# ACCOP: Adaptive Cost-Constrained and Delay-Optimized Data Allocation over Parallel Opportunistic Networks

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***Abstract*— As wireless and mobile technologies are becoming increasingly pervasive, an uninterrupted connectivity in mobile devices is becoming a necessity rather than a luxury. When dealing with challenged networking environments, this necessity becomes harder to achieve in the absence of end-to-end paths from servers to mobiles. One of the main techniques employed to such conditions is to simultaneously use parallel available networks. In this work, we tackle the problem of data allocation to parallel networks in challenged environments, targeting a minimized delay while abiding by user preset budget. We propose ACCOP, an Adaptive, Cost-Constrained, and delay-OPtimized data-to-channel allocation scheme that efficiently exploits parallel channels typically accessible from the mobile devices. Our technique replaces the traditional, inefficient, and brute-force schemes through employing Lagrange multipliers to minimize the delivery delay. Furthermore, we show how ACCOP can dynamically adjust to the changing network conditions. Through analytical and experimental tools, we demonstrate that our system achieves faster delivery and higher performance while remaining computationally inexpensive.**

***Keywords- Opportunistic Networks, Challenged Networks, Data-to-channel Allocation, Fuzzy Logic, Parallel Networks***

## I. INTRODUCTION

A delay tolerant network (DTN), also called challenged network, is characterized by node mobility, intermittent connectivity, large delay, low data rate, and the absence of an end-to-end routing path [1]. Due to these inherent peculiarities, general networking practices cannot be transplanted to challenged networks but instead need to be revisited and refined. In particular, the Mobile Ad hoc NETworking (MANET) paradigm, which depends on packet forwarding over multiple hops, falls short of providing adequate performance levels. The main reason behind that is the fact that MANETS consider mobility as an issue to overcome rather than an opportunity to exploit. Accordingly, the field of opportunistic networks evolved as a possible solution that opportunistically utilizes any possible resource available, including mobility, to achieve faster data delivery and to maximize throughput.

The majority of attempts in this field have focused on improving the routing protocols to efficiently utilize mobility [2,3]. Other solutions were based on central infrastructures which assist the end devices by aggregating the messages into bundles [4]. Parallel networks have been also investigated to minimize delivery delays by splitting the data on multiple channels to be delivered simultaneously [5].

With the increased availability of multiple heterogeneous networks on mobile devices, it has become essential to leverage such opportunities for enhanced network connectivity. Combined with data bundling (i.e. message aggregation), these networks provide a resource efficient solution, which is well suited to the underlying model of challenged networks. In this work, we tackle the problem of efficient data fragmentation over the parallel networks, taking into account network conditions and user spending plan. We present ACCOP, an Adaptive Cost-Constrained and delay-Optimized data allocation scheme over Parallel opportunistic networks. The contribution of ACCOP is twofold. First, it provides a novel, computationally efficient scheme for data-to-channel allocation over opportunistic networks that minimizes the delay while conforming to a user-preset cost plan. Second, ACCOP makes use of fuzzy decision making to model the uncertainty and mitigate the staleness of the estimated network throughput. This scheme is totally built on the application layer, thus it does not necessitate lower level modifications to the running protocols nor cross-layer communication.

For system evaluation, we use the ONE (Opportunistic Network Environment) simulator [7], and we compare against the existing systems, showing the advantages our system provides.

In the next section, we present our description of the problem at hand. A survey of related work is presented in section III. We propose the ACCOP scheme in section IV. Then we introduce the throughput estimation mechanism in section V. The evaluation of our system comes next. We conclude this paper in section VII.

## II. PROBLEM DESCRIPTION

Our system model is presented in Figure 1. The major components are the Stationary Agent (SA), the mobile agents (MA), the wireless access points (WAP), the cellular base stations, and the Low-Earth-Orbit (LEO) satellites. The SA is a server connected to the Internet with storage and processing capabilities. It pre-fetches data requested by an MA from the appropriate servers (web servers, file servers, email servers, etc). When the MA is in a position to receive the data, the

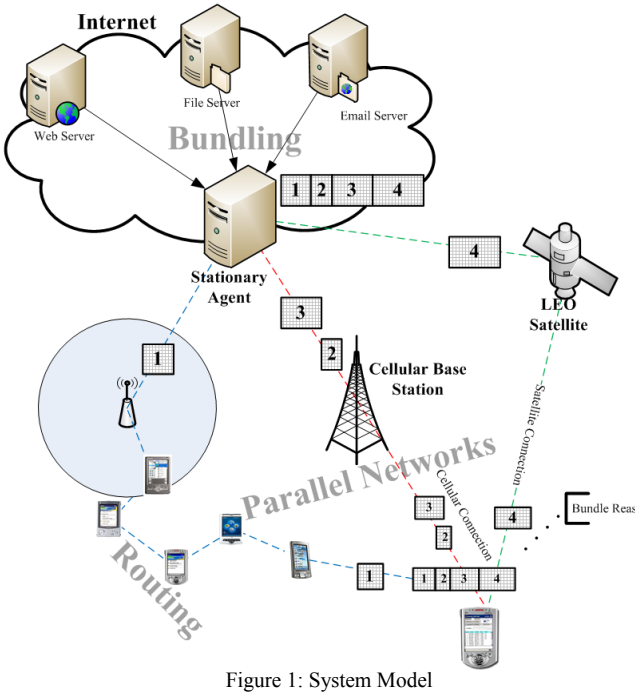



Figure 1: System Model

gathered data is aggregated into structures called *bundles*, using application level techniques such as [8]. The bundles are then sent using one or more parallel (possibly heterogeneous) networks according to the ACCOP scheme. One of the principal channels used is the challenged network which utilizes WLAN. For this channel, data delivery is not restricted to direct connections to the access points. Routing and forwarding techniques are exploited to extend the reachability of the access points. Multiple forwarding actions may take place before the mini-bundle reaches the destination that is out of the reach of the wireless coverage. At the destination, data is reassembled using the associated sequence numbers before being ready for use.

Exploiting both disruption handling mechanisms, parallel networks and bundling, allows attaining better user experience via higher availability periods. However, this combination gives rise to an interesting problem: how should the bundles be sent over the parallel channels to minimize the end-to-end delay? The problem becomes more challenging when adding the fact that each channel has a different cost per data unit, and that a user usually prefers to set a maximum budget on his data consumption. The simplistic solution [9] consists of dividing the bundles into smaller units of predetermined size, called *mini-bundles*, enumerating all the possible distributions over the existing channels, and choosing the one which minimizes the delay while staying within the assigned budget. However, this solution suffers two limitations. First, it sets an a priori constraint on the size of the mini bundle, which is not guaranteed to result in a minimum delay in the steps that follow. Second, it follows the brute-force, computationally expensive technique of enumerating all the possibilities, relying on the preset granularity of a mini-bundle size. On the other hand, our scheme allows obtaining the optimal division over the different channels, resulting in the minimum delay, before selecting the mini-bundles' size.

## III. Related Work

Previous works have studied the effectiveness of parallel channels in challenged networks. Consequently, several architectures were proposed based on this concept, some of which are considered below.

The first type of such architectures is that capable of switching between parallel networks for purposes of data transfer. Examples include the MAC layer implementation of seamless session management, which allows for transparent alternation between the different technologies [21]. This concept is employed in [22], which introduces a sample heterogeneous delay tolerant network where nodes are allowed to utilize any of Cellular/WiMAX/WiFi networks in addition to routing schemes. Moreover, the authors of [31] present a cross-layer architecture that uses elaborate fuzzy-logic techniques to decide on the most appropriate accessible channel. It performs decisions based on Quality of Service (QoS) and application-specific factors. These architectures differ from ours in that the channels are not simultaneously used, but rather alternated between, and in that they mainly rely on cross-layer solutions.

Another category of heterogeneous networks are those that simultaneously send different data types on different networks. It has been proposed to use parallel networks not only as channels for data transfer but also as means for sending control data to decide on the best data channel. The *Cellular Assisted Heterogeneous Networking* (CAHN) architecture is one such example [21]. This concept of dedicating one channel for sending control information is readily employed in many systems in order to aid in routing decisions as in [24]. These attempts are detached from ours in the sense that they are designed for sending heterogeneous data on heterogeneous channels while our system sends the data fragments (possibly from same source) on multiple, not necessarily heterogeneous, channels.

The closest type of architecture to our system is that of ParaNets [1], which was devised for challenged networks protocols, enabling devices to simultaneously utilize multiple heterogeneous networks when available. ParaNets-based data-to-channel allocation techniques have been investigated in the recent years. The first system proposed was *ParaNets-Enabled Data Bundling System for Intermittent Connections (DBS-IC)* [5], which takes into account the nominal bandwidth of the underlying technologies and the maximum affordable cost set by the user. The major limitations of this scheme were its reliance on brute-force, computationally expensive techniques in addition to its inadaptability to the variable network conditions. Accordingly, its authors later developed ParaNets-Enabled DBS-IC with dynamic data-to-channel allocation strategies [9]. This allocation scheme was built on the work presented in [1] and [5], and suggested that measuring the channel conditions and adapting to it significantly improves the previous scheme. Nevertheless, they did not clearly present their adaptability mechanism. Moreover, they still depended on brute-force computations of all possible data-to-channel allocations. These limitations are the ones addressed by our scheme.

It is worth mentioning that fuzzy logic, on which our throughput estimation is built, has been previously applied in delay tolerant networking scenarios. In [22], fuzzy decision making was utilized to choose between the different radio technologies while, in [23], the decision mechanism was targeted for the server selection. Moreover, several works have

used fuzzy logic in routing algorithms for challenged networks ([25,26]).

## IV. ACCOP SCHEME

We tackle the shortcomings of the brute-force approach to data-to-channel allocation by investigating an analytical optimization method, which theoretically produces the best distribution of the mini-bundles over the parallel channels. We show that, for the case of three networks, we can arrive at closed form equations, allowing the computation of the specific share of each network. The cases with more than three accessible networks can be analogously analyzed although they are highly uncommon in challenged networks [1, 5] and usually inconvenient from a battery power perspective.

To solve the optimization problem at hand, we use the Lagrange multipliers technique, which is typically applied on an objective function subject to multiple constraints [10]. In our case, these constraints are related to the measured network conditions and the maximum affordable cost set by the user. For ease of presentation, and without loss of modularity, we consider the scenario of 3 accessible data networks: WLAN (IEEE 802.11g), 3G (UMTS), and satellite (LEO [11]). Moreover, we choose throughput as the metric for measuring network conditions. Consequently, our network assessment remains at the application layer. We also base our estimates on the passive network measurement paradigm [12], where the data packets are post-processed to locally characterize the network properties. Such technique is used to avoid the costly pilot packets (i.e. regularly sent beacons) which vastly increase the estimation overhead. Nevertheless, this might introduce some staleness in the throughput estimates, thus we tackle this problem in the following section.

Modeling the problem using Lagrange Multipliers results in an objective function to be minimized, subject to multiple constraints. In our case, the value to be determined is the data size to be allocated to each channel in order to minimize the end-to-end delay. Formally, we cast the problem as follows:

- Objective function: $D(X,Y,Z) = \max\left\{\frac{X}{T_W}, \frac{Y}{T_C}, \frac{Z}{T_S}\right\}$ (1)
- Output variables $X, Y, Z = \underset{X,Y,Z}{\text{argmin}}\ D(X,Y,Z)$ (2)
- Constraints:
  - Cost: $C_W X + C_C Y + C_S Z \le K$ (3)
  - Size: $X+Y+Z=S$ (4)
  - Non-negativity: $X \ge 0, Y \ge 0, Z \ge 0$ (5)

The variables used are defined as:

- $D(X,Y,Z)$: total end-to-end time taken to deliver a data bundle to the requesting node through the multiple channels.
- $X,Y,Z$: size of data (in bytes) allocated to WLAN, UMTS, and satellite channels respectively.
- $T_W, T_C, T_S$: throughput (in bytes/sec) sensed on WLAN, cellular (UMTS), and satellite channels respectively.
- W, C, and S subscripts: WLAN, cellular (UMTS), and satellite channels respectively.
- $C_W, C_C, C_S$: cost/byte for data transmission on WLAN, cellular (UMTS), and satellite channels respectively.
- K: maximum cost affordable by the user.
- S: total size of the data bundle

The objective function expresses the delivery delay, envisioned by the application, as the maximum delay among the different channels. Each channel's estimated delay is the ratio of the data size to the sensed channel throughput. We have an external user-specified constraint on the maximum affordable cost. An inherent system constraint is the total bundle size, which should be equal to the summation of the mini-bundles' sizes. A trivial constraint is the fact that the size allocated to each channel should have a positive value.

The goal is to find X, Y, Z that minimize $D(X,Y,Z)$. For space constraints, we omit the derivation from this paper. In the full paper [17], we show that, using the generalization of Lagrange Multipliers known as Karush-Kuhn-Tucker (KKT) theorem [13], this optimization problem can be reduced to 1) solving three linear systems of equations, 2) checking the compliance of the solutions with a set of conditions, and 3) selecting among the complying solutions the ones corresponding to minimal delay. We further simplify the first step by showing that a closed form solution for the systems is attainable. In sum, the device has at hand a set of 25 possible solutions, from which it has to choose the one that results in minimum delay. Equation (6) shows a sample of the equations the mobile device has to evaluate. The rest of the equations are not shown due to space constraints:

$$(X,Y,Z) = \text{argmin}_{(X,Y,Z)}\left\{D\left(i_1 = \frac{K}{C_W + \frac{T_C}{T_W}C_C}, \frac{T_C}{T_W}i_1, 0\right),\right.$$
$$D\left(\frac{K}{C_W + \frac{T_S}{T_W}C_S}, 0, \frac{K}{C_S + \frac{T_W}{T_S}C_W}\right),\ D\left(i_3 = \frac{S}{1 + \frac{T_C}{T_W} + \frac{T_S}{T_W}}, \frac{T_C}{T_W}i_3, \frac{T_S}{T_W}i_3\right),$$
$$\left. D\left(S - i_4, i_4 = \frac{K - SC_C}{C_C - C_W}, 0\right),\ \ldots\right\} \quad (6)$$

Before plugging the parameters into the solutions, we can verify their compliance to the non-negativity and the cost constraints. This results in further pruning the set of possible solutions to less than 25.

## V. ADAPTABILITY TO CHANNEL VARIATIONS

The delay minimization scheme used above assumes the presence of decent estimates of the channels' throughput. However, this assumption is not easily guaranteed, especially in wireless media. It is further exacerbated in the case of delay tolerant networks where the end-to-end delay reaches high ceilings. Apparently, the active network sampling, relying on systematically sending pilot packets, does not carry much improvement over the passive network sampling since the associated overhead is too expensive given the scantly resources available. Accordingly, it is evident that we should select the low-overhead passive network sampling technique, updating the node's view of network state upon data delivery. In what follows, we present a method of targeting this estimation problem, based on fuzzy decision making. Our methodology operates at the application layer. It is also decoupled from the delay optimization module. Other estimation schemes can be similarly integrated with the ACCOP scheme, and ours is an

attempt towards realizing better estimates in the context of opportunistic networks.

To achieve good estimates in the presence of network uncertainties, it is necessary to appropriately combine the previous estimates with the newly sensed values through an averaging operation. In the case when other factors enter in assessing the network, the combination mechanism needs to be adaptable and extendable. Fuzzy decision making is well tailored for these two goals. . Contrary to the traditional set theory, Fuzzy Set Theory allows partial membership to sets (i.e. belonging to a set to a certain degree). Accordingly, fuzzy logic underlies approximate reasoning, providing a better alternative for modeling uncertainty than the typical combination of predicate logic and probability-based schemes [14]. Furthermore, fuzzy logic allows dealing with several types of uncertainty within a single conceptual framework. In heterogeneous networks, it allows a technology-independent knowledge representation, which can fit multiple radio technologies, network protocols, and user applications [15]. In sum, this technique is used for modeling uncertainty, preserving modularity, and keeping the system easily adjustable for new input metrics. The interested reader can refer to [16] for a comprehensive survey of fuzzy logic and its applications.

Figure 2 provides an illustrative diagram of our fuzzy-based estimation algorithm, which is triggered whenever the device senses a new value of the channel throughput. The system takes as inputs the *newly sensed throughput*, the *estimated throughput*, and the *time stamp difference* between both measurements. The difference between the throughput timestamps determines the weight to be allocated to each of the new and old measurements in calculating the next estimate of the throughput. After being *normalized* to a fixed range, these values undergo *fuzzification* according to the membership functions described below. They pass through the fuzzy inference system that outputs a fuzzy throughput estimate, which is *defuzzified* to output a crisp value. Finally, the estimate is *denormalized* to get the actual throughput estimate.

We associate with time three fuzzy levels: L (low), M (medium), and H (high) and with throughput five levels: VL (very low), L (low), M (medium), H (high), and VH (very high). The membership functions of the *time stamp difference* and the *throughput* input parameters are both triangular with a left and a right shoulder. Figure 3 shows a normalized version

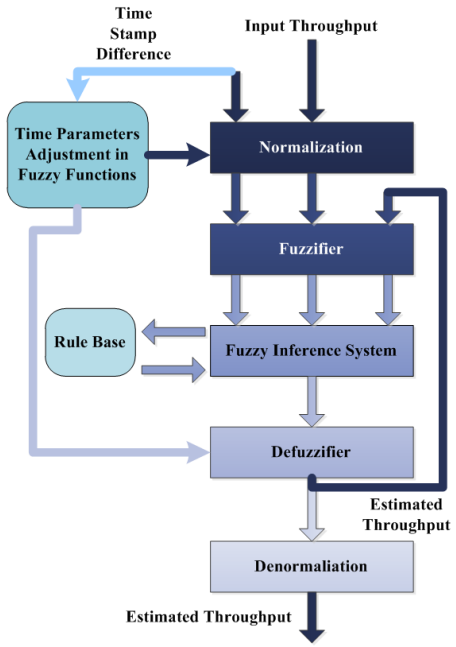
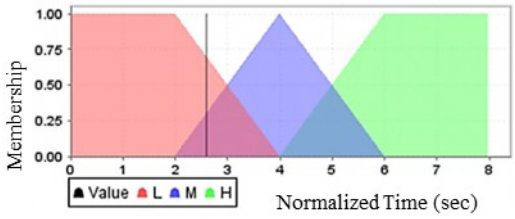



Figure 2: Throughput estimation via fuzzy decision making




of the time difference membership function. The boundaries of the time membership functions are dynamically updated based on the frequency of updates using a weighted average. The intuition behind this adaptability is that if a too large or too small $T_{max}$ is selected, a low frequency of updates (which logically implies that newly emerging values should be given a greater weight) will be indistinguishable from a high frequency of updates (where the recent estimate should possess a higher weight). Similarly, the throughput membership function's boundaries are adapted to the recently sensed values. The details of the fuzzification, defuzzification, and the rule base are omitted for space constraints and included in the full paper [17].

## VI. System Evaluation

In what follows, we describe the details of the simulations performed, whose results provide evidence for the effectiveness of our system.

### A. Simulation Environment

Simulations were performed using the *Opportunistic Network Environment* (ONE) simulator [16], which is specifically designed for challenged networks' evaluation. The choice for ONE over ns-2 or OPNET was motivated by its widespread use in the opportunistic networking community due to its generic support for DTN testing. For implementing the fuzzy-based throughput estimation mechanism, we used the jFuzzyLogic Java package [18].

We compare ACCOP to *ParaNets-Enabled Data Bundling System for Intermittent Connections* with dynamic data-to-channel allocation strategies [9], which we will shortly denote by *DBS-IC-DA*. The latter is based on the brute force method for computing the data allocation contributing to minimum delay. It is an evolved version in a series of data-to-channel allocation systems [4,9,19] and is, up to our knowledge, the only system whose functionality is comparable to ours. These systems all share the brute force technique of delay minimization, but differ in their adaptation to varying channel conditions. We are comparing against the system which is

Table II: Simulation environment parameters

| | |
|---|---|
| **Hardware Components** | Operating System: Microsoft Windows Vista<br>Intel Xeon Quad core 2.66 GHz |
| **Environment** | Number of SAs = 1<br>SA buffer size = 2000MB<br>Number of MAs = 30<br>MA buffer size = 1MB |
| **Movement Model** | MA model = Random-Waypoint<br>SA model = Stationary<br>MA wait time = [0, 20]s<br>MA speed = [2.7, 5.4] m/s |
| **Parallel Channel Characteristics** | **Costs Per Data Size:**<br>WLAN = 0$/MB<br>Cellular = 0.5$/MB<br>Satellite = 0.65$/MB<br>**Nominal Throughput:**<br>WLAN = 2.4Mbps<br>Cellular = 14.4Mbps<br>Satellite = 10Mbps |

claimed to have the best adaptation technique among its predecessors.

Our simulated system is a version of ACCOP with three accessible communication technologies (WLAN, UMTS, and satellite). The WLAN channel relies on an opportunistic routing technique, which is a variant of the spray and wait algorithm [20]. We used one node as a static agent (SA) for data bundling while the other nodes are mobile agents (MA), whose target is to transmit and receive data to and from the SA.

A summary of the major simulation parameters we used is presented in Table I. It is noteworthy to mention that the cost of WLAN is taken as zero due to the fact that payment is usually done for the service provision rather than for data consumption. In addition, WLAN nominal throughput is decreased to a value typical in challenged environments. Although we use the Random Waypoint mobility model at this stage, future work is intended to do the performance evaluation on real-world mobility traces.

### *B. Simulation Results*

The simulation results presented here are based on the following performance measures:

1) Probability of successful data delivery to the request initiator
2) Average data delivery delay from the time the request is issued to the time data reaches the request initiator.

Figure 4 is based on a maximum cost randomly chosen from the range [0.1, 0.2] $/MB. It shows the effect of the mini-bundles' number on the probability of data delivery. DBS-IC-DA is based on dividing the bundled data into mini-bundles of a specific size, considering all the possible permutations among the channels, and selecting the one with minimum expected delay. With DBS-IC-DA, we notice that it is necessary to divide each bundle into at least 25 mini-bundles, before reaching the same delivery rate of the ACCOP's scheme. Even when this is achieved, it comes at a higher computational complexity. We have shown previously that the device using ACCOP has to plug in the parameters into a maximum of 25 equations, and then choose the minimum. On the other hand, it can be shown that the number of possible allocations to the three channels in the DBS-IC-DA scheme, assuming a preset number of mini-bundles N is given by:

$$\sum_{i=0}^{N}(N+1-i) = N(N+3)/2+1. \quad (7)$$

In this scheme, the more mini-bundles (i.e. higher granularity) considered, the higher the chance of approaching the lowest delay is. As an example, consider the case of 25 mini-bundles, where the device has to consider 351 different combinations followed by 350 comparisons before deciding on the best choice. Therefore, the computations needed are 14 times higher than ACCOP. The quadratic variation of the number of permutations and comparisons with the number of mini-bundles makes high granularity very expensive. For the same computational cost (25 equations) as ACCOP, the attained granularity with DBS-IC-DA is around 5 mini-bundles, which still gives a probability of delivery well below that of ACCOP.

To further illustrate the inaccuracy of the brute force method, we present in Figure 5 the variation of the fraction of data allocated to each channel as the number of mini-bundles

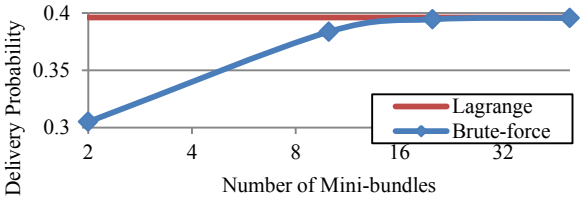



Figure 4: Delivery probability variation with variable granularity

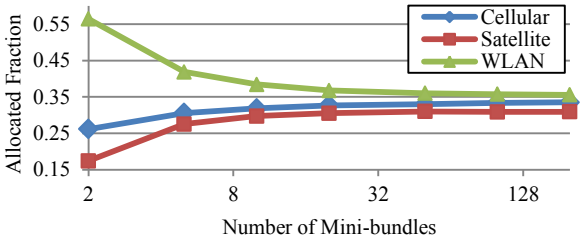



Figure 5: Allocated percentage per channel with variable granularity

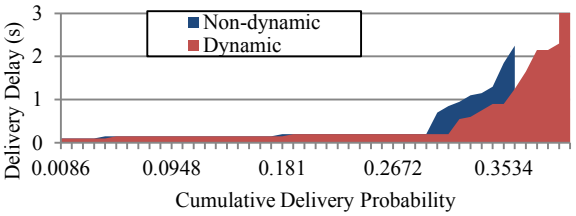



Figure 6: Delivery delay variation with cumulative delivery probability

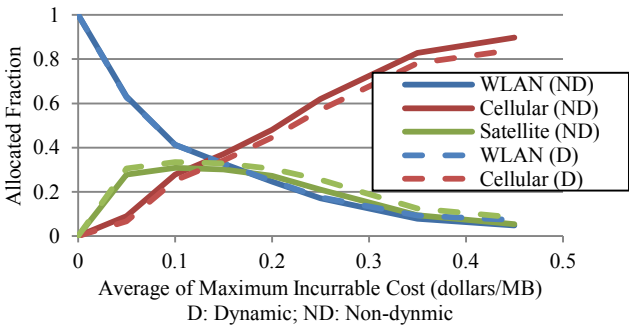



Figure 7: Allocation fraction per channel vs. affordable cost

increases. We notice that when few mini-bundles are considered, the technique has low granularity, so the allocation scheme produces results which significantly stray from the ones obtained with more mini-bundles. The percentages allocated to the channels converge to their stable values only after the number of mini-bundles reaches high values. By then, the computational overhead becomes substantial.

Now that we have illustrated the effectiveness of the Lagrange based calculations of ACCOP, we move to the assessment of the throughput estimation block. To get an insight into the improvements gained, we perform the comparison against the non-dynamic version of ACCOP. The justification is twofold. First, the authors of [9] do not provide sufficient description of their throughput estimation to be able to replicate and compare against. Second, their channel allocation scheme is difficult to test isolated from its adaptability to network parameters. Accordingly, the system we are comparing against in this part differs from ACCOP in its fixed throughput values which were pre-assigned to be the nominal values for the technologies employed in each channel.

Figure 6 illustrates a subtle point in establishing a fair comparison between the delivery delays of the systems at hand. The delay is plotted against the cumulative delivery probability. The motivation behind this is that these systems have different delivery probabilities. From a delay perspective, the system with higher delivery rate has changed the delay of some of its previously undelivered packets from an infinite to a finite value. Accordingly, these packets might take more time to get delivered, but this time cannot be seen as a performance loss. As shown in Figure 6, the delay of the dynamic system is lower than that of the non-dynamic version for the same values of cumulative delivery probability. When the latter increases beyond the overlapping region, the delay of the delivered data in the dynamic system is still lower than the supposedly infinite delay of the undelivered data.

In Figure 7, we show the trend of variation of the fraction of data allocated per channel with the maximum affordable cost by the user. As expected, for zero cost, all data is transported via WLAN while for higher allowable costs the reliance on cellular channel increases to around 90%. Although the satellite channel is more costly and of lower bandwidth than the cellular one, it is still used when smaller delays are desired to assist the cellular channel. Notice that since this graph shows the average data allocation percentage, it can be deduced that there is a uniform variation around the nominal values of the throughput for each technology. This by no means implies that the static method and the dynamic method are similar. The adaptability is effective in determining the allocation for best delay according to the instantaneous throughput rather than the average one.

## VII. CONCLUSION

ACCOP provides a novel efficient solution for the data-to-channel allocation problem in opportunistic networks. Instead of relying on brute-force calculations, ACCOP uses Lagrange multipliers to arrive at deterministic equations, which result in the minimal delay possible while adhering to the user's preset budget. To account for the varying channel conditions we presented a fuzzy-logic-based approach for throughput estimation over the different channels. In addition to mitigating the parameters' staleness, this fuzzy scheme models the inherent uncertainty of throughput measurements. Our system evaluation verified our claims of ACCOP's superiority in terms of delivery probability and end-to-end delay.

Future work on this topic includes investigating further methods for adapting to the varying network parameters. This is simplified by the fuzzy decision making technique we employed, which supports incorporating heterogeneous metrics. Furthermore, we aim to implement the system and to test it on mobile phones, to prove its effectiveness in practice. Our ultimate goal is to integrate ACCOP as a module into a larger system for opportunistic networking, which combines new routing schemes with ACCOP for further enhancements.

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