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An Energy Packet Network model for mobile networks with energy harvesting

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Abstract: Mobile communications are a powerful contributor to social and economic development worldwide, including in less developed or remote parts of the world. However they are large users of electricity through their base stations, backhaul networks and Cloud servers, so that they have a large environmental impact when they use the electric grid. On the other hand, they could operate with renewable energy sources and thus reduce their CO2 impact and be accessible even in areas where the electric grid is unavailable or unreliable. The counterpart is that intermittent sources of energy, such as photovoltaic and wind, can affect the quality of service (QoS) that is experienced by mobile users. Thus in this paper we model the performance of mobile telecommunications that use intermittent and renewable energy sources. In such cases to analyse the performance of such systems, both the energy supply and the network traffic, can be modeled as random processes, and we develop mathematical models using the Energy Packet Network paradigm, where both data and energy flows are discretised. QoS metrics for the users are computed based on the traffic intensity and the availability of energy.

Key Words: mobile networks, Energy Packet Networks, off-grid communications, sustainability, renewable energy, quality of service

1. Introduction

Electrical energy is needed to manufacture, operate and cool ICT equipment, and the electrical energy consumption needed to operate ICT systems is growing worldwide, exceeding 900 TWH per year in 2012, or more than the electricity consumption of Japan [1]. Thus it would be useful to operate ICT systems, at least partially, with renewable sources of energy such as photovoltaic and wind, in order to reduce their environmental impact. Although ICT systems are typically designed with the expectation that a steady and reliable source of stable electricity is available everywhere, this is not always the case in the developing world where renewable sources of energy can compensate for the unreliability or unavailability of the electricity grid.

Thus the use of intermittent renewable energy is needed both to limit the environmental impact of ICT systems, and to offer mobile services in remote or less developed parts of the world where mobile telephony plays a key role in development [2]. According to the Brookings Institution, in 2015

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the fraction of the African population with access to mobile telephony (39%) exceeds the population having access to electricity (32%) [3] and are contributors to economic growth in both developed and developing nations [10]. However in developing economies, availability of electricity can be a stumbling block and the number of off-grid and poor-grid base stations (BSs) is growing globally by 16% between 2014 and 2020 [11].

Photovoltaic, and other energy harvesters with batteries, present a huge potential for the mobile industry, provided investments are low and operating costs (mainly the maintenance) is not too high. The prices of solar energy systems have fallen and the average cost of a solar cell in Jan. 2017 is only about \$0.36 per watt [12]. Small wind turbines also make wind energy and hybrid solar-wind systems [14] more affordable, with complementary profiles so that energy may be harvested over different periods of the day and night [15]. Furthermore, battery costs are expected to fall, with substantial performance improvements. Finally, although in the past rural sites have relied on expensive satellite connections, future solutions may utilise cheaper multi-hop wireless technologies, especially for local clusters of mobile communications.

In such systems, it is also very important to limit energy consumption and energy wastage, by meeting minimal QoS objectives. Thus significant progress was made in techniques to forward DPs at the minimum rate with energy harvesting [18, 19], while it is possible to use Opportunistic Communications to extend the range of small low energy devices [9]. Optimality results concerning energy scheduling are available under full knowledge [20–24]. With only online information, infinite horizon results have also been published [25, 26].

1.1 Contributions of the paper

In this paper the Energy Packet Network (EPN) approach is used for systems analysis of a backhaul multi-hop connection of a wireless mobile network. The EPN model uses a discretised representation of energy, in terms of Energy Packets (EPs), and of voice or other traffic that is being carried in digital form as Data Packets (DPs) [33, 34, 36]. In the EPN framework, batteries are represented as discrete energy buffers, and renewable energy flows into the batteries in the form of random processes of EP arrivals. Also, DPs arrive from outside the network in the form of a random process representing the data or multimedia traffic being generated by end users. Data Packets (DPs) can be stored in data buffers, and DPs leaving some node on the backhaul, may enter the next node or leave the system as shown in Fig. 1.

The approach called Power Packets developed in [4, 5] aims at the use of a single entity (the power packet) to forward both energy and data. Although not yet widely known or used in industry, it proposes a discrete representation that unifies the flow of data and energy in a single entity, which may be useful for building novel digital circuits and digital systems [42]. Our EPN approach differs in that, as with most currently used digital architectures, we keep separate the flow of data, as data packets (DPs), and energy as energy packets (EPs), and our purpose is to analyse performance (e.g. DP loss and delays, DP throughput) as a function of the flow of intermittent energy, and that we may analyse the energy consumption as a function of workload represented by DP flows. EPN conveniently maps batteries or capacitors into EP queues, and data buffers into DP queues.

Thus the main objective of this paper is to analyse the performance of a multi-hop backhaul network as in Fig. 1, which operates with an intermittent supply of energy. We examine a system where user packets arrive to Node 1 at rate λ, and travel through all the N nodes of the backhaul network. Each node i also receives cross traffic at rate Λ_i which leaves the node and this section of the backhaul network after receiving service.

Since we focus on the impact of intermittent energy on the packet loss and delay, we consider a situation where the energy related losses of DPs are much more frequent than other packet losses due to noise, interference, router errors, and the effects of protocols such as CSMA. On the other hand, we carefully analyse the random packet losses due to the lack of energy in some of the nodes, and assume that packet losses will create "repeated calls" with some probability p which can be varied to represent the type of traffic considered. For instance if the DPs represent real-time traffic or voice, p will be very small or zero, while if the DPs represent UDP data connections, then p will be close to 1. is not assumed but computed from the other model assumptions. These repeated calls due losses caused by the lack of energy will significantly affect congestion, and will create further energy consumption in the system. Furthermore we assume that each node can receive and transmit packets simultaneously so that it is equipped with two antennas. We analyse three cases:

- The first case is the "best case": we assume that the backhaul network is so fast that no buffering of data packets is needed. Furthermore, we assume that the system is so efficiently designed that each node only consumes energy when it is actually processing and forwarding packets, while no energy is consumed when a node is inactive. Packet loss is assumed to occur when a packet attempts to transit through a node that has run out of energy, as when its energy battery is depleted and its energy source (grid or harvesting) is not providing power. This best case assumes a futuristic system which is very fast so that data buffering is not needed. Furthermore, it assumes that the equipment's power consumption is directly proportional to the load; this is what modern digital equipment tries to do, and it goes to "sleep" as soon as there is no work to do. Such systems have been suggested, for instance, in [17].

- The second case assumes that nodes store packets until they can be forwarded, and the nodes are kept on even when they have no packets to forward. Contrary to the previous case, they consume the same amount of energy, independently of whether they have data packets to forward or not. Many current base stations stay on at full power even when they have no work to do, since they need to respond instantaneously of a 24-hour basis. In addition, we suppose that the system uses memory technologies that preserve the stored data packets even when a node is not powered due to lack of energy in its battery or its external energy sources do not provide power. Thus, in this case packets in the memory of a node are preserved, while those in transit may be lost. Currently, memory technologies exist, that do not need energy to maintain the data they have stored.

- The third case is the "worst case": it is similar to the second one, but we assume that nodes that run out of energy will lose all the packets that they store in their memory.

For all of these cases, we derive expressions for the average number of packet retransmissions needed to achieve successful forwarding of a packet, the packet loss probabilities, and the resulting network delays when packets are buffered, on a single multi-hop path in the backhaul network. We include the effect of intermittent power supply at all of the nodes, and cross traffic at each node. We expect that this analytical approach can be extended to general network topologies in future work.

1.2 Energy harvesting for wireless communications

Energy harvesting has received much attention in the wireless communication literature, with a large body of work focusing on techniques that allow communication networks to operate optimally with limited energy. In this context, mathematical models capturing the interactions between the information and energy planes have been proposed based on Markov processes and queueing theory [27, 28, 35, 37], risk theory [30] and diffusion processes [31]. The models enable the study of networks and operational conditions that can balance the energy needs for sensing, communications and computing, with the availability of renewable and intermittent sources of energy, so as to achieve energy neutrality [32]. While most of these studies focus on the fundamental analysis and optimisation methods that can be used in energy harvesting wireless and wired communications, they do not specifically address mobile networks, nor do they propose architectures or overall system designs.

2. Energy Packet Modelling of a multi-hop wireless backhaul network

Using the abstraction of an EPN, whereby the amount of energy needed to transmit a single data packet is represented as a discrete quantity [37], has been used to optimise the flow of a mix of renewable and fuel generated energy sources for the multiple real-time needs of ICT systems, with utility functions that can prioritise these needs.

In this section, we use a similar approach to analyse the performance of the multi-hop backhaul of a mobile access network of Fig. 1. We assume that the user calls flow as DPs. Thus we consider a multihop connection traversing the nodes $\mathbf{N}_1, \ \ldots \ , \mathbf{N}_N$, which may be BSs, WiFi nodes, or routers, each of them operating with intermittent harvested energy.

A mobile connection or "user", transmits a flow of DPs along the full path, and if a DP cannot be forwarded (or transmitted in the case of wireless relays) by any of the nodes $\mathbf{N}_i$ to node $\mathbf{N}_{i+1}$, $1 \leq i \leq N$, then *it is lost* and will be have to be *retransmitted from the first node* $\mathbf{N}_1$ *with probability* p. A packet is also lost if node $\mathbf{N}_N$ is unable to forward the DP to the end user or to the backbone network. Thus, not all lost DPs, but only a fraction p are creating repeated calls and are retransmitted.

Since we focus on a system with intermittent energy, we simplify matters by assuming that DPs are only on the path when one of the nodes has run out of energy, and the probability p recognises the fact that only a fraction p of DPs belong to flows which require retransmission, as with text messaging or data, but typically not for real-time data such as voice.

With specific reference to Fig. 1, we assume that $\mathbf{N}_1$ receives end-to-end user traffic (typically voice or SMS) which travels over N nodes, until it reaches its destination. Though in practice we would expect N to be a small integer, here we conduct the analysis for arbitrary N.

2.1 Traffic assumptions

We assume that end users on mobile phones generate input *fresh user traffic*, at an aggregate rate of λ DPs/sec to $\mathbf{N}_1$, and we assume that this externally arriving user traffic is a Poisson process. Each node $\mathbf{N}_i$ $1 \leq i \leq N$ also receives local cross-traffic as a Poisson flow Λ_i DPs/sec. All these *external arrival processes* are assumed to be independent of each other. Clearly, this *mathematical assumption* that the externally arriving traffic flow from mobile is a Poisson processes, enables us to compute analytical expressions, as in many other recent studies such as [38].

Since we construct a queueing network model with feedback loops, despite the fact that external arrival processes are assumed to be Poisson, the internal total traffic flows will not always be Poisson. Here, we also assume that the memory buffers in each node are of unlimited size, which appears reasonable with current technologies and the lower congestion rates that may be encountered in remote locations.

2.2 Modelling the energy storage system

Each node $\mathbf{N}_i$ operates with energy from its battery which is either harvested at rate γ_i^H, or received from the grid at rate γ_i^g, or both, so that the total energy supply rates at the nodes are $\gamma_1, \ \ldots \ , \gamma_N$, where $\gamma_i = \gamma_i^H \ + \ \gamma_i^g$, respectively. Note that in the types of systems we are studying, not only is γ_i^H the average value of an intermittent, i.e. random, process, but so is γ_i^g because the power from the electricity grid can vary intermittently due to overloads, instability, and unreliable generators, power lines and transformers. These rates are given in Energy Packets (EP) per second, where an EP is a unit that corresponds to the energy consumed by the corresponding node to process and forward one DP. By this we mean that an EP at $\mathbf{N}_i$ can be different from an EP at node j for $i \neq j$ if they are based on different equipment models. However, since we can identify their energy consumption characteristics, we can identify the specific value (in Joules) of one energy packet at each node. Thus γ_i represents the average inflow of power (EPs/sec) at $\mathbf{N}_i$ normalised to that node's energy consumption for one DP processed and forwarded at the node.

The EPs received by a node are first stored in a battery or "energy store (ES)" of unlimited capacity, although this assumption can be relaxed in the analysis described below. We also suppose that the battery at $\mathbf{N}_i$ leaks at rate δ_i, so that one EP is lost in an exponentially distributed time of average value δ_i^{-1}; again we assume that this quantity is given in local units of EPs/sec. We assume also that the nodes are so efficient that they *only* use energy when they process, forward (or transmit) a packet.

Using the approach in [36], the ratio of the energy arrival rate to the energy consumption rate at $\mathbf{N}_i$ yields the probability π_i that the node's battery contains at least one EP:

$$\pi_i = \frac{\gamma_i}{\delta_i + \Lambda_i + \lambda_i}. \quad (1)$$

This formula does *not require* that EPs arrive to the node's battery according to a Poisson process, nor that the EP inter-leakage and depletion times are exponentially distributed. Note that the numerator of 1 is the arrival rate of EPs into the battery at node $\mathbf{N}_i$, while the denominator represents the sum of the leakage rate at the battery, plus the energy consumption of one EP per arriving DP (either loaclly or along the multi-node path). Thus, depletions from the battery result from leakage (equivalent to service times), and energy consumption (equivalent to "negative customers" [41], which have been analysed without limiting assumptions such as Poisson arrivals, allowing general (and even dependent) inter-arrival and service times, using Stationary Point Process Theory [43].

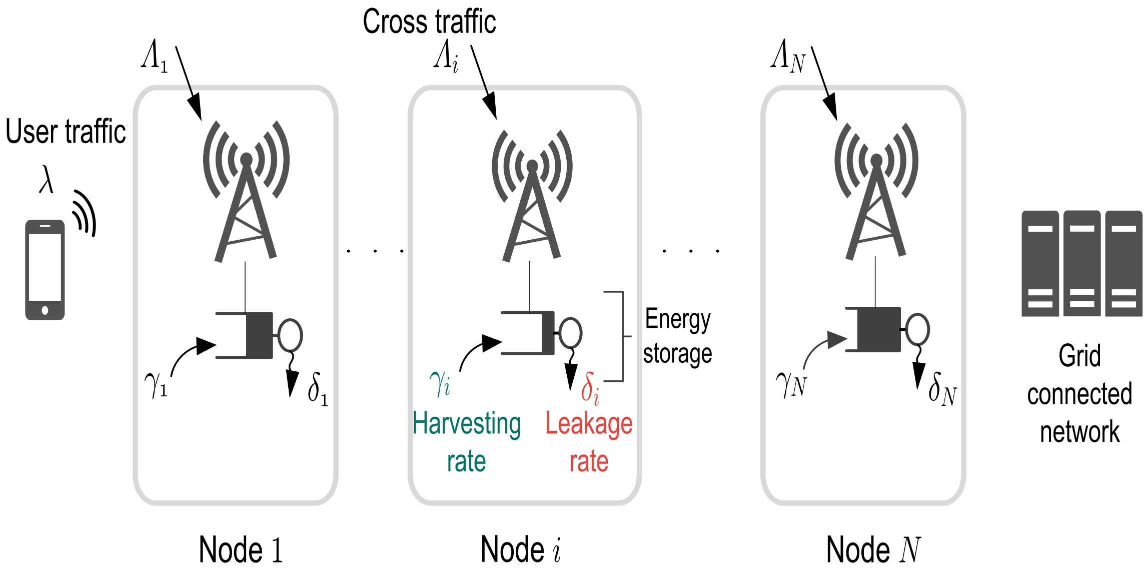

Fig. 1. Schematic representation of a multi-hop mobile access network with intermittent energy.

We first consider an ideal system where each node uses energy very efficiently, and does not consume energy at all when there are no packets at a node. We also assume that the nodes are fast enough, and the traffic rates small enough in comparison, so that DPs do not queue at the nodes. In this case, the loss probability L_i at node $\mathbf{N}_i$ is the probability that the energy at that node is depleted [34], or equivalently that its battery is empty:

$$L_i \ = \ 1 \ - \ \frac{\gamma_i}{\delta_i + \Lambda_i + \lambda_i}, \quad (2)$$

where λ_i is the user traffic entering node $2 \leq i \leq N$ on the path:

$$\lambda_i \ = \ (1 \ - \ L_{i-1})\lambda_{i-1} = \lambda_1 \prod_{j=1}^{i-1}(1 - L_j). \quad (3)$$

The total DP loss probability L on the path is then:

$$L \ = \ 1 \ - \ \prod_{i=1}^{N} \ (1 \ - \ L_i). \quad (4)$$

Now if λ is a given value of the traffic rate of DPs that the user forwards on the path, then the effective user flow rate entering at node $\mathbf{N}_1$ includes this traffic plus the traffic from all the DPs that need to be forwarded, namely:

$$\lambda_1 = \lambda + p.L.\lambda_1 \ = \frac{\lambda}{1 \ - \ p.L}, \quad (5)$$

where p and λ are given, while L is calculated from (4).

3. Nodes with packet storage

In the previous section, batteries are represented by queues that store EPs, while the assumption is made that the system is so fast and the traffic sufficiently small that DP queues need not be represented. Now, again using the EPN formalism [33], we extend the approach to the case where each node $\mathbf{N}_i$ on the path from $\mathbf{N}_1$ to $\mathbf{N}_N$ has a queue of unlimited length which stores DPs and services them in first-in-first-out (FIFO) order. Furthermore, in the present case we assume that the node uses the same amount of energy even when it has no DPs to forward, i.e. when its DP queue is empty. These assumptions are realistic when a node has to remain awake constantly to manage various functions it needs to accomplish, in addition to forwarding packets.

We will assume that the packet forwarding and transmission time at node $\mathbf{N}_i$ is exponentially distributed with parameter μ_i. Here we also assume the node $\mathbf{N}_i$ consumes one EP for each ${\mu_i}^{-1}$, whether it is idle or not.

Thus the DPs that belong to the connection (user) will move packets at rate λ_1 into the first node's queue and at rate λ_i into the DP queue at $\mathbf{N}_i$, though in this case these values are not the same as in (4) because the loss probabilities have changed. Some semiconductor memories may lose the stored data when power is interrupted. However here we suppose that the memory technology that we use saves the data even when there is an interruption in the power supply, so that only the packet which was at the head of the queue and being transmitted, is lost lost.

Again, using the Energy Packet Network modeling approach [34], we compute the probability π_i that the power supply is *not* interrupted due to lack of energy at node $\mathbf{N}_i$:

$$\pi_i = \frac{\gamma_i}{\delta_i + \mu_i}, \tag{6}$$

since we have assumed that the nodes consume energy independently of the packet forwarding rate. We point out again that the formula for π_i does *not* depend on assuming that the arrival process of EPs is Poisson, or that the EP depletion intervals for leakage and energy are exponentially distributed. Indeed, the formula is broadly valid for general EP inter-arrival and removal processes [41, 43].

In the sequel we consider two cases: a system equipped with a memory for DPs which can store packets (and not lose them) even when its energy supply is depleted, and one which loses all stored packets when it runs out of energy.

3.1 DPs stored in a node are not lost due to lack of energy

In this favorable case, when a node has run out of energy some DPs will be lost, namely those that are arriving into the node, plus the DPs being forwarded from the nodes when they run out of energy. All other stored DPs will remain in memory, and will be forwarded later when the node's battery again contains energy. Thus for any node $\mathbf{N}_i$ we define λ_i^I as the total *user traffic flowing in the N-node path that enters the node.* λ_i^O is the total user traffic flowing in the path that leaves node $\mathbf{N}_i$. Then for we will have:

$$\lambda_1^I = \lambda_e\ \pi_1,\ \text{and}\ \lambda_i^I = \lambda_{i-1}^O\ \pi_i,\quad 2 \le i \le N, \tag{7}$$

where λ_e is the total user traffic (including packet retransmissions due to loses) that enters the N-node path, and whenever the node has energy then it will be able to input and store an incoming DP, but the incoming DP will be lost if the node runs out of energy. Also:

$$\lambda_i^O = \frac{\lambda_i^I}{\lambda_i^I + \Lambda_i}\mu_i \rho_i \pi_i, \tag{8}$$

because the outgoing DP is a user DP on the N-node path with probability $\frac{\lambda_i^I}{\lambda_i^I + \Lambda_i}$. There will be an outgoing DP at rate μ_i when there are DPs stored in the node, which occurs with probability ρ_i.

Since in this part, energy replenishment and depletion is independent of the node's workload, the probability ρ_i that the DP queue $\mathbf{N}_i$ is non-empty is:

$$\rho_i = \frac{\lambda_i^I + \Lambda_i}{\mu_i \pi_i}, \tag{9}$$

and we remain with:

$$\lambda_i^O = \lambda_i^I, \text{ and } \lambda_N^O = \lambda_e \prod_{i=1}^{N} \pi_i. \tag{10}$$

Since all of the lost packets have to be retransmitted, for an arrival rate λ of fresh user DPs that arrive to the first node, we will have a total effective arrival rate of packets:

$$\lambda_e = \frac{\lambda}{1 - p.[1 - \prod_{i=1}^{N} \frac{\gamma_i}{\delta_i + \mu_i}]}, \tag{11}$$

and

$$\lambda_i^I = \lambda_e \ . \prod_{j=1}^{i} \frac{\gamma_j}{\delta_j + \mu_j}. \tag{12}$$

We next compute the average end-to-end packet delay D, taking into account the effect of packet loss at each node along the N-hop path. Let d_i be the average packet delay at node $\mathbf{N}_i$ which is obtained by applying Little's theorem:

$$d_i = \frac{1}{\lambda_i^I + \Lambda_i} \frac{\rho_i}{1 - \rho_i} \tag{13}$$

where $\rho_i/(1-\rho_i)$ is the average DP queue size.

The total average delay D for *packets that are delivered successfully* is then:

$$D = \frac{p \sum_{i=1}^{N} (1-\pi_i) \prod_{j=1}^{i-1} \pi_j [\sum_{j=1}^{i-1} d_j + D] + \prod_{j=1}^{N} \pi_j \sum_{j=1}^{N} d_j}{p(1 - \prod_{j=1}^{N} \pi_j) + \prod_{j=1}^{N} \pi_j}$$

Here if a packet is not admitted at node $\mathbf{N}_i$ due to lack of energy, which occurs with probability $(1-\pi_i)\prod_{j=1}^{i-1}\pi_j$, then it restarts from node $\mathbf{N}_1$ with probability p having already incurred the sum of average delays along the path up to but not including the i-th node, and it will require another D units of time on average to traverse the path. On the other hand, a packet is delivered successfully with probability $\prod_{i=1}^{N}\pi_i$, in which case the total time spent in the network is the sum of the average delays along the N hops. Since we do not wish to include the delay for packets that are lost but not retransmitted, the probabilities on the right hand side are normalised by the total probability of retransmission after loss or success. The final expression for D then follows from direct algebraic manipulation of the above equation yielding:

$$D = \sum_{i=1}^{N} d_i + p \frac{\sum_{i=2}^{N} \left[(1-\pi_i) \prod_{j=1}^{i-1} \pi_j (\sum_{j=1}^{i-1} d_j)\right]}{\prod_{j=1}^{N} \pi_j} \tag{14}$$

3.2 When stored DPs are lost for lack of energy

Contrary to Section 3.1, in this section we assume that if a node runs out of energy, all the packets stored at the node will be lost. This is a worst case, and it also needs to be considered. As in Section 3.1, we assume that each node is being constantly powered and that its energy consumption is independent of its workload, so that the probability π_i that a node's battery is *not* depleted is given by (6).

The analysis we develop is based on exact analytical results concerning G-Networks with "batch removal" (sometimes also called "catastrophes") [13, 44], for the cascade network of queues that models the N nodes along the path from source to destination. Each node $i \geq 2$ receives DPs at rate λ_i^C from its predecessor node upstream. It also receives DPs in a Poisson process at rate Λ_i directly from other sources. The first node receives a total end user traffic of λ_E which includes the external arrivals from the user which is assumed to be a Poisson flow of rate λ.

The first node on the path receives the end user's DPs in a Poisson process of rate λ from outside the network, and when the i-th node's battery is non-empty with probability π_i computed from (6), it forwards user packets at rate μ_i to its successor, and the "cross" traffic entering the node at rate

Λ_i just leaves the node after a service time. On the other hand, if at the end of a DP service time the node's battery is depleted, which occurs with probability $D_i = 1 - \pi_i$, then all the DPs at node $\mathbf{N}_i$ are lost.

Using the analysis for an arbitrarily interconnected network of this kind in [13], for $2 \leq i \leq N$ we obtain the probability q_i that node $\mathbf{N}_i$ is busy serving DPs, as the non-linear expression:

$$q_i = \frac{\Lambda_i + \lambda_i^C}{\mu_i.\pi_i + \mu_i.D_i\frac{q_i}{1-q_i}}, \tag{15}$$

where:

$$\lambda_i^C = \frac{\lambda_{i-1}^C}{\lambda_{i-1}^C + \Lambda_i} q_{i-1}.\mu_{i-1}\pi_{i-1} . \tag{16}$$

For the first node on the path we have:

$$q_1 = \frac{\Lambda_1 + \lambda_E}{\mu_1.\pi_1 + \mu_1.D_1\frac{q_1}{1-q_1}}. \tag{17}$$

Thus we can compute the loss probability L_1^C of end-user DPs going through node 1 as:

$$1 - L_1^C = \frac{q_1\mu_1\pi_1}{\lambda_E}\frac{\lambda_E}{\Lambda_1 + \lambda_E} = [\ 1 + \frac{q_1(1-\pi_1)}{\pi_1(1-q_1)}]^{-1} , \tag{18}$$

and for the loss L_i^C through node $2 \leq i \leq N$, using (15) we will have:

$$1 - L_i^C = \frac{q_i\mu_i\pi_i}{\lambda_i^C}\frac{\lambda_i^C}{\Lambda_i + \lambda_i^C} = [\ 1 + \frac{q_i(1-\pi_i)}{\pi_i(1-q_i)}]^{-1} . \tag{19}$$

The effective rate at which user packets enter the path (including packet retransmissions) is then:

$$\lambda_E = \lambda + p\lambda_E[1 - \prod_{i=1}^{N}(1 - L_i^C)], \tag{20}$$

or obviously:

$$\lambda_E = \frac{\lambda}{1 - p[1 - \prod_{i=1}^{N}(1 - L_i^C)]}. \tag{21}$$

T, the average end-to-end packet delay is:

$$\begin{aligned} T &= \Big\{p\sum_{i=1}^{N} L_i^C \prod_{j=1}^{i-1}(1 - L_j^C)[\sum_{j=1}^{i-1}\tau_j + \hat{\tau}_i + T] + \\ &\quad \prod_{j=1}^{N}(1 - L_j^C)\sum_{j=1}^{N}\tau_j\Big\} \Big/ \Big\{p[1 - \prod_{j=1}^{N}(1 - L_j^C)] + \prod_{j=1}^{N}(1 - L_j^C)\Big\} \\ &= \sum_{i=1}^{N}\tau_i + p\frac{\sum_{i=1}^{N}\left[L_i^C\prod_{j=1}^{i-1}(1 - L_j^C)(\sum_{j=1}^{i-1}\tau_j + \hat{\tau}_i)\right]}{\prod_{j=1}^{N}(1 - L_j^C)} \end{aligned} \tag{22}$$

where τ_i is the average delay at node $\mathbf{N}_i$ for packets that are transmitted successfully by the node, which follows from Little's formula:

$$\tau_i = \frac{1}{\lambda_i^C + \Lambda_i}\frac{q_i}{1 - q_i} \tag{23}$$

and $\hat{\tau}_i$ is the average delay for DPs that are lost due to lack of energy at $\mathbf{N}_i$:

$$\hat{\tau}_i = \frac{1}{(1 - \pi_i)\mu_i q_i} \tag{24}$$

4. Discussion of results

To illustrate the analytical approach we have discussed, in Fig. 2 we present numerical examples that compare all three cases considered in the above sections. We plot the curves for three values of the total number of nodes on the path $N = 1,\ 5,\ 10$. The parameter values are, for all nodes $\gamma_i = 0.9,\ \delta_i = 0.1,\ \Lambda_i = 0.9$, with a user traffic rate of $\lambda = 0.1$ DP/sec and $\mu = 1$ DP/sec. The x-axis is the proportion p of lost DPs that need to be retransmitted, ranging from 0.1 to 1. The y-axis is the total average number of DP transmissions per forwarded user DP, i.e. the ratio of the effective user flow rate (denoted λ_1 in (5), λ_e in (11) and λ_E in (21) related to the three respective models) to the traffic rate λ that the user forwards on the path. We see that the user transmits each packet once when $p = 0$, regardless of the data buffering scheme of the network, and that the number of transmissions increases steadily with p. However, for any particular value of N, the system with data storage and permanent memory (i.e. where DPs are not lost for lack of energy) achieves the best performance, followed by the system without data storage, while the one with storage and non-permanent memory causes the largest number of transmissions per DP.

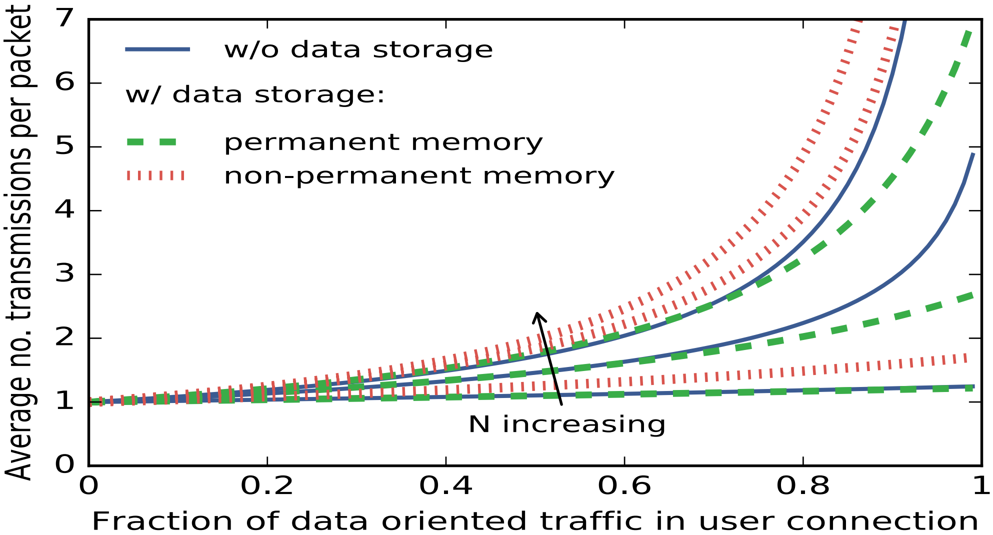

Fig. 2. Average number of transmissions per DP versus the fraction p of DPs that must be retransmitted if lost. The length of the path traversed by user traffic is set to $N = 1,\ 5,\ 10$ hops. Other parameters are $\lambda = 0.1$ DP/sec, $\Lambda = 0.9$ DP/sec, $\gamma = 0.9$ EP/sec, $\delta = 0.1$ EP/sec, and the service rate of the DPs is $\mu = 0.9$ DP/s.

In Fig. 3 we plot the total loss probability L and the average number of transmissions per DP against p and against λ. When packets are not stored at intermediate nodes, we see that the loss probability is more sensitive to λ than p, both of which contribute to congestion and energy depletion; but the effect of p is more pronounced on the number of retransmissions. On the other hand, both parameters have no effect on the loss probability when the node consumes the same amount of EPs when it is idle and when it is not idle. However, if all packets stored at a node are lost when the node runs out of energy, then the multi-hop path experiences much higher packet loss which does not vary significantly with λ or p, while the number of retransmissions grow very fast with p. Figure 4 compares the two cases that include DP storage, with regard to the total average end-to-end delay for user DP, which includes the retransmissions due to DP loss, and includes all the possible times a DP is in transit before it is successfully forwarded through all the N nodes. We set the following values: $N = 5$ and the cross traffic rate is identical at each node is set to $\Lambda = 0.4$ DP/sec. We vary λ between 0.01 and 0.3 and plot the results for three values of p to represent the nature of the traffic mix ranging from mostly data oriented user traffic with $p = 0.9$, or traffic which is mostly voice with $p = 0.1$, and balanced traffic with $p = 0.5$.

The results indicate that for $p = 0.1$ the end-to-end average delays are significantly lower when

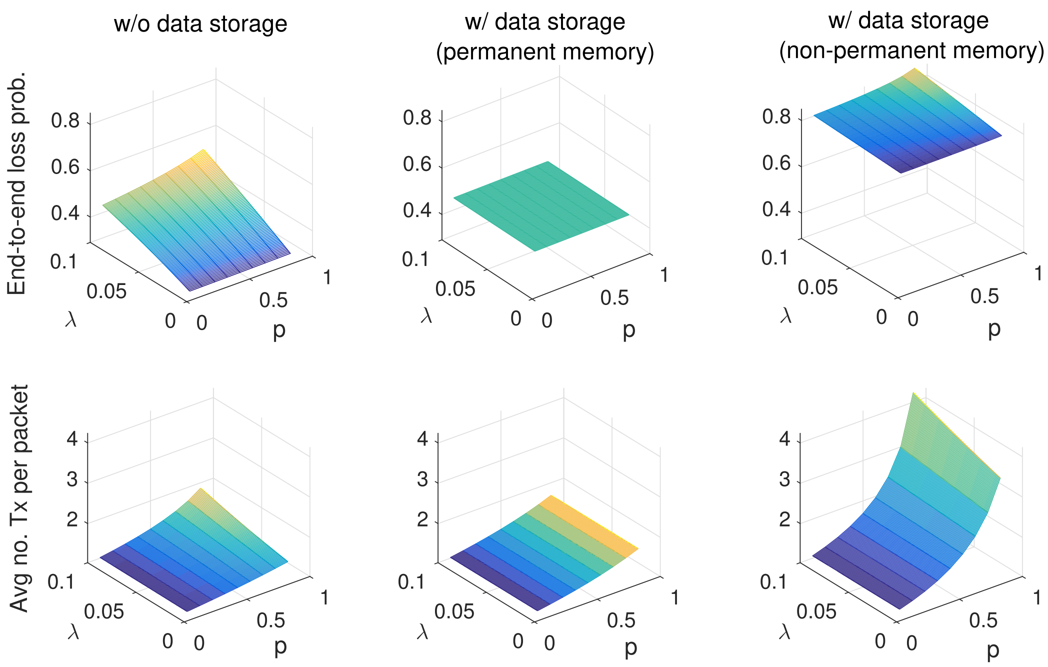

Fig. 3. The end-to-end loss probability (top) and average number of transmissions per DP (bottom) against the DP rate λ and the fraction p of DPs that must be retransmitted if lost. The number of hops in the path traversed by the user traffic is fixed at $N = 3$, while the other parameters are as in Fig. 2.

DPs are lost for lack of energy, due to lower congestion at the DP queues and the total delay being dominated by packets that traverse the path successfully on the first attempt. On the other hand, the large effect of retransmissions can be clearly observed for $p = 0.5$ and $p = 0.9$, where the results show that for small values of λ, the total average delay is significantly lower when DPs are *not* lost for lack of energy. However this is only observed for small values of λ.

When λ increases beyond certain levels, the end-to-end delays are significantly increased by the presence of the stored packets that are forwarded at each node before the packets that arrive from the end-to-end traffic encounters. Thus in a certain sense, the massive packet losses at the nodes that are unable to store packets when they run out of energy, have an interesting "randomising or round-robin effect" which results in an increase of the priority of the end-to-end packets which do not have to wait for the previously stored packets to be served in first-in-first-out order.

5. Conclusions

In conclusion, we recall that universal mobile coverage is of great value to human activity and economic development at all stages, but the cost of installing a stable and reliable power grid everywhere is very high. Also, the production of energy from renewable sources that are close to the points of consumption (such as base stations) is more sustainable and efficient (by avoiding line losses) than the use of power grids.

Thus in this paper we have briefly surveyed some challenges and opportunities associated with deploying energy harvesting wireless services when energy harvesting can be used to replace or complement power from the grid, and discussed the related enabling technologies.

Then we have introduced a novel EPN based approach to analyse the packet loss probabilities and related quality of service of multi-hop backhaul networks that use intermittent or unreliable sources of power, and the models we develop provide some interesting insights into the operations of such systems.

Because of its importance and cost-effectiveness, we can expect that there will be further work on the design and analysis of mobile networks that operate with intermittent and renewable energy. We also hope that this present paper can provide some insights and a way forward for future research in

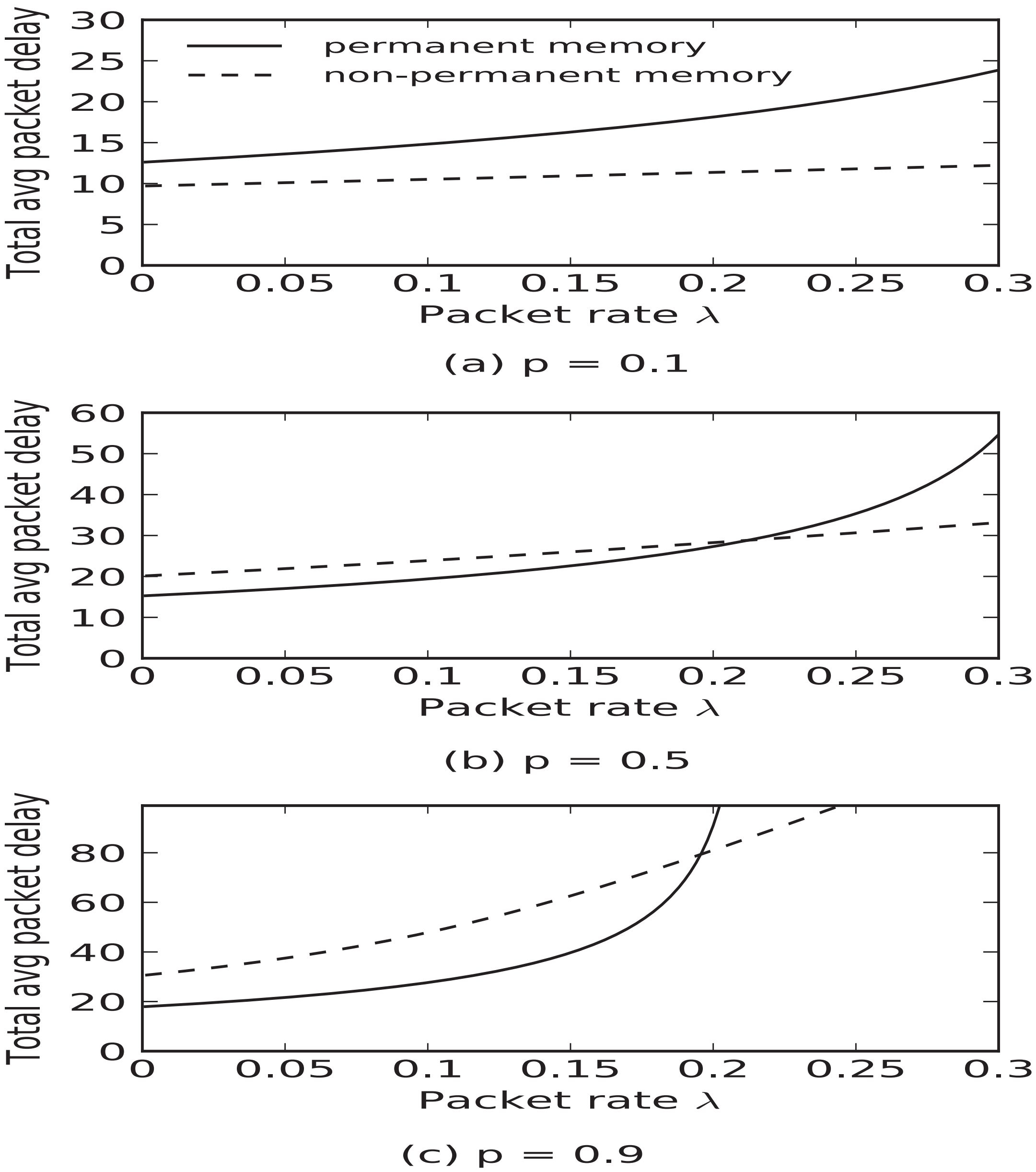

Fig. 4. Total average packet delay, including the retransmissions of lost packets, versus the arrival rate λ for (a) voice dominated traffic ($p = 0.1$), (b) balanced traffic ($p = 0.5$), and (c) data oriented traffic ($p = 0.9$). The number of nodes on the multi-hop path is $N = 5$ and each node handles additional cross traffic with rate $\Lambda = 0.4$ DP/sec. The other parameters are as in Fig. 2.

this area.

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Appendix

A. G-Networks and Energy Packet Networks (EPN)

The G-network model [39, 40] is an open network of v queues with C classes of customers, that was first introduced in [6, 8]. All queues have i.i.d. exponential service times of rate $r(1), \ldots, r(v)$ which are identical for all classes of customers. It has been developed in a series of papers from [6] to [7]. The model we will describe here corresponds to a multi-class G-Network with Batch Removal [13] which also includes the effect of Triggers [29].

The G-Network has three types of customers, all of which may belong to one of the C classes: "positive" and "negative" customers, and "triggers". Positive customers are the normal queueing network customers which request and obtain service at the queues. Positive customers can belong to C classes, and they move through the network. After completing service and leaving a node i, a normal customer of class c can become:

- A positive customer of class c' at node j with probability $\Pi_{c,i,c',j}$, and we denote the corresponding transition probability matrix as $\Pi = [\Pi_{c,i,c',j}]$, or
- It can leave the network with probability $\delta_{c,i}$, or
- It can change into a negative customer of class c' and join node j with probability $n_{c,i,c',j}$, in which case it will remove, or "instantaneously serve", a batch of maximum size $B_{c',j}$ of positive customers of class c' at queue j. Here $B_{c,i,c',j}$ is a random variable with probability distribution $\pi_{c',j,s} = Prob[B_{c',j} = s] \geq 0$ for any integer $s \geq 1$. Thus if the negative customer arrives to queue j at time t, and the number positive customers of class c' at j at that time is $K_{c',j}(t)$, then a total of $max\ [K_{c',j}(t), B_{c',j}]$ positive customers of class c' will be instantaneously removed from the queue at j. If $K_{c',j}(t) = 0$ then the negative customer itself disappears and not customer is removed from queue j.
- Finally, the positive customer of class c leaving queue i can become a "trigger" of class c' at queue j with probability $T_{c,i,c',j}$, in which case it will move a class c' customer from queue j to queue l, and that customer becomes a class c'' customer at queue l, with probability $Q_{c',j,c'',l} \geq 0$. If queue j does not contain a class c' customer when the trigger arrives to queue j, then no customer is transferred from j to l, and the trigger disappears.
- The effect of a negative customer and of a trigger are instantaneous: they occur in zero time. Furthermore, both a negative customer and a trigger will itself disappear after they have visited queue j.
- Queues also have *external* positive, negative and trigger type customer arrivals of rates $\lambda^+_{c,i}$, $\lambda^-_{c,i}$, $\lambda^T_{c,i}$ which can differ for each class c and queue i, according to independent Poisson processes at each of the queues. Furthermore, externally arriving customers will have exactly the same effect at a queue as the ones that arrive from another queue.
- The probabilities that we have introduced above have the following constraints:

$$1 = d_{c,i} + \sum_{c'=1,j=1}^{C,v} [\Pi_{c,i,c',j} + n_{c,i,c',j} + T_{c,i,c',j}]\ \forall\ c, i,$$
$$\sum_{c''=1,l=1}^{C,v} Q_{c',j,c'',l}\ \forall\ c', j,$$
$$\sum_{s=1}^{\infty} \pi_{c',j,s} \leq 1\ \forall\ c', j.$$

Th multi-hop backhaul network show in Fig. 1 is modelled as an EPN using G-Network theory, limited to three classes of positive customers, i.e. C = 3. Classes 1, 2 represent the data packets (DPs), and Class 3 represents the Energy Packets (EPs). The model includes $v = 2.N$ queues, where queues 1 through N only store DPs and represent data buffers, while queues $N+1$ through $2N$ only store EPs and represent batteries. DPs cannot become EPs, and vice-versa, so that $\Pi_{1,i,3,j} = \Pi_{2,i,3,j} = \Pi_{3,l,1,m} = \Pi_{3,l,2,m} = 0$ for any $i, m = 1,\ ...\ N;\ j, l = N+1,\ ...\ 2N$. Furthermore EPs cannot enter a data buffer so that $\Pi_{3,j,3,i} = 0$ for $i = 1,\ ...\ N;\ j = N+1,\ ...\ 2N$.

The external arrival of:

- DPs from end users is represented by the Class 1 of positive customer arrivals to DP queue 1, with arrival rate $\lambda^+_{1,1} = \lambda_1 > 0$. They will move along the cascade of N nodes so that $\Pi_{1,i,1,i+1} = 1$ for $i = 1, \ ... \ N-1$. They will leave the the network into the grid from node N so that $d_{1,i} = 0, \ 1 \leq i \leq N-1$ and $d_{1,N} = 1$.

- DPs from cross traffic is represented by $\lambda^+_{2,i} = \Lambda_i \geq 00$ for $1 \leq i \leq N$. They depart the system from the local node that they enter so that $d_{2,i} = 1, \ 1 \leq i \leq N$

- EPs from energy harvesting (or possibly the electricity grid) arrive into the EP queue or battery at each node so that we have $\lambda^+_{3,j} = \gamma_j > 0$. We note that the EB or EP queue i has a leakage at rate δ_i.

- EPs coming from energy buffer $N+i$ act as "triggers", so they move a DP from queue i to queue $i+1$, for $1 \leq i \leq N-1$, or to the exit of the network to the wired backbone of $i = N$.

- Note that in the text of the paper, for reasons of simplicity, we note the energy buffer $i+N$ as the energy buffer i, since at each network node i we can consider that there is an energy buffer and a packet buffer.

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