Computer Networks 108 (2016) 55–65

Contents lists available at ScienceDirect

Computer Networks

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

When are network coding based dynamic multi-homing techniques beneficial?

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ARTICLE INFO

Article history:
Received 31 October 2015
Revised 17 June 2016
Accepted 1 August 2016
Available online 3 August 2016

Keywords:
Multi-homing
Network coding
Wireless networks
Time-varying channels
Resource allocation

ABSTRACT

Mechanisms that can cope with unreliable wireless channels in an efficient manner are required due to the increasing number of resource constrained devices. Concurrent use of multiple communications technologies can be instrumental towards improving services to mobile devices in heterogeneous networks. In our previous work, we developed an optimization framework to generate channel-aware transmission policies for multi-homed devices under different cost criteria. Our formulation considers network coding as a key technique that simplifies load allocation across multiple channels and provides high resiliency under time-varying channel conditions. This paper seeks to explore the parameter space and identify the operating regions where dynamic coded policies offer most improvement over static ones in terms of energy consumption and channel utilization. We leverage meta-heuristics to find different local optima, while also tracking the intermediate solutions to map operating regions above 3 dB and 5 dB. Our results show a large set of relevant configurations where high resource efficiency can be obtained with the proposed transmission mechanisms.

1. Introduction

Nowadays mobile devices are equipped with a multitude of heterogeneous wireless interfaces that offer diverse bandwidth, reliability, and latency at different energy and economic costs. In this scenario of convergence of heterogeneous radio access technologies, multi-homing allows end devices to be simultaneously connected to and exchange data on multiple network interfaces, thereby increasing reliability and quality of service (QoS) of content delivery [1].

Typically, only one interface is used at a time, chosen according to static, pre-defined priorities: use Wi-Fi if possible, 3G otherwise, and Bluetooth for specific applications. This approach is consistent with today's business model for mobile connectivity, but it is not efficient in terms of managing network resources, or decreasing economic costs [2]. The interface to use should be chosen according to application and user requirements, as well as device and network context.

Current proposals, recently reviewed in [3], include network centric [4–7], user centric [8–12] and hybrid [13,14] approaches that trigger vertical handovers in heterogeneous wireless networks using a variety of techniques, e.g., stochastic linear programming [4], game theory [5], multiple-attribute decision making [15,16], grey relationship analysis [10], as well as concepts borrowed from economic modelling like profit [12], surplus [11], or utility functions [7]. Context-aware frameworks for vertical handovers have also been proposed [17–20]; however, they do not consider simultaneous use of more than one radio technology, which is a common limitation present in network selection work [21,22].

The emergence of multi-homing and the feasibility of unicast communication over multiple paths [23] opens up the possibility to use different interfaces simultaneously. In [24], the authors propose a scheme for choosing the access technology to use for each new flow upon arrival partitioning the flows over multiple radio access technologies. A framework for simultaneous use of 3G and WLAN by multi-homed devices is proposed in [25], considering the specificities of multilayer HTTP and video traffic, but the approach separates the traffic into multiple flows and makes a static allocation of those flows. These and similar proposals provide little or no adaptability to the inherent channel quality variations of wireless systems [26–31].

Adaptive resource allocation algorithms that choose which data to send/request through each available interface based on network conditions, traffic load, available energy, among other constraints are thus instrumental to leverage the full potential of converged heterogeneous wireless communications [32–34]. We note

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http://dx.doi.org/10.1016/j.comnet.2016.08.002
1389-1286/

that none of these works provide a framework for exploring the parameter space and evaluating achievable gains, nor do they consider network coding exploring opportunistic transmissions in the context of multiple paths in converged heterogeneous wireless networks with time-varying channels.

Network coding, initially proposed in [35], constitutes a disruptive paradigm that relies on mixing (coding) packets end-to-end or at intermediate nodes in the network rather than storing and forwarding them [36,37]. Random linear combinations are sufficient to achieve the maximum capacity of a network with probability exponentially approaching 1 with the code length [38] while attaining minimum delay [39,40]. From a receiver's perspective, it is no longer crucial to focus on gathering specific packets, but to gather enough linearly independent coded packets to recover the original information. This enables network coding to exploit multiple routes and/or network topologies seamlessly by dynamically shifting traffic between different paths, without concerning about coordination or packet scheduling problems. By exploring redundant network capacity, network coding reduces the need for complex management schemes, allows decentralised operation, and increases the robustness and resilience to topology/network changes and even link failures [38,41].

For transmissions in packet erasure channels, network coding provides robustness against packet losses and highly dynamic network conditions [36,38,42,43]. These traits make network coding very appealing for the volatile environments typical of heterogeneous wireless networks, especially when data may be transmitted simultaneously using different technologies as is enabled by multihoming.

Network coding is a block-coding operation where each block represents a generation. Other block-based codes used on packet erasure channels such as Automatic Repeat reQuest (ARQ) error-control codes [44], although achieving optimal throughput, have increased delay [36], and end-to-end Forward Error Correction (FEC) codes [45] do not achieve the optimal throughput due to the inherent redundancy adaptation to the end-to-end loss rate [36]. Digital fountain codes, such as Luby Transform (LT) codes [46] or Raptor codes [47] which are based on LT codes, low-density parity-check (LDPC) codes [48], turbo codes [49] and even Reed-Solomon codes [50] are examples of FEC codes. Usually, large block sizes are required to maximize capacity which add extra delay; less delay comes with the expense of a less efficient code. As FEC codes are used end-to-end, since intermediate nodes do not perform coding operations and confine themselves to relay packets, in [51] the authors propose the use of network-embedded FEC; however, nodes need to wait until sufficient packets are received for decode and further re-encode of a new data segment which adds extra delay to the system, while network coding would allow the immediate decode and re-encode of each packet.

Recent work on network coding has considered the use of multiple interfaces to improve Quality of Experience [52] with an economical cost objective and to minimize completion time of a file transfer [53]. In [54] our goal was to leverage network coding techniques optimising how to share load among the available interfaces between multi-homed devices over heterogeneous, time-varying wireless networks. Thereby we focused on a user-centric approach, formulating and solving a resource allocation problem for deciding when and under which conditions the offered traffic load should be transmitted on each available path. The numerical results proved that dynamic allocation policies using network coding improved resource usage efficiency by reducing energy consumption and/or channel utilization in some selected (and specific) scenarios.

In this article we extend and generalise that work by evaluating the actual potential impact of the proposed optimal policies. This work uses Simulated Annealing (SA) meta-heuristics to efficiently explore the parameter space and fully understand the advantages of dynamic allocation policies that adapt to the volatile channel characteristics; we compare their performance with the use of static policies, as are common in state-of-the-art devices, identifying under which operating conditions the reduction of energy consumption and channel utilization are most significant.

The rest of this article is organized as follows. Section 2 summarizes from [54] our mathematical framework for the problem, the static and dynamic allocation policies for heterogeneous wireless networks, and the metrics for performance evaluation. Section 3 presents our meta-heuristics to explore the parameter space. In Section 4 we present the best operating regions obtained for the performance of the proposed policies using numerical evaluations. In Section 5 we discuss the results, and Section 6 presents our conclusions.

2. Framework

We consider the problem of transmission of data packets from a source to a destination in a time-slotted system, where two independent channels are available[1]. Both source and destination can be relay nodes in a network. Our framework determines the amount of offered traffic load that should be sent on each channel. At each time slot, the source can transmit random linear network coded packets [38] through both channels (sending a different coded packet in each), one channel, or can decide not to transmit in that time slot. Given that packets arrive randomly at the sender, we consider an online network coding approach [37,55].

We assume an independent Gilbert–Elliott model for the channel [56,57]. Fig. 1 illustrates the scenario. We consider that each channel i can transmit using a combination of a set of modulation and (physical-layer) coding pairs, $\mathcal{M}_i$. $M_{ij} \in \mathcal{M}_i$ represents the jth available modulation and physical-layer coding pair available to channel i. $D(M_{ij})$ represents the fraction of useful information bits in a slot when transmitting with M_{ij}. Packet erasure (loss) probabilities on the ith channel for the good and bad channel state for modulation $M_{i,j}$ are represented by $e_{(i,g,M_{ij})}$ and $e_{(i,b,M_{ij})}$, respectively. The probability of channel i to remain in state $c \in \{b, g\}$ is given by $p_c^{(i)}$.

We assume that a genie indicates the joint channel state $C = (c_1, c_2)$ of the two channels, i.e., the probabilities of packet loss in each channel, at each time slot. However, the event of a packet loss is not known *a priori* to the genie.

We define $Pr_{(i,C,M_{ij})}$ and $\alpha_{(i,C,M_{ij})}$ as the probability of transmission through channel i during the joint channel state C using M_{ij} and the fraction of the data to be transmitted through channel i during the joint channel state C using M_{ij}, respectively. π_C constitutes the stationary probability of the joint channel state C, which can be easily determined through standard finite Markov chain techniques using $p_g^{(i)}$ and $p_b^{(i)}$ for $i = 1, 2$. The stationary probabilities π_g and π_b for each channel are obtained by:

$$\pi_g^{(i)} = \frac{1 - p_b^{(i)}}{2 - p_g^{(i)} - p_b^{(i)}}; \; \pi_b^{(i)} = \frac{1 - p_g^{(i)}}{2 - p_g^{(i)} - p_b^{(i)}}. \tag{1}$$

The utilization of channel i in our system is given by

$$U_i([Pr_{(i,C,M_{ij})}]) = \sum_{M_{ij} \in \mathcal{M}_i, C \in \{b,g\}^2} Pr_{(i,C,M_{ij})} \pi_C. \tag{2}$$

We define the total channel utilization of the system as $U = \sum_i U_i$, although other metrics can be used as cost functions for our optimization problem, e.g., minimizing the maximum of the U_i's.

[1] This framework can easily be generalized to more than 2 channels.

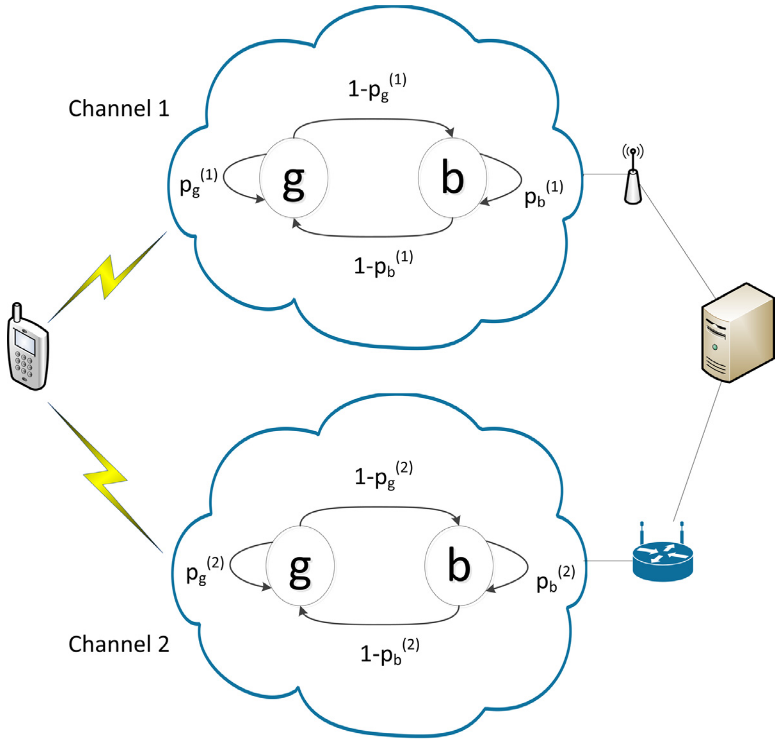

Fig. 1. Source (mobile device) can connect to two different channel interfaces to transmit random linear network coded packets in a time-slotted system to a destination. Both source and destination can be relay nodes in a network. An independent Gilbert–Elliott model and only one modulation and (physical-layer) coding pairs are assumed for each channel.

Table 1
Notations.

Notation	Definition
λ	Source rate
$Pr_{(i,C,M_{ij})}$	Probability of transmission through channel i during the channel state C using M_{ij}
$\alpha_{(i,C,M_{ij})}$	Fraction of the data to be transmitted through channel i during the channel state C using M_{ij}
$e_{i,g,M_{ij}}$	Packet erasure probability for the good state of ith channel using the jth available modulation and physical-layer coding pair
$e_{i,b,M_{ij}}$	Packet erasure probability for the bad state of ith channel using the jth available modulation and physical-layer coding pair
$\pi_g^{(i)}$	Stationary probability of the good state of ith channel
$\pi_b^{(i)}$	Stationary probability of the bad state of ith channel
M_{ij}	The jth available modulation and physical-layer coding pair available to ith channel
$D(M_{ij})$	The fraction of useful information bits in a slot when transmitting with M_{ij}
E_i	Energy consumption of ith channel
U_i	Utilization of ith channel
ξ_i	Energy cost per slot of ith channel

If the use of channel i has an associated energy cost, the energy spent per slot in channel i is given by

$$\xi_i([Pr_{(i,C,M_{ij})}]) = \sum_{M_{ij}\in\mathcal{M}_j, C\in\{b,g\}^2} E_i Pr_{(i,C,M_{ij})}\pi_C \quad (3)$$

and the total energy cost per slot of the system is given by $E = \sum_i \xi_i$. Table 1 summarises the notations used in this work.

The resource optimization problem for a desired cost function $\mathcal{F}$ from our framework using network coding is given by:

$$\min_{[Pr_{(i,C,M_{ij})}]} \quad \mathcal{F} \quad (4)$$

subject to

$$\sum_{M_{ij}\in\mathcal{M}} Pr_{(i,C,M_{ij})} \in [0,1], \quad \forall C \in \{g,b\}^2, i \in \{1,2\}$$

$$\sum_{M_{ij}\in\mathcal{M}, i\in\{1,2\}, C\in\{g,b\}^2} \alpha_{(i,C,M_{ij})} = 1$$

$$((1-e_{(i,c_i,M_{ij})})D(M_{ij}))Pr_{(i,C,M_{ij})}\pi_C = \lambda\alpha_{(i,C,M_{ij})},$$
$$\forall C = (c_1, c_2) \in \{g,b\}^2, i \in \{1,2\}, M_{ij} \in \mathcal{M}.$$

The last condition captures the fact that the probability of channel i transmitting in a given channel state using M_{ij} is linked to the mean usage of the channel during that state, e.g., $\lambda\alpha_{(1,C,M_{1j})}/[D(M_{1j})(1-e_{(1,c_1)})]$ for channel 1.

The optimal policy for a given channel state C and source rate λ is given by the vector $[Pr_{(i,C,M_{ij})}]$ that results from this optimization. Note that the probability of transmitting through channel 1 and channel 2 is independent, thus transmission over two channels or no channels at each time slot is possible. In this work we make the assumption of transmission of data flows, avoiding the granularity of data packets. In addition, we assume that we transmit the least possible redundancy per original data packet over a long period of time, which requires infinite queue size [58]. While there is a performance degradation in terms of delay from adding extra information, assuming transmission of a finite number of data packets may not allow us to reach the same performance as transmission of data flows. We consider our approach a good approximation as online network coding allows the creation of large windows of coded packets, which approximate a flow. Our framework can perform an optimal resource allocation, as the infinite queue size allows to store the coded packets while awaiting a good channel.

2.1. Comparison policies

We define the following two fixed policies in the transmission of packets:

- Fixed policy channel 1 (FP1) - Policy where all available resources (time slots) from channel 1 are used before allocating slots for transmission from channel 2. If the arrival rate is low enough, only channel 1 will be active.
- Fixed policy channel 2 (FP2) - Same as FPC1 policy except resources (time slots) from channel 2 are used first and resources from channel 1 are used only if needed to support a given data rate.

and the two dynamic policies:

- Dynamic policy optimizing channel utilization (DPOCU) - Optimal policy in terms of reduction of channel utilization, where the channel assignments are decided by solving problem (4) for the cost function: $\mathcal{F} = \sum_i U_i(Pr_{(i,C,M_{ij})})$.
- Dynamic policy optimizing energy consumption (DPOEC) - Optimal policy in terms of reduction of energy consumption, where the channel assignments are decided by solving problem (4) for the cost function: $\mathcal{F} = \sum_i E_i U_i(Pr_{(i,C,M_{ij})})$.

2.2. Metrics

We define two metrics to quantify the advantages of using dynamic policies rather than fixed policies.

- Channel Utilization Gap of DPOCU: is the difference of channel utilization between a policy P_i and channel utilization optimal policy DPOCU for the same channel conditions. The value is presented in decibel (dB) and is calculated as $10 \log \left(U_{P_i}/U_{DPOCU}\right)$.
- Energy Consumption Gap of DPOEC: is the difference of energy consumption between a policy P_i and the energy optimal policy DPOEC, under the same channel conditions. The value is expressed in decibel (dB) and is calculated as $10 \log \left(\xi_{P_i}/\xi_{DPOEC}\right)$.

As an example, consider that the Channel Utilization Gap of DPOCU is 3 dB when compared to FP1. This means that DPOCU uses the channel 50% less than FP1. A larger value of the gap is associated with a larger reduction in channel utilization achievable by the DPOCU policy. The same logic applies for the energy consumption metric.

3. Simulated Annealing meta-heuristics

The optimization framework and the dynamic network coding policies proved to provide efficient, channel-aware load allocation for multi-homed devices under different cost criteria in our previous work [54]. However, every parameter had to be manually adjusted in an attempt to find a combination that provided considerable gains. It is impossible to understand which areas of the parameter space can provide better results following that methodology. Therefore, it is imperative to explore the parameter space automatically.

Traditional problem solving strategies either guarantee to find the global solution, but are too expensive in terms of computation, e.g., memory usage or processing time, or they get caught in local optima. Recent algorithms are capable of escaping the local optima while searching for the global optimum. Simulated Annealing (SA) is a probabilistic method for efficiently exploring the search space in order to find near optimal (global) solutions [59,60]. Meta-heuristics, such as SA, generally find good solutions by exploring a large set of the feasible solutions, which allow us to explore the areas of the parameter space that provide better results.

Algorithm 1: SA algorithm.

begin
  t ← 0; /* Time */
  initialize T; /* Temperature */
  select a current point v_c at random; /* v_c is composed by λ, $e_{(i,c_i,M_{i,j})}$, π_C, E_i, for $\forall C = (c_1, c_2) \in \{g, b\}^2, i \in \{1, 2\}, M_{ij} \in \mathcal{M}$. */
  evaluate v_c;
  /* Evaluation is performed by obtaining the value corresponding to the minimum between a dynamic policy and other policies. */
  $v_b \leftarrow v_c$;
  repeat
    repeat
      Select a new point v_n in the neighbourhood of v_c;/* Change randomly a single parameter according to a predefined step. */
      if *evaluation*(v_n) > *evaluation*(v_c) **then**
        $v_c \leftarrow v_n$;
        if *evaluation*(v_c) > *evaluation*(v_b) **then**
          $v_b \leftarrow v_c$;
      else
        if $random[0,1) < exp\left(-\frac{evaluation(v_c) - evaluation(v_n)}{T}\right)$ **then**
          $v_c \leftarrow v_n$;
      end
    until *termination condition*/* termination condition - Max # of iterations is not reached. */;
    T ← f(T,t); /* Cooling Ratio */
    t ← t+1;
  until *halting condition*/* halting condition - Max # of times v_c is not changed. */;
end

This work uses SA meta-heuristics to efficiently explore the parameter space to fully understand the advantages of resource allocation policies that dynamically adapt to the volatile channel characteristics and identify under which operating conditions, i.e., areas of the parameter space, the reduction of energy consumption and channel utilization are most significant.

We use SA to select parameter sets and evaluate them using the mathematical framework described in the previous section, and thus SA is driven by a theoretical analysis. Algorithm 1 presents our SA formulation for the problem. The SA algorithm starts by initializing and assigning a random value to a parameter set composed of source rate, erasure probabilities and stationary probabilities to each channel. The stationary probabilities for each channel must sum up to 1 and, therefore, we just need to randomly assign one value to one state of each channel. The parameter set is evaluated according to the achievable gains of the dynamic network coding policies, DPOCU or DPOEC, and the result of the evaluation (a solution) is the minimum of the Channel Utilization Gap or Energy Consumption Gap. In other words, in the algorithm, a solution corresponds to the minimum of the Channel Utilization Gap

Table 2
Parameters range and counters values.

Parameter	Range/Value	Step
λ	0.1 – 2	0.1
$e_{1,g}$	0.01 – 0.20	0.01
$e_{1,b}$	0.21 – 0.90	0.01
$e_{2,g}$	0.01 – 0.20	0.01
$e_{2,b}$	0.21 – 0.90	0.01
$\pi_g^{(1)}$	0.05 – 0.95	0.01
$\pi_b^{(1)}$	0.05 – 0.95	0.01
$\pi_g^{(2)}$	0.05 – 0.95	0.01
$\pi_b^{(2)}$	0.05 – 0.95	0.01
E_1	1 – 8	0.05
E_2	1	–
Halting	500	–
Termination	360	–
Temperature	25	0.025

of DPOCU or the Energy Consumption Gap of DPOEC with respect to any other policy. For example, if a parameter set results in a Channel Utilization Gap of DPOCU with respect to FP1 of 2 dB, in a Channel Utilization Gap of DPOCU with respect to FP2 of 3 dB, and in Channel Utilization Gap of DPOCU with respect to DPOEC of 4 dB, the solution obtained is 2 dB which corresponds to the minimum between the three values, i.e., our results correspond to the minimum achievable gain for each explored point of the parameter space.

The initial parameter set us the *Current Solution,* v_c, which corresponds to the current solution to which other solutions in its parameters' neighbourhood shall be compared to. At the beginning, this solution also corresponds to the *Best Solution,* v_b. The *Best Solution* is the best solution obtained so far, and, at the end of the algorithm, desirably it should yield the global optimum. In each step of the algorithm, we select a new parameter set to be our *Candidate Solution,* v_n, originated from a change to a single parameter in the *Current Solution*, and evaluate it. Therefore, the neighbourhoods are composed of solutions around the *Current Solution* at the distance of one change in one parameter, either decreasing or increasing its value by a predefined step. If the *Candidate Solution* provides a better solution than the *Current Solution*, we accept it as our new *Current Solution*. If it is the same or lower, we accept it if $random[0,1) < \exp(-\frac{evaluation(v_c)-evaluation(v_n)}{Temperature})$, which is adjusted by the parameter temperature. The reason why we record both *Current Solution* and *Best Solution* is because we can accept a *Candidate Solution* as *Current Solution* even if it provides a worse solution than the previous *Current Solution*. However, as we iterate over the outer loop, the value of the temperature will decrease, and the acceptance of worse solutions will be less frequent. At the beginning, this algorithm resembles a random search, thus avoiding possible local optima, and, at the end, it resembles a standard hill-climber. To avoid infinite generation of iterations, we set a halting condition as the maximum number of times that the algorithm does not change the *Current Solution*, and a termination condition as the maximum number of iterations the algorithm runs with the same temperature value. Every time the algorithm changes the value of *Current Solution*, the counter of halting condition is reset, since the algorithm accepted a new solution and possibly new better and different solutions are reachable. Please note that different heuristics could lead to different (higher or lower) results.

4. Results

We focus our analysis in two different scenarios: (i) *Channels with same energy consumptions* where we have two different channels with the same energy consumption and fixed data rate (e.g., same modulation and coding pairs), but with different erasure and stationary probabilities for each channel state; (ii) *Channels with different energy consumptions* where we have two different channels, with the same fixed data rate, but with different erasure and stationary probabilities for each channel state, and different energy consumptions. Therefore, the packet erasure probabilities on the i-th channel for the good and bad channel state are from now on represented by the terms $e_{(i,g)}$ and $e_{(i,b)}$, respectively, and both channels send the same fraction of useful information bits in a slot ($D(M_{ij})$).

Having both channels with the same data rate allows us to simplify the analysis. If we had more configurations for the channels, having the possibility of different data rates in each channel, we would increase our parameter space, but we would also increase the areas where the dynamic policies provide better performance. The opportunities to transmit in good channel conditions and good data rates would possibly increase, and, ultimately, the results would stress even further the importance of the framework.

We performed 1000 analyses for each scenario using MATLAB. The analyses were performed in parallel in the Avalanche cluster at the High Performance Computing at the Faculdade de Engenharia da Universidade do Porto [61]. The cluster has 29 nodes, each with 16 cores and between 64 GB and 128 GB of RAM; however, due to quota limitations, no more than 300 analyses could run at the same time. The execution of all analyses lasted for two and one half days. Although the parameter space explored by *Candidate Solution* is larger, during analyses we only recorded the *Best Solution* and *Current Solution* values since the effort in terms of disk to record all *Candidate Solution* was infeasible.

The arrival rate, the parameters of the Gilbert–Elliot model, and energy consumption for each channel were allowed to vary according to the values presented in Table 2. The ranges of the values were selected to constitute a reasonable representation of possible conditions. Channels can have an erasure probability between 0.01 and 0.20 for the good states, 0.21 and 0.90 for the bad states, and stationary probabilities in each state between 0.05 and 0.95. Table 2 also presents the values chosen for the counters of the halting and the termination conditions, and the temperature cooling ratio. The tuning of these values was made in a trial and error approach and we selected the values that provided a good trade-off between the diversity of parameter space search and the duration of the analyses. Each analysis sets the initial parameters at random within the ranges of Table 2. Each generation of a new neighbourhood is accomplished by a change to a single parameter according to the step defined in that table.

4.1. Channels with same energy consumption

When the two channels have the same energy consumption ($E_1 = E_2$), the Channel Utilization Gap of DPOCU behaves the same as the Energy Consumption Gap of DPOEC with respect to the fixed policies. Fig. 2 shows the distribution of the final *Best Solution* and the corresponding parameters for the Channel Utilization Gap of DPOCU. The results show that a large percentage of all *Best Solution* (83%) are approximately 5.4 dB and a significant percentage of the *Best Solution* (14%) obtained are approximately 7 dB. The best solutions of both Channel Utilization Gap of DPOCU and Energy Consumption Gap of DPOEC with respect to the fixed policies are obtained with high and low erasure probabilities for the good and bad states of the channels, respectively, and with low and high stationary probabilities for the good and bad state, respectively. The best results are obtained for small λ (0.2 or 0.3), that is, the best results are obtained when the offered traffic load is low and the dynamic policies can take advantage of opportunistic transmissions and select the best moment to transmit. The dynamic policies use the good states of both channels instead of using the bad states, and it is here where our dynamic policies have

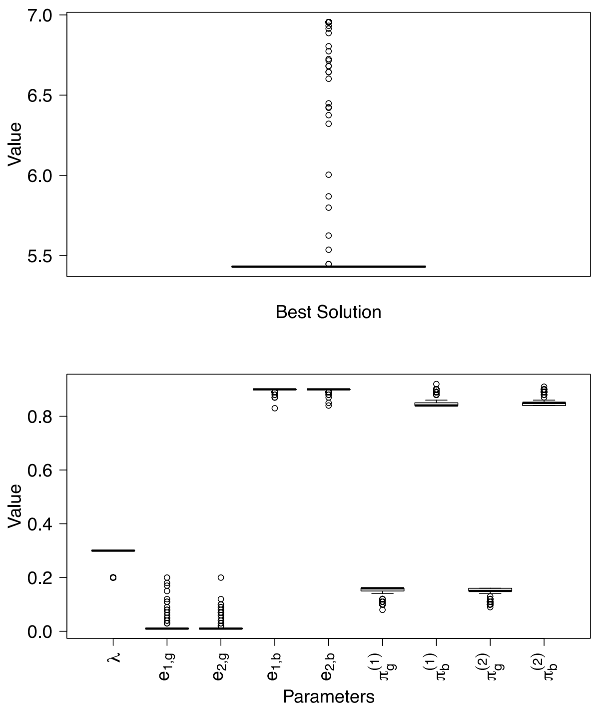

Fig. 2. Boxplot of the final best solutions on top and boxplot of the parameters on bottom, for the Channel Utilization Gap of DPOCU (same as Energy Consumption Gap of DPOEC) with respect to the fixed policies. Maximum *Best Solution* obtained is ≈ 7 dB, minimum *Best Solution* obtained, and equal to the median, is ≈ 5.43 dB, and the mean of the *Best Solution* is ≈ 5.67 dB.

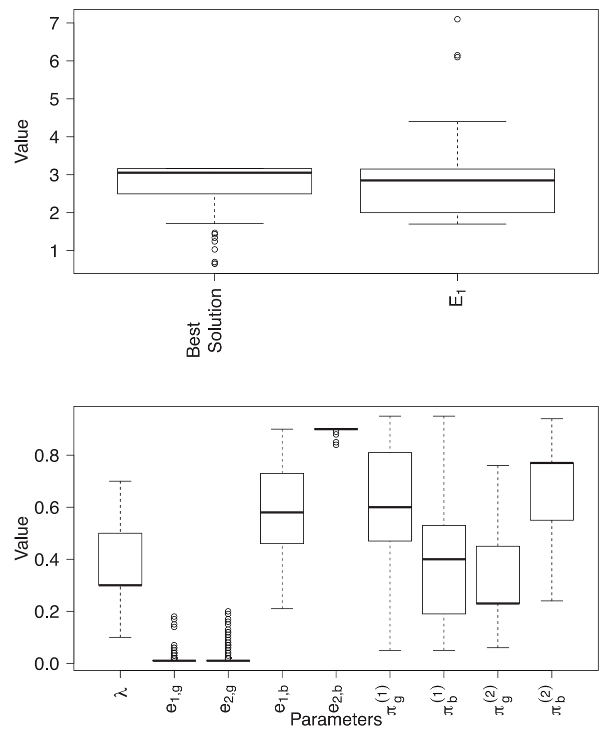

Fig. 4. Boxplot of the final best solutions and energy consumption of channel 1 on top and boxplot of the parameters on bottom, for the Energy Consumption Gap of DPOEC with respect both to the fixed policies and DPOCU. Maximum Best Solution obtained is ≈ 3.16 dB, minimum Best solution obtained is ≈ 0.65 dB, median is ≈ 3.05 dB, and the mean of the Best Solution is ≈ 2.91 dB.

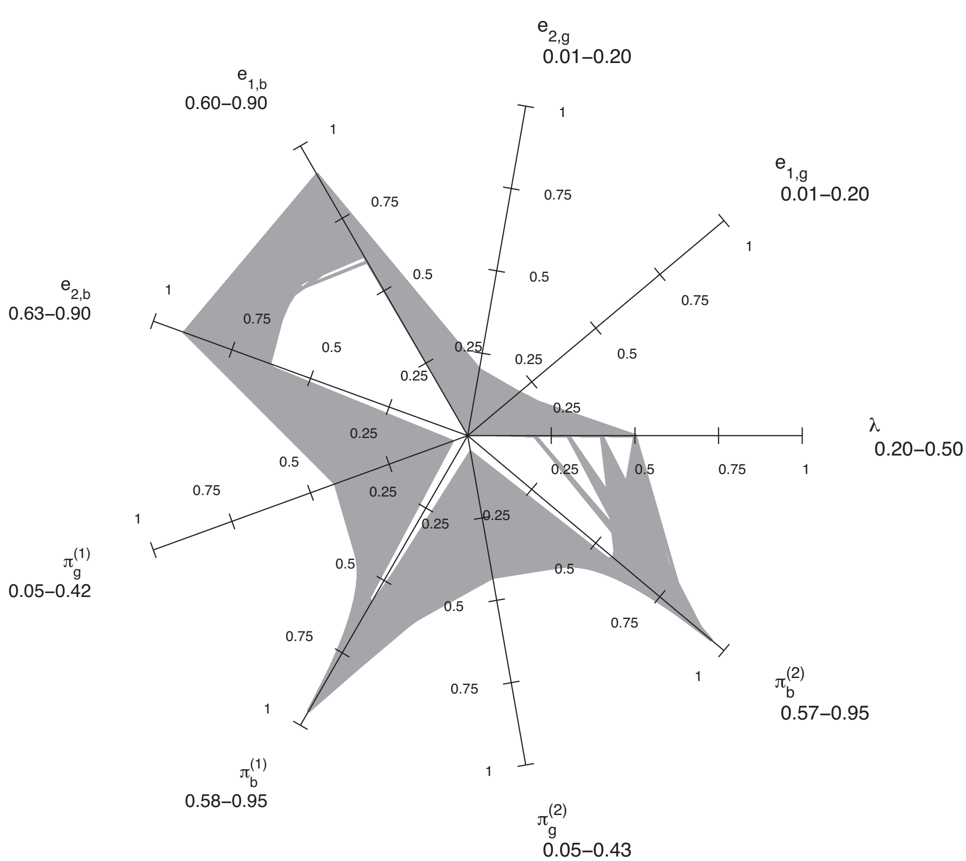

Fig. 3. Spider chart for all *Current Solution* that provide a Channel Utilization gap of DPOCU (same as Energy Consumption Gap of DPOEC) with respect to the fixed policies above 3 dB.

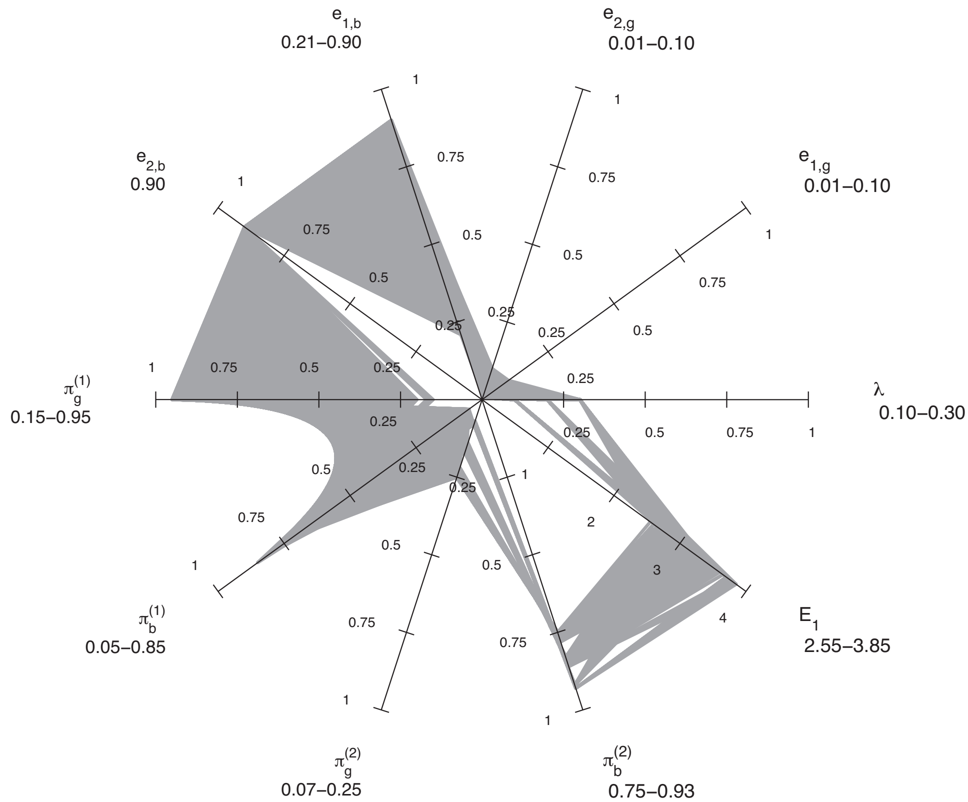

Fig. 5. Spider chart for all *Current Solution* that provide an Energy Consumption Gap of DPOEC with respect both to the fixed policies and DPOCU above 3 dB.

advantage in comparison to the fixed policies. FP1 uses resources (time slots) from both good and bad states of channel 1 before using resources of the channel 2, and FP2 uses resources from both good and bad states of channel 2 before using resources of channel 1. The higher the stationary probabilities of the bad states and lower the stationary probabilities of the good states are, the more gains DPOCU and DPOEC achieve with respect to the other policies and, thus, the higher the Channel Utilization Gap of DPOCU and Energy Consumption Gap of DPOEC are.

To have a visual perspective of the areas of the parameter space explored by all accepted *Current Solution* during analyses, Fig. 3 presents a spider chart with the solutions that provide a Channel Utilization Gap of DPOCU (same as Energy Consumption Gap of DPOEC) with respect to the fixed policies above 3 dB, having the figure sampled 1:1000 for visualization purposes. In the figure each individual solution is obtained by a unique combination of parameters. In the analyses we obtained around 3 million solutions above 3 dB of gap (4.67% of all unique *Current Solution* accepted) and, approximately, 384,000 above 5 dB (0.6% of all unique *Current Solution* accepted). Fig. 3 includes in the edges of each axis the range that each parameter varied in all accepted *Current Solution*.

4.2. Channels with different energy consumptions

In this scenario, channel 1 and channel 2 can have different energy consumptions. For a matter of efficiency, we fix the energy consumption of channel 2 to 1, i.e., $E_2 = 1$, and let the energy consumption of channel 1 vary on values higher or equal than 1, i.e., $E_1 \geq 1$. Next, we present the results obtained for the Energy Consumption Gap of DPOEC with respect both to the fixed policies and the dynamic DPOCU. Later, we present the results obtained for the Energy Consumption Gap of DPOEC when it is compared only to the fixed policies.

4.2.1. Energy Consumption Gap of DPOEC with respect both to the fixed policies and DPOCU

Fig. 4 shows the distribution of the final *Best Solution* and the corresponding parameters for the Energy Consumption Gap of DPOEC as well as the ranges of the energy consumption of channel 1 in all analyses. Please note that the Energy Consumption Gap of DPOEC here is compared both to the fixed and to the dynamic DPOCU policies. The mean of all obtainable *Best Solution* is approximately 2.9 dB, while the maximum and minimum *Best Solution* are 3.16 and 0.65 dB, respectively. The best solutions are obtained when the energy consumption of channel 1 is $E_1 \approx 3 \times E_2$ and with high erasure probabilities for the good state of both channels and low erasure probabilities for the bad state of channel 2. We now observe a larger and higher distribution for the offered traffic load.

For DPOEC to have advantage with respect to FP1, the fixed policy that transmits always first in both states of channel 1, which consumes more energy than channel 2, it suffices for DPOEC to use channel 1 and channel 2 in the good states. In order for DPOEC to have advantage with respect to FP2, the fixed policy that transmits always first in both states of channel 2, but consumes less energy than channel 1, it is necessary that the stationary probability in the good state of channel 2 ($\pi_g^{(2)}$) is lower enough than the homologous of channel 1 ($\pi_g^{(1)}$). FP2 will always use channel 2 in both states, but will not benefit from channel 1 good state.

For DPOEC to have advantage towards DPOCU it is necessary for the erasure probability of channel 1 in the bad state ($e_{(1,\,b)}$) to be better (lower) than the erasure probability of channel 2 in the bad state ($e_{(2,\,b)}$); otherwise, DPOCU would choose channel 2, which is the channel with the lowest energy consumption, and would match DPOEC. Furthermore, DPOCU chooses first a state of channel 1 with the same erasure probabilities as channel 2 only when channel 1 has higher stationary probabilities in the good state.

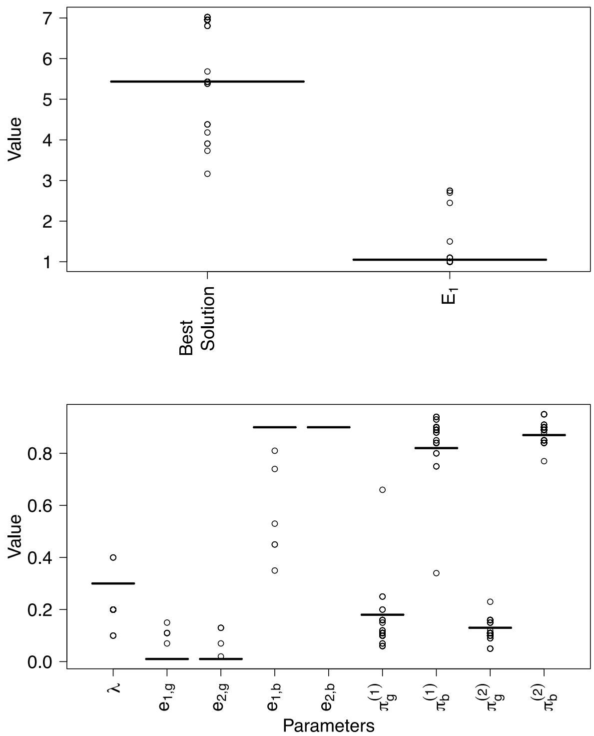

Fig. 6. Boxplot of the final best solutions and energy consumption of channel 1 on top and boxplot of the parameters on bottom, for the Energy Consumption Gap of DPOEC with respect only to the fixed policies. Maximum *Best Solution* obtained is ≈ 7.02 dB, minimum *Best Solution* obtained is ≈ 3.17 dB, median is ≈ 5.44 dB, and the mean of the *Best Solution* is ≈ 5.68 dB.

To have a visual perspective of the areas of the parameter space explored by all accepted *Current Solution* during analyses, Fig. 5 presents a spider chart with the ones that provide an Energy Consumption Gap of DPOEC with respect only to the fixed policies above 3 dB, having the figure sampled 1:1000 for visualization purposes. In the analyses we obtained over 1.4 million solutions above 3 dB of gap. The figure also includes in the edges of each axis the range that each parameter varied in all accepted solutions.

4.2.2. Energy Consumption Gap of DPOEC with respect only to the fixed policies

Fig. 6 shows that the results obtained for the Energy Consumption Gap of DPOEC with respect only to the fixed policies are different from the results obtained in the previous section. In this case we obtain the maximum Energy Consumption Gap of DPOEC in all scenarios with the value of 7.02 dB when the energy consumption of channel 1 is $E_1 = 1.05 \times E_2$. Nevertheless, it is clear now that, in the previous section, DPOCU prevented the algorithm from exploring solutions of the Energy Consumption Gap of DPOEC where the energy consumption of channel 1 was low. When the energy consumptions of both channels are close, DPOEC has the same performance as DPOCU (see Section 4.1), which means the algorithm needed to find areas of the parameter space where DPOEC had advantage when compared to DPOCU. Now that we exclude DPOCU from the analysis, the results shows a similarity with the ones obtained in Section 4.1.

Fig. 7 shows the relation of the maximum *Best Solution* of the Energy Consumption Gap of DPOEC with respect only to the fixed policies and the energy consumption of channel 1. We performed an extra set of analyses where we set the energy consumption of channel 1 static at $E_1 = 2, 4, 6, 8$ times the consumption of channel 2, E_2. In general, the increase of channel 1 energy consumption leads to the reduction of the value of the *Best Solution* achievable, that is, to the reduction of the possible gains using a dynamic policy. When channel 1 consumes more energy and in higher quantities than channel 2, the dynamic policy DPOEC cannot use the good state of channel 1 because it is very damaging in terms of energy cost, and, thus, DPOEC will choose both states of channel 2 and will be similar to the fixed policy FP2. These results are somewhat non intuitive, because it would be expected that, if one channel consumes more energy, we would gain more in using dynamic policies; however, in fact, the best scenarios for the dynamic policies are when we can explore the use of the good state of both channels and both channels have roughly the same energy consumption.

5. Discussion

From the results, we can conclude that the best savings over fixed policies come from situations where the device can connect at the same time to two similar channels of the same technol-

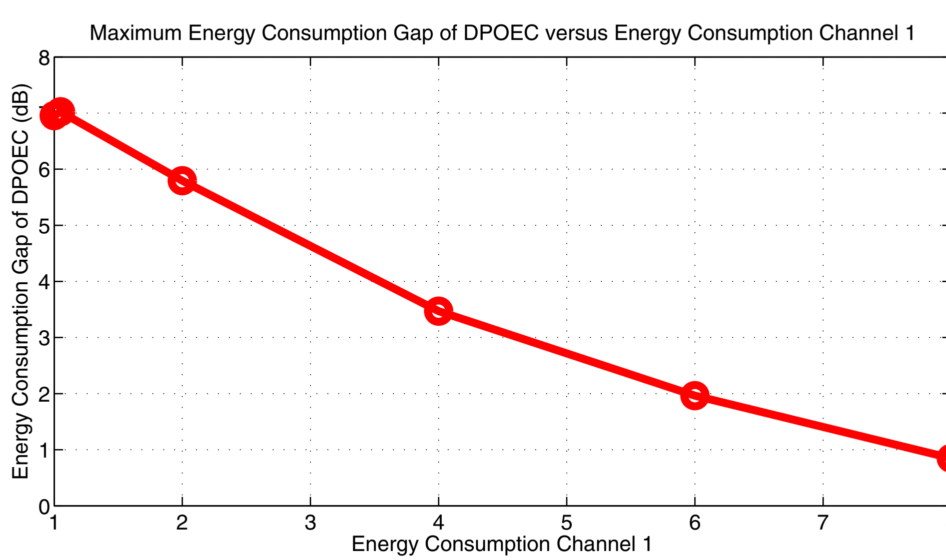

Fig. 7. Relation between the maximum *Best Solution* of the Energy Consumption Gap of DPOEC with respect only to the fixed policies and the energy consumption of channel 1. The maximum is achieved for $E1 = 1.05 \times E_2$. The achievable Energy Consumption Gap of DPOEC decreases with the increase of the energy consumption of channel 1.

Table 3
Maximum, mean, and median gains (in dB) obtained for the Channel Utilization Gap of DPOCU (same as Energy Consumption Gap of DPOEC when the two channels have the same energy consumption) with respect to the fixed policies under good, medium, and bad channel conditions.

		Channel 1	Channel 2	Either channel	Both channels
Good	Max	2.0931	2.0396	2.0931	1.4840
	Mean	0.0798	0.0795	0.0877	0.0599
	Median	0	0	0	0
Medium	Max	3.9482	3.9451	3.9482	3.8340
	Mean	0.4726	0.3841	0.3881	0.5806
	Median	0.0639	0.0202	0.0163	0.2264
Bad	Max	6.9553	6.9553	6.9553	6.9553
	Mean	1.5284	1.2813	1.0934	2.4875
	Median	0.6371	0.2399	0.2164	2.9796

ogy/network, like for example two Wi-Fi links, two 3G links, because the achievable gains decrease with the difference in energy needs between the links. To allow the dynamic policies to explore the best opportunities for transmission of the offered traffic load, both channels should have low error rates on the good state. High error rates or very high offered traffic load reduce these opportunities.

The dynamic policies outperform the fixed policies especially for bad channel conditions, that is, for high stationary probabilities of the bad states. To better analyse this, we define three channel quality classes for each channel $i \in \{1, 2\}$ according to the stationary probabilities: good conditions occur for $\pi_g^{(i)} \in [2/3, 1]$, medium conditions occur for $\pi_g^{(i)} \in [1/3, 2/3[$, and bad conditions occur for $\pi_g^{(i)} \in [0, 1/3]$. Table 3 provides another view of the results previously shown in Section 4.1, showing the maximum, mean, and median gains obtained for each class for the Channel Utilization Gap of DPOCU. The results are separated according to which channel has the channel conditions identified on the left, i.e. depending on whether it is channel 1, channel 2, either channel, or both channels stationary probabilities that belong to the channel quality class.

We observe that having longer periods of medium or bad channel conditions leads to higher gains, confirming the results from Fig. 2. Conversely, when at least one of the channels is bad the gains are on average above 1 dB, and when both channels are bad the average gain is more than 2 dB.

Bad channel conditions occur often in real wireless and cellular networks and often there is more than one possible communication link, e.g. dense Wi-Fi deployments or indoor cellular coverage. Our results show that using network coding for taking advantage of multiple available links enables using less resources, e.g. channel time, to provide the desired service to the user. Better results occur for low offered traffic load since dynamic policies can take advantage of opportunistic transmissions and decide the best allocation, while for high offered traffic load it is necessary to transmit even under bad channel conditions.

6. Conclusions

In this paper we sought to identify the operating regions under which dynamic coded policies bring most benefits in terms of resource efficiency. We proposed meta-heuristics to explore the parameter space, not only to find different local optima, but also to map areas whose performance is above a certain level. The results demonstrated that opportunistic assignment of the traffic load over heterogeneous time-varying channels can in fact achieve considerable gains. In particular, dynamic network coding policies allow energy consumption and channel utilization savings over 5 dB with respect to the best static policy in a large number of scenarios. Future work shall focus on scheduling algorithms that can implement the policies through single packet decisions, incorporate unreliable estimates of the channel, and explicit trade-offs between delay, energy, and economic cost.

Acknowledgements

We thank the anonymous reviewers for their helpful feedback. We would like to thank André Moreira for the discussions along the COHERENT project. This work was partially supported by the project I-City for Future Health NORTE-07-0124-FEDER-000068, by the European Project FP7 - Future Cities FP7-REGPOT-2012-2013-1, by PT Inovação, by the Green Mobile Cloud project granted by the Danish Council for Independent Research (DFF - 0602-01372B), and by Fundação para a Ciência e a Tecnologia under the project UID/EEA/ 50008/2013 in the scope of R&D Unit 50008, financed by the applicable financial framework (FCT/MEC through national funds and when applicable co-funded by FEDER - PT2020 partnership agreement).

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