Smartphone-Assisted Energy Efficient Data Communication for Wearable Devices

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Abstract

In dynamically changing network environments, no single data communication approaches for wearable devices are guaranteed to yield the best performance-cost ratio. To illustrate how different approaches perform in different environments, we conduct a theoretical analysis to four basic approaches that rely on either Wi-Fi, or smartphone-tethered cellular network, or both, to transmit data on wearable devices. In order to achieve energy efficient data communication on wearable devices (and associated smartphones), we propose a Lyapunov based on-line approach designation mechanism that dynamically chooses an appropriate data communication approach based on data transmission queue, estimated network conditions and the device moving speed. Due to the property of Lyapunov optimization framework, the proposed mechanism is able to minimize the power consumption of data communication for wearable devices (and associated smartphones) while meeting the delay time constraint. Moreover, it requires no prior knowledge of future network conditions and data request arrivals. Our trace-driven simulations demonstrate that our on-line designation mechanism delivers very close performance to the mechanism that can foresee the future, leaving very little space for further improvement.

Keywords: wearable devices, smartphones, data communication, energy-efficiency, delay time

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1. Introduction

Recently, the emerging wearable devices, such as Google Glass and Apple Watch, reveal great potentials to bring up another heated wave of technological enthusiasm. Their portability and hands-free interaction with humans will fundamentally change how the physical world is augmented by the seamless integration with the virtual world. Indeed, wearable devices are now fulfilling the vision of Internet of Things [1][2][3].

Though blessed with such vision, wearable devices will inevitably be faced with the issue of limited battery life, due to their inherent small form factor and the slow progress in battery technology. This generation of wearable devices are usually not equipped with cellular interface, and thus require being connected with smartphones via Bluetooth or other means of communications in order to be fully functional, such as making phone calls and sending/receiving SMS. Such continuous connection requirement further worsens the battery life on wearable devices.

One effective way to prolong the battery life on wearable devices is to improve the energy efficiency of their data communication [4]. Different types of network interface for data communication impose different power consumption. Normally, wearable devices can connect to Wi-Fi Access Points (AP) via their built-in Wi-Fi interface, or cellular stations via Bluetooth-tethering by their associated smartphones. Wi-Fi is generally more efficient than other network interfaces in terms of power consumption per unit speed [5]. However, blindly minimizing the energy consumption on wearable devices (i.e., using Wi-Fi) may lead to unexpectedly long delay in response, since Wi-Fi is not always available or stable. On the other hand, cellular network has a much wider coverage than Wi-Fi. However, relying on cellular network can greatly accelerate the battery draining on smartphones.

In this paper, we focus on the problem of energy-efficient data communication between wearable devices, smartphones, Wi-Fi APs and cellular stations. The goal is to jointly minimize the energy consumption of data communication on both smartphones and wearable devices subject to a delay time constraint. Yet, there exist two major challenges to solve the problem. First, the solution must be easily applied to most off-the-shelf platforms, as nowadays wearable devices and smartphones may run on different operating systems. The proposed solution should work irrespective of the operating systems running on the devices. Second, the solution must perform equally well in both static and mobile environments in terms of energy efficiency. In mobile environments, Wi-Fi AP availability and quality change constantly due to user mobility [6], resulting in significantly different performance. Since it is fundamentally difficult to predict the variation in Wi-Fi AP availability and quality, the solution must avoid using prediction-based techniques.

Contributions. *To have cross-platform support*, we investigate four approaches that users can actually adopt in practice to enable data communication for both devices. These approaches do not require system-level code modification, or complicated coordination between both devices. However, our theoretical analysis shows that they deliver different performance in achieved bandwidth and power consumption across a variety of environments. *To perform equally well in static and mobile environments*, we propose a Lyapunov-based on-line designation mechanism to determine which approach to adopt so as to minimize energy consumption while ensuring quality of service (e.g., delay time). Due to the property of Lyapunov optimization framework, the proposed mechanism does not require any prior knowledge of future network conditions and data request arrivals. It uses smartphones to monitor environment information (e.g., network bandwidth and density), as well as data transmission queue to make energy efficient decisions.

To evaluate the performance of our on-line designation mechanism, we conduct extensive trace-driven simulations. To do so, we collect two types of real-world traces, user request traces and network availability and quality traces, both of which have a significant impact on the performance of our mechanism. Using these real-world traces makes it possible to compare our mechanism with others in a controlled environment, yet being able to generate convincing results.

We compare our mechanism against static mechanisms that only adopt one fixed approach, as well as other dynamic mechanisms that adopt approaches based on different rules. Simulation results show that our mechanism delivers consistently better performance than static mechanisms and other dynamic mechanisms. We also demonstrate that the performance of our mechanism is very close to the ideal mechanism that can foresee the future, leaving very little space for further improvement.

The rest of the paper is organized as follows. We present the problem formulation in Section 2. Followed is the pool of practical approaches in Section 3 and the on-line approach designation mechanism in Section 4. We evaluate our proposed mechanism and present the trace-driven simulation results in Section 5. Related work can be found in Section 6. Finally, we conclude this paper in Section 7.

2. Problem Formulation

2.1. System Model

We consider a new mobile computing model, where wearable devices, smartphones, Wi-Fi APs and cellular stations are actively involved in data transmissions. The smartphone is equipped with cellular, Wi-Fi and Bluetooth interfaces, and can decide whether to enable Bluetooth tethering to provide network access to the associated wearable device. The wearable device is only equipped with Wi-Fi and Bluetooth, and will first attempt to establish network connections via Bluetooth tethering on the smartphone, and if failed, will repeat the attempt via Wi-Fi. Now, we make several reasonable assumptions as follows. Cellular stations are deployed in such a way that it provides its users with constantly stable access to Internet, while Wi-Fi APs only provide intermittent network connections with varying quality. The smartphone maintains a constant connection with the wearable device via Bluetooth, since it is necessary for the latter to take over basic functions available on the former, such as making phone calls and sending text messages. Both devices are also assumed to

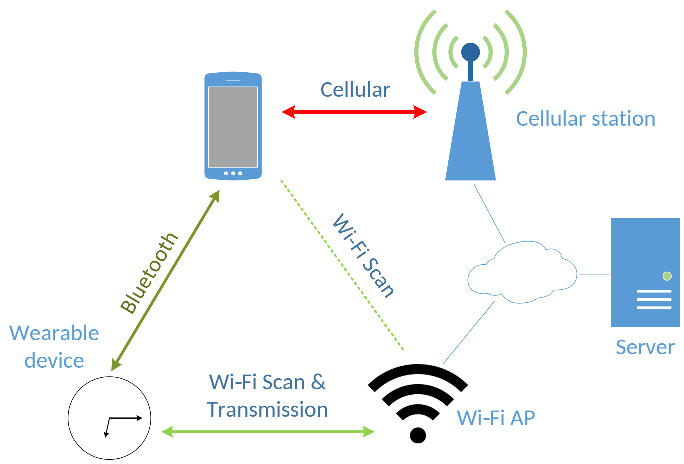


Figure 1: Data Communication Model

keep Wi-Fi turned on, and Wi-Fi is in Power Saving Mode (PSM) when not used to save energy. Figure. 1 gives an overview of the established model.

Based on the model, we focus on the problem of energy efficient data communication among wearable device, smartphone, APs and cellular stations. The wearable device needs to transmit data to and download data from remote servers. It can either tether the smartphone or connect to an AP for data communication between itself and remote servers. To solve the problem, we need to design efficient methods to coordinate the communication among devices according to available wireless resources around the wearable device, as shown in Fig. 1. Specifically, we study the problem of *minimizing the overall energy consumption of both the wearable device and the smartphone subject to some delay time requirement.*

A theoretical optimal solution would be easy to obtain for this problem, if we could foresee all the relevant information in the future, such as paths that users will take, request arrival time, etc. However, such assumption is not realistic in practice, as users move randomly in unknown environments, and request Internet connections randomly. Although prediction techniques may be applied to estimate future information, they are expensive yet unable to guarantee accurate estimates for all predictions. Moreover, solutions generated under erroneous estimates would incur even more energy consumption than those without any predictions.

2.2. Approach Designation Mechamism Overview

To make this problem more tractable, we investigate a pool of practical approaches for data communication, from which we dynamically designate one that achieves good energy efficiency while satisfying the delay time requirement. These practical approaches vary in different performance metrics, such as power consumption for different devices and incurred delay time. Now, the new problem becomes *how to designate approaches to minimize the overall energy consumption subject to some delay time requirements*. Note that, adopting a limited number of practical approaches shrinks the set of feasible solutions, thus possibly risking not finding any solutions that are theoretically optimal to the original problem. Nevertheless, these practical approaches represent a set of feasible solutions that we can easily apply to most off-the-shelf platforms, and thus fit better with the real-world use case.

Like the original problem, an optimal solution to the new problem also requires foreseeing the future. In other words, all inputs should be given in advance so as to optimally designate approaches, which, again, is not realistic in practice. This leads us to propose an on-line approach designation mechanism that makes decisions only based on historical and present environment information, such as AP quality and user moving speed. Meanwhile, this mechanism should not assume any probability distributions of AP inter-arrival times, AP connection times and request inter-arrival times. Finally, the proposed on-line designation mechanism should be able to produce near-optimal results as compared to that assuming knowledge of the future. Figure. 2 plots a high-level description of the proposed mechanism.

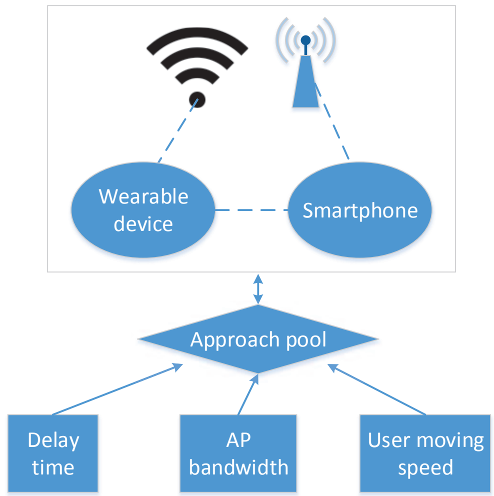


Figure 2: Approach Designation Mechanism Overview

3. Practical Approach Pool

In this section, we investigate a pool of practical approaches for data communication among the wearable device, the smartphone, APs, and cellular stations. They are practical and lightweight in the sense that they impose no system-level code modification and thus can be easily applied to most off-the-shelf platforms. We conduct a theoretical analysis to the performance of each approach, and show that no single data communication approach can guarantee to yield the best performance across a variety of environments.

3.1. Approach Overview

We investigate four approaches that differ in wearable devices' using network interface and delay requirement, which are described as follows.

- **Approach C**: *Delay-Free Cellular Only Data Communication* enables wearable devices to access remote servers through the smartphone's cellular network. To this end, the smartphone should enable Bluetooth tethering. Considering that cellular network is normally available, we expect that Approach C incurs little to no delays for any incoming requests except for the inherent cellular network delay.

- **Approach W**: *Delay-Ignorant WiFi Only Data Communication* requires wearable devices to wait for Wi-Fi connections irrespective of any specified maximum tolerable delay time. Approach W does not require smartphones to assist wearable devices to gain network access.

- **Approach CW**: *Combined Cellular and WiFi Data Communication* takes advantage of both cellular and Wi-Fi network, where the wearable device is connected with remote servers via either Bluetooth tethering provided by the smartphone or their own Wi-Fi interface. The smartphone enables Bluetooth tethering only when no usable APs are found nearby. The wearable device does not explicitly tell the smartphone to enable Bluetooth tethering.

- **Approach CWD**: *Delay-Tolerant Cellular and WiFi Data Communication* favors delay-tolerant applications for more data transmission via WiFi. The smartphone does not turn on Bluetooth tethering until confirming no nearby APs have been found for a continuous period of time, which is normally set to D_{max} to satisfy the delay time requirement.

Note that these approaches are ad hoc and thus do not require coordination between wearable devices and smartphones. The smartphones makes decisions of enabling tethering only based on whether Wi-Fi is available or not, while wearable devices always choose, if any, the more energy efficient interface to communicate. Such ad hoc approaches eliminate the need of system-level code modification, and thereby can be easily applied to different platforms.

3.2. Performance Analysis

Now, we give a theoretical analysis of the performance of each approach. We assume that Wi-Fi connection times and inter-connection times follow exponential distributions with $\mu = \frac{\overline{v}}{R}$ [7] and $\theta \approx 2R\overline{v}\rho$ [8], respectively, where $\overline{v}$

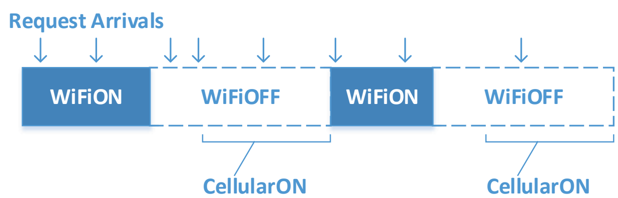


Figure 3: The denotation of network states in the simulation.

is the average moving speed, R is the common effective transmission range of Wi-Fi APs, and ρ is the density of deployed Wi-Fi APs. In addition, we assume that Wi-Fi bandwidth B_w and cellular bandwidth B_c follow exponential distributions with rate λ_w and λ_c, respectively. The bandwidth of Bluetooth is assumed to be stable, denoted by B_b. We use WiFiON to denote the state that Wi-Fi APs are available, and WiFiOFF otherwise. For Approach CWD, we also explicitly use CellularON to denote when the cellular network can be used. A typical state switch graph is shown in Figure. 3.

In Approach C, the achieved bandwidth can be expressed as $\min(B_c, B_b)$, since the slowest link in the transmission determines the maximum bandwidth. Thus, the expected bandwidth achieved by Approach C is

$$\begin{aligned}\mathbb{E}[B_{Appr\_C}] &= \mathbb{E}[B_c|B_c < B_b] \cdot Pr(B_c < B_b) + \\ &\quad B_b \cdot Pr(B_c \geq B_b) \\ &= \lambda_c^{-1} - (\lambda_c^{-1} + B_b)e^{-\lambda_c B_b} + B_b e^{-\lambda_c B_b} \\ &= \lambda_c^{-1}(1 - e^{-\lambda_c B_b}).\end{aligned}$$

We simplify the expected overall power consumption, including the smartphone and the wearable device, of Approach C as follows:

$$\mathbb{E}[P_{Appr\_C}] = P_b^1 + P_b^2 + P_c^2 + P_{proc}^2,$$

where P_b^1 is the power consumption of Bluetooth transmission on the wearable device, and P_b^2, P_c^2, and P_{proc}^2 are the power consumption of Bluetooth transmission, cellular transmission, and tethering-related data processing on the smartphone, respectively.

In Approach W, the bandwidth is only available when Wi-Fi is connected, which has a probability of $\frac{\mu^{-1}}{\mu^{-1}+\theta^{-1}}$. Thus, the expected bandwidth achieved by Approach W

$$\begin{aligned}\mathbb{E}[B_{Appr\_W}] &= \mathbb{E}[B_w] \cdot Pr(WiFiON) \\ &= \lambda_w^{-1} \cdot \frac{\mu^{-1}}{\mu^{-1}+\theta^{-1}} \\ &= \frac{2\lambda_w^{-1}R^2\rho}{1+2R^2\rho}.\end{aligned}$$

The expected overall power consumption of Approach W is

$$\mathbb{E}[P_{Appr\_W}] = P_w^1 Pr(WiFiON) + P_{w\_scan}^1 + P_{w\_scan}^2,$$

where P_w^1 is the power consumption of Wi-Fi transmission on the wearable device, and $P_{w\_scan}^1$ and $P_{w\_scan}^2$ are the power consumption of Wi-Fi scanning on the wearable device and the smartphone, respectively.

In Approach CW, the bandwidth achieved is equal to that achieved by Approach C when Wi-Fi is not connected. When Wi-Fi is connected, the bandwidth achieved is equal to the Wi-Fi bandwidth. Thus, the expected bandwidth achieved by Approach CW

$$\begin{aligned}\mathbb{E}[B_{Appr\_CW}] &= \mathbb{E}[B_{Appr\_C}] \cdot Pr(WiFiOFF) + \\ &\quad \mathbb{E}[B_w] \cdot Pr(WiFiON) \\ &= \lambda_c^{-1}(1-e^{-\lambda_c B_b}) \cdot \frac{\theta^{-1}}{\mu^{-1}+\theta^{-1}} + \\ &\quad \lambda_w^{-1} \cdot \frac{\mu^{-1}}{\mu^{-1}+\theta^{-1}} \\ &= \frac{\lambda_c^{-1}(1-e^{-\lambda_c B_b}) + 2\lambda_w^{-1}R^2\rho}{1+2R^2\rho}.\end{aligned}$$

The expected overall power consumption is simplified as

$$\begin{aligned}\mathbb{E}[P_{Appr\_CW}] = {} & \mathbb{E}[P_{Appr\_C}] Pr(WiFiOFF) + \\ & P_w^1 Pr(WiFiON) + P_{w\_scan}^1 + P_{w\_scan}^2.\end{aligned}$$

In Approach CWD, the cellular network is only used when the Wi-Fi disconnection time exceeds D_{max}. The usage of cellular network is thus substantially

Table 1: Power Consumption for Different Operations

Operation	Value	Operation	Value
P_w^1	1450 mw	$P_{w\_scan}^1$	1000 mw
P_b^1	430 mw	$P_{w\_scan}^2$	1000 mw
P_b^2	430 mw	P_c^2	1400 mw
P_{proc}^2	1100 mw		

reduced. The average usage time of cellular network is recalculated as follows,

$$\begin{aligned} \mathbb{E}[t_c'] = &(\mathbb{E}[t_c|t_c > D_{max}] - D_{max}) \cdot Pr(t_c > D_{max}) + \\ &0 \cdot Pr(t_c \leq D_{max}) \\ = &\theta^{-1} e^{-\theta D_{max}}. \end{aligned} \tag{1}$$

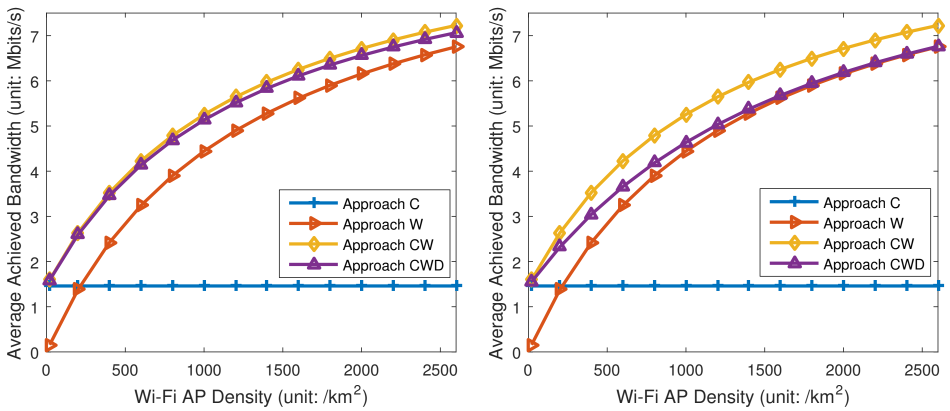
Thus, the expected bandwidth achieved by Approach CWD

$$\begin{aligned} \mathbb{E}[B_{Appr\_CWD}] = &\mathbb{E}[B_{Appr\_C}] \cdot Pr(CellularON) + \\ &\mathbb{E}[B_w] \cdot Pr(WiFiON) \\ = &\lambda_c^{-1}(1 - e^{-\lambda_c B_b}) \cdot \frac{\mathbb{E}[t_c']}{\mu^{-1} + \theta^{-1}} + \\ &\lambda_w^{-1} \cdot \frac{\mu^{-1}}{\mu^{-1} + \theta^{-1}} \\ = &\frac{\lambda_c^{-1} e^{-2R\overline{v}\rho D_{max}}(1 - e^{-\lambda_c B_b}) + 2\lambda_w^{-1} R^2 \rho}{1 + 2R^2\rho}. \end{aligned}$$

The expected overall power consumption of Approach CWD is

$$\begin{aligned} \mathbb{E}[P_{Appr\_CWD}] = &\mathbb{E}[P_{Appr\_C}] Pr(CellularON) + \\ &P_w^1 Pr(WiFiON) + P_{w\_scan}^1 + P_{w\_scan}^2. \end{aligned}$$

We study how two variables, i.e., the average moving speed $\overline{v}$ and the AP density ρ, affect the performance of each approach. These two variables combine to determine the mean AP connection time and inter-connection time. We consider different network environment by setting different values to the average bandwidth of Wi-Fi and cellular network, since network conditions may

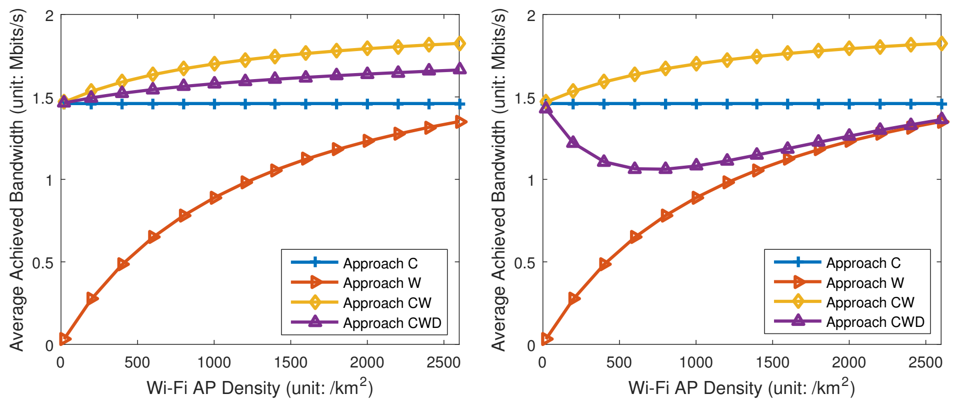


(a) $\overline{v} = 0.2\ m/s$ (b) $\overline{v} = 1.8\ m/s$

Figure 4: The effect of Wi-Fi AP density ρ on the average bandwidth achieved for different moving speeds when Wi-Fi bandwidth is *higher* than cellular bandwidth on average.

greatly affect the data transmission efficiency. We set the effective transmission range R of APs to 20 m, considering the complexity of dynamic environments. According to the literature [9], we set the power consumption of different operations involved in the data transmission as shown in Table 1. The Bluetooth bandwidth is set to 2 Mbit/second. The parameter D_{max} for Approach CWD is set to 20 seconds.

We first compare four approaches when Wi-Fi bandwidth is in general higher than cellular bandwidth. We set the average bandwidth λ_w^{-1} and λ_c^{-1} to 10 Mbit/second and 3 Mbit/second, respectively. Figure 4 shows how Wi-Fi AP density ρ affects the average bandwidth achieved for different moving speeds. Except for Approach C, as ρ increases, the average achieved bandwidth for other approaches increases in general. Higher AP density increases the probability of using Wi-Fi for data transmission, and Wi-Fi has higher bandwidth than cellular network on average, thus resulting on higher average bandwidth achieved for approaches except Approach C. However, when rho is particular small (e.g., lower than 200), Approach W has the least average bandwidth, because for



(a) $\overline{v} = 0.2\ m/s$

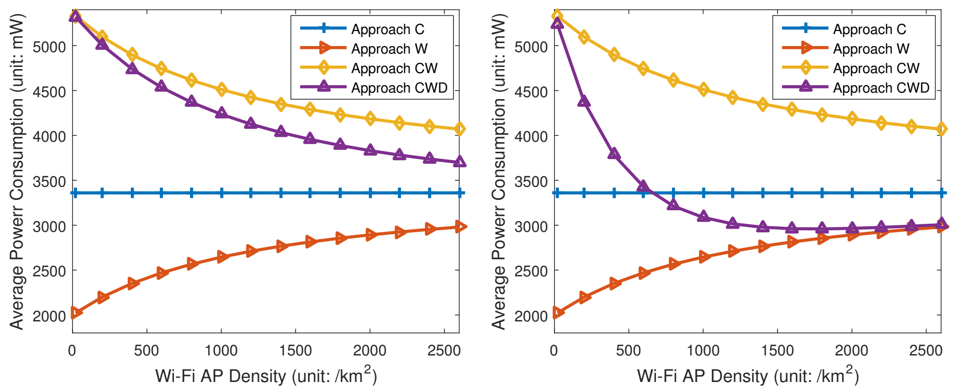
(b) $\overline{v} = 1.8\ m/s$

Figure 5: The effect of Wi-Fi AP density ρ on the average bandwidth achieved for different moving speeds when Wi-Fi bandwidth is *lower* than cellular bandwidth on average.

most of the time, no data are transmitted due to the unavailability of Wi-Fi.

Comparing Figure 4a and Figure 4b, we observe that the moving speed only has an impact on the performance of Approach CWD. When $\overline{v}$ is small, Approach CWD exhibits similar performance as Approach CW, because according to Equation 1, small $\overline{v}$ results in higher average usage time of cellular network. When $\overline{v}$ is large, however, the average bandwidth achieved by Approach CWD approaches Approach W, as ρ increases. This is due to the reduced average usage time of cellular network. In other words, the portion of time when no data are transmitted increases, thus resulting in lower average bandwidth.

We then compare four approaches when Wi-Fi bandwidth is in general lower than cellular bandwidth. We set the average bandwidth λ_w^{-1} and λ_c^{-1} to 2 Mbit/second and 3 Mbit/second, respectively. Worsened Wi-Fi network conditions can lead to undesirable performance of approaches that rely on Wi-Fi, as illustrated in Figure 5. Approach W has the lowest average bandwidth among all, even though it increases as ρ increases. However, Approach C that only uses cellular network does not have the highest average bandwidth, because the maximum Bluetooth bandwidth limits the maximum average bandwidth that



(a) $\overline{v} = 0.2\ m/s$ (b) $\overline{v} = 1.8\ m/s$

Figure 6: The effect of Wi-Fi AP density ρ on the average power consumption achieved for different moving speeds.

can be achieved by using cellular network.

The performance of Approach CWD depends on the moving speed. In particular, Figure 5b shows that the average bandwidth achieved by Approach CWD first decreases and then increases, as ρ increases. As the AP density starts to increase, more data are transmitted via Wi-Fi, which, in turn, increases the portion of time when no data are transmitted, because Wi-Fi disconnection occurs more frequently. However, as the AP density exceeds some threshold value and continues to increase, the usage of cellular network drops, and yet the usage of Wi-Fi network increases, which combine to result in higher average bandwidth.

Figure 6 shows how Wi-Fi AP density and the moving speeds affect the average power consumption of each approach, regardless of Wi-Fi and cellular bandwidth. Approach W has the lowest average power consumption among all, even though it increases as ρ increases. Approach CW has the highest average power consumption, because it incurs the cost of Wi-Fi scanning, and also uses the energy-hungry cellular network tethering. However, as ρ increases, the average power consumption of Approach CW and Approach CWD both decreases. In particular, when $\overline{v}$ is large, the average power consumption of Approach CWD starts to approach that of Approach W, as shown in Figure 6b.

This is due to the increased usage of Wi-Fi network, which incurs less energy than using cellular network.

4. Approach Designation Mechanism

In real-world scenarios, AP availability and quality change dynamically as people move around, and the inter-arrival time and data size of requests also vary with different user habits. As shown in last section, no single approach from the approach pool can deliver consistently good performance across a variety of environments. This section presents the on-line approach designation mechanism, which aims at minimizing the energy consumption of our proposed model in such dynamic scenarios.

4.1. Lyapunov Based Algorithm

To achieve the goal of energy minimization, we adopt the Lyapunov optimization framework to designate an approach from the approach pool dynamically. Due to the property of the framework, the resulting algorithm is able to optimize the energy efficiency while keeping the delay time within certain constraint. In the following, we present how we derive the Lyapunov based algorithm, and how it achieves the goal.

We consider a discrete-time model where the approach designation occurs at time $(t_1, t_2, \ldots)$. Let A_i denote the amount of data that arrive in the timeslot (t_i, t_{i+1}), C_i denote the amount of successfully transmitted data in the timeslot (t_i, t_{i+1}), and Q_i denote the queue backlog (number of bits in queue) at time t_i. In practice, the queue backlog Q_i represents the size of data that are not yet transferred on wearable devices. We model C_i as the output of a function, i.e.,

$$C_i \triangleq G(\sigma_i, \overline{B}_i, Q_i, P_i),$$

where σ_i represents the approach designated in the timeslot (t_i, t_{i+1}), $\overline{B}_i$ is the average bandwidth achieved in the timeslot (t_i, t_{i+1}), and P_i is the overall power consumption in the timeslot (t_i, t_{i+1}). Note that P_i consists of the power consumption on both wearable devices and smartphones. C_i is always less than or equal to Q_i. Over time, the queue backlog evolves as follows:

$$Q_{i+1} = Q_i - C_i + A_i. \tag{2}$$

Assuming that there are n timeslots, our goal is to minimize the average power consumption on both wearable devices and smartphones

$$\overline{P} = \frac{\sum_{i=1}^{n} P_i}{n},$$

while keeping Q_i within a certain value.

According to the Lyapunov optimization framework, we define the Lyapunov function as:

$$L(Q_i) \triangleq \frac{1}{2} Q_i^2,$$

and the one-step Lyapunov drift as:

$$\Delta(Q_i) \triangleq \mathbb{E}\{L(Q_{i+1}) - L(Q_i) | Q_i\}.$$

$L(Q_i)$ is defined as the half of the squared queue backlog. Using the squared value is one of the common ways to evaluate the system in stochastic processes. $\Delta(Q_i)$ is the conditional expectation of the change of the Lyapunov function. It shows the accumulated change of the size of the transmission queue. It must be smaller than or equal to certain value so that the queue does not grow unlimitedly.

From (2), we have

$$\begin{aligned} \frac{1}{2} Q_{i+1}^2 &= \frac{1}{2}(Q_i - C_i + A_i)^2 \\ &\leq \frac{1}{2}(Q_i^2 + C_i^2 + A_i^2) - Q_i(C_i - A_i), \end{aligned} \tag{3}$$

since A_i and C_i are non-negative. Take expectation with respect to Q_i on both sides of (3), and then we have

$$\begin{aligned} \Delta(Q_i) \leq & \frac{1}{2}\mathbb{E}\{C_i^2 + A_i^2 | Q_i\} + Q_i \mathbb{E}\{A_i | Q_i\} \\ & - Q_i \mathbb{E}\{C_i | Q_i\} \\ = & D_i + Q_i \mathbb{E}\{A_i | Q_i\} - Q_i \mathbb{E}\{C_i | Q_i\}, \end{aligned} \tag{4}$$

where

$$D_i = \frac{1}{2}\mathbb{E}\{C_i^2 + A_i^2|Q_i\}.$$

By adding a penalty, the Lyapunov framework is able to minimize the objective specified in the penalty while keeping the queue length finite. Hence, we add a weighted conditional expectation of power consumption to both sides of (4), which now becomes

$$\begin{aligned} &\Delta(Q_i) + \alpha\mathbb{E}\{P_i|Q_i\} \\ \leq &D_i + Q_i\mathbb{E}\{A_i|Q_i\} - Q_i\mathbb{E}\{C_i|Q_i\} + \alpha\mathbb{E}\{P_i|Q_i\} \\ = &D_i + Q_i\mathbb{E}\{A_i|Q_i\} - \mathbb{E}\{Q_i\mathbb{E}\{C_i|\sigma, \overline{B}_i, Q_i, P_i\} - \alpha P_i|Q_i\}. \end{aligned} \tag{5}$$

Note that based on the Lyapunov optimization framework, the choice of α can affect the tradeoff between the power consumption and delay time. In our trace-based simulations, we validate the effect of α on the performance of the proposed algorithm.

To minimize the left-hand-side of (5), it is equivalent of maximizing the negative terms and minimizing the positive terms on the right-hand-side. Since we can only determine the designated approach σ, we thus maximize the negative term:

$$\mathbb{E}\{Q_i\mathbb{E}\{C_i|\sigma, \overline{B}_i, Q_i, P_i\} - \alpha P_i|Q_i\}.$$

Therefore, the designated approach σ_i in the timeslot (t_i, t_{i+1}) can be obtained as follows:

$$\sigma_i = \arg\max_{\sigma\in\Omega} \left\{Q_i\mathbb{E}\{C_i|\sigma, \overline{B}_i, Q_i, P_i\} - \alpha P_i\right\}, \tag{6}$$

where Ω is the set of the four proposed approaches that can be designated.

4.2. Practical Consideration

The proposed Lyapunov algorithm requires to know the bandwidth that can be achieved by each approach in order to designate one approach that maximizes the equation 6. We have shown the expected bandwidth and the expected overall power consumption achieved by each approach in Section 3, which are related to the average bandwidth of Wi-Fi and cellular network, the AP density and the moving speed. In the following, we illustrate how we obtain these related variables.

Average bandwidth of Wi-Fi and cellular network: We keep track of the bandwidth of any network used during each interval by recording the transmission time of requested data. These bandwidth data are then used to estimate the average bandwidth of Wi-Fi and cellular network by filtering out obvious outliers. Since network conditions may vary both temporally and spatially, we only consider bandwidth data that are recorded most recently.

Average user speed: The movement sensor on the smartphone can be readily used to detect user movement. We are particularly interested in the average speed $\overline{v}_i$ of the user during last interval, since this information shows how fast the user is leaving current environment. Various localization methods on mobile devices can also be utilized to help decide the moving speed.

AP density: Suppose we regard an area as a set of square grids to simplify analysis. In this paper, we use AP density to denote the ratio of the number of square grids covered by useable APs over the total number of visited square grids, instead of the number of APs per square grid. This is justified due to the fact that several APs may cluster in a square grid while other grids are not covered, which may inaccurately infer that the user is in a dense AP environment. This information is approximated via AP scanning and movement sensing on the smartphone. Note that such approximation is performed separately during each interval, with results denoted by ρ_i. We take the latest approximation result as the reference for the next approach designation.

5. Evaluation

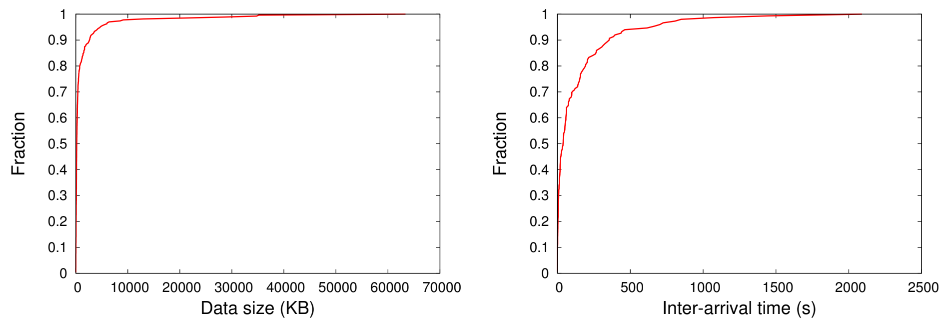
In this section, we evaluate the performance of our proposed approach designation mechanism through extensive trace-driven simulations. We first present the methodology we adopt, and then the results of our comparison experiments.

5.1. Methodology

Overview. To understand the performance of our approach designation mechanism, we conduct extensive trace-driven simulations. Two types of traces were collected, i.e., request arrival traces and network availability and quality traces, both of which have a significant impact on the performance of our mechanism. Request arrival traces were retrieved from analyzing the network logs in five mobile devices. Network availability and quality traces were generated by manually testing network bandwidth and tracking network availability at different environments. We present the trace collection in more detail in next section.

In the simulation, we compare our approach designation mechanism with four basic approaches, as well as three mechanisms that designate approaches differently from ours. We also describe the performance metrics we adopt to compare different approaches. Since our simulations are based on real traces, we believe that they serve as a good reference for our future work of implementations.

Trace Collection. We collected request arrival traces via Android smartphones. To capture the data size and arrival time of requests, we installed an app, called *Network Log*, on five Android smartphones. Network Log provides very detailed statistics about app connections, such as bytes transmitted and timestamps for each established connection. We recruited five volunteers to carry these smartphones as their main communication tool, with Network Log running in the background for one week. Note that we are only interested in those connections logged in the daytime, thereby eliminating connections logged in the nighttime. We aggregated the bytes transmitted in connections that share the same source and destination IP address, regarded as one request. Then we divided these requests into a number of segments with each segment consisting of requests collected in one day. Thus, we obtained 35 segments. Each segment is served as one request arrival trace, consisting of a timestamped sequence of request arrivals and their data size. Figure. 7a and Figure. 7b plot the distributions of the data size and inter-arrival time of requests. We observe that more than 80% of request data size is lower than 1000 KB, and 80% of inter-arrival



(a) CDF: Request Data Size

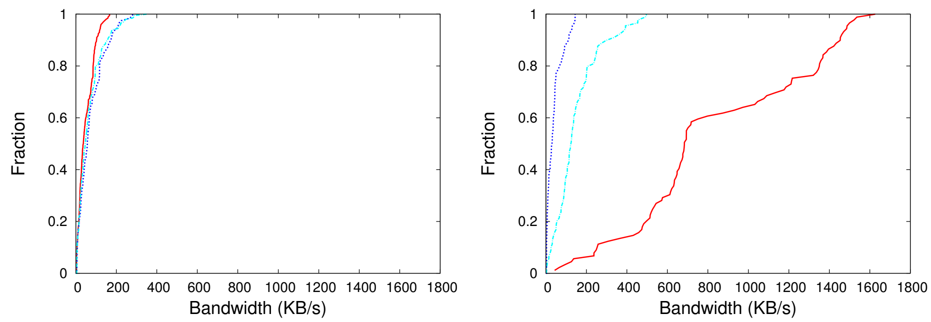
(b) CDF: Request Inter-arrival Time

Figure 7: Request Traces

time is shorter than 200 seconds.

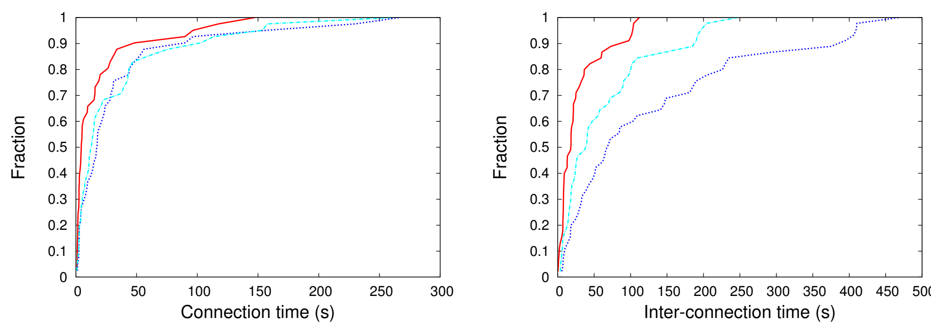
We collected network quality traces by manually testing the bandwidth of cellular network and Wi-Fi at different environments. We used an Android smartphone with *SpeedTest* installed to test both download and upload bandwidth at three different locations. For simplicity, we averaged the tested upload and download bandwidth as the bandwidth for an AP. Note that the density of Wi-Fi AP deployment varies with each location, while the bandwidth available for each Wi-Fi AP is affected by multiple factors, such as server load, congestion and AP-user distance. We walked in different speeds for two hours at each location, and tested the bandwidth of both Wi-Fi (if any) and cellular network (3G) every 20 seconds. As a result, we collected 20 traces for each location. Each network quality trace is a timestamped sequence of available Wi-Fi APs and cellar network with corresponding bandwidth. Figure. 8a and Figure. 8b depict the CDFs of bandwidth for cellular network (3G) and Wi-Fi observed at three different locations, respectively.

To capture fine-grained network availability traces, we wrote a simple Android app that takes advantage of `ConnectivityManager` to record the connection time and disconnection time with Wi-Fi and cellular network, respectively. `ConnectivityManager` is an API provided in the Android framework that can monitor network connections and send broadcast intents when network connec-



(a) CDF: Cellular Bandwidth (b) CDF: Wi-Fi Bandwidth

Figure 8: Network Bandwidth Traces



(a) CDF: Wi-Fi Connection Time (b) CDF: Wi-Fi Inter-connection Time

Figure 9: Wi-Fi Connection Traces

tivity changes. Conveniently, we managed to collect the network availability traces while collecting network quality traces, since we ran the app in the background on the same smartphone used to test bandwidth. We find that cellular network connections are quite stable, so we do not show the availability result of cellular network. Figure. 9a and Figure. 9b show the distributions of connection time and inter-connection time of Wi-Fi.

In Figure. 8a and Figure. 8b, we find that the bandwidth of cellular network (3G) at different locations does not vary a lot, which, however, is not case for Wi-Fi. The bandwidth of Wi-Fi at Location A (marked as the red line) is generally much higher than that at other locations. The inter-connection time of Wi-Fi also shows location-specific patterns, as shown in Figure. 9b. Location A has the highest AP density among all. On the other hand, the connection time of Wi-Fi at different locations share very similar patterns. This partially validates the assumption of exponential probability distribution for Wi-Fi connection time, whose rate is only related to Wi-Fi's effective coverage range and user moving speed.

Set-up and Comparison. We conduct the trace-driven simulation based on the custom simulator we develop for evaluating the performance of four basic approaches in Section IV. Instead of deriving the request arrival rate λ and Wi-Fi AP arrival rate θ and departure rate μ based on given user moving speed $\overline{v}$ and Wi-Fi AP density ρ, now we serve one request trace and one network trace at a time to the simulator as the input for one simulation run. One request trace is a list of recorded requests in every timeslot, while one network trace is a list of bandwidths recorded in every timeslot, ordered by recording time. When no requests are recorded or network bandwidth is not available, the request or the bandwidth is recorded as zero. Unavailable network bandwidth can be caused by several factors, such as human mobility, and network failure. Therefore, the network trace served in our simulation reflects how the bandwidth changes in the real-world situation, including human mobility. Based on the network trace, we estimate the average user speed $\overline{v} = \frac{\mu}{R}$ and Wi-Fi AP density $\rho = \frac{\theta}{2R\overline{v}}$ by backwards derivation. The maximum tolerable time D_{max} is set to 20 seconds.

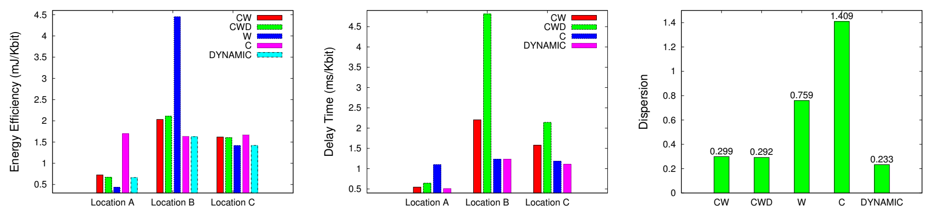
Normally, a new request is fulfilled upon its arrival, if the interface for the available network is allowed in the adopted approach and is idle. For example, Wi-Fi is idle in the state of WiFiON using Approach CW. Otherwise, the request is buffered in the waiting queue. When a request departures, namely completed, the next request in the queue, if any, goes through the same process as above. We also define the starting point of WiFiON, WiFiOFF and CellularON as three events, each of which attempts to fulfill the remaining requests in the queue, if any, via the corresponding interface upon triggering. Note that a request that fails to complete during a state will be put back to the queue with the data not transmitted.

First, we compare our approach designation mechanism with four basic approaches across a variety of scenarios. Then, we study how α would affect the performance of the proposed mechanism. Also, we compare our mechanism with three different approach designation mechanism – RANDOM, LOCAL-OPTIMAL and PREDICTIVE.

The RANDOM mechanism chooses one approach randomly from the approach pool, regardless of current network conditions, request delay time requirement, etc. The LOCAL-OPTIMAL mechanism strives to select the approach that yields the most energy-efficient performance at present, without considering the possible variation in network quality or availability in the future. The PREDICTIVE mechanism is the ideal approach designation mechanism, which can foresee the information of the Wi-Fi AP availability and quality in the future, and thus can make optimal approach designation decisions.

Performance Metrics. We use two terms, energy consumption per data unit size e_b and delay time per data unit size d_b, to characterize the performance of each method. By doing so, we manage to compare different methods under different request patterns. When calculating the energy consumption, we consider all the energy consumption associated with data communication for wearable devices, as defined in Section 3.2, including energy consumption incurred on smartphones due to tethering. The delay time is calculated based on the arrival time of data requests on wearable devices, and their arrival time on remote servers. Note that it has implicitly included the Bluetooth data transmission time, and the data processing delay of cellular interface on smartphones.

We also introduce another term, called dispersion σ, to further show how each method performs. Let e_{min} and d_{min} denote the minimum energy consumption per data unit size and the minimum delay time per data unit size, respectively, among all the methods. The dispersion σ is then defined as the Euclidean distance between (e_b, d_b) and (e_{min}, d_{min}). By definition, the dispersion σ indicates how far the actual result is from the optimal (e_{min} and d_{min}). Theoretically, the smaller σ is, the better the corresponding method performs.



(a) Energy Efficiency

(b) Delay Time

(c) Dispersion at Location A

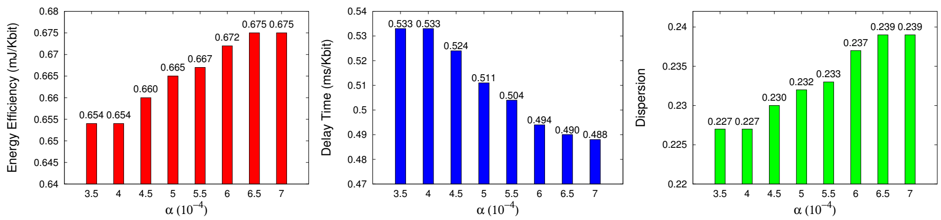
Figure 10: Comparison between Approach CW, Approach CWD, Apporach W, Approach C and our mechanism (denoted as DYNAMIC)

5.2. Performance Results

Performance against four basic approaches. We first compare our approach designation mechanism with all the four basic approaches. We set α to 0.0005 for our mechanism in the simulation. The comparison results are shown in Figure. 10.

In Figure. 10a, we observe that Approach W has the highest energy efficiency at Location A and our mechanism has the highest at Location B and C. It is not surprising to see the good performance of Approach W in energy efficiency, since data transmission via Wi-Fi at Location A is generally much more energy efficient than that via cellular network and Bluetooth combined. However, this is all at the cost of incurring excessively large delay time, which is not shown in the other two figures. At location A, Approach CWD achieves almost the same energy efficiency as our mechanism, but performs much worse at other two locations. Except Approach W, our mechanism delivers the best performance in energy efficiency across all locations.

In Figure. 10b, we find that our mechanism incurs the smallest delay time across all the locations, even better than the delay-free Approach C and Approach CW. This result suggests that delaying data communication strategically does not only improve energy efficiency, but also help reduce the overall delay time. It is worthwhile to mention that our mechanism makes approach designation decisions merely based on previous and current monitored variables, which



(a) Energy Efficiency (b) Delay Time (c) Dispersion

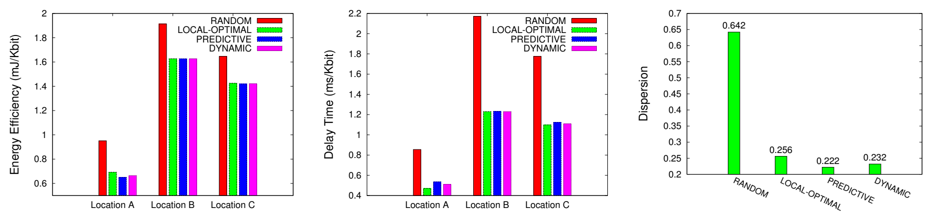
Figure 11: Comparison between Different α for our mechanism at Location A

already delivers such good performance.

Now, we may be interested in the overall performance of our mechanism. A good solution should not only achieve good energy efficiency, but also good time efficiency. In order to compare the overall performance, we first find e_{min} and d_{min} from the results of all solutions compared for different locations. Then, we calculate the dispersion for each solution, with results plotted in Figure. 10c. Note that only dispersion at Location A is shown, since dispersion at other locations are extremely small, making it hard to display in the figure. The results show that our mechanism exhibits the lowest dispersion across all locations, 20% lower than the second lowest Approach CWD, and 83% lower than Approach C.

Performance for different α. To show how our mechanism performs under different α, we vary α from 0.00035 to 0.0007 with steps of 0.00005. Figure. 11 plots the results of the comparison for different α at Location A. Results at other locations do not reveal such obvious changing trend as at Location A, therefore not shown here.

In Figure. 11a, we notice that when α is below 0.0004, our mechanism delivers the highest energy efficiency, but also incurs the largest delay time, as shown in Figure. 11b. As α increases, the energy consumption increases, while the delay time decreases. This makes sense, because larger α leads to more adoption of Approach CW. To evaluate the overall performance under different α, we show the calculated dispersion in Figure. 11c based on the same (e_{min},



(a) Energy Efficiency (b) Delay Time (c) Dispersion at Location A

Figure 12: Comparison with other approach designation mechanisms

d_{min}). When α is below 0.0004, our mechanism achieves the lowest dispersion, although the incurred delay time is the largest among all. Thus, to get optimized performance, α should be smaller than 0.0004.

Comparison with other approach designation mechanisms. Finally, we compare our mechanism with other approach designation mechanisms. We set α to 0.0005 during the comparison experiments. Figure. 12 depicts the performance of all comparing solutions across all locations, except that the dispersion comparison only shows the results at Location A.

As described in the section of simulation setups, Location B and Location C have very poor Wi-Fi networks, under which the local-optimal, the predictive and our Lyapunov based dynamic mechanisms may all choose to use cellular works for most data communications. This explains why the performance differences are so small among these three mechanisms on Location B and Location C. However, on Location A that has much better Wi-Fi networks, we show that our mechanism achieves better time efficiency than the predictive, and achieves better energy efficiency than the local-optimal. Specifically, in Figure. 12a, we note that the PREDICTIVE mechanism exhibits the best energy efficiency, irrespectively of locations. This is not surprising, as the PREDICTIVE mechanism utilizes its knowledge of future information to make optimal decisions. On the other hand, our mechanism delivers very close performance to PREDICTIVE, which we did not expect beforehand. In Figure. 12b, the LOCAL-OPTIMAL mechanism incurs the smallest delay time, since it strives to use the network with best bandwidth without delaying data transmissions. PREDICTIVE incurs higher delay time, because it may delay data transmissions to use better network. Obviously, the gains from using better network does not offset the cost of extra delaying time at Location A. From Figure. 12c, we conclude that the performance of our on-line mechanism is very close to that of the offline PREDICTIVE mechanism, only 4.5% lower. This also indicates that knowing the future is not as helpful as what we normally think.

Discussion. The local-optimal and predictive mechanisms are not realistic in practice. In order to calculate the energy and time efficiency, both mechanism must have the knowledge of the network bandwidth and data request arrivals for the next timeslot(s). In our simulation, as traces of all time are served at once, it is possible for these two mechanisms to calculate the metrics before making the selection decisions. However, in practice, it is difficult to predict the future, which makes them inapplicable. On the other hand, our Lyapunov based mechanism does not assume any knowledge of the future, and is highly robust to the changes of network bandwidths and data request arrival rates. It only uses the estimations based on previous recorded network bandwidth, and the data transmission queue length to make selection decisions. Yet, it achieves very good energy and time efficiency, which makes it highly desirable in practice.

6. Related Work

6.1. Data Offloading

Recently, data offloading in smartphone-based scenarios has been an active research topic. Basically, the idea is to offload data transmission from cellular network to Wi-Fi for better energy efficiency [10]. Based on the Lyapunov optimization framework, SALSA [11] utilizes channel conditions and local information to make link selection decisions, achieving an near-optimal energy-delay tradeoff on smartphones. BreadCrumbs [12] and Wiffler [13] strive to delay data transfers so as to offload more data on Wi-Fi, based on its prediction on future Wi-Fi connectivity. Recent study [14] shows that 80% of generated data can be offloaded to Wi-Fi networks from cellular networks when a delay of 30 minutes can be tolerated. Coff [15] is a contact-duration-aware offloading scheme for delay-tolerant networks in order to accommodate the increasingly popular large-size multimedia contents. Another work [16] proposes four low-overhead schemes (Adaptive, Decision Tree-based, Hybrid and Lazy) to dynamically and adaptively deduce an application's delay tolerance.

Another trending topic of data offloading is device-to-device (D2D) offloading in opportunistic networking. Based on Reinforcement Learning framework, the work [17] proposes an adaptive cellular traffic offloading approach in opportunistic networks, and studies the performance of two well-known learning algorithms: Actor-Critic and Q-Learning. To provide efficient use of personal device storage, theu authors propose algorithms that maximize the data transferred in D2D connections [18]. The work [19] proposes an adaptive and scalable energy-aware data offloading algorithm for opportunistic networks, which is shown to be robust against the distributions of node density and initial content availability. PI-SOFA [20] is a framework that integrates the awareness of both interest and power capability of a candidate node within the forwarding decision process.

Our work borrows ideas from above work, but focuses on a distinctly different problem, i.e., how to jointly minimize the energy consumption on both smartphones and wearable devices. The addition of wearable devices makes all previous approaches inapplicable.

6.2. Wi-Fi Selection

Wi-Fi AP scanning and selection have also gained much attention in the past years. The discovery and choice of Wi-Fi APs can significantly affect the efficiency of data transmission on Wi-Fi. WiFisense [8] is an adaptive Wi-Fi sensing algorithm that employs user mobility information to further increase Wi-Fi usage and improve energy efficiency. A new association metric, called estimated available bandwidth, is presented in [21] with which a station can find the AP that provides the maximum achievable throughput among scanned

APs. To improve Wi-Fi reliability, ViFi [22] opportunistically exploits base station diversity to minimize disruptions and support interactive applications for mobile clients. Recent work [23] estimates the strongest channel by utilizing channel responses extracted from off-the-shelf wireless chipsets, without probing any additional channels. Our work can be well complemented by all these methods on discovering and selecting Wi-Fi APs.

7. Conclusion

The widespread adoption of wearable devices as people's daily devices is challenged by their short battery life. In this paper, we propose a smartphone-assisted data communication mechanism to improve the energy efficiency on both wearable devices and smartphones. This mechanism considers four approaches that users can actually adopt on different platforms. In order to perform equally well in both static and mobile environment, we propose an on-line approach designation mechanism to determine which approach to adopt. Our mechanism requires only smartphones to monitor environment information and does not assume knowledge of the future. To evaluate the performance of our proposed mechanism, we conduct trace-driven simulations. We show that our proposed mechanism outperforms static mechanisms and other dynamic mechanisms, and delivers very close performance to the ideal one that can foresee the future. In our future work, we will focus on developing a thorough theoretical analysis of our proposed algorithm, as well as implementations and real-world evaluations.

Acknowledgement

This work is supported by HK PolyU G-YBAD and G-YBJV.

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