degradation, especially for the first station.

*7.3.2. Bandwidth allocation comparison.* In Figures 14 and 15, the bandwidth allocations of the SE&GD and the CF&DP techniques are depicted for each satellite station. This time, the application of the CF&DP technique guarantees more sensible differences in the bandwidth allocations, since the SE&GD technique reacts to fading variations only when the first strong attenuation at station 1 arises (after around 500 s of simulation). This is due to the fact that, in the first 500 s, the bandwidth attenuation at station 2 does not imply high loss probability values and, as a consequence, also the gradient component of station 2 does not reveal high differences with respect to the gradient values of station 1. On the other hand, the CF&DP technique, owing to its perfect feedback over the fading states, is always able to perform small changes in the

 

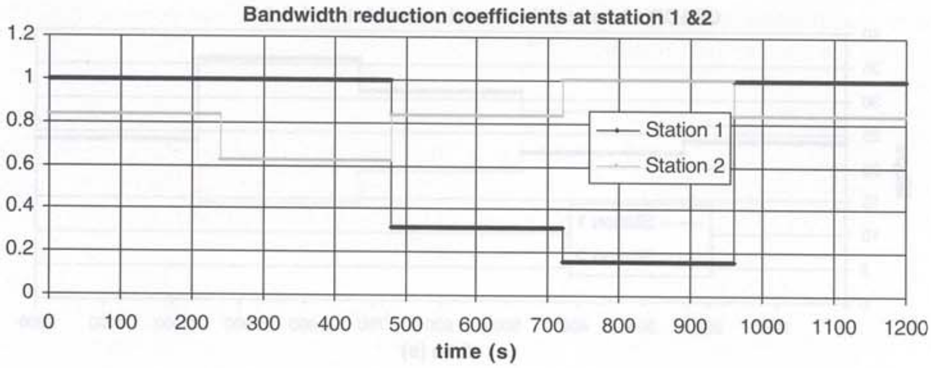


Figure 13. Fading changes scenario, bandwidth reduction coefficients (taken from real traffic traces).

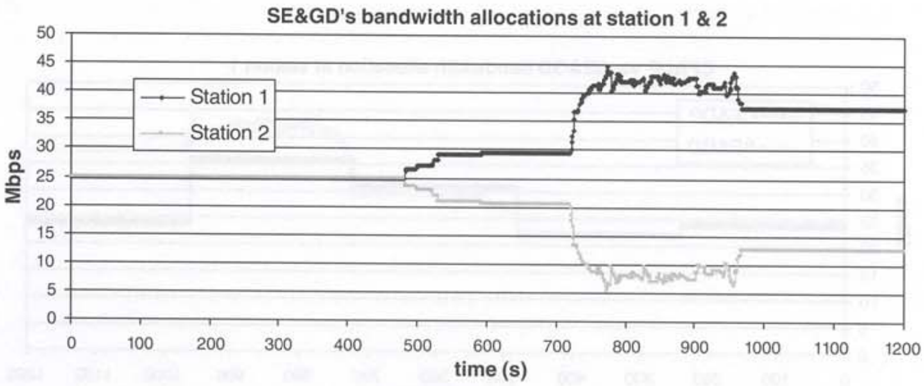


Figure 14. Fading changes scenario, SE&GD's bandwidth allocation.

bandwidth allocation, as is clear by looking at its bandwidth allocations in the first 500 s of simulation. Anyway, this fact does not allow the CF&DP technique to outperform the SE&GD's performance. If we look at the bandwidth allocations during the strong peaks of fading attenuations at station 1 (after the first 500 s of simulation), we note that the CF&DP technique, as in the previous simulation scenario, is not able to reach the optimal resource allocation, particularly when station 1 is affected by the fading level giving rise to $\phi_1 = 0.15625$. On the other hand, since the SE&GD technique continuously updates the gradient estimation values, it is able to find the new equilibrium point at a higher value in the bandwidth allocation for station 1. Such difference is emphasized in Figure 16, where the aforementioned techniques are compared with respect to the bandwidth allocation at station 1.

*7.3.3. Loss performance.* Finally, the obtained loss probability performance is shown in Figure 17, where the presence of estimation errors over the state of the traffic load is also taken into account. As in the latter simulation scenario, '*CF&DP ErrX*' means that the feedback over the state of the first station underestimates the real traffic load with a percentual error of $X$%. Looking at the obtained results, it is quite clear how the SE&GD technique is able to reach the best performance. Even though, this time, the CF&DP technique reveals a performance more

 

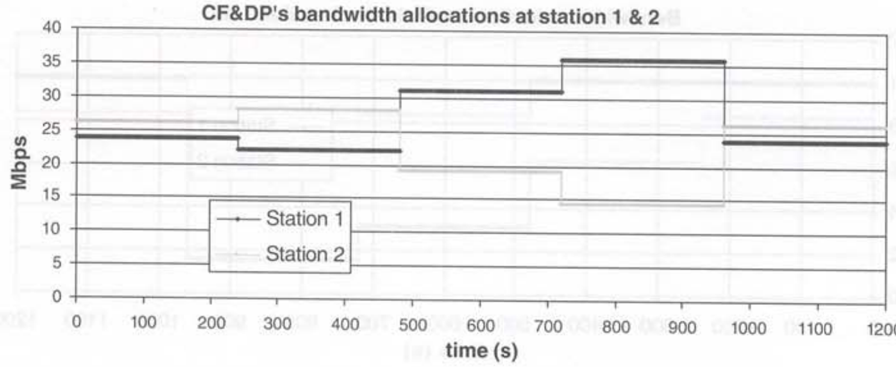


Figure 15. Fading changes scenario, CF&DP's bandwidth allocation.

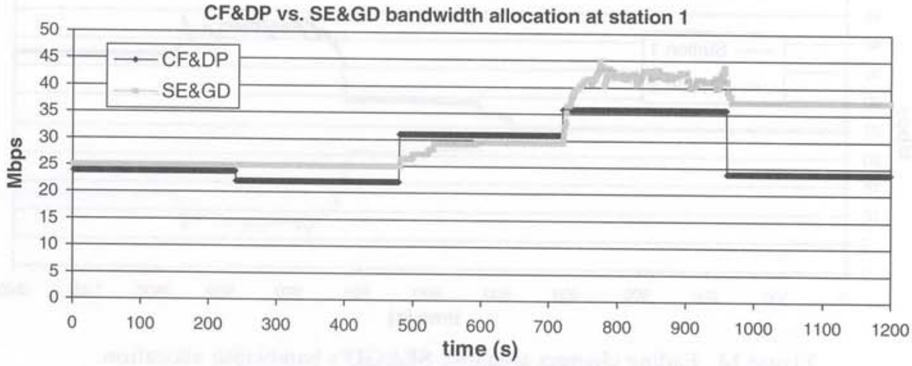


Figure 16. Fading changes scenario, CF&DP versus SE&GD's bandwidth allocation at station 1.

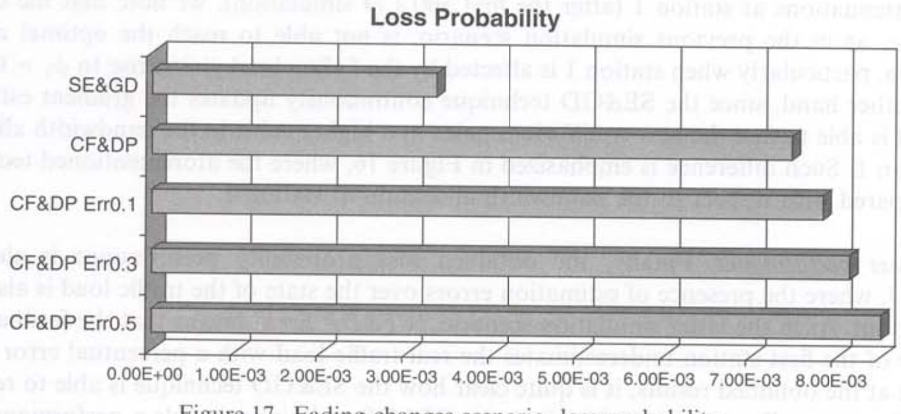


Figure 17. Fading changes scenario, loss probability.

 

insensitive with respect to estimation errors over the traffic state (because the major impact over the system performance is due to the effect of the fading changes), it is far away to maintain the optimal solution of the resource allocation problem.

*7.3.4. A possible drawback of the SE&GD approach.* One final remark is necessary concerning the SE&GD's bandwidth allocations in this simulation scenario. If we look at the SE&GD's bandwidth allocations in the last 240 s of simulation, we can observe that the equilibrium point reached by the SE&GD technique with respect to the last fading values ($\phi_1 = 1.0, \phi_2 = 0.8333$) is far away from the one expected. In fact, the optimal solution for the last 240 s should be quite close to an equally distributed resource allocation as happens in the CF&DP case. On the contrary, the SE&GD's bandwidth allocation remains quite close to the previous one that corresponds to the fading values $\phi_1 = 0.15625, \phi_2 = 1.0$. This is due to the fact that, even if a strong change in the fading levels of the time intervals [725;960] [960;1200] arises, the gradient values computed during the time interval [960;1200] are very low and, as a consequence, they are not sufficient to carry on the bandwidth allocation to a new equilibrium point closer to an equal distribution. The rationale behind such inefficiency comes from the fact that, for the particular sample paths shown in Figures 14–16, using the SE&GD technique, very low loss values are observed for both stations in the time interval [960;1200] and, as a consequence, also the loss derivatives achieve low values, thus leading to a sub-optimal bandwidth allocation for the last time interval [960;1200].

This would suggest a deeper investigation concerning the possibility of reaching only a sub-optimal resource allocation under the SE&GD approach, with respect to particular realizations of the stochastic processes. This issue is currently subject of ongoing research, taking into account not only further simulation scenarios for the resource allocation problem addressed in this paper, but also for other resource allocation frameworks (for example in the context of terrestrial wireless or QoS networks).

*7.3.5. Remarks on the performance metric of interest.*

1. *Loss Probability* versus other performance metrics. The proposed methodology is not necessarily devoted to the *Loss Probability* optimization. Other metrics of interest can be taken into account (e.g. delay, delay jitter). The only concern is related to the need of derivative estimation procedures suitable for the chosen performance metrics. In References [13, 14, 17, 19, 52] it is shown that other PA techniques are available for derivative estimation procedures pertinent for other performance indexes (such as blocking probability, buffer workload).
2. *Guaranteed Performance* versus *Best Effort* traffic management. The proposed methodology does not take into account any strict *quality of service* (QoS) constraint. Therefore, it yields dynamic bandwidth allocation schemes appropriate for *best effort* traffic (*TCP/IP*, *ABR*, as in References [8, 22, 23]). However, it should be also useful to enforce CAC mechanisms (as, e.g. in References [22, 23]). In this perspective, our research effort is currently devoted to employ other derivative estimation procedures, suitable to manage the network at the call level. The idea is to apply an on-line surrogate approach similar to the one presented in this work, based on a derivative estimator of the blocking probability of the connection requests (see, e.g. Reference [13] and references therein).

 

*7.4. Variable MAU's dimensions and reallocation time interval's length*

As mentioned in Section 5, the reallocation period $\hat{t}$ becomes a critical parameter in a satellite environment under different traffic conditions. We now take a closer look into this topic.

Suppose that no fading degradations affect the satellite system composed by two active stations. Variable $\lambda_{\text{burst}}$ are considered. The other system parameters are the same as in the simulation scenario addressed in Section 7.1 (variable traffic load).

Figure 18 depicts, with respect to different traffic load conditions, the advantage of adopting an 'ideal' period of 0.1 s in place of the one adopted, 1.0 s. We show in this way that, in our case, the ideal period does not involve a strong enhancement in the system performance, while fixing the period to 10.0 s induces a much more significant detriment.

Also the size of the MAU is a very important parameter in the discrete optimization problem addressed here. Its excessive granularity would involve a heavy computational burden for the CF&DP approach, thus limiting its applicability in real time. On the other hand, if the MAU is sized to a large value, the accuracy of the solution could be strongly deteriorated. Figure 19 depicts this problem at various traffic conditions. The simulation parameters are again the ones adopted in the variable reallocation period scenario presented in Figure 18. Figure 19 shows

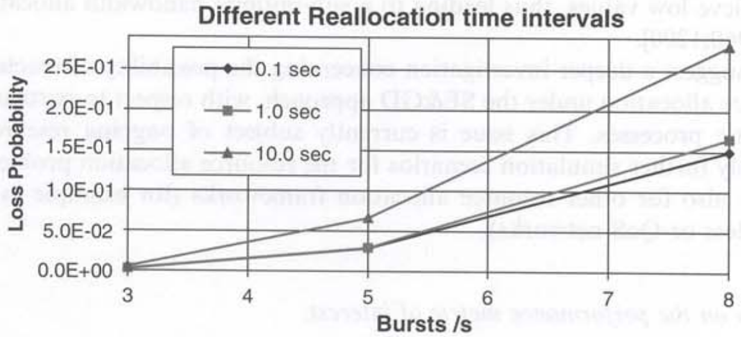


Figure 18. Reallocation time interval's length: impact over the loss probability performance.

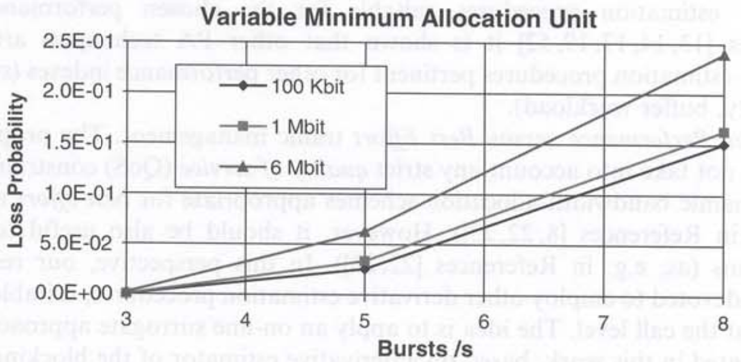


Figure 19. MAU's dimension: impact over the loss probability performance.

 

that the case of MAU = 1.0 Mbps does not achieve largely worse performance than the case of MAU = 100.0 kbps, while the situation is strongly different for MAU = 6.0 Mbps, particularly at high traffic loads.

## 8. CONCLUSIONS AND FUTURE WORK

A novel optimization algorithm, called SE&GD (*sensitivity estimation* and *gradient descent* approach), based on the gradient estimation of the IPA technique has been applied to react to fading effects and traffic load changes over a satellite network. Such optimization algorithm, due to its sensitivity estimation capability, does not need any closed-form expression of the performance measure. The SE&GD optimization approach has been compared with an optimization technique based on a *closed-form* expression of a performance measure and on the application of *dynamic programming* (CF&DP).

The proposed simulation results have shown how the SE&GD technique allows strong performance improvements in both variable fading and traffic scenarios. More in particular, SE&GD reveals to be a very effective technique in real on-line operating conditions, since it permits to compute sensitivity estimations based only on sample paths of the real system, and to catch the main features of the stochastic system ('*active learning*' [11]), in order to optimally react when variations in the environment take place. This last conclusion is supported by the fact that no feedback about fading level or traffic load is necessary for the application of the IPA sensitivity estimation procedure. Moreover, its suitability in real on-line optimization scenarios is due to the fact that the SE&GD technique requires a lighter computational effort with respect to the CF&DP algorithm.

Future work includes the application of the proposed SE&GD approach in order to solve other resource allocation problems for other important QoS parameters, such as delay and delay jitter. Different application scenarios will be taken into consideration, for example for both terrestrial wireless and QoS networks.

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