Cost- and Energy-Aware Multi-Flow Mobile Data Offloading under Time Dependent Pricing

Cheng Zhang*, Bo Gu†§, Zhi Liu‡§, Kyoko Yamori¶§, and Yoshiaki Tanaka‖§
*Department of Computer Science and Communications Engineering, Waseda University, Tokyo, 169-0072 Japan
†Department of Information and Communications Engineering, Kogakuin University, Tokyo, 192-0015 Japan
‡Department of Mathematical and Systems Engineering, Shizuoka University, Shizuoka, 432-8561 Japan
§Global Information and Telecommunication Institute, Waseda University, Tokyo, 169-8555 Japan
¶Department of Management Information, Asahi University, Mizuho-shi, 501-0296 Japan
‖Department of Communications and Computer Engineering, Waseda University, Tokyo, 169-8555 Japan
Email: cheng.zhang@akane.waseda.jp, bo.gu@cc.kogakuin.ac.jp,
liu@shizuoka.ac.jp,kyamori@alice.asahi-u.ac.jp, ytanaka@waseda.jp

***Abstract*—Nowadays, mobile network operators (MNOs) are trying to deploy wireless local area network (LAN) to offload mobile data from their cellular networks to complementary wireless LAN for congestion relief and cost savings. However, these network-centric methods do not take into consideration mobile user's (MU's) interests of monetary cost, energy consumption, and applications' deadlines. How the MU decides whether to offload their traffic to a complementary wireless LAN is non-trivial and important issue. Previous studies assume that MNO adopts usage-based pricing for mobile data, which only cares about how much a MU consumes data but not when a MU consumes data. In this paper, we study the MU's policy to minimize his monetary cost and energy consumption under time-dependent pricing (TDP). We formulate MU's wireless LAN offloading problem as a finite-horizon discrete-time Markov decision process (MDP) and establish an optimal policy by a dynamic programming based algorithm. Extensive simulations are conducted to validate our proposed offloading algorithm.**

***Index Terms*—wireless LAN, mobile data offloading, Markov decision process, dynamic programming, time-dependent pricing, TDP**

I. Introduction

Global mobile traffic is increasing quickly. According to the Cisco visual networking index [1], while monthly global mobile data traffic will be 49 exabytes by 2021, global mobile data traffic has reached 7.2 exabytes per month at the end of 2016, up from 4.4 exabytes per month at the end of 2015. On the other hand, the growth rate of the mobile network capacity is far from satisfying that kind of the demand, which has become a major problem for wireless mobile network operators (MNOs). Even though 5G technology is promising for providing huge wireless network capacity [2], the development process is long and the cost is high. There are two different approaches has been proposed to solve the wireless resource shortage problem: (i) To use economic methods that change MUs' usage pattern. This kind of approach do not increase network capacity, but tries to allocate the existing resource in a effective and efficient way. For example, the pricing model of MNOs for mobile data has evolved from flat rate pricing, to usage-based pricing (UBP) [3][4], then to time dependent pricing (TDP) [5][6]. While the UBP considers how much MU consumes mobile data, TDP cares about when MU consumes data, which is shown effective to reduce congestion in traffic peak time. (ii) To deploy cost-efficient complementary networks (such as wireless LAN and femtocells) to increase mobile networks? capacity. The use of complementary network technologies for delivering data originally targeted for cellular networks is called *mobile data offloading*. Mobile data offloading is facilitated by new standards such as Hotspot 2.0 [7] and the 3GPP Access Network Discovery and Selection Function (ANDSF) standard [8], with which information of network (such as price and network load) can be broadcasted to MUs in real-time.

There are many works related to the wireless LAN offloading problem. However, previous works either considered the wireless LAN offloading problem from the network providers' perspective without considering the MU's quality of service (QoS) [9][10], or studied wireless LAN offloading from the MU's perspective [11][12] [13][14], but without taking the energy consumption as well as cost problems into consideration.

[15][16] studied wireless LAN offloading problem from MU's perspective. While single-flow mobile date offloading was considered in [15], we studied multi-flow mobile data offloading problem in which a MU has multiple applications to transmit data simultaneously with different deadlines in [16]. MU's target was to minimize its total cost, while taking monetary cost, preference for energy consumption, application's delay tolerance into consideration. One assumption in [15][16] was that MNO adopts usage based pricing. In usage based pricing, MU has no incentive to avoid using mobile network even if the network is in congestion status. Since time-dependent pricing gives MU incentive to avoid utilizing mobile network, one question may be asked is as follows: *How does MU set policy to save monetary cost and energy cost in the mobile data offloading process if time-dependent pricing is adopted?* In this paper, we try to answer this question by incorporating time-dependent pricing into own optimization

978-3-901882-98-2 © 2017 IFIP

framework. We formulated the wireless LAN offloading problem as a finite-horizon discrete-time Markov decision process [17][18][19]. A dynamic programming (DP) based optimal offloading algorithm is proposed with time-dependent pricing.

The rest of this paper is organized as follows. Section II illustrates the system model. Section III formulates the user's wireless LAN offloading problem as discrete-time finite-horizon Markov decision process and proposes a dynamic programming based algorithm. Section IV illustrates the simulation and results. Finally, we conclude this paper in Section V.

II. System Model

Since the cellular network coverage is rather high, it is assumed that the MU is always in a cellular network, but not always can access wireless LAN access points (APs). The wireless LAN APs are usually deployed at home, stations, shopping malls and so on. Therefore, we assume that wireless LAN access is location-dependent. We mainly focus on applications with data of relative large size and delay-tolerance to download, for example, applications like software updates, file downloads. The MU has M files to download from a remote server. Each file formulates a flow, and the set of flows is denoted as $\mathcal{M}=\{1,...,M\}$. Each flow $j \in \mathcal{M}$ has a deadline T^j. $\boldsymbol{T}=(T^1,T^2,...,T^M)$ is the deadline vector for the MU's M flows. Without loss of generality, it is assumed that $T^1 \leq T^2 \leq ... \leq T^M$. We consider a slotted time system as $t\in\mathcal{T}=\{1,...,T^M\}$. To simplify the analysis, we use limited discrete locations instead of infinite continuous locations. It is assumed that a MU can move in L possible locations, which is denoted as set $\mathcal{L}=\{1,...,L\}$. While the cellular network is available at all the locations, the availability of wireless LAN network is dependent on location $l \in \mathcal{L}$. The MU has to make a decision on what network to select and how to allocate the available data rate among M flows at location l at time t by considering total monetary cost, energy consumption and remaining time for data transmission. As in [14][15][16] the MU's decision making problem can be modeled as a finite-horizon Markov decision process.

We define the system *state* at t as in Eq. (1)

$$\boldsymbol{s}_t = \{l_t, \boldsymbol{b}_t\} \tag{1}$$

where $l_t \in \mathcal{L}=\{1,...,L\}$ is the MU's location index at time t, which can be obtained from GPS. $\mathcal{L}$ is the location set. $\boldsymbol{b}_t=(b_t^1,b_t^2,...,b_t^M)$ is the vector of remaining file sizes of all M flows at time t, $b_t^j \in \mathcal{B}^j = [0, B^j]$ for all $j \in \mathcal{M}$. B^j is the total remaining data size for flow j. $\mathcal{B}=(\mathcal{B}^1,\mathcal{B}^2,...,\mathcal{B}^M)$, is the set vector of remaining data.

The MU's *action* a_t at each decision epoch t is to determine whether to transmit data through wireless LAN (if wireless LAN is available), or cellular network, or just keep idle and how to allocate the network data rate to M flows. Therefore, the MU's action vector is denoted as in Eq. (2)

$$\boldsymbol{a}_t = (\boldsymbol{a}_{t,c}, \boldsymbol{a}_{t,w}) \tag{2}$$

where $\boldsymbol{a}_{t,c} = (a_{t,c}^1, a_{t,c}^2, ..., a_{t,c}^M)$ denotes the vector of cellular network allocated data rates, $a_{t,c}^j$ denotes the cellular data rate allocated to flow $j \in\mathcal{M}$, and $\boldsymbol{a}_{t,w} = (a_{t,w}^1, a_{t,w}^2, ..., a_{t,w}^M)$ denotes the vector of wireless LAN network allocated data rates, and $a_{t,w}^j$ denotes the wireless LAN rate allocated to flow $j \in\mathcal{M}$. Here the subscript c and w stand for cellular network and wireless LAN, respectively. Please note that $a_{t,w}^1$, $a_{t,w}^2$, ..., $a_{t,w}^M$ all can be 0 if the MU is not in the coverage area of wireless LAN AP. Even though it is technically possible that wireless LAN and cellular network can be used at the same time, we assume that the MU can not use wireless LAN and cellular network at the same time. We make this assumption for two reasons: (i) If we restrict the MU to use only one network interface at the same time slot, then the MU's device may be used for longer time for the same amount of left battery. (ii) Nowadays smartphones, such as an iPhone, can only use one network interface at the same time. We can easily implement our algorithms on a MU's device without changing the hardware or OS of the smartphone if we have this assumption. At time t, MU may choose to use wireless LAN (if wireless LAN is available) or cellular network, or not to use any network. If the MU chooses wireless LAN at t, the wireless LAN network allocated data rate to flow j, $a_{t,w}^j$, is greater than 0, and the MU does not use cellular network in this case, then $a_{t,c}^j = 0$. On the other hand, if the MU chooses cellular network at t, the cellular network allocated data rate to flow j, $a_{t,c}^j$, is greater than 0, and the MU does not use wireless LAN in this case, then $a_{t,w}^j = 0$. $a_{t,n}^j$, $n \in \{c, w\}$ should not be greater than the remaining file size b_t^j for flow $j \in\mathcal{M}$.

The sum data rate of all the flows of cellular network and wireless LAN are denoted as $a_{t,c} = \sum_{j\in\mathcal{M}} a_{t,c}^j$ and $a_{t,w} = \sum_{j\in\mathcal{M}} a_{t,w}^j$, respectively. $a_{t,c}$ and $a_{t,w}$ should satisfy the following conditions.

$$a_{t,c} \leq \gamma_c^l \tag{3}$$

$$a_{t,w} \leq \gamma_w^l \tag{4}$$

γ_c^l and γ_w^l are the maximum data rates of cellular network and wireless LAN, respectively, at each location l.

At each epoch t, three factors affect the MU's decision.

1) *monetary cost*: it is the payment from the MU to the network service provider. We assume that MNO adopts time-dependent pricing, which is denoted as p_c^t at time t. Please note that this is different from previous works [15][16] that use usage-based pricing. It is assumed that wireless LAN is free of charge. We define the monetary cost $c_t(\boldsymbol{s}_t, \boldsymbol{a}_t)$ as in Eq. (5)

$$c_t(\boldsymbol{s}_t, \boldsymbol{a}_t) = p_c^t \sum_{j\in\mathcal{M}} \min\{b_t^j, a_{t,c}^j\} \tag{5}$$

2) *energy consumption*: it is the energy consumed when transmitting data through wireless LAN or cellular network. We denote the MU's awareness of energy as

TABLE I
NOTATIONS SUMMARY.

Notation	Description
$\mathcal{M}$	$\mathcal{M}$={1, ..., M}, MU's M flows set.
$\boldsymbol{T}$	$\boldsymbol{T}$=($T^1, T^2, ..., T^M$), MU's deadline vector.
t	$t \in \mathcal{T}^M$, the specific decision epoch of MU.
$\mathcal{L}$	$\mathcal{L}$={1, ..., L}, the location set of MU.
$\mathcal{B}^j$	$\mathcal{B}^j \subseteq [0, ..., b_t^j]$, the total size of MU's j flow. $j \in \mathcal{M}$.
$\boldsymbol{b}_t$	$\boldsymbol{b}_t$=($b_t^1, b_t^2, ..., b_t^M$), vector of remaining file size.
$\boldsymbol{s}_t$	$\boldsymbol{s}_t = (l_t, \boldsymbol{b}_t)$, state of MU.
l_t	$l_t \in \mathcal{L}$, MU's location index at time t.
$a_{t,c}^j$	cellular data rate allocated to flow $j \in \mathcal{M}$ at time t
$a_{t,w}^j$	wireless LAN data rate allocated to flow $j \in \mathcal{M}$ at time t
$\boldsymbol{a}_{t,c}$	$\boldsymbol{a}_{t,c} = \{a_{t,c}^1, a_{t,c}^2, ..., a_{t,c}^M\}$
$\boldsymbol{a}_{t,w}$	$\boldsymbol{a}_{t,w} = \{a_{t,w}^1, a_{t,w}^2, ..., a_{t,w}^M\}$
$\boldsymbol{a}_t$	$\boldsymbol{a}_t = (\boldsymbol{a}_{t,c}, \boldsymbol{a}_{t,w})$
$a_{t,c}$	$a_{t,c} = \sum_{j \in \mathcal{M}} a_{t,c}^j$
$a_{t,w}$	$a_{t,w} = \sum_{j \in \mathcal{M}} a_{t,w}^j$
γ_c^l	cellular throughput in bps at location l.
γ_w^l	wireless LAN throughput in bps at location l.
ε_c^l	energy consumption rate of celllar network in joule/bits at location l.
ε_w^l	energy consumption rate of wireless LAN in joule/bits at location l.
θ_t	energy preference of MU at t.
p_c^t	MNO's time-depend price for mobile data at time t.
$\hat{c}_{T^M+1}(\cdot)$	MU's penalty function for remaining data at $T^M + 1$.
$\xi_t(\boldsymbol{s}_t, \boldsymbol{a}_t)$	MU's energy consumption at t.
ϕ_t	$\mathcal{L} \times \mathcal{K} \to \mathcal{A}$, transmission decision at t.
π	$\pi = \{\phi_t(l, b),\ \forall\ t \in \mathcal{T}^M, l \in \mathcal{L}, b \in \mathcal{B}\}$, MU's policy.

in Eq. (6)

$$\begin{aligned}\xi_t(\boldsymbol{s}_t, \boldsymbol{a}_t) =&\theta_t(\varepsilon_c^l \sum_{j \in \mathcal{M}} \min\{b_t^j, a_{t,c}^j\} \\ &+ \varepsilon_w^l \sum_{j \in \mathcal{M}} \min\{b_t^j, a_{t,w}^j\})\end{aligned} \tag{6}$$

where ε_c^l is the energy consumption rate of the cellular network in joule/bits at location l and ε_w^l is the energy consumption rate of the wireless LAN in joule/bits at location l. It has been shown in [20] that both ε_c^l and ε_w^l decrease with throughput, which means that low transmission speed consumes more energy when transmitting the same amount of data. According to [21], the energy consumptions for downlink and uplink are different. Therefore, the energy consumption parameters ε_c^l and ε_w^l should be differentiated for downlink or uplink, respectively. In this paper, we do not differentiate the parameters for downlink or uplink because only the downlink case is considered. Nevertheless, our proposed algorithms are also applicable for uplink scenarios with energy consumption parameters for uplink. θ_t is the MU's preference for energy consumption at time t. θ_t is the weight on energy consumption set by the MU. Small θ_t means that the MU cares less on energy consumption. For example, if the MU can soon charge his smartphone, he may set θ_t to a small value, or if the MU is in an urgent status and could not charge within a short time, he may set a large value for θ_t. $\theta_t = 0$ means that the MU does not consider energy consumption at all in the process of data offloading

3) *penalty*: if the data transmission does not finish in deadline T^j, $j \in \mathcal{M}$, the penalty for the MU is defined as Eq. (7).

$$\hat{c}_{T^j+1}(\boldsymbol{s}_{T^j+1}) = \hat{c}_{T^j+1}(l_{T^j+1}, \boldsymbol{b}_{T^j+1}) = g(\boldsymbol{b}_{T^j+1}) \tag{7}$$

where $g(\cdot)$ is a non-negative non-decreasing function. $T^j + 1$ means that the penalty is calculated after deadline T^j.

The probabilities associated with different state changes are called transition probabilities. We denote *transition probability* as in Eq. (8)

$$\Pr(\boldsymbol{s}_{t+1} | \boldsymbol{s}_t, \boldsymbol{a}_t) \tag{8}$$

Eq. (8) shows the probability of state $\boldsymbol{s}_{t+1}$ if action $\boldsymbol{s}_t$ is chosen at state $\boldsymbol{s}_t$. It is assumed that the remaining size is independent of location change, therefore

$$\begin{aligned}\Pr(\boldsymbol{s}_{t+1} | \boldsymbol{s}_t, \boldsymbol{a}_t) &= \Pr((l_{t+1}, \boldsymbol{b}_{t+1}) | (l_t, \boldsymbol{b}_t), \boldsymbol{a}_t) \\ &= p_{l_{t+1}, l_t} \Pr(\boldsymbol{b}_{t+1} | (l_t, \boldsymbol{b}_t), \boldsymbol{a}_t)\end{aligned} \tag{9}$$

where

$$\begin{aligned}&\Pr(\boldsymbol{b}_{t+1} | (l_t, \boldsymbol{b}_t), \boldsymbol{a}_t) \\ &= \begin{cases} 1 & \text{if } \boldsymbol{b}_{t+1} = [\boldsymbol{b}_t - \boldsymbol{a}_{t,c} - \boldsymbol{a}_{t,w}]^+ \\ 0 & \text{otherwise} \end{cases}\end{aligned} \tag{10}$$

$[\boldsymbol{x}]^+$ is equal to $\max\{\boldsymbol{x}, 0\}$. The MU's probability from l to l_{t+1} is denoted as p_{l_{t+1}, l_t}, which is assumed as known (see Assumption 1).

Assumption 1: The MU's mobile probability to move from the current location to the next location is known in advance. The MU's mobility pattern can be derived from the MU's historical data, which has been widely studied in the literature, such as [13].

The MU's *policy* is defined as in Eq. (11)

$$\pi = \left\{\phi_t(l_t, \boldsymbol{b}_t),\ \forall\ t \in \mathcal{T}, l \in \mathcal{L}, \boldsymbol{b}_t \in \mathcal{B}\right\} \tag{11}$$

where $\phi_t(l_t, \boldsymbol{b}_t)$ is a function mapping from state $\boldsymbol{s}_t = (l_t, \boldsymbol{b}_t)$ to a decision action at t. The set of π is denoted as Π. If policy π is adopted, the state is denoted as $\boldsymbol{s}_t^\pi$.

The objective of the MU is to the minimize the expected total cost (include the monetary cost and the energy consumption) from $t = 1$ to $t = T^M$ and penalty at $t = T^M + 1$ with an a optimal π^* (see Eq. (12))

$$\min_{\pi \in \Pi} E_{s_1}^\pi \left[\sum_{t=1}^{T^M} r_t(\boldsymbol{s}_t^\pi, \boldsymbol{a}_t) + \sum_{j \in \mathcal{M}} \hat{c}_{T^j+1}(\boldsymbol{s}_{T^j+1}^\pi) \right] \tag{12}$$

where $r_t(\boldsymbol{s}_t, \boldsymbol{a}_t)$ is the sum of the monetary cost and the energy consumption as in Eq. (13)

$$r_t(\boldsymbol{s}_t, \boldsymbol{a}_t) = c_t(\boldsymbol{s}_t, \boldsymbol{a}_t) + \xi_t(\boldsymbol{s}_t, \boldsymbol{a}_t) \tag{13}$$

Please note that the optimal action at each t does not lead to the optimal solution for the problem in Eq. (12). At each time t, not only the cost for the current time t should be considered, but also the future expected cost.

III. Dynamic Programming Based Algorithm

The MU's network selection and rate allocation problem has been formulated as a standard finite-horizon discrete-time Markov decision process (MDP). The target of the MU is to choose a set of actions to minimize his cost as shown in Eq. (12). In this section, we propose a dynamic programming based algorithm to solve the problem in Eq. (12).

For a MDP problem, it is important to identify the *optimality equation* (or *Bellman equation*) [22]. Denote $\mathcal{V}_t(\boldsymbol{s}_t)$ as the minimal expected total cost of the MU from t to $T^M + 1$ at state $\boldsymbol{s}_t$. The Bellman equation is defined as in Eq. (14).

$$\mathcal{V}_t(\boldsymbol{s}_t) = \min_{\boldsymbol{a}_t} \left\{ Q_t(\boldsymbol{s}_t, \boldsymbol{a}_t) \right\} \tag{14}$$

where for $l \in \mathcal{L}$, $\boldsymbol{b} \in \mathcal{B}$, we have

$$\begin{aligned}
Q_t(\boldsymbol{s}_t, \boldsymbol{a}_t) &= r_t(\boldsymbol{s}_t, \boldsymbol{a}_t) + \sum_{l_{t+1}\in\mathcal{L}} \sum_{\boldsymbol{b}_{t+1}\in\mathcal{B}} \Pr(\boldsymbol{s}_{t+1}|\boldsymbol{s}_t, \boldsymbol{a}_t)\mathcal{V}_{t+1}(\boldsymbol{s}_{t+1}) \\
&= \underbrace{c_t(\boldsymbol{s}_t, \boldsymbol{a}_t) + \xi_t(\boldsymbol{s}_t, \boldsymbol{a}_t)}_{\text{cost for the current } t} \\
&\quad + \underbrace{\sum_{l_{t+1}\in\mathcal{L}} \sum_{\boldsymbol{b}_{t+1}\in\mathcal{B}} \Pr((l_{t+1}, \boldsymbol{b}_{t+1})|(l, \boldsymbol{b}), \boldsymbol{a}_t)\mathcal{V}_{t+1}(l_{t+1}, \boldsymbol{b}_{t+1})}_{\text{expected future cost start from } t+1} \\
&= p_c \sum_{j\in\mathcal{M}} \min\{b_t^j, a_{t,c}^j\} \\
&\quad + \theta_t(\varepsilon_c^l \sum_{j\in\mathcal{M}} \min\{b_t^j, a_{t,c}^j\} + \varepsilon_w^l \sum_{j\in\mathcal{M}} \min\{b_t^j, a_{t,w}^j\}) \\
&\quad + \sum_{l_{t+1}\in\mathcal{L}} p_{l_{t+1},l_t} \mathcal{V}_{t+1}(l_{t+1}, [\boldsymbol{b}_t - \boldsymbol{a}_{t,c} - \boldsymbol{a}_{t,w}]^+)
\end{aligned} \tag{15}$$

Based on the Bellman equation Eq. (14), we propose Algorithm 1. In the optimal policy calculation phase, the optimal policy is calculated by backward induction from epoch T^M to 1, where $\sigma > 0$ is the granularity of the total data size $|\mathcal{B}|$. Then, the MU's offloading data policy is decided in each slot in the offloading data transmission phase. It is obvious that the time complexity of Algorithm 1 is $O(|\mathcal{T}^M||\mathcal{L}||\mathcal{B}|/\sigma)$.

Theorem 1: The policy $\pi^* = \left\{\phi_t^*(l_t, \boldsymbol{b}_t),\ \forall\ t \in \mathcal{T}, l \in \mathcal{L}, \boldsymbol{b} \in \mathcal{B}\right\}$ generated in Algorithm 1 is the problem (12)'s optimal solution.

Proof: It is obvious according to the principle of optimality defined in [22].

Q.E.D

Algorithm 1: Dynamic Programming Based Algorithm

```
Optimal Policy Calculation Phase
Set V_{T^M+1}(l, b), ∀ l ∈ L, k ∈ B by Eq. (7)
Set t:=T^M
while t ≥ 1 :
    for l_t ∈ L :
        Set b_t :=0
        for b_t ∈ B :
            Calculate Q_t(s_t, a_t) using Eq. (14)
            Set φ*_t(l_t, b_t) := arg min_{a_t} {Q_t(s_t, a_t)}
            Set V_t(l, b) := Q_t(s_t, φ*_t(l_t, b_t))
            Set b_t:=b_t + σ
        end for
    end for
    Set t:=t − 1
end while
The optimal policy π* is generated for the following offloading data transmission phase

Offloading Data Transmission Phase
Set t := 1, b := B
while t ≤ T^M and b_t > 0 :
    l_t is determined from GPS
    Set action a_t := φ*_t(l_t, b_t) according to π* (the optimal policy)
        Set b_t :=[b_t − a_{t,c} − a_{t,w}]^+
    end if
    Set t := t + 1
end while
```

IV. Performance Evaluation

In this section, the performances of our proposed DP based offloading algorithm under time-dependent pricing, which is denoted as *proposed DP TDP*, is evaluated by comparing them with DP based offloading algorithm and heuristic offloading algorithm under usage-based pricing in [16]. The two algorithms in [16] are denoted as *DP UBP* and *heuristic UBP*, respectively. Both the *DP UBP* and *heuristic UBP* algorithms adopted usage-based pricing for cellular network which could not solve the congestion problem at a given time. The *DP UBP* algorithm is optimal but with high time complexity, while *heuristic UBP* algorithm can get approximate solution with very low time complexity. Our proposed *proposed DP TDP* algorithm gives network users time-dependent incentives when the congestion happens. We developed a simulator by Python 2.7, which can be downloaded from URL link (https://github.com/aqian2006/OffloadingTDP).

TABLE II
Energy vs. Throughput.

Throughput (Mbps)	Energy (joule/Mb)
11.257	0.7107
16.529	0.484
21.433	0.3733

A four by four grid is used in simulation. Therefore, L is 16. Wireless LAN APs are randomly deployed in L locations. The cellular usage price is assumed as 1.5 yen/Mbyte. The average Wireless LAN throughput $\gamma_{t,w}^l$ is assumed as 15 Mbps[1], while average cellular network throughput $\gamma_{t,c}^l$ is 10 Mbps[2]. We generate wireless LAN throughput for each AP from a truncated normal distribution, and the mean and standard deviation are assumed as 15Mbps and 6Mbps respectively. The wireless LAN throughput is in the range [9Mbps, 21Mbps]. Similarly, we generate cellular throughput from a truncated normal distribution, and the mean and

[1] We tested repeatedly with an iPhone 5s on the public wireless LAN APs of one of the biggest Japanese wireless carriers. The average throughput was 15 Mbps.

[2] We also tested with an iPhone 5s on one of the biggest Japanese wireless carriers' cellular network. We use the value 10 Mbps for average cellular throughput.

standard deviation are assumed as 10Mbps and 5Mbps respectively. The cellular network throughput is in range [5Mbps, 15Mbps]. σ in Algorithm 1 is assumed as 1 Mbits. For MNO's time-dependent price p_c^t, it is generated from uniform distribution [1, 2] (yen per Mbyte) at each time t, while the usage based price for *DP UBP* and *heuristic UBP* is assumed as the mean of the uniform distribution 1.5 yen per Mbyte. Time for each epoch is 1 seconds. The penalty function is assumed as $g(\boldsymbol{b}_t)$=2 $\sum_{j\in\mathcal{M}} b_t^j$. Please refer to Table III for the parameters used in the simulation.

Because the energy consumption rate is a decreasing

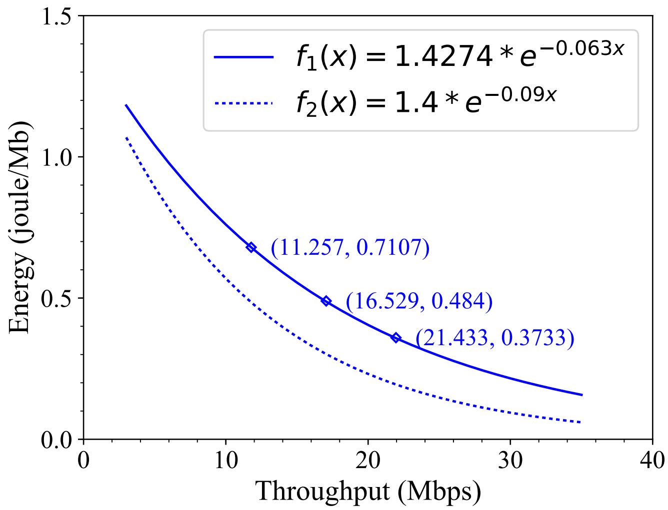

Fig. 1. Energy consumption (joule/Mb) vs. Throughput (Mbps).

function of throughput, we have the sample data from [23] (see Table II). We then fit the sample data by a exponential function $f_1(x) = 1.4274 * \mathrm{e}^{-0.063x}$ as shown in Fig. 1. We also made a new energy-throughput function as $f_2(x) = 1.4 * \mathrm{e}^{-0.09x}$, which is just lower than $f_1(x)$. We basically use $f_1(x)$ if we do not explicitly point out. Please note that the energy consumption rate of cellular and wireless LAN may be different for the same throughput, but we assume they are the same and use the same fitting function as in Fig. 1.

Fig.2 shows the comparison of monetary cost among *Proposed DP TDP*, *DP UBP*, and *Heuristic UBP* algorithms with different number of APs. It can be seen that the monetary cost of *Proposed DP TDP UBP* is comparable to that of *DP UBP* algorithm, and the *Heuristic UBP* is highest. With a large number of wireless LAN APs deployed, the chance of using cheap wireless LAN increases. Therefore, the MU can reduce his monetary cost by using cheap wireless LAN. Therefore, all three algorithms' monetary costs decreases with the number of APs.

Fig.3 shows how the MU's energy consumption changes with the number of deployed APs under the two energy-throughput functions $f_1(x)$ and $f_2(x)$. The energy consumption of *DP UBP* algorithm is similar to that of *Proposed DP TDP UBP* with either $f_1(x)$ or $f_2(x)$. And the energy consumption of *Heuristic UBP* is much higher than

TABLE III
PARAMETERS IN THE SIMULATION.

Parameters	Value
L	16
$\boldsymbol{B}$	$\boldsymbol{B}$ = (500, 550, 600, 650) Mbits
$\mathcal{T}$	$\mathcal{T}$ = (140, 280, 420, 560)
Number of wireless LAN APs	8
σ	1 Mbits
time slot	1 seconds
average of γ_c^l	10 Mbps
standard deviation of γ_c^l	5 Mpbs
average of γ_w^l	15 Mbps
standard deviation of γ_w^l	6 Mpbs
$p_{l,l}$	0.6
p_{l_{t+1},l_t}	(1-0.6)/#neigbour locations
p_c^t	from uniform distribution [1, 2] (yen/Mbyte)
$g(\boldsymbol{b}_t)$	$g(\boldsymbol{b}_t)$=2 $\sum_{j\in\mathcal{M}} b_t^j$

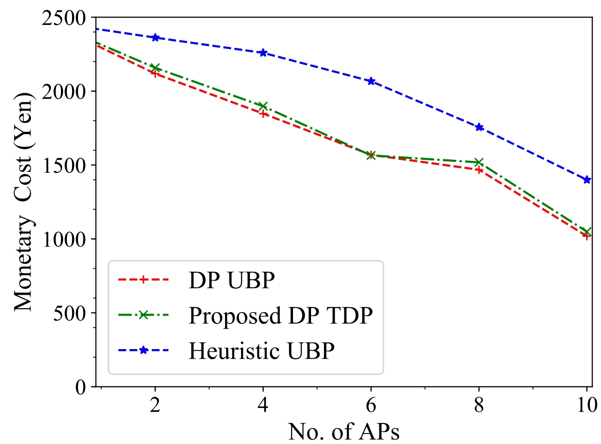

Fig. 2. Monetary cost (yen) vs. No. of APs.

other two algorithms with both $f_1(x)$ and $f_2(x)$. It shows that the energy consumptions of all three algorithms just slightly decrease with the number of APs. The reason is that the energy consumption depends on the throughput. The larger the throughput, the lower is the energy consumption. With large number of wireless LAN APs, the MU has more chance to use wireless LAN with high throughput since the average throughput of a wireless LAN is assumed as higher than that of cellular network (see Table III).

V. Conclusion

In this paper, we studied the MU's policy to minimize his monetary cost and energy consumption under time-dependent pricing when he choose whether to offloading his traffic from cellular network to complementary wireless LAN. We formulate MU's wireless LAN offloading problem as a finite-horizon discrete-time Markov decision process and establish an optimal policy by a dynamic programming based algorithm. The simulation results showed that the dynamic programming based offloading algorithm is effective under both time-dependent pricing and usage based pricing.

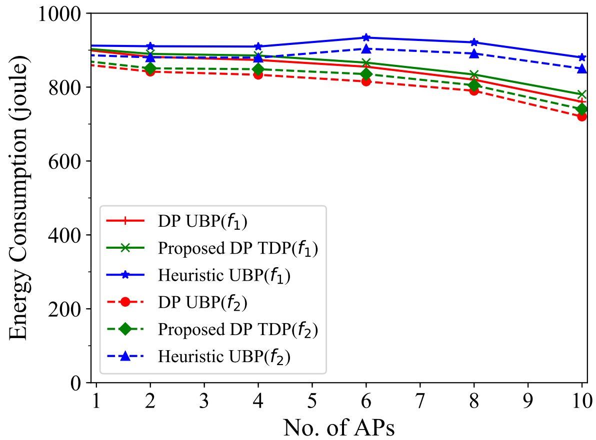

Fig. 3. Energy consumption (joule) vs. No. of APs with different energy-throughput functions f_1 and f_2.

In the future, we are going to analyze the interaction among multiple MUs by considering multiple MUs which move and select the wireless access method independently. It is also interesting to analyze the optimum strategy of MNO against the optimum strategies of MUs by adopting a Stackelberg game based approach, and analyze the interaction between MNO and MUs.

Acknowledgements

This work is part of the Grant-in-Aid for Young Scientists (B) research programme with grant number 16K18109, which is financed by Japan Society for the Promotion of Science (JSPS).

References

[1] Cisco Systems, "Cisco visual networking index: Global mobile data traffic forecast update, 2016-2021," March 2017.

[2] Q. C. Li, H. Niu, A. T. Papathanassiou, and G. Wu, "5G network capacity: Key elements and technologies," *IEEE Veh. Technol. Mag.*, vol. 9, no. 1, pp. 71–78, March 2014.

[3] D. Goldman, "Comcast scraps broadband cap, moves to usage-based billing," *CNN Money*, May 2012.

[4] A. Odlyzko, B. S. Arnaud, E. Stallman, and M. Weinberg, "Know your limits: Considering the role of data caps and usage based billing in internet access service," *Public Knowledge White Paper*, April 23 2012.

[5] C. Zhang, B. Gu, K. Yamori, S. Xu, and Y. Tanaka, "Duopoly competition in time-dependent pricing for improving revenue of network service providers," *IEICE Trans. Commun.*, vol. E96-B, no. 12, pp. 2964–2975, Dec. 2013.

[6] ——, "Oligopoly competition in time-dependent pricing for improving revenue of network service providers with complete and incomplete information," *IEICE Trans. Commun.*, vol. E98-B, no. 1, pp. 30–32, Jan. 2015.

[7] Cisco Systems, "The future of hotspots: Making Wi-Fi as secure and easy to use as cellular," *White Paper*, 2011.

[8] Alcatel and British Telecommunications, "Wi-Fi roaming building on andsf and hotspot2.0," *White Paper*, 2012.

[9] L. Gao, G. Iosifidis, J. Huang, L. Tassiulas, and D. Li, "Bargaining-based mobile data offloading," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1114–1125, June 2014.

[10] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "A double-auction mechanism for mobile data-offloading markets," *IEEE/ACM Trans. Netw.*, vol. 22, no. 4, pp. 1271–1284, Aug. 2014.

[11] A. Balasubramanian, R. Mahajan, and A. Venkataramani, "Augmenting mobile 3g using Wi-Fi," in *Proc. 8th international conference on Mobile systems, applications, and services (MobiSys 2010)*, June 2010, pp. 209–222.

[12] K. Lee, J. Lee, Y. Yi, I. Rhee, and S. Chong, "Mobile data offloading: How much can Wi-Fi deliver?" *IEEE/ACM Trans. Netw.*, vol. 21, no. 2, pp. 536–550, April 2013.

[13] Y. Im, C. Joe-Wong, S. Ha, S. Sen, T. T. Kwon, and M. Chiang, "AMUSE: Empowering users for cost-aware offloading with throughput-delay tradeoffs," in *Proc. IEEE Conference on Computer Communications (INFOCOM 2013)*, April 2013, pp. 435–439.

[14] M. H. Cheung and J. Huang, "DAWN: Delay-aware Wi-Fi offloading and network selection," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 6, pp. 1214 – 1223, June 2015.

[15] C. Zhang, B. Gu, Z. Liu, K. Yamori, and Y. Tanaka, "A reinforcement learning approach for cost- and energy-aware mobile data offloading," *Proc. 16th Asia-Pacific Network Operations and Management Symposium (APNOMS 2016), Kanazawa, Japan*, pp. 1–6, Oct. 2016.

[16] ——, "Cost- and energy-aware multi-flow mobile data offloading using markov decision process," *IEICE Trans. Commun.*, vol. E101-B, no. 3, Mar. 2018.

[17] Z. Liu, C. Zhang, M. Dong, B. Gu, Y. Ji, and Y. Tanaka, "Markov-decision-process-assisted consumer scheduling in a networked smart grid," *IEEE Access*, vol. 5, pp. 2448–2458, March 2017.

[18] Z. Liu, G. Cheung, and Y. Ji, "Distributed markov decision process in cooperative peer-to-peer repair for WWAN video broadcast," *Proc. 2011 IEEE International Conference on Multimedia and Expo (ICME 2011), Barcelona, Spain*, pp. 1–6, July 2011.

[19] ——, "Optimizing distributed source coding for interactive multiview video streaming over lossy networks," *IEEE Trans. Circuits and Systems for Video Technology*, vol. 23, no. 10, pp. 1781–1794, Oct. 2013.

[20] A. Y. Ding, B. Han, Y. Xiao, P. Hui, A. Srinivasank, M. Kojo, and S. Tarkoma, "Enabling energy-aware collaborative mobile data offloading for smartphones," in *Proc. 10th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON 2013)*, June 2013, pp. 487–495.

[21] N. Balasubramanian, A. Balasubramanian, and A. Venkataramani, "Energy consumption in mobile phones: a measurement study and implications for network applications," *Proc. 9th ACM SIGCOMM Conference on Internet Measurement (IMC 2009), Chicago, Illinois, USA*, pp. 280–293, July 2009.

[22] R. Bellman, *Dynamic Programming*, Princeton University Press, 1957.

[23] A. Murabito, "A comparison of efficiency, throughput, and energy requirements of wireless access points," *Report of InterOperability Laboratory, University of New Hampshire*, March 2009. [Online]. Available: http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white_paper_c11-520862.pdf