Signal Aware Multi-Path TCP

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***Abstract*—Mobile devices have been augmented by Multi-path TCP (MPTCP), enabling them to exploit the path diversity. Signal aware MPTCP (SA-MPTCP) takes the signal quality, playing a significant role in energy waste, into account to enhance MPTCP energy consumption. The problem is formulated as a decision making problem under uncertainty, endeavoring to optimize energy efficiency by selecting the best policy. The simulation results for bulk data transfer show that 42% and 17% energy have been saved in uploading and downloading compared to the base MPTCP, respectively.**

I. INTRODUCTION

Multi-path Transmission Control Protocol (MPTCP) is one of the promising solutions introduced recently to boost TCP performance by leveraging path diversity [1], [2]. However, conventional MPTCP suffers from energy inefficiency in mobile phones. In particular, when a mobile phone experiences poor signal strength, not merely is an adverse effect on energy consumption inevitable, but also user experience degradation, like delays is unavoidable. In this paper we address how MPTCP should manage the interfaces, when facing low signal strength.

The comparison of TCP over LTE and WiFi with MPTCP in terms of energy efficiency has been discussed in [3] by modeling, measuring and simulations. The authors proposed eMPTCP, which manages subflows expected energy efficiency based on available throughput. In fact, eMPTCP is the most similar work to us; nonetheless, authors only considered the downloading case. Moreover, to estimate the available throughput, they sampled downloaded bytes, which introduces the overhead to a network. In addition, eMPTCP tries to predict the changes by Holt-Winters exponential smoothing algorithm, which is not as efficient as observing the signal quality.

In order to utilize path diversity of MPTCP while optimizing energy efficiency, it strives to find answers for realizations of the following requirements. Firstly, the paper examine how a mobile device could optimize energy consumption whilst experiencing low level of signal strength. Secondly, we should identify the difference between uploading and downloading cases wherein MPTCP is more energy efficient than LTE or WiFi. The objective of this paper is to address the energy efficiency challenges, and to propose Signal Aware MPTCP (SA-MPTCP) solution to augment battery life span.

II. PROPOSED MODEL

The proposed model aims to optimize the transmission energy consumption as a utility function based on signal strength. In the following, we describe the underlying network model and assumptions for the problem at hand.

TABLE I: Packet transfer coefficients [3]

		LTE	WiFi
Download	α^d	10.04	4.64
	β_d	-0.89	-0.81
Upload	α^u	13.34	3.61
	β_u	-0.83	-0.66

A. Energy model

The energy model introduced in [3], is the only proposed model that analyses energy consumption for WiFi, cellular networks and MPTCP. Considering this fact, we turn the same concept in describing network model to account. We assume that the mobile device is equipped with two interfaces to transmit data. Let's denote each interface by i, and for simplicity, let's assume $i = w$ and $i = l$ represent the WiFi and LTE interface, respectively. Available uplink and downlink throughput for interface i is denoted by $B_{u,i}$ and $B_{d,i}$, respectively. The energy consumption in uploading data for interface i which is based on Joule (J) per byte (B), is defined by E_i^u, which is given as

$$E_i^u = (\alpha_i^u \times B_{u,i}^{\beta_i^u}) \quad (\mu J/B), \tag{1}$$

where α_i^u and β_i^u are upload packet transfer coefficients of interface i, which are obtained through regression model in [3]. Similarly, for download case the energy consumption for data transmission is given as

$$E_i^d = (\alpha_i^d \times B_{d,i}^{\beta_i^d}) \quad (\mu J/B), \tag{2}$$

where α_i^d and β_i^d are download packet transfer coefficient in interface i. Hence, total energy consumption of interface i in downlink and uplink can be formulated as $\mathcal{E}_i$ which is given as

$$\mathcal{E}_i = E_i^u \times U_i + E_i^d \times D_i \quad (J), \tag{3}$$

where U_i and D_i are size of uploading and downloading files in bytes for interface i, respectively. In [3], it has been shown that due to the concurrent use of interfaces (WiFi and LTE) in MPTCP, the energy consumption is less than total energy consumption of WiFi and LTE, when they are not used jointly. MPTCP energy consumption denoted as $\mathcal{E}_m$ can be written as

$$\mathcal{E}_m = (\mathcal{E}_w + \mathcal{E}_l) - \theta, \tag{4}$$

where θ represents the shared component energy. In MPTCP about 13% ∼16% energy would be consumed simultaneously [3]. Thus, in this paper we considered θ as a fixed number 14.5%. Packet transfer coefficients for different platforms based on uplink and downlink are shown on table I.

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B. Signal quality estimation

Hidden Markov model (HMM) is employed to capture the time-varying signal quality states. The rationale behind applying HMM relies on its ability to capture diverse statistical properties. HMM represents the probability distribution functions over observation sequences. The HMM signal quality is introduced by the following: a set of hidden states of the signal quality for interface i, $\mathcal{Q}_i = \{q_i^1, q_i^2, ..., q_i^n\}$, where q_1^i is minimum and q_i^n is maximum signal quality for interface i, respectively. It is worth adding here that each signal quality corresponds to specific uplink and downlink throughputs. Signal quality states transition probability matrix for interface i, $P^{q_i} = [p^{q_i}(q_i^k|q_i^j), q_i^1 \leq q_i^j, q_i^k \leq q_i^n]$. An observation set for interface i, $\mathcal{O}^{q_i} = \{\mathsf{snr}_i^1, \mathsf{snr}_i^2, ..., \mathsf{snr}_i^n\}$. The signal quality observation probability matrix for interface i is defined as, $\phi^{q_i} = [\varphi_i^k(\mathsf{snr}_i^j) = p_i(\mathsf{snr}_i^j|q_i^k), q_i^1 \leq q_i^j \leq q_i^n, \mathsf{snr}_i^j \in O^{q_i}]$; moreover, the initial state probability vector for interface i is given as, $\varpi^{q_i} = [p_i(q_i^1 = q_i^k), q_i^1 \leq q_i^k \leq q_i^n]$, where n is the number of states.

III. POMDP PROBLEM FORMULATION

Due to the fact that the exact system state is not clear for a mobile device, the problem is formulated as POMDP, which is introduced in the following.

A. Definitions

Mobile device decision making is based on the assumption that the system dynamics are determined by an MDP, but the mobile phone cannot directly observe the underlying states. In reality a mobile phone could read the RSSI easily; however, the exact uplink and downlink throughput is not clear. A POMDP consists of the following elements: decision epochs, states, actions, observations, observations emission probabilities, states transition probabilities and rewards. The mobile device can make a decision about tuning one or both interfaces to active mode in each time epoch, where $\mathcal{T} = \{1, 2, .., y\}$ represent a set of decision epoch. Let $\mathcal{S} = \mathcal{Q}^1 \times \mathcal{Q}^2 = \{(q_1^1, q_2^1), (q_1^1, q_2^2), ..., (q_1^n, q_2^n)\} = \{s_1, s_2, ..., s_N\}$ represent the total state space, where $\mathcal{N} = |\mathcal{Q}_1| \times |\mathcal{Q}_2|$. Each state corresponds to specific WiFi and LTE signal quality, which include both uplink and downlink throughput. The action space $\mathcal{A} = \{(on, on), (on, off), (off, on)\}$ denotes a set of all possible actions for both interfaces. Without loss of generality, let's assume that the first interface is LTE and the second interface is WiFi; consequently, (on, off) means LTE interface is active and the WiFi interface is idle. Let $\mathcal{O} = \{(\mathsf{snr}_1^1, \mathsf{snr}_2^1), (\mathsf{snr}_1^1, \mathsf{snr}_2^2), ..., (\mathsf{snr}_1^n, \mathsf{snr}_2^n)$ represents the observations set. Each observation belongs to one of the observation ranges, and when a mobile reads the RSSI, it classifies it as one of the observations. Let $\zeta(s_t)$ give the signals quality state of the compound state s_t. Conditioned on current state s_t and action a_t at time, the observation emission probability is defied as

$$p(O|s_t, a_t) = p(\mathsf{snr}_i|\zeta(s_t), a_t)p(\mathsf{snr}_j|\zeta(s_t), a_t). \quad (5)$$

Consequently, the transition probability for the next state is $p(s_{t+1} = s_j|s_t = s_i, a_i)$. Since the state transition probability is the product of all state transition probabilities, we can rewrite it as

$$p(s_{t+1}|s_t, a_t) = p^{q_i}(\zeta(s_{t+1})|\zeta(s_t))p^{q_j}(\zeta(s_{t+1})|\zeta(s_t)) \times \sum_{\mathsf{snr}_i \in Q_i} \sum_{\mathsf{snr}_j \in Q_j} p(\mathsf{snr}_i|\zeta(s_t), a_t)p(\mathsf{snr}_j|\zeta(s_t), a_t). \quad (6)$$

At time-slot t, when the action a_t is taken, the system shifts to the state s_{t+1}; therefore, the system incurs costs expressed as $c(s_t, a_t, s_{t+1})$.

Before discussing decision rules and policies, we need to shed light on cost calculation. From (3), it is clear that the energy consumption has a tight relationship with the throughput and file size; however, since in our system model we could calculate the relative cost, and the throughput has a direct relation with file size, so we don't need to take an exact file size into account. The only thing which is essential for our calculation is the throughput. Moreover, since the transfered packet sizes have a one-to-one relation with throughput, we can easily estimate the reward only as a throughput function. For instance, the WiFi cost function could be written as $\mathcal{E}_w = E_w^u + E_w^d$. Moreover, for MPTCP, the amount of transfered packets would be the function of LTE and WiFi throughput. let's denote the summation of LTE and WiFi throughput as x; consequently, the energy consumption for MPTCP would be written as

$$\mathcal{E}_m = \frac{\mathcal{E}_w}{x} + (1 - \frac{\mathcal{E}_l}{x}) - \theta. \quad (7)$$

In this paper we only consider bulk data transfer. For bulk data transfer the maximum estimated throughput would be used, respectively. Let's define the expected immediate cost as

$$c(s_t, a_t) = \begin{cases} (\frac{\mathcal{E}_w}{x} + (1 - \frac{\mathcal{E}_l}{x})) - \theta & a = \text{(on,on)} \\ \mathcal{E}_l & a = \text{(on,off)}. \\ \mathcal{E}_w & a = \text{(off,on)} \end{cases} \quad (8)$$

Solving a POMDP problem requires solving a MDP problem; thus, we first formulate the problem as a fully observable MDP. Finding a policy or a decision rule is a preeminent problem in MDP. In our MDP problem, the objective is minimizing the expected long-term reward defined as

$$v^\pi(s) = \min_\pi \mathbb{E}^\pi\{\sum_{t=1}^{T} \gamma^t c_t^\pi(s_t, a_t^\pi(s_t))\}. \quad (9)$$

Despite providing the basis for finding the optimal solution properties by (9), solving (9) would be computationally expensive. Let us define a policy by π, which in MDP tries to map states to actions. The goal of MDP is to find a policy π that minimizes some cumulative function of the stochastic costs. Given a cost criterion, a policy has an expected value for every state, which specifies how much cost the mobile phone expects to receive from following the policy in that state. Policy π^* is an optimal policy if there is no policy π', and no state s such that value of π' be lower than the value of π. Letting value of being at state $t+1$ as $v_{t+1}(s_{t+1})$, then in each time step we look for an action which has the smallest cost. let's define it as

$$a_t^*(s_t) = \arg\min_{a_t \in A_t} (c_t(s_t, a_t) + \gamma v_{t+1}(s_{t+1}), \quad (10)$$

where γ is a discount factor ($0 \leq \gamma < 1$). Because this value shows the cost a mobile device incurs during one time period in the future, we may discount it by a factor γ. By employing optimal action $a_t^*(s_t)$, the optimal value equation is defined as

$$\begin{aligned} v_t(s_t) &= \arg\min_{a_t \in A_t} \big(c_t(s_t, a_t) + \gamma v_{t+1}\big(s_{t+1}(s_t, a_t)\big)\big) \\ &= c_t\big(s_t, a^*(s_t)\big) + \gamma v_{t+1}\big(s_{t+1}(s_t, a^*(s_t))\big). \end{aligned} \tag{11}$$

However, since the problem is stochastic and the new information would be available after a decision, we need to add uncertainty to (11)

$$\begin{aligned} v_t(s_t) = \min\Big\{ & c_t(s_t, a_t) \\ & + \gamma \sum_{s_{t+1} \in S} p(s_{t+1}|s_t, a_t) v_{t+1}(s_{t+1})) \Big\}, \end{aligned} \tag{12}$$

where (12) is the standard bellman equation [4]. Let's define π_t as a decision rule at time-slot t which describes an action a_t given s_t. Due to the fact that we seek the best action in each state minimizing over policies, the expected reward provided by a policy π from time t onward is defined as

$$F_t^\pi(s_t) = \mathbb{E}\Big[\sum_{t+1}^{T-1} c_{t+1}(s_{t+1}, a_{t+1}^*(s_{t+1})) + c_t(s_t)\Big| s_t\Big], \tag{13}$$

where $F_t^\pi(s_t)$ represents the expected total cost in state s at time t followed by a policy π from time t onward. To find (13) solution, we need to recursively calculate v_t^π. It has been shown that (13) is equal to $v_t^\pi(s_t)$ [5]. By letting $v_t(s_t)$ be a solution for (12), we would have

$$F_t^* = \min_{\pi \in \Pi} F_t^\pi(s_t) = v_t(s_t). \tag{14}$$

There are several strategies to solve the infinite horizon optimization problems: for instance, value iteration, or policy iteration algorithms [5]. In this paper we apply the value iteration, which is the most widely used algorithm to estimate the value function iteratively.

B. POMDP optimal algorithm

As has been discussed before, in POMDP the system state is not known directly; however, by employing observations and making the belief state, the optimal action could be obtained. Lets define history $\mathcal{H}_t$ as actions, observations and costs sequences at time-slot t as

$$\mathcal{H}_t = a_0, o_1, r_1, ..., a_{t-1}, o_t, r_t. \tag{15}$$

then the belief state $z(h)$ is the probability distribution over states conditioned on the history

$$z(h) = (P[s_t = s_1|\mathcal{H}_t = h], ..., P[s_t = s_n|\mathcal{H}_t = h]). \tag{16}$$

The belief states at time-slot t could be written as

$$z_t = p(s_t|o_t, a_t, o_{t-1}, a_{t-1}, ..., o_0, a_0, s_0). \tag{17}$$

Both history and belief state have the Markov property since the previous actions and observations satisfy the Markov model. The optimal action could be figured out by calculating the prior distribution $p(s_{t-1})$ over states. It is worth adding here that the belief state should be calculated recessively by Bayes' rule. By having the observation o_{t+1} in hand and action a_t, the belief distribution at time $t+1$ can be written as

$$\begin{aligned} z_{t+1} &= p(s_{t+1}|o_{t+1}, a_t, z_t) = \frac{p(o_{t+1}|s_{t+1}, a_t, z_t)p(s_{t+1}|a_t, z_t)}{p(o_{t+1}|a_t, z_t)} \\ &= \frac{p(o_{t+1}|s_{t+1}, a_t)\sum_{s\in S} p(s_{t+1}|a_t, z_t, s_t)p(s_t|a_t, z_t)}{p(o_{t+1}|a_t, z_t)} \\ &= \kappa p(o_{t+1}|s_{t+1}, a_t)\sum_{s\in S} p(s_{t+1}|a_t, z_t, s_t)p(s_t|a_t, z_t), \end{aligned} \tag{18}$$

where $\kappa = p(o_{t+1}|a_t, z_t)$ is the normalizing factor [6]. Since in POMDP, the optimal cost is based on belief state; therefore, in each state the optimal policy should be executed and the belief state would be the infinite expected sum of costs. Let $v^*(z)$ be the optimal value function in state z, then

$$v^*(z) = \min_{a\in A}[c(z, a) + \gamma \sum_{z_{t+1}\in Z} p(o|a, z)v^*(z_{t+1})]. \tag{19}$$

where $c(z, a)$ is defied as

$$c(z, a) = \sum_{s\in S} z(s)c(s, a). \tag{20}$$

It has been maintained that solving POMDP is similar to solving MDP by updating belief state [7]; thus, by applying dynamic programing on MDP, the optimal value over the belief state can be calculated. Nevertheless, the problem has large dimensions, and applying POMDP algorithms may not be feasible for a mobile device. Moreover, the mobile phone decision should be taken very quickly; therefore, we employed a heuristic algorithm to find the suboptimal policies.

The Maximum Likelihood Policy Heuristic (MLPH) [8] leverages the action corresponding to the MDP solution by employing the ML state as the solution to the POMDP. At time slot t the belief $z_t(s_t)$ could be written as

$$\pi_{ML(z_t)} = \pi^*_{MDP}(\arg\min_s(z_t(s_t))). \tag{21}$$

then the optimal policy for state s_t can be obtained by

$$\begin{aligned} &\pi^*_{MDP}(s_t) \in \arg\min_{a\in A} \\ &\Big\{c_t(s_t, a_t) + \gamma \sum_{s_{t+1}\in S} p(s_{t+1}|s_t, a_t)v_{t+1}(s_{t+1})\Big\}, \end{aligned} \tag{22}$$

where $v_{t+1}(s_{t+1})$ can be determined by Bellman equation (12) via value iteration algorithm. We used the MLPH within the SA-MPTCP algorithm to make it more agile. Where SA-MPTCP is presented in the following algorithm.

IV. Simulation

In this section, simulations are conducted on Network Simulator 3 (NS-3) to corroborate the efficiency of the proposed algorithm. Here, we assume twelve states based on received SNRs. In Fig. 1 energy consumption in bulk uplink transmission for three actions in each state is shown. MPTCP has been chosen only in the ninth state, which indicates that MPTCP is not energy efficient in most cases. The reason behind this optimal policy relies on the quality of LTE signal strength, where it is in the highest level, and WiFi, where it

ALGORITHM 1: ***SA-MPTCP Algorithm***

Input : *WiFi RSSI, LTE RSSI*
Output: *Best Policy for each state*
Begin
Read WiFi and LTE RSSI
Determine the optimal policy $\pi^*_{MDP}(s)$ *by MLPH*
if *action* $a =$ *(on,off)* **then**
  Enable MPTCP in backup mode
  Establish LTE sub-flow, postpone WiFi sub-flow establishment
else if *action* $a =$ *(off,on)* **then**
  Enable MPTCP in backup mode
  Establish WiFi sub-flow, postpone LTE sub-flow establishment
else
  Enable MPTCP in full mode
end
End

has poor quality. Generally the reason behind using WiFi as a more preferred policy, compared to MPTCP in uploading can be explained by the LTE uplink energy coefficient which is approximately four times bigger than WiFi. This is due to the fact that Macro Base Station (MBS) is deployed to provide broad coverage over an area, then the associated users to MBS is likely located farther compared to the user associated to WiFi. Considering this issue, MBS consumes more power to satisfy desired quality of level compared to WiFi.

In Fig. 2 energy consumption for downlink transmission with selected policy is shown. Despite the lower number of MPTCP selection in uploading bulk data, MPTCP has been chosen four times in downloading case. SA-MPTCP has chosen states 6 and 7, because LTE and WiFi signal quality have an average throughput value leading to make MPTCP the best choice; nevertheless, in the eighth state WiFi has a better energy efficiency, because the throughput is so high. Another interesting observation is that when LTE signal quality is poor, MPTCP is dominated by WiFi performance. Since both interfaces are exploited and there is nonzero probability that LTE channel suffers from poor signal strength; using WiFi in this circumstance not only improve energy efficiency, but also it enhances the throughput compared to MPTCP.

Fig. 3 represents the energy consumption and throughput behavior for bulk data transfer in different platforms. As can be seen, while MPTCP has the highest throughput, SA-MPTCP achieves the lowest energy consumption. Furthermore, SA-MPTCP is more efficient in terms of throughput compared to LTE and WiFi.

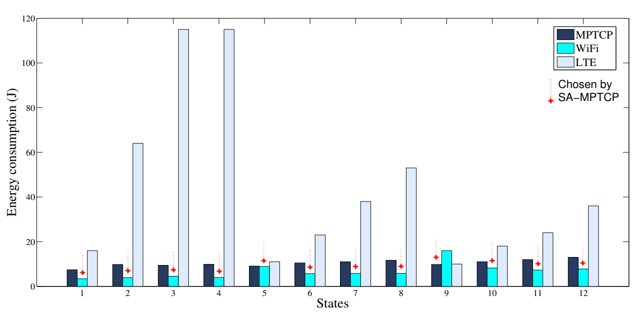


Fig. 1: Uplink energy consumption for bulk traffic

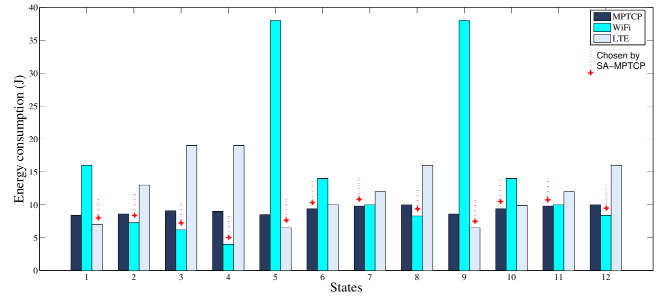
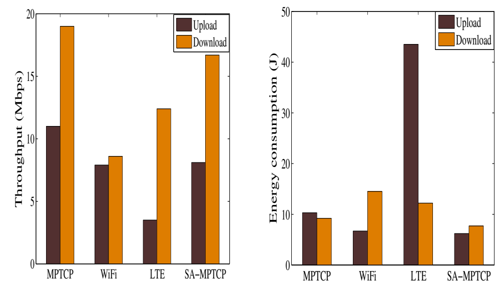


Fig. 2: Downlink energy consumption for bulk traffic



(a) Throughput (b) Energy

Fig. 3: Throughput and energy comparison for bulk data transfer

V. Conclusion

We proposed a control mechanism for MPTCP based on Partially Observable Markov Decision Process to enhance energy saving. The optimal control problem was formulated as a Markov Decision Process by taking SNRs as an observation. Performance of the proposed mechanism was evaluated and compared with the different platforms for bulk data transfer. The results indicate that the proposed mechanism significantly outperforms other platforms.

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