
P. Camarda¹, M. Castellano¹, G. Piscitelli¹, D. Striccoli¹, G. Tomasicchio²

(¹) Department of Electrical and Electronic Engineering
Politecnico di Bari, Via Orabona 4, 70126 Bari, Italy
camarda@poliba.it, castellano@deemail.poliba.it

(²) Alenia Spazio, Business Multimedia Unit
Via Bona 85, 00156 Roma, Italy
g.tomasicchio@roma.alespazio.it

Abstract: Advanced traffic management based on the Dynamic Resource Assignment allows a broadband satellite system such as EuroSkyWay (ESW) to dynamically assign the resources of connections. The mechanisms of the dynamic assignment exploit variations of Burstiness exhibited by real time and non real time Variable Bit Rate traffic sources to perform an optimised resource redistribution. The efficiency of the Dynamic Bandwidth Allocation Capability (DBAC) depends on the accuracy of the traffic source description; inaccurate assessment of the arrival process will cause an overhead and a degraded utilisation of system resources.

In this paper simulated results about a flexible traffic burstiness predictor for dynamic bandwidth resource allocation based on neural network is presented. The approach is able to an online computation of expected resource request implementing traffic resource assignment by using a sub-symbolic adaptive representation of the traffic source. An accurate design of neural network architecture and the low-cost industrial availability of this novel technology lead to an optimal trade-off between customer satisfaction in terms of QoS and system resource optimization also in terms of network operator revenue.

1 Introduction

EuroSkyWay is a geostationary satellite network, with regenerative payload based on a circuit-switching scheme [2]. Advanced Resource Management (RM) and Bandwidth Allocation capabilities allow ESW network to fully adapt to the diversified terrestrial traffic by properly allocating the satellite resources for a proper support to efficient switching connectivity services for future broadband data-communication scenarios [3]. ESW adopts a Dynamic Resource Management (DRM) pertaining to dynamic assignment and releases the bandwidth resources required from VBR connections once it has been established. The EuroSkyWay system has been conceived to provide efficient connectivity services to users located within the coverage area of a satellite constellation with high capacity on-board processing payloads. ESW will provide multimedia symmetric and asymmetric, unidirectional or bi-directional, point-to-point or point-to-multipoint connectivity services. The ESW Ground Segment is partitioned in two segments: Control Segment and Traffic Segment. The Control segment includes the Network Operation Centre (NOC) and the Satellite Operation Centre (SOC).

ESW-NOC is composed by the following four subsystems:

- Network Control Centre (NCC) which implements those real-time functions needed for provision of connectivity services
- Network Management Centre (NMC) which implements the overall Network monitoring and control functions
- Customer Care Centre (CCC) which supports the relationships with customers and service management functions
- Data Base Control System (DBCS) provides a common database facility shared by all NOC subsystems.

ESW is designed to serve both fixed and mobile users, and provides flexible data rate services, depending upon user application and terminal type. The Traffic Segment covers the Network Elements enabling the users to have access to ESW connectivity services. The ESW network ground segment architecture uses different Network Elements: Satellite terminals (SaT) for End Users, Provider terminals (PrT) for Service Providers and Gateway terminals (GTW) for Telecom operators interfacing terrestrial networks.

In this paper, a resource requesting scheme by means of Neural Network Burstiness Predictor architecture [4, 5] in the framework of the EuroSkyWay system is presented; this adopted novel
approach towards the problem of a dynamic resource management is called ARAS (Adaptive Resource Assignment System). The approach is able to compute the expected resource request in real-time, implementing direct adaptive traffic resource management without an analytical representation of the traffic, but using a sub-symbolic description of burstiness. In ARAS, a traffic source is characterized via the number of active Frame Units belonging to the ESW's frame structure; the characterization is based on the prediction. Three MPEG-1 traffic sources are considered in the experiment. The training data set for the artificial neural network is collected by means of another MPEG-1 trace. To validate the proposed algorithms, several simulation experiments have been carried out, comparing a fixed scheme approach with the proposed NN-based mechanism.

2 ESW Dynamic Resource Management Architecture

A functional diagram of the ESW Connection Management and Resource Management architectures is represented in Fig. 1.

![Fig. 1 - ESW CM and RM Functional Architectures](image)

The entities responsible for the RM functionality are placed in the terminals and on-board. The Traffic Resource Manager (TRM) is a portion of the on board baseband processor. On the ESW terminal side a traffic management agent inter-operates with the TRM through an inner Resource Management Entity (RM-E).

The Connection Management (CM) functionality is hosted by an NCC sub-system named Connection Control Manager (CCM) which also invokes a Connection Admission Control (CAC) procedure. On the ESW terminal side a Connection Control Agent inter-operates with the CCM.
through an inner *Connection Control Entity* (CC-E). Between the CC-E and the RM-E the traffic generated by each source is sustained by means of buffers. The RM functionality is implemented at MAC layer, the CM one is implemented at *ESW Layer 3*, as depicted in Fig. 2.

![Fig. 2 - CM and RM functions mapped on the ESW protocol stack](image)

When a traffic source requests ESW for connectivity services, a connection has to be assigned to it via an ESW connection set-up procedure which is carried out at layer 3. This procedure will accept the incoming connection only if there are enough system resources for the network to be able to guarantee the negotiated QoS level maintaining the currently active connections.

The connection acceptance relies on an ESW Connection Profile which states the traffic contract parameters the network will grant to the connection. These parameters are:

- Service category (A, B, C, D)
- Maximum Cell Transfer Delay (Max CTD)
- Peak to Peak cell Delay Variation (p-t-p CDV)
- Cell Loss Ratio (CLR)
- Peak Data Rate (PDR)
- Utilisation Factor (UF)
- Maximum Burst Size (MBS)

The service categories foreseen for ESW are listed in Tab. 1 with the correspondent relevant traffic features.
At setup time the most suited connection typology is selected depending on the results of the mapping between services supported by the overlying Networks (OLN) and the ESW service category previously described by means of an Interworking Function.

At connection set-up time a univocal connection identifier is assigned to each connection, the EuroSkyWay Virtual Connection Identifier (EVCI). To support a bi-directional traffic exchange, two different EVCIs must be supplied pertaining to the forward and backward connection (i.e. the connection coming from the calling user to the called one and vice versa).

EuroSkyWay RM implements two distinct assignment typologies:

- **guaranteed assignment**
- **dynamic assignment**

A connection is defined with **guaranteed assignment** if the resources it requires are assigned to the parties involved in the communication process for the whole connection duration. In principle guaranteed assignment connections are well suited to support Constant Bit Rate (CBR) traffic. A connection is defined with a **dynamic assignment** if the resources are not assigned to the connection for the whole call duration.

ESW Dynamic assignment mechanism is suitable to define services provided for traffic source with the following characteristics:

- Variable Bit Rate both real time and non-real time (rt-VBR, nrt-VBR);
- no stringent jitter (peak to peak CDV) constraint\(^1\);
- high on/off behaviour or Burstiness

The burstiness is defined as the ratio: \( \frac{T_{ON} + T_{OFF}}{T_{ON}} \)

---

\(^1\) B and C service classes prescribe different constraints about CDV, as shown in Table 1.
where \( T_{ON} \) is the duration of the active time of a traffic source while \( T_{OFF} \) is the duration of the inactive one\(^2\).

The ESW dynamic assignment mechanism aims at exploiting variations of burstiness exhibited by B and C class sources, to perform an optimised redistribution of those resources to other connections (pre-emption). To this aim the MAC layer foresees a couple of messages which can be transferred in the RM environment between Terminals and the TRM named Capacity Request Messages (CRMs).

CRMs can be of two types:

- Out of Band Capacity Request (OBCR)
- In Band Capacity Request (IBCR)

The OBCR is used by the Resources Request Channel (RRC) command when no other resources are available for a given connection. The OBCR mechanism is applied even if the first request of resources from a new connection just set up. In case the transmitting party is still allowed to send data, it can place an IBCR, setting the appropriate request fields in the tributary traffic. An example of dynamic assignment for an ESW connection is depicted in Fig. 3, where the resources which are not used by a connection may be assigned automatically to other connections by the TRM.

![Fig. 3 – Example of Dynamic Resource Assignment](image)

Both IBCR and OBCR messages specify the EVCI which they refer to and the resource duration expressed in ESW Frames is 26.5 ms. Although the ESW dynamic assignment mechanism assures, in a simple way, the traffic following in terms of assigned resource, an inaccurate assessment of the \( T_{ON} \) will cause an increase in the number of CRMs and a degraded utilisation of unused resources within the system. Moreover, mainly due to the round trip delay needed to perform a complete handshake between terminal and TRM, a degradation of the CDV also occurs as a consequence of the frequent usage of CRMs.

\(^2\) The ratio has to be intended as a relationship between mean values calculated on a given time window.
The number of frames assigned to the traffic source should be strictly related to the appropriate assessment of the activity period that the bursty source will exhibit in the future. A rough solution to assess this value is based on the knowledge for each VBR source, of both the size of the buffers depicted in Fig. 1 and the PDR declared within the relevant ESW connection profile.

3 The Adaptive Resource Assignment System

The architecture of an Adaptive Resource Assignment System (ARAS) is shown in Fig. 5.

Fig. 4 – ARAS architecture

The Burstiness Predictor module provides the estimation of the resource amount to be required in advance for the system to cope with the high time-varying bursty behaviour that a traffic source may show. Fig. 4 depicts how these modules interact with the other elements of the overall ESW system. The key factors which are addressed by the integration of a Burstiness predictor in the current RM Architecture are the following:

- Improved accuracy in the activity period assessment, due to the fact that the Neural Networks have the ability to learn the behaviour features of a traffic source;
- Reduced CDV, essentially due to a lower usage of the buffers, because the prediction ability reduces the time delay between the capacity request time on the terminal side and the actual availability time of the requested resources after the TRM have granted them.

The predictor design is provided by means of Neural Networks (NNs). NNs are able to discover complex relationships by samples. In terms of modelling the statistical behavior of source traffic to optimize the use of the ESW resources, NN can offer a good representation of the problem without knowing an analytical description of the traffic [6]. The approach here proposed is to employ the Neural Networks as a tool to characterize the time varying process of the source and hence to
predict its future behavior over a certain monitoring period [7]. One hidden layer feed-forward back propagations neural network is trained to learn the relationship between the characteristics of the source and the future resource amount required to support it. The basic idea is to enable the NNs to predict future samples of this high time-varying process, which is also bursty with significant correlations [8].

A specific description of the above mentioned functional modules will be given in the next sections.

**Fig. 5 – Dynamic Resource Assignment Architecture**
3.1 Extracting Features for Bursty Traffic Source

Three different types of user terminals (hereafter called Satellite Terminals or SaTs) will be supported by the ESW Satellite system. SaTs are classified as A, B or C type depending on the maximum user data rate in the uplink, which is reported in Tab. 2.

<table>
<thead>
<tr>
<th>SaT type</th>
<th>User Data Rate (Kbit/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>160</td>
</tr>
<tr>
<td>B</td>
<td>512</td>
</tr>
<tr>
<td>C</td>
<td>2048</td>
</tr>
</tbody>
</table>

Tab. 2 - Uplink data rate in correspondence of each SaT type

Each carrier will be organised according to a Frame structure:

- The Frame Unit (FU), having a length of 680 bits, whose duration depends on the terminal SaT type.
- The Frame, which is the basic unit; it is a set of N Frame Units, with N depending on the terminal SaT type; the Frame has a constant duration of 26.5 ms, regardless of the terminal SaT type.

A single Frame is composed of a number N of FU. The number N and the duration of the FU both depend on the terminal SaT or Carrier Group type data rate, according to Tab. 3:

<table>
<thead>
<tr>
<th>Carrier Group Type</th>
<th># FU per Frame N</th>
<th>FU duration (μs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SaT-A</td>
<td>10</td>
<td>2650</td>
</tr>
<tr>
<td>SaT-B</td>
<td>32</td>
<td>828.125</td>
</tr>
<tr>
<td>SaT-C</td>
<td>128</td>
<td>207.03125</td>
</tr>
</tbody>
</table>

Tab. 3 - FU number and duration in correspondence of each SaT type

A Frame Unit contains a single ESW cell, having a constant length of 60 bytes (or 480 bits), and a Forward Error Correction (FEC) section added to each ESW cell to increase the immunity against noise.

The Adaptive Resource Assignment approach provides a prediction of the number \( N_f \) of Frame Units which will be active in each step \( T_s \) with a time span also equal to \( T_s \), (see Fig. 6). This time
step is $T_S = p \cdot T_{FrameESW}$ a multiple of the ESW Frame duration ($T_{FrameESW} = 26.5\,\text{ms}$). The time step $T_S$, or *Sampling Period*, is the time interval between two subsequent predictions. This implies that the maximum frequency for the CRMs’ emissions is now limited by $1/T_S$. Moreover, supposing $p \geq 12$, then the advance time provided by the prediction is about equal to round trip delay between the ESW terminal and the onboard TRM\(^3\).

The Feature Extractor architecture is composed of the following elements:

- a sampler with *Sampling Period* $T_S$;

\[ \begin{array}{c}
\text{Predictor Output timing} \\
\hline
N_f = 4 \\
\hline
T_{on} T_{on} T_{on} T_{on} \ldots \quad T_{off} T_{off} T_{off} T_{off} \ldots \\
\hline
0 \quad T_S \quad 2T_S \quad 3T_S \\
\end{array} \]

*Fig. 6 – The timing features of the Burstiness Predictor*

- an Active Frame Count Process $N_f(t, t + T_S)$ which makes an on-line measure of the traffic burstiness through a count of the number of active Frame Units observed during an interval $T_S$ of a sampled arrival process (see Fig. 7),

- a Shift Register with capacity $T_m = S \cdot T_S$ storing for each $T_S$ the above mentioned on-line measure.

\[^3\text{This is true if the internal processing delay is neglected}\]
Fig. 7 – Feature Extraction scheme

The architecture shown in Fig. 7 refers to each source. In the sampling window $T_s$, a multiple of the frame duration, the Sampler tags each Frame Unit with a binary digit in accordance with the active or inactive state. As it will be further explained, $T_s$ is the time in advance during which the predictor provides a number of Frame Units assessed between 0 and $M \cdot p$ (where $M$ is the number of Frame Units in an ESW Frame; i.e., $M = 128$ for ESW Sat-C terminal). An Active Frames Count Process counts how many Frame Units have been active in $T_s$. These counts are loaded in a Shift Register spanning a time duration of $T_m = S \cdot T_s$. The shifting mechanism at the Shift Register level implements a sliding window large $T_m$ moving with step of $T_s$. The NN provides, from the past bursty behavior of the source $S_i$, the expected number of Frame Units which will be active in the next $T_s$ time period.

The larger accuracy that a neural predictor exhibits in the frame assessment with respect to rough size buffer mechanisms guarantees a better utilization of the resources among all traffic sources.
3.2 The Neural Network module

The Neural Network (NN) used in the ARAS architecture calculates a bursty correlation of the active Frame Units diffused in the arrival process on the time interval $T_a = S \times T_f$. The NN learns the relationship between the characteristics of the traffic source arrival process and the related estimation in advance of the number of active Frame Units $N_{fON}$, with $0 \leq N_f \leq M \cdot p$ required to support it in the next interval $T_s$. The adopted NN model is shown in Fig. 8 and is assumed to be fed from the previously described feature vector to implement the detector block. It is a three-layered feed-forward neural architecture and detail can be found in [4,5].

![Neural Network topology](image)

The neural network produces a prediction system which, starting from the analysis of the feature vector in the appropriate feature space, makes the final decision about the event providing the indication of the amount of resource request which will be dynamically assigned.

Fig. 9 illustrates the basic idea in training the NN to act as a predictor. For each input, the network produces an output which is then compared to the desired output (target) [11]. The arrival process is represented by the data $[N_f(i+1)]$ which is the NN target output. It represents the number of active Frame Units to the time $i+1$, measured in $T_s$ intervals, a multiple of the frame ESW ($T_s = p \cdot T_{frame, ESW}$). The data $[N_f(i+1)]$ provides the NN with the arrival process information from which the predictions will be made. The NN predicts the arrival process variations by exploiting the inherent correlations that exist.
For training purposes, the NN input data vector \([N_f(i-S+1), N_f(i-S+2), \ldots, N_f(i-1), N_f(i)]\) contains \(S\) elements representing the measured number of active Frame Units in the preceding \(S\) intervals \(T_S\).

The duration of the measurement period \(T_m = S \cdot T_S\) must be chosen such that the effect of correlation is well captured. The NN then tries to match the target output data \([N_f(i+1)]\) with its predicted output data \([N_f(i+1)]\) by adjusting its weights. It then follows that when the input data bypass the delay unit, the output \([N_f(i+1)]\) is a prediction of the number of active Frame Units in the future \(T_S\) step. The delay unit, shown in Fig. 9, delays its input \([N_f(i+1)]\) of one \(T_S\) time step. Assuming that the NN requires a negligible amount of time to compute output, the NN, after training, provides estimations for the value of active Frame Units \([N_f(i+1)]\) one step in advance.

For each epoch, test data set is fed in input to the network and the Root Mean Square error (RMS) is evaluated. The training phase is stopped when the overtraining effect \([10]\) is observed and the best synaptic matrix is frozen.

### 3.3 The Decision Logic module

The Decision Logic module implements a decision making facility able to trigger the proper CRM at the RM-E of the terminal. Both the CRM formats require the relevant EVCI and the predicted \(N_f\) to be specified.

Each decision logic module acts on the basis of the following information:

- traffic contract parameters within the relevant ESW Connection Profile
- predicted number of active Frame Units \(N_f\) in the next period \(T_S\)
- Traffic source Buffer load status
The output of this module involves the invocation or not of a primitive such as Make_Resource_Req(EVCIi ,Nf) to be processed at MAC layer from the RM-E entity within the terminal.

4 Simulation Results

Extensive simulations were performed to obtain the NN's data set, for training phase and also to assess the performance of various NN architectures. The Frame Unit arrival process, resulting from the packetized video source, was simulated. Assuming a video source packetized for using ESW network, in the case of Sat-C terminal type, the maximum number of active Frame Units is 128 in each ESW frame; an ATM cell, or Frame Units ESW, has size 53 bytes with 48 bytes of payload, and the frame ESW interarrival time $T_{frame\ ESW}$ is 26.5ms. An important parameter which must be defined is the sampling period $T_S$. The choice of this parameter is influenced by the type of prediction of the traffic and also by the system architecture. In this application it has been found to be around 400ms. NN is trained to predict the number of active Frame Units for the next sampling period $T_S$ based upon the $S$ past values of the number of active Frame Units count process.

4.1 Traffic Source

The source data utilized for our analysis consist of portions of video streams codified with the MPEG-1 video standard compression [12,13]. The particular type of compression adopted generates a Variable Bit Rate (VBR) type of traffic, in which there is a high variability between adjacent frames of the video stream; the number of bits present in each frame of the video sequence can vary, based on the dynamic evolution of the scenes. Each of the video frames is transmitted in a constant time interval, depending on the transmission rate of the video frames (the transmission rate adopted in this case is 25 frames per second; in this way, each video frame is transmitted in 40 milliseconds).

The first step is to establish the number of active Frame Units in a temporal window generically chosen of $M$ frames ESW. In each of these windows, we have to count the total number of Frame Units that contain some video data (these Frame Units will be marked as 1 to indicate the fact that there is some data in them, while if a frame unit is empty, it will be marked as 0). For each window, the total number of active Frame Units is counted and then stored in a text file. All the portions of video streams utilized in our experiments have a length of 40,000 video frames.
4.2 Performance Metrics

In the performance metrics we introduce the resource utilization factors which will be used in the next sections. The $F_{NN}$ is the utilization factor for the flexible scheme based on NN. Let $\theta_i$ and $\text{used}_{\text{capacity}}$, respectively the bandwidth predicted and bandwidth utilized at the $i^{th}$ time step.

It will be:

$$F_{NN} = 1 - \frac{\sum_{i=0}^{T_{TOT}} \left[ \frac{\text{used}_{\text{capacity}}}{\theta_i} \right]}{T_{TOT}} \cdot 100\%$$

(4.1)

It can be noted that the upper bound of the used capacity $\text{used}_{\text{capacity}}$ is equal to $\theta_i$.

Let now $\text{needed}_{\text{capacity}}$ the bandwidth required at the $i^{th}$ time step. Let us define:

$$d_i = \theta_i - \text{needed}_{\text{capacity}}$$

(4.2)

If $d_i \geq 0$ then the bandwidth is overestimated and a waste of bandwidth will occur. If $d_i < 0$ the bandwidth is underestimated and there will be data losses. The total amount of Lost Frame Units (LFU) is taken into account in the following loss factor:

$$LFU = \frac{\text{total active Frame Units discarded}}{\text{total active Frame Units}} \cdot 100\%$$

(4.3)

Moreover, a study on the NN behaviour can be done adding a fixed amount of bandwidth $\sigma$ to the NN predicted bandwidth at the aim to reduce the total amount of lost Frame Units. A merit figure can be obtained plotting the $F_{NN}$ and LFU factors versus $\sigma$, where $\sigma$ is expressed in terms of percentage of the satellite terminal capacity.

4.3 Neural Network Training Phase

The training data set for the NN is now collected. This data set comes from a variable bit rate video trace codified using MPEG-1 algorithm. The movie contains a mixture of material ranging from low complexity scenes to scenes with high action.

The data set has been chosen imposing the value of $p=16$ in order it covers at least the Round Trip Time. Therefore the period between one prediction and the next has been chosen equal to $T_s = p \cdot T_{\text{frame},SW} = 16 \cdot 26.5ms = 424ms$. On the other hand, the duration of the measure period $T_m$ has been chosen imposing $S=4$, which settles down the dimension of the sliding window implemented with the Shift Register. The $S=4$ value has been chosen after a series of experiments.

---

4 The maximum associable bandwidth for the single step is always fixed within 2048 Frame Units.
carried out on different NN architectures. It has been noted that the training error observed for a large number of epochs is almost the same for NN architectures with the input neurons greater than 3. In this case the less complex NN architecture can be chosen. In the sequel the selected NN(4-9-1) will be used with the synaptic matrix frozen at the 2000th epoch.

5 Experimental Results

In this section the effectiveness of the proposed ARAS is studied for ESW Sat-C terminal with capacity equal to 128 Frame Units, by demonstrating its capability to produce the prediction of the Nf number of active Frame Units in the next sampling period Ts. It means validates the NN proposed using different MPEG-1 real video traces than used in NN training/test design phase.

Three MPEG-1 video traces are examined. For each video trace an input data of 40000 frames, equal to approximately 30 minutes of film, have been considered with a transmission rate of 25 video frames per second. With the purpose to evaluate the effectiveness of the predictive approach, in terms of reliability, we introduce the step by step comparison between the needed number of the active Frame Units Nf\text{needed}, requested by the video trace, and the predicted number of the active Frame Units Nf\text{predicted}, estimated by the neural network. In such a way, we can extract a reliability index α, given by the step by step relationship:

$$\alpha = \frac{N_f{\text{needed}}}{N_f{\text{predicted}}} \quad (4.4)$$

The behavior of the reliability index α, the distribution of the d indexes as defined in (4.2) and the FNN and LFU factors are shown in Fig. 10 for the “James Bond” video trace and in Fig. 11 for “Jurassic Park” video traces.

![Fig. 10 – “James Bond” video trace: a) the Active Frame Units profile, b) the Reliability index and c) the d distribution.](image-url)
Fig. 11 – “Jurassic Park” video trace: a) the Active Frame Units profile, b) the Reliability index and c) the distribution.

In Fig. 12 are shown the indexes performed by the Neural Network using the same video trace “Talk show” on which the selected NN has been trained. The NN validation emerges comparing Fig. 12 with Fig. 10 and Fig. 11 since there is a good agreement among them.

Fig. 12 – Temporal distribution, Reliability index and Distribution for training’s video trace, the “Talk Show”

The predictive scheme shows an high utilization factor between 80% and 90% against a reasonable lost frame unit less than 20%. Moreover, higher QoS based user terminal can be considered (low LFU values) using utilization factor with high values between 60% and 80%, as shown in Fig 13. The estimated bandwidth follows well the real one. In other words, the neural network can predict the number of the active Frame Units present in the next time step $T_S$. The ESW bandwidth resource management will be able to use the estimated resources, by IBCR/OBCR signalling, with an advance of $p$ ESW frames, taking into account the Round Trip Time delay.
6 Conclusions

In this paper a flexible Adaptive Resource Assignment System for the EuroSkyWay broadband satellite system has been presented in the complex scenario of the transmission of bursty VBR video sources. This approach when applied to the ESW satellite terminal component is able to compute in advance the needed bandwidth resources in an efficient way. An accurate design of neural network architecture and the low-cost industrial availability of this novel technology lead to an optimal trade-off between customer satisfaction and system resource optimization also in terms of network operator revenue.
References


