Proactive QoE Provisioning in Heterogeneous Access Networks using Hidden Markov Models and Reinforcement Learning

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Abstract

Quality of Experience (QoE) provisioning in heterogeneous access networks (HANs) can be achieved via handoffs. The current approaches for QoE-aware handoffs either lack the availability of a network path probing method or lack the availability of efficient methods for QoE prediction. Further, the current approaches do not explore the benefits of proactive QoE-aware handoffs such that user’s QoE is maximized by learning from past network conditions and by actions taken by the mobile device regarding handoffs. In this paper, our contributions are two-fold. First, we propose, develop and validate a novel method for QoE prediction based on passive probing. Our method is based on hidden Markov models and Multi-homed Mobility Management Protocol which eliminates the need for additional probe packets for QoE prediction. It achieves the average QoE prediction accuracy of 97%. Second, we propose, develop and validate a novel reinforcement learning based method for proactive QoE-aware handoffs. We show that our method outperforms existing approaches by reducing the number of vertical handoffs by 60.65% while maintaining high QoE levels and by extending crucial functionality such as passive probing mechanisms.

Keywords: handoff, hidden Markov models, multi-homing, probing, Reinforcement Learning, Quality of Experience

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Table 1: List of notations used in this paper.

| Notation | Meaning |
|----------|---------|
| $i$      | a network interface |
| $\Gamma$ | handoff function |
| $E$      | expected reward function |
| $\Delta$ | average number of handoffs |
| $\Phi$   | QoE prediction accuracy |
| $t$      | time-stamp/decision epoch |
| $A$      | a set of actions |
| $a_t$    | context attribute at $t$ |
| $w_j$    | weight of an attribute |
| $E_t$    | an observation/evidence at $t$ |
| $\mu$    | mean |
| $\sigma^2$ | variance |
| $T_M$    | transition matrix |
| $p$      | initial state distribution/prior |
| $\Theta$ | model parameters |
| $R$      | a reward function |
| $\pi$    | a policy |
| $S$      | set of system states |
| $\gamma$ | discount factor |
| $\alpha$ | learning rate |

1 Introduction

Mobile devices such as tablets and smartphones can connect to heterogeneous access networks (HANs) using a plethora of wireless technologies such as WiFi and 4G. Users using their mobile devices may roam in HANs while moving from one wireless network to another. Users usually associate some expectations while accessing applications on their mobile devices [1]. These expectations along with their cognitive and behavioural states and network quality of service (QoS), may dictate their quality of experience (QoE) [1, 2, 3]. If users are satisfied with their QoE, they may stay with the current telecommunication operator else they may switch to a new operator. For instance, in 2011, Vodafone Australia nearly lost 440,000 customers to different operators such as Telstra and Optus due to customer dissatisfaction [1]. Telecommunication operators are interested in maximizing their revenue by trying to retain their customers. On the other hand, users consider

[1]http://www.itnews.com.au/News/290168,vodafone-australia-churn-nears-half-a-million-for-2011.aspx (retrieved 03/09/15).
operators that meet their QoE. Thus, there is a need to facilitate QoE while users roam in
HANs such that both telecommunication operators and users are satisfied [4].

QoE provisioning in HANs can be achieved through handoffs [5, 6], codec-switching
[7], codec bitrate manipulation [8, 9], and routing [10]. This paper addresses the challenge
of QoE provisioning in HANs using handoffs. A handoff is a process of migrating from
one network access point (AP) to another (belonging to the same of different wireless
networks) [11]. Handoffs are usually facilitated by mobility protocols such as Mobile
IPv4/v6 [12, 13], Multi-homed Mobile IP [14], and Stream Control Transmission Protocol
(SCTP) [15]. During handoffs, a mobile node (MN) goes through several phases such as,
network discovery, network registration and network configuration. These phases may
cause severe degradation to user’s QoE due to increase in delay, jitter and packet losses
[16, 17, 7]. Since the late 1990’s, much work has been done to optimize handoffs in
HANs (see, [18, 19]). However, there is a dearth of research considering the challenge of
QoE-aware handoffs in HANs [5, 18].

One of the major challenges for QoE-aware handoff is accurate QoE prediction for
the available wireless networks [5, 20]. Further, HANs are prone to stochastic network
conditions such as wireless network congestion and wireless signal fading. Most of the
approaches [21, 22, 23, 24] to handoffs do not explore the benefits of QoE prediction
for QoE-aware handoffs [5, 20]. Few approaches [25, 6, 26, 27, 28], consider QoE-
aware handoffs, but assume the availability of underlying network path probing schemes
to predict user’s QoE [26, 20]. This assumption is unrealistic and severely hinders QoE
provisioning in HANs [20]. Lastly, current methods [23, 6, 26, 27, 28] for QoE-aware
handoffs are myopic and inefficient i.e., these methods do not consider learning about
previous network conditions and actions (regarding handoffs) taken by the MN for QoE
provisioning, therefore, limiting their ability to make efficient QoE-aware handoffs [5].
We assert that efficient QoE prediction and provisioning in HANs remain an unresolved
and a challenging problem [5, 18, 20, 29].

1.1 Our Contributions

In this paper, our contributions are two-fold. In particular, we present:

1. A novel method for end-to-end QoE prediction using a passive probing mechanism
   based on hidden Markov models (HMMs) [30] and Multi-homed Mobility Management
   Protocol (M-MIP) [14]. The proposed method eliminates the need for
   additional probe packets on network interfaces while predicting QoE states accu-
rately. To the best of our knowledge, the method proposed in this paper is the first to integrate QoE prediction capabilities directly into a mobility management protocol. Our results show that average QoE prediction accuracy of 97% is achieved considering WLAN and a cellular network.

2. A novel method for proactive QoE-aware handoffs based on Reinforcement Learning (RL) [31]. We compare our method with Multimedia Mobility Manager (M4) [23] and a naive scheme (similar to [21, 22]) and show that our proposed method outperforms them by reducing the average number of handoffs by 60.65%.

The rest of the paper is organized as follows. Section 2 presents the related work. Section 3 presents PRONET, our approach for proactive context-aware QoE provisioning in HANs. Section 4 presents two analytical models for QoE prediction and for proactive QoE-aware handoffs. Section 4 presents our results based on extensive simulations and real trace-based analysis. Finally, section 5 presents the conclusion and future work.

2 Related Work

2.1 Handoffs in Heterogeneous Access Networks

Significant interest in the areas of vertical handoffs and HANs has been shown in the past decade [11, 32, 33, 34, 21, 35, 36, 22, 23, 7, 18, 6, 19]. The term vertical handoff came into existence in late 1990s during the inception of The Bay Area Research Wireless Access Network (BARWAN) project [37]. The main aim of the BARWAN project was to develop a wireless overlay network structure and to facilitate vertical handoffs with minimum latency. An overlay network structure consists of different overlays (or cells) of different sizes belonging to different wireless network technologies such as Infrared, WaveLan and Richonet.

Stemm and Katz [11] proposed a system to facilitate vertical handoffs in overlay networks. Their system considered handoffs between Infrared, WaveLan and Richonet wireless network technologies. The authors considered MIPv4 [38] protocol for mobility management where the handoffs were triggered based on signal to noise ratio (SNR) values. The authors proved that vertical handoffs between different overlays were possible with handoff latencies in the range of 181 ms to 2.53 sec, making roaming feasible.

Wang et al. [32] presented a novel policy-based system for vertical handoffs. Policies were based on cost, power and network conditions. Their policy model computed costs
based on parameters such as bandwidth and power. The proposed model was flexible to a certain degree, that a user had choices between the parameters to facilitate user-centric handoffs i.e., he/she could choose bandwidth over cost or vice versa. The main advantage of their model was that it provided seamless connectivity without human intervention. Policies were also clearly defined and could be modelled as per user requirements.

McNair and Zhu [35] presented the design and performance issues for achieving adaptable vertical handoffs in a multi-network 4G environment. They discussed the possible architectural components and handoff metrics that can be used in conjunction with the conventional signal strength measurements to facilitate vertical handoffs. We classify the aforementioned methods as traditional methods as they mainly consider layer 2 (of the OSI protocol stack [39]) parameters to trigger handoffs. These parameters include signal strength, bit error rate and beacons.

Since the later-half of 2003, context-aware methods were proposed by several researchers [33, 34, 36, 22]. Context is any information that assists in determining a situation(s) related to a user, network or device [40]. In this paper, we define context as any information that assists in facilitating QoE-aware handoffs. Context can be static and dynamic. Static context does not change often, while dynamic context changes over a period of time and is difficult to predict. Static context may include user’s application preferences, their security requirements and cost. Dynamic context may include user location, velocity, network load, battery power, memory/CPU utilization, presence and SNR. Context can be collected via sensors such as GPS for collecting user’s x and y location coordinates. It can also be collected via probes. For example, probe packets sent between the two network entities can be used to determine QoS statistics such as delay and packet loss [41]. The aim of context-aware methods is to consider a combination of several parameters to facilitate efficient handoffs.

Prehofer and Wei [33] presented a framework for context-aware vertical handoffs. in particular, they developed a flexible context exchange protocol incorporating mobile agents for context collection. However, the authors do not perform any experimental/simulation studies to validate their proposed system.

Indulska and Balasubramanian [34] presented a context-aware handoff solution for WLAN and GPRS networks. The authors divided context into four categories i.e., sensed context: such as user location and QoS; static context: such as device capability in terms of CPU type, screen size and content capability; profiled context: such as personal settings and user cellular network profile; and derived context: such as network profile. The authors did not consider mobility management protocols, instead they relied on proxy
agents on gateway nodes to relay network traffic between different networks. The authors using experimentation validate that their method can facilitate vertical handoffs.

Vidales et al. [36] presented a context-aware and policy based solution called PROTON. However, their policies were difficult to formulate and integrate in a real system. The authors however, presented a thorough investigation of the effects of MIPv6 mobility management protocol on vertical handoffs.

Most of the context-aware methods are based on multi-attribute decision making (MADM) [42] which utilizes several context attribute values to determine a single scalar value. The network with a higher scalar value is the target for a handoff. For example, Indulska and Balasubramanian [34] used Analytic Hierarchy Process (AHP) for handoffs between WLAN and 3G. Nasser and Hasswa and Hassanein [22] used Simple Additive Weighting (SAW) for handoffs between WLAN and a cellular network.

We assert that in HANs, context can be highly dynamic and stochastic i.e., it can change in a very short period of time and is uncertain; it can be imperfect; it can exhibit a range of temporal characteristics; it can have several alternative representations; it can be interrelated; it can be distributed; and it may not be available at a particular time. The timely collection and processing of context may be crucial as it may loose its accuracy. The aforementioned methods may not efficiently deal with uncertain context as they simply utilize available context attribute values at current time-stamp $t$ to facilitate a handoff. In this paper, we argue for and develop context-aware methods consider past and present context attribute values to learn about the best time to make a QoE-aware handoff.

Stevens-Navarro, Lin and Wong [24] presented a Markov Decision Process (MDP) based method to facilitate handoffs in HANs. Their scheme learns from current QoS values and past decisions regarding handoffs to select the best wireless network for a handoff at time $t$. The authors compared their results with MADM-based methods (e.g., SAW and TOPSIS) and show that their method achieves higher expected total reward and lower expected number of handoffs. However, their method do not facilitate QoE-aware handoffs and assume that the path probing method is present to determine QoS values. This assumption is quite strict and unrealistic. In reality, QoS parameters have to be estimated by either using passive or active probing. The QoS parameter values may also be provided by any third party to the MN, if present on the network.
2.2 QoE Provisioning in Heterogeneous Access Networks

As discussed in section 1, QoE provisioning using handoffs necessitate accurate path probing mechanisms such that a MN can predict user’s QoE. Hidden Markov models (HMMs) [30] have been successfully applied [43, 44, 45, 20] to model both wired and wireless network characteristics. For example, Liu, Matta and Crovella [44] considered HMMs and a pair of RTT probe packets to classify different types of losses in wireless networks. However, their scheme was limited to classification of congestion and wireless losses and did not consider users’ QoE.

Tao and Guérin [45] estimated Internet path performance using HMMs. Their approach was similar to [43] but they extended this work by looking into sensitivity analysis of the model. They also predicted the application behaviour with different characteristics such as varying packet losses. The authors considered an active probing mechanism to estimate and predict packet losses using HMMs. They show that their approach works well in case of isolated packet losses but is not accurate in case of bursty packet losses. This approach was also limited to wired networks and did not consider stochastic wireless network impairments such as signal fading, network congestion and handoffs. Finally, active probing utilized in their approach requires additional probe packets which increases bandwidth and monitoring costs. Compared to [45], in this paper, we develop a passive probing mechanism based on HMMs and M-MIP to estimate and predict user’s QoE HANs. Our scheme do not require additional probe packets thereby minimizing network bandwidth and monitoring costs.

Tao et al. [46] presented a methodology for QoE-aware path switching in wired networks. Their QoE prediction method was based on predicting the mean opinion score (MOS) score for all network paths based on simple Markov predictors. The main assumptions of the proposed method were: the frequency of path-switching was low, the delay variation was low and the effects of delay and path-switching could be mitigated by the playback mechanisms. These assumptions are restrictive, and may not be suitable in case of HANs, where a user may move quite suddenly and abruptly in HANs leading to delay variation, abrupt handoffs due to signal fading, and packet losses. All these factors can significantly hamper users’ QoE [47].

Marsh and Grönvall [16] and Marsh, Grönvall and Hammer [48] presented a study on the effects of handoffs on VoIP applications. The authors developed a PSTN-based VoIP test bed to evaluate the performance of VoIP applications in IEEE 802.11b networks. The authors evaluated VoIP call quality based on six parameters including packet loss, delay,
jitter, link layer retransmissions, transmission rate and signal to noise ratio (SNR). The authors also developed a network score as a function of SNR, bandwidth, delay, jitter and packet losses which validate that all of these parameters affect users’ QoE in WLAN. However, the problem with their approach was that they do not map QoS parameters to QoE and hence, conclusive results could not be obtained from end users’ perspective.

Mobisense Project [49 7 50] was carried out at Deutsche Telecom, Germany to investigate the effects of handoffs on users’ QoE. The results from this project were based on WiFi and HSDPA networks. The authors studied the impact of delay, audio bandwidth, packet loss and codec-switchover on users’ QoE. It was concluded that packet loss is the most important parameter that significantly degrades users’ QoE followed by audio bandwidth. However, the authors do not propose methods for QoE-aware handoffs in HANs.

Piamrat et al. [25 6] and Varela and Laulajainen [26], presented methods for QoE-aware handoffs based on the Pseudo-Subjective Quality Assessment (PSQA) metric [51]. The PSQA metric maps parameters such as percentage of packet loss and mean loss burst size to MOS based on Random Neural Networks (RNNs). The problem with RNN is that it require a large number of training samples for performing accurate prediction. This limits its ability to learn continuously in an on-line and unsupervised manner.

Rosario et al. [27] and Quadros et al. [28] presented a method for QoE-aware handoffs by focussing on video QoE. The authors aimed at estimating QoE using neural networks. In [28], they extended their scheme presented in [27] and proposed a handoff initiation method using the IEEE 802.21 Media Independent Handover scheme. However, as mentioned previously, neural network based mechanisms require large amounts of training data. Further, the authors do not consider methods for network path probing and mobility management. Further, these methods are myopic and inefficient as they do not consider learning about previous network conditions and actions (regarding handoffs) taken by the MN for QoE provisioning. Therefore, limiting their ability to make efficient QoE-aware handoffs.

Tabrizi, Farhadi and Cioffi [52] presented a Q-learning based method for handoff management in HANs. Their proposed scheme looks promising. However, as with the other state-of-the-art methods for QoE provisioning in HANs (e.g., [25 6 26 27 28]), the authors do not present a generic path probing scheme and the integration of their mechanism with a mobility management system. These systems were mainly validated using simulation studies and using real world prototype systems, leading to methods that may not work well in reality and may hinder efficient QoE-aware handoffs in HANs.
2.3 Research Challenges

From the discussion presented in this section, we identify the following two research challenges for efficient QoE provisioning in HANs.

- **QoE prediction in heterogeneous access networks:** The current approaches [23, 25, 53, 26, 6] for QoE-aware handoffs are limited. These approaches lack the availability of efficient QoE prediction mechanisms. Further, approaches such as [25, 26, 6] assume the availability of path probing mechanism to make QoE-aware handoffs. These assumptions are unrealistic and can severely hinder QoE provisioning in HANs [5, 26, 20]. We assert that current approaches to QoE-aware handoffs lack efficient network path probing mechanisms and methods for accurate QoE prediction in HANs. Path monitoring is not a new concept. Tao et al. [45] and Liu, Matta and Crovella [44] proposed to use active and passive probing to estimate network path quality. Åhlund and Zaslavsky [14, 41] proposed the use of passive probing mechanisms using mobility management protocols for estimating network path quality for making handoffs. However, these approaches were either used for wired network environments or do not consider QoE prediction in HANs [20]. Thus, there is a need to develop novel methods for QoE prediction in HANs.

- **Proactive QoE provisioning in heterogeneous access networks:** The current approaches [23, 25, 53, 26, 6] do not consider proactive QoE-aware handoffs by learning from past and possible future network conditions. Network conditions in HANs are stochastic due to uncertain and time-varying characteristics of the network medium. Thus, there is a need to develop techniques that are resilient to such problems by learning from underlying network conditions and past actions taken by a MN regarding handoffs such that users’ QoE is maximized [5].

Compared to the aforementioned state-of-the-art methods, in this paper, we propose, develop and validate novel methods for: i.) QoE prediction using hidden Markov models and M-MIP-based passive probing mechanism; and ii.) proactive QoE provisioning using a Reinforcement Learning mechanism. To the best of our knowledge, none of the methods in the state-of-the-art presents such a comprehensive treatment of the problem of proactive QoE provisioning in HANs.
3 PRONET: An Approach for Proactive QoE-Aware Mobility Management in Heterogeneous Access Networks

This section presents PRONET—An approach for proactive context-Aware mobility Management to facilitate QoE-aware handoffs (see Fig. 1.). It follows a cognitive networking approach where a mobile node is able to sense the current network conditions, and then plan, decide and act under these conditions to achieve end-to-end goals [5, 54]. In this paper, PRONET aims to reduce the number of handoffs while maximizing user’s QoE. We consider a scenario where a mobile node (MN) incorporating PRONET roams in HANs. The MN collects context attributes values such as network delay and predicts user’s QoE states using hidden Markov models (HMMs) [30]. The predicted QoE states are used by the Q-learning algorithm [55] to proactively select the best network interface for handoff. The challenges addressed by PRONET are written as:

1. Maximize QoE prediction accuracy ($\Phi$) for two wireless network interfaces ($i = |2|; WLAN & Cellular$). This can be written as:

$$\max(\Phi) \forall i \in I$$ (1)

2. For a given handoff function ($\Gamma(\bullet)$), maximize user’s $QoE$ and reduce the average number of handoffs ($\Delta$) between two wireless network interfaces ($i = |2|; WLAN & Cellular$). This can be written as:

$$\max(QoE)$$ (2)

$$\min(\Delta)$$ (3)

For vertical handoff decision problem, $\Gamma(\bullet)$ can be written as:

$$\Gamma = w_j(QoE_i) + (1 - w_j)(Cost_i)$$ (4)

where $w_j$ represents the weights associated with each parameter, $QoE$ and $Cost$ and $\sum_{j=0}^{N}w_j = 1$. Cost can be monitory cost, signaling cost and handoff switching cost.

Both challenges necessitate accurate QoE prediction and provisioning which can be achieved by developing accurate path probing mechanisms [5, 26] and by developing
proactive methods for QoE-aware handoffs in HANs \cite{5,20}. The MNs can either use active or passive network path probing for QoE prediction. In case of active probing, extra probe packets are injected in the network to mimic application traffic flow between two end-systems. Based on delay and packet losses observed using these probes, network states can be estimated, for example, “network is congested” or “network is not congested”. However, this technique while being beneficial, leads to an increase in bandwidth requirements. Another probing technique is passive probing. In this technique, the application traffic flow itself is used to estimate path quality statistics without requiring additional probe packets. Thus, bandwidth savings are made while estimating the path quality. However, passive probing technique is application specific. In this paper, we argue for application independent passive probing techniques which can be used to monitor all network interfaces of MNs, simultaneously. In HANs, multi-homed mobility management protocols such as M-MIP \cite{56} are considered for application session continuity using handoffs. These protocols implement signaling mechanisms such as binding updates (BU) and binding acknowledgments (BA) to handle events like packet flow redirection. Thus, in this paper:

- We propose to use BU and BA packets as probe packets. Thus, eliminating the need for additional probe packets generated on all the network interfaces. Further, this method remains independent of any application type.

- We propose to use HMMs trained using the one-way delay (OWD) or round trip time delay (RTT) computed using the BA and BU packets to estimate and predict QoE for VoIP applications.
We propose to use the Reinforcement Learning method (Q-learning) to facilitate proactive handoffs that maximizes user’s QoE over time while minimizing the average number of vertical handoffs.

Fig. 2 shows our high-level approach for network path quality prediction using HMMs and M-MIP. A MN periodically exchange BU and BA messages with the home agent (HA) or the correspondent node (CN). For each BU sent by the MN to HA/CA, a corresponding BA is sent from HA/CN to MN. The amount of time spent between sending a BA from HA/CN to MN is the OWD. The amount of time spent between sending a BU from MN and receiving a corresponding BA from HA/CN is the RTT delay. The RTT delay is estimated at the network layer (considering the OSI model [39]) of MN. By using RTT delay values, clock synchronization is not required between the MN and HA as compared to OWD. The HMM takes this OWD/RTT value as an input and try to predict the corresponding QoE state at the application layer. This problem is not trivial as the HMMs need to discover the hidden QoE states from the underlying network conditions.

Fig. 3 shows our method (represented as a dynamic decision network) for proactive QoE-aware handoffs where we consider Reinforcement Learning (RL) [55]. In particular, the prediction results from the HMM are taken as inputs by the RL algorithm to proactively select the best network interface, \( i \in I \) in terms of QoE. In this paper, we consider Q-learning [55] as the RL method. Using Q-Learning, a MN learns an action-value pair to select the best available network that maximizes user’s QoE. We will show later that our integrated approach (PRONET) minimizes the average number of handoffs (which causes increase in packet loss and jitter [16, 7]) while maintaining high QoE levels. In the following sections, we present two analytical models for QoE prediction and provisioning in HANs.

### 3.1 Hidden Markov Models for QoE Prediction

We consider discrete-time HMMs [30] for QoE prediction in HANs. HMMs are temporal probabilistic models in which a system state, in our case a QoE state, is described by a single discrete random variable. Fig. 4 shows our HMM for QoE prediction.

**System states:** We use the notation \( S'_{QoE_n} \) to represent the QoE state at time \( t \) where \( t \in T \) and \( T \) is the set of finite integers. At a given \( t \), our system can be in any state \( n \in N \). For example, \( |N| = 5 \). Thus, the state space can be written as \( \{ S'_{QoE_1}, S'_{QoE_2}, \ldots, S'_{QoE_5} \} \). When a system is in a particular state \( S'_{QoE_n} \), it outputs an observation or evidence (\( E' \)).
Figure 2: MN calculates one-way (OWD) or round-trip time (RTT) delay using BU and BA messages. These delay values are then used by HMM for QoE prediction. The predicted QoE values are then used by RL algorithm for proactive QoE adaption.

Figure 3: A dynamic decision network (DDN) representation of a QoE provisioning scheme.
Figure 4: Hidden Markov model (HMM) for QoE prediction using OWD or RTT delay calculated using BA and BU of M-MIP.

**Observations:** In our system, the evidence is the current OWD/RTT delay value which is modelled as a Gaussian distribution in the form of: $P(E|S_{QoE}) = \mathcal{N}[E; \mu, \sigma^2]$, where $\mu$ is the mean and $\sigma^2$ is the variance. To describe state evolution over time, a QoE state transition matrix ($T_M$) is defined. In this paper, we consider a first-order Markov process i.e., the current state is dependent only on previous state. It is shown in [44, 45] that first-order Markov process is sufficient for modelling temporal characteristics of a network channel (both wired and wireless). Thus, $T_M$ is defined as: $P(S_{t+1}|S_t^{-1})$. To start the process, an initial state distribution is defined. It is represented as $p = P(S_{t=0}^t)$. 

**Learning model parameters:** In HMMs, the problem of learning is that of learning the model parameters $\Theta$:$\{\mu, \sigma^2, p, T_M\}$. We consider the use of expectation maximization (EM) algorithm to train our HMMs. In EM algorithm, there are two main steps: E-step which computes posteriors over states and the M-step which adjusts the model parameters to maximize the likelihood of posteriors calculated in the E-step. It is an iterative process leading to a guaranteed increase in log-likelihood of the model ($\log(\Theta)$) until convergence.

**State prediction:** After learning the model parameters using EM, our main task is to perform QoE state prediction. It is a task of computing posterior distribution over the future states, given evidence till now. In this paper, we are interested in one-step QoE prediction.

### 3.2 Reinforcement Learning for Proactive QoE-aware Handoffs

The previous section considered the challenge of QoE prediction over time in stochastic HANs conditions. In this section, we consider the challenge of proactive QoE provisioning in HANs based on reinforcement learning (RL) [55]. In this paper, we consider Q-learning as the RL algorithm [55]. Using Q-Learning algorithm, our agent, the MN, learns an action-value pair to select the best available network that maximizes
user’s QoE. The aim of our agent is to predict QoE for all network interfaces $I$ and then proactively select a network interface $i$ that maximize user’s QoE; where $i \in I$ and $|I| = 2$ and $I = \{”WLAN” or ”Cellular”\}$. This process of learning and adaptation repeats until the system stops.

### 3.2.1 Agent Design and System Model

To proactively select a network $i \in I$, MDP is considered incorporating a tuple $(TM, R, A, \pi, S, \gamma)$. We use $S^{[2]}$ and $TM$ from the previous section representing the state and the transition model of the agent, respectively. $\gamma \in [0, 1)$ is called the discount factor. Our agent, the MN, senses the environment (e.g., network conditions) and then using HMMs predicts the QoE states $\forall I$. Based on the predicted QoE state, it selects $i$ that maximizes user’s QoE in the long run. An agent and the environment interacts with each other continually at fixed time-steps or decision epochs ($t = 0, 1, 2, ..., n; t \in T$). $S^t_i$ and $S^{t+1}_i$ denotes the QoE state for all the network interfaces $i \in I$. Further, $S^t_i$ and $S^{t+1}_i$ have their own independent sensor models $E^t_i$ and $E^{t+1}_i$. These models are learnt independently using HMMs described in the previous section.

**States:** Compared to [24, 57, 58], we do not consider crude QoS metrics for state representation as it can lead to an explosion in state space and increase in algorithm’s convergence time [58]. This is due to the fact that the QoS values related to delay, jitter, bandwidth and packet loss rate are continuous. Thus, to represent them as individual states, they have to be quantized into finite bins of size $|N|$. This way, the complexity grows quickly as the state space will be the Cartesian product of all states related to each QoS parameter for each network interface. It can be expressed as: $I \times S^{ Delay(|N|)}_i \times S^{ jitter(|N|)}_i \times S^{ packetloss(|N|)}_i \times S^{ bandwidth(|N|)}_i$; where $I$ is the number of network interfaces. Further, in reality, quantization of the state space may lead to a decrease in prediction accuracy [51].

To alleviate this problem, in this paper, we propose to use finite QoE states learnt using HMMs. For example, MOS values in the range of 1 and 1.9 denotes state 1; MOS values in the range of 2 and 3.5 denotes state 2 and MOS values in the range of 3.51 and 5 denotes state 3. It is important to note that our HMMs will automatically discover these QoE states based on the training data. This way, the complexity of $I \times S^{ Delay(|N|)}_i \times S^{ jitter(|N|)}_i \times S^{ packetloss(|N|)}_i \times S^{ bandwidth(|N|)}_i$ is substantially reduced to just $I \times S^{ QoE[2to5]}_i$. In this paper, we assume that QoE is computed using the ITU-T E-Model

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2 We now use the term $S'$ instead of $S^{QoE}_t$ to represent QoE state at $t$. 

15
However, QoE can be computed using any methods presented in the state-of-the-art. To determine complex QoE metric such as the ITU-T E-Model, all parameters of the model should be known. In this paper, we show that only one parameter (e.g., RTT delay/OWD) can be used to predict QoE states using HMMs, eliminating the need for all additional parameter values.

Actions: At each $t$, an agent observes the environment state(s), $S_t$. Based on the observed state, an agent selects an action, $a_t \in A$: $A$ denotes the set of actions, where $|A| = 2$; and $A = \{\text{“select } i\text{” or “select } i + 1\text{”}\}$.

Rewards: After selecting an action $a_t$, the agent receives a numerical reward, $r_{t+1} \in \mathbb{R}(S)$ where $\mathbb{R} : S \mapsto \mathbb{R}$ is the reward function. After a reward is received, the agent then transitions to the new state represented as $S_{t+1}$.

Policy: The mapping of a state to action ($\pi : S \mapsto A$) is called a policy, $\pi$. In a stochastic environment, when each policy is executed, it leads to a different environment history. Thus, the quality of policy is determined by considering total rewards it receives at each $t$ in the long run.

The reward function reflects QoE and cost associated with the chosen $i$. It is important to understand that in RL problems, positive rewards (e.g., related to QoE) are usually given to the agent for every correct action it takes. On the other hand, negative rewards (e.g., related to cost) are given to the agent when it makes a wrong decision. Costs can be related to signaling, monitory budget or both. We use Eq. 4 to determine our reward function. Therefore, $\mathbb{R}(s)$ can be substituted for $\Gamma(\bullet)$. Thus, we now write the reward as:

$$\mathbb{R}(s) = w_j(QoE_t) + (1 - w_j)(Cost_t)$$

(5)

where $f(QoE)$ and $f(cost)$ can be solved by the following equations:

$$f(QoE) = \begin{cases} 
1, & \text{if } QoE_t \geq QoE_{max} \\
\frac{QoE_t - QoE_{min}}{QoE_{max} - QoE_{min}}, & \text{if } QoE_{min} < QoE_t < QoE_{max} \\
0, & \text{if } QoE_t \leq QoE_{min} 
\end{cases}$$

(6)

$$f(Cost) = \begin{cases} 
1, & \text{if } 0 < Cost_t \leq Cost_{min} \\
\frac{Cost_t - Cost_{min}}{Cost_{max} - Cost_{min}}, & \text{if } Cost_{min} < Cost_t < Cost_{max} \\
0, & \text{if } Cost_t \geq Cost_{max} 
\end{cases}$$

(7)
where $QoE_t$ represents the QoE state value at time $t$. Similarly, $Cost_t$ represents the cost at time $t$ and $w_j$ represents the weights associated with each parameter, $QoE_t$ and $Cost_t$ and $\sum_{j=0}^{N} w_j = 1$.

The aim of our agent is to choose actions over time to maximize the total payoff or utility ($U$). The agent executes some policy ($\pi$) when it is in some state $S$ i.e., an agent takes an action $a = \pi(S)$. Thus, we write $U^\pi(S)$ as:

$$U^\pi(S) = E \left[ \sum_{t=0}^{\infty} \gamma^t \mathcal{R}(S^t)|\pi, S_0 = S \right]$$  \hspace{1cm} (8)

The utility function $U(S)$ enables the agent to select actions ($a$) that maximize the expected utility. The next task is to find an optimal policy represented as $\pi^*$ at each time $t$ that $\text{argmax}(\mathcal{R}(s))$. It can be denoted as:

$$\pi^* = \text{argmax}_{\pi} E \left[ \sum_{t=0}^{\infty} \gamma^t \mathcal{R}(S^t)|\pi \right]$$  \hspace{1cm} (9)

The utility function $U(S)$ lets the agent select actions using the maximum utility principle i.e., an agent chooses actions that maximizes the expected utility of the next state $S_{t+1}$. It is denoted as:

$$\pi^*(S) = \text{argmax}_a \sum_{S^t+1} TM(S, a, S^t+1)U(S^t+1)$$  \hspace{1cm} (10)

From [31], we note that the utility of the state is the immediate reward $\mathcal{R}(S)$ plus the discounted utility of next state $S^{t+1}$, provided an optimal action is chosen. Here $TM$ is the transition matrix as mentioned in section 3.1. Thus, the utility of the state can be written as:

$$U(S) = \mathcal{R}(S^t) + \gamma \text{max}_a \sum_{S^t+1} TM(S, a, S^t+1)U(S^t+1)$$  \hspace{1cm} (11)

This equation is the well-known Bellman equation [31] where $\mathcal{R}(S^t)$ is the immediate reward which is received by starting from the current state; $\gamma \text{max}_a \sum_{S^t+1} TM(S, a, S^t+1)U(S^t+1)$ is the expected sum of discounted rewards by starting from the state $S^{t+1}$. $S^{t+1}$ is distributed based on $TM(S, a, S^t+1)$ which is the distribution over where the agent will end up after executing the first action $a$. Bellman equations are used to solve $U(S)$ efficiently. Bellman equation can be solved using the value and policy iteration algorithms [31, 55].
However, it requires that the $TM(S, a, S^{t+1})$ is known which might be hard to estimate in stochastic network conditions in HANs. Thus, we consider the Reinforcement Learning techniques to learn and select optimal actions under uncertainty. In particular, we consider the Q-learning algorithm [55].

3.2.2 Q-learning for Proactive QoE-aware Handoffs

We consider M-MIP enabled MN (Q-learning agent) that roams in HANs. The design of our agent is given in Fig. 5. At each time $t$, the agent observes a QoE state (predicted using HMMs) and receives a reward. It then learns and selects an action $a$ that maximizes the reward at the next state $S^{t+1}$ at time $t + 1$. In Q-learning, the Q-value or $Q(S, a)$ is maintained in the Q-table of size $|S| \times |A|$. The immediate reward $\mathcal{R}(S)$ is the maximum reward the agent receives at $t + 1$ by performing $a$ at $t$. For each $(S, a)$, an action $a$ is either rewarded or punished. For example, $Q(S_t(i=WLAN)) = "QoE is excellent", a = "do not handoff to HSDPA"$ will be rewarded and $Q(S_t(i=WLAN)) = "QoE is excellent", a = "handoff to HSDPA"$ will be punished. This is because, in the first case, QoE is “excellent” and there is no need to make a handoff. In the second case, the agent should learn via punishment that if QoE is “excellent”, handoffs should not occur. In case of rewards, the Q-values are increased. In case of punishments, the Q-values are decreased. This process of learning the $state – action$ continues till the goal state (or system stops) is reached. Thus, the expected reward $E[\bullet]$ is the sum of discounted rewards an agent collects in the long run. Thus, the value of taking an action $a$ in state $S$ given a policy $\pi$ is denoted as $Q^\pi(S, a)$. It determines the expected return starting from $S$, taking an action $a$ and then following a policy $\pi$. It can be written as:

$$Q^\pi(S, a) = E \left[ \sum_{t=0}^{\infty} \gamma^t \mathcal{R}(S^t) | S_0 = S, a_0 = a, \pi \right]$$ (12)

$Q^\pi$ is known as the action-value function for $\pi$. The optimal policy $\pi$ shares the same action-value function, $Q^\pi$ Thus, the optimal state-value function can be written as:

$$Q^*(S, a) = \max_\pi Q^\pi(S, a)$$ (13)

i.e., for all states $S$, and all actions $a \in A$, the state-action pair $(S, a)$ provides expected return for taking $a$ in $S$ and then following the optimal $\pi$. Thus, we can write $Q(S, a)$ in
Algorithm 1 An Algorithm for Proactive QoE-aware Handoffs.

Inputs: State (S), reward signal (ℜ)
Output: An action, \( a \in A \)

Initialize
\[
S, \ a, \ Q(S, a) \leftarrow 0, \ \Real \leftarrow 0
\]

Run
/* Network discovery */
1. Using RSSI, discover \( i \in I \)
   For each \( i \in I \)
      if \( \text{RSSI}(i) \geq \text{threshold}(\text{RSSI}(i)) \)
         2. Connect to \( i \)
      End if
   End for
/* Network configuration */
For each \( i \in I \)
   3. Establish tunnel with HA
End for
/* Proactive QoE-aware handoff */
if "exploitation mode" == "true"
   4. Predict the state \( S \) using HMM
   5. Select \( a \) randomly and execute it
   6. Go to 4 and repeat till the end of session
Else if
   For each \( i \in I \)
      /* Exploration mode */
      7. Predict the state \( S \) using HMM
      8. Select \( a \) with \( \max Q(S, a) \) and execute it
      9. Receive \( \Real \)
      10. Update the \( Q(S, a) \) using Eq. 15
      11. Go to 6 and repeat till the end of session
   End if
End for
End
terms of $U(S)$ (Eq. 11). It can be written as:

$$U(S) = \max_a Q(S, a)$$  \hspace{1cm} (14)

The aim of $Q(S, a)$ is to learn the action value function. Q-learning is a model-free RL approach and does not require $TM(S, a, S^{t+1})$ and can directly relate to the utility values. It can be solved recursively using the following update equation:

$$Q(S, a) \leftarrow Q(S, a) + \alpha [\mathcal{R}(S) + \gamma \max_{a'} Q(S^{t+1}, a') - Q(S, a)].$$  \hspace{1cm} (15)

$\alpha$ is the learning rate which determines how much time the agent should spend in learning the policies. This equation is calculated whenever an action $a$ is executed in state $S'$ leading to state $S^{t+1}$. It has been proved when this equation is executed infinite number of times, $Q'$ converges to $Q^*$ with probability one where the learning rate $\alpha$ decreases to $0$ \cite{Barto}. Note that the agent can choose to be in either exploration mode or in the exploitation mode. In the exploration mode, the agent will select a random action to pursue learning. However, in the exploitation mode, the agent will automatically select an action $a$ corresponding to a state $S$ which has the maximum value in the Q-table. 

Algorithm 1 presents the algorithm for proactive QoE-aware handoffs in HANs. In this paper, we assumed two networks i.e., WLAN and cellular. In case more networks are to
be incorporated (say, LTE), another HMM for LTE interface can be learnt based on the BU/BA messages received for that network interface. On the other hand, in the Q-learning algorithm, the Q-table will have can also be easily extended by adding the corresponding states for the LTE interface.

4 Results Validation

4.1 QoE Prediction in WLAN Using One-way Delay

In this section, we use our HMM-based method to estimate and predict QoE states based on passive one-way delay (OWD). The OWD was calculated at the mobile node (MN) using binding acknowledgment (BA) packets sent from the home agent (HA)/correspondent node (CN) to MN.

4.1.1 Simulation Setup

We performed several simulation studies using OPNET™ network simulator [61] and considered cases such as wireless network congestion. Our simulation scenario is shown in Fig. 6. Table 2 shows the parameters and their values used for performing simulations in case of wireless network congestion. We considered a MN, HA, CN and three additional wireless nodes (WNs). To saturate the IEEE 802.11b access point (AP), we set up the WNs to generate additional background UDP traffic. The maximum achievable bit rate was approximately 5Mb/s after which the AP dropped all packets due to buffer overflow. A CN generated an additional 5 UDP packets (to mimic probe packets similar to BA) per second to help the MN calculate path delay and QoE statistics. Based on [62], we selected the size of each BA packet as 24 bytes, generating 960 bps as the M-MIP overhead.

During simulations, once the network reached its steady state, the MN initiated a voice call to the CN and calculated OWD and QoE using the probe packets. From simulation studies, we concluded that in case of heavy UDP traffic, wireless network congestion occurred due to increased end-to-end delay which in turn caused ITU-T E-Model [59] mean opinion score (MOS) to vary. In case of ITU-T G.711 voice codec, the average MOS was 2.06. On the other hand, in case of ITU-T G.729 voice codec, the average MOS was 2.41. The collected time series of OWD and the MOS were used to train the HMMs.
Figure 6: Wireless network congestion scenario.

Table 2: Simulation setup parameters.

| Parameter              | Values                      |
|------------------------|-----------------------------|
| Codec                  | ITU-T G.711 & ITU-T G.729   |
| Network technology     | IEEE 802.11b                |
| No. of probe packets   | 2,5,10                      |
| Size of the probe packet | 24 bytes & 48 bytes        |
| Movement pattern       | stationary                  |
| Simulation time        | 16 minutes                  |
| No. of simulations     | 100                         |
4.1.2 Numerical Analysis

To validate our proposed method, we initially considered 2 BA packets (as probe packets) per second to calculate the OWD. However, the HMMs could not efficiently predict QoE states on one second basis due to missing BA values caused by bursty packet losses. Further, it may happen that BA packets arrive too late (RTT/OWD>\(t_{\text{threshold}}\)), where for example, \(t_{\text{threshold}} = 0.650\ \text{sec}\) in case of ITU-T G.729 codec \([59, 63]\). This led us to study the impact of 5 and 10 BA packets per second for calculating the OWD and predicting user’s QoE. From the simulation studies, we concluded that 5 UDP packets per second are sufficient for QoE prediction even in case of high and bursty packet loss conditions.

To predict QoE states, we collected data using 100 simulation runs (with different random seeds) and analyzed results related to both ITU-T G.711 and ITU-T G.729 voice codecs. Similar to \([64]\), we randomly selected 10 files out of 100 for each codec to train the HMMs. Each file consisted of a 101 second time-series of OWD and the corresponding QoE values. We used BayesNet Toolbox for MATLAB \([65]\) for model parameter learning using EM algorithm and QoE state prediction. One of the best approaches for evaluating a model’s prediction accuracy is to perform cross-validation \([31]\). In cross-validation, some fraction of the data is kept for training and the remaining data is used as the test data. The training data and the test data are randomly chosen for each fold. For our model validation, we considered 2- and 10-fold cross-validation.

We trained the HMMs based on three states. State 1 corresponds to QoE values less than 2. State 2 corresponds to QoE values greater than or equal to 2 and less than 3. Finally, state 3 corresponds to QoE values greater than or equal to 3. For the sake of brevity, table 3 shows the learnt model parameters for ITU-T G.711 voice codec in case of wireless network network congestion. The prior matrix \((p)\) and the transition matrix \((TM)\) were estimated as follows:

\[
\rho_{\text{congestion WLAN}(G711)} = \begin{bmatrix} 0.6000 & 0.2000 & 0.2000 \end{bmatrix}.
\]

\[
TM_{\text{congestion WLAN}(G711)} = \begin{bmatrix} 0.9279 & 0.0596 & 0.0125 \\ 0.2817 & 0.3803 & 0.3380 \\ 0.0400 & 0.2400 & 0.7200 \end{bmatrix}.
\]

From the learnt transition matrix \((TM_{\text{congestion WLAN}(G711)})\) in case of ITU-T G711 codec, we conclude that if the QoE on the path is either state 1 or 3, it is likely that the QoE states will remain constant for some time. If the QoE on path is in state 2, it is likely that QoE
Table 3: HMM parameters learnt for ITU-T G.711 codec in case of WLAN network congestion.

|            | State 1 | State 2 | State 3 |
|------------|---------|---------|---------|
| mean (μ)   | 0.4850  | 0.1302  | 0.0462  |
| var (σ²)   | 0.0576  | 0.0010  | 0.0006  |

Figure 7: Prediction accuracy of HMM in case of WLAN congestion. 1.) ITU-T G.711 codec. 2.) ITU-T G.729 codec.

will fluctuate between state 1 and state 3. Fig 7. shows our model’s prediction accuracy in case of WLAN congestion. The average prediction accuracy was approximately 94% considering both ITU-T G.711 and ITU-T G.729 voice codecs. Fig 8. shows an example of how HMMs can predict QoE states in complex network conditions such as WLAN network congestion. These results clearly validate that HMMs can accurately predict QoE in case of WLAN network congestion. We conclude that our scheme performs very well in case of both isolated as well as bursty packet losses, and in cases where OWD fluctuates significantly.

4.2 QoE Prediction Using Round Trip Time Delay

In this section, we use the BA/BU packet pairs belonging to M-MIP [56] for passive RTT measurements. These RTT measurements are used by HMMs to predict the QoE states for WLAN and CDMA 2000 networks.

4.2.1 Experimental Setup

Fig. 2 shows our targeted scenario. A multi-homed MN, can roam between WLAN and cellular networks. The MN keeps on learning and predicting the QoE states by using the
RTT values computed using the BU/BA packets exchanged between the MN and HA/CN. For results validation, we obtained an experimental data set from the authors in [23]. This data set contains 12 different time series of RTT delay values for both WLAN and CDMA 2000 network interfaces corresponding to 12 different experimental runs. These experiments were conducted to understand the effects of roaming and handoffs on VoIP applications. The RTT values were calculated at 1 second time interval while the MN was on-the-move at different speeds (20 km/h and 30 km/h). Note that the ITU-T E-Model [59] uses OWD values to estimate MOS. Therefore, in this data set, we used the RTT measurements and divided them by 2 to derive the corresponding QoE values. We then used the RTT and QoE values to train HMMs. The trained HMMs were used to predict the QoE. As mentioned previously, the parameters for HMMs were learnt using the EM algorithm in MATLAB. The model validation was done based on 2-fold cross validation.

4.2.2 Results Analysis

We considered 2 and 3-state HMMs for QoE learning and prediction. State 1 corresponds to QoE values less than 2. State 2 corresponds to QoE values greater than or equal to 2 and less than 4. Finally, state 3 corresponds to QoE values greater than or equal to 4. In case of WLAN, our HMMs sufficiently learnt using only two states, i.e., using state 1 and state 3. There were very few state 2 values and we folded them to state 3. This did not lead to the loss of prediction accuracy. In case of CDMA 2000 network, there was sufficient data related to all three states which was used for learning the model parameters. Table 4 shows the learnt model parameters for ITU-T G.729 voice codec in case of WLAN and CDMA 2000 network interfaces. The estimated transition matrix and prior are as follows:

\[
p_{WLAN}^{G729} = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad T_{WLAN}^{G729} = \begin{bmatrix} 0.9500 & 0.0500 \\ 0.0654 & 0.9346 \end{bmatrix}
\]

\[
p_{CDMA2000}^{G729} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}, \quad T_{CDMA2000}^{G729} = \begin{bmatrix} 0.7852 & 0.1333 & 0.0815 \\ 0.1111 & 0.8148 & 0.0741 \\ 0.0696 & 0.0435 & 0.8870 \end{bmatrix}
\]

From the learnt model parameters, and in case of WLAN, we conclude that once the QoE is in state 1 or 3, it remains stable with probabilities greater than 90%. This suggests that WLAN either provides excellent QoE (state 3) or performs poorly (state 1). The poor performance was attributed to the MN moving out of the coverage area of WLAN and connecting to CDMA2000 network interface. In case of CDMA2000 network interface, once the QoE is in a particular state, it is likely that it will not fluctuate much. However,
Table 4: HMM parameters learnt for ITU-T G.729 codec in case of roaming.

(a) WLAN network interface

| State | State 1 | State 2 |
|-------|---------|---------|
| mean ($\mu$) | 0.9905 | 0.0519 |
| var ($\sigma^2$) | 0.0044 | 0.0079 |

(b) CDMA 2000 network interface.

| State | State 1 | State 2 | State 3 |
|-------|---------|---------|---------|
| mean ($\mu$) | 0.9519 | 0.6401 | 0.2857 |
| var ($\sigma^2$) | 0.0055 | 0.0076 | 0.0025 |

Figure 8: Figure showing HMM and M-MIP based method can accurately predict QoE in case of WLAN congestion.

In case of the ITU-T G.711 voice codec, if the QoE is in state 2, there is a high probability that it might switch to either state 1 or 3.

Fig 9 shows the prediction accuracy of the proposed method for two voice codecs and for both WLAN and CDMA2000 network interfaces. Fig. 10 shows the capability of HMMs for QoE prediction for CDMA 2000 network interface. The prediction accuracy was 100% for WLAN and the prediction accuracy for CDMA2000 was 95.60%. Thus, the average prediction accuracy was 97.80%. From experimental analysis, we conclude that HMMs can model complex time-series pertaining to QoE in realistic network settings and are extremely beneficial for accurate QoE prediction.
Figure 9: Prediction accuracy using HMMs for WLAN and CDMA2000 network interfaces using experimental data set. 1.) WLAN with ITU-T G.711 codec. 2.) WLAN with ITU-T G.729 codec. 3.) CDMA2000 with ITU-T G.711 codec. 4.) CDMA2000 with ITU-T G.729 codec.

Figure 10: Figure showing HMM and M-MIP based method can accurately predict QoE in case of cellular network.
4.3 Proactive QoE Provisioning using Reinforcement Learning in Heterogeneous Access Networks

The previous section concluded that HMMs can accurately predict users’ QoE in HANs. We now extend our HMM based approach to facilitate proactive QoE-aware handoffs in HANs. In particular, our agent, the MN, predicts the QoE state using HMMs and then selects an optimal action (regarding handoffs) based on the Q-value function as shown in Algorithm 1.

4.3.1 Minimizing the Number of Handoffs Using HMMs and Reinforcement learning

To validate our proposed approach, we compare our results with Multimedia Mobility Manager (M4) [23] and a naive scheme similar to multi-attribute decision making (MADM) methods [21, 22, 19]. We chose the number of handoffs as a criterion for results analysis. M4 considers the relative network load (RNL) metric [66] for network load-aware handoffs. The RNL metric considers the running average of RTT jitter values to estimate the load on access networks. The RTT values are computed based on the BU/BA pair sent between the MN and HA/CN. The RNL metric is computed as follows:

\[
RNL = Z_n + cJ_n \quad (16)
\]

\[
Z_n = \frac{1}{h}RTT_n + \frac{h-1}{h}Z_{n-1} \quad (17)
\]

\[
RTT_n = R_n - S_n \quad (18)
\]

\[
D_n = RTT_n - RTT_{n-1} \quad (19)
\]

\[
J_n = \frac{1}{h}|D_n| + \frac{h-1}{h}J_{n-1} \quad (20)
\]

where, \( S_j \) is the time to send the BU packet \( j \in n \) from the MN to HA/CN and \( R_j \) is the time of arrival of the BA packet (corresponding to packet \( j \)) from the HA/CN to the MN. \( h \) is the history window for calculating the weighted average, where \( h = 5 \) is considered to be an optimal value [23, 41]. \( c \) represents the weight of the RTT value compared to the RTT jitter value. For example, if \( c = 5 \), it means that the RTT jitter value contributes 5 times more than the RTT value. Finally, the variables \( Z \), \( D \) and \( J \)
are initialized as: $Z_0 = RT T_0$; $D_0 = 0$; and $J_0 = D_1$. The network with lower RNL value will be the target for handoff. $M^4$ using the RNL metric assumes that handoffs based on network load prediction will be beneficial for a wide range of applications, especially real-time applications such as VoIP.

As mentioned previously, a naive scheme on the other hand, is similar to MADM methods [21,22] and aims at selecting a network providing best QoS at a particular time $t$. Thus, for example, a network $i$ providing best QoS in terms of bandwidth ($B_i$), delay ($D_i$), jitter ($JIT_i$) and packet loss ratio ($PLR_i$) will be the target for handoff. The QoS function for a particular network $i$ can be written as [22]:

$$QoS_i = w_B * B_i + w_D * \frac{1}{D_i} + w_{JIT} * \frac{1}{JIT_i} + w_{PLR} * \frac{1}{PLR_i}$$

(21)

where $i \in I$; $w_B, w_D, w_{JIT}$ and $w_{PLR}$ are the set of weights; and $w_B + w_D + w_{JIT} + w_{PLR} = 1$. The network $i$ with higher $QoS$ value will be the target for handoff.

To compare our method with $M^4$ and the naive method, we formulated a hypothesis that our method should reduce the expected number of vertical handoffs while maximizing user’s QoE. Our hypothesis was based on the fact that $M^4$ and the naive methods consider precise RNL and QoS values for handoffs. In both methods, even the very close RNL or QoS values on network interfaces can cause sudden handoffs. Using these methods, handoffs can occur even if the QoE level is same on both network interfaces, which might not be optimal. On the contrary, our method considers finite states to represent QoE where the HMMs directly learn and predicts QoE. Further, the Q-value function learns the optimal action-value pair for proactive QoE-aware handoffs. We now consider the problem of reducing expected number of handoffs ($\Delta$) between two network interfaces (WLAN and CDMA 2000) while maximizing user’s QoE. For a vertical handoff decision problem, we used the reward function ($R$) defined in Eq. 5. To avoid ping-pong effects during handoffs, we chose the same hysteresis margin proposed in [23] and considered ITU-T G.711 and ITU-T G.729 voice codecs for results analysis. In the Q-learning algorithm (Eq. 15), we selected $\alpha = 0.80$ and $\gamma = 0.95$.

For results analysis, we again considered the experimental data set from the authors in [23] (see section 6.2.1 for the discussion on experimental setup). In this paper, our proposed method considers delay values to predict QoE. Further, $M^4$ also considers the delay values to compute the RNL metric. Thus, for comparative analysis, the naive method only considers delay ($D_i$) determine $QoS_i$. The table 5 shows that the proposed method almost matches the best case method where our method reduces the average number of
Table 5: Results showing expected number of handoffs reduced by proposed scheme compared to Naive scheme and $M^4$.

| Cases  | Best | Naive | $M^4$ | Proposed | Reduction against Naive | Reduction against $M^4$ |
|--------|------|-------|-------|----------|-------------------------|-------------------------|
| ITU-T G.729 | 21   | 63    | 52    | 21       | 66.67%                  | 59.61%                  |
| ITU-T G.711 | 21   | 64    | 52    | 24       | 62.50%                  | 53.84%                  |

unnecessary handoffs by almost 56% compared to $M^4$. Similarly, compared to the naive scheme, the proposed method reduces the average number of handoffs by approximately 65%. The difference in the number of handoffs for ITU-T G.711 and ITU-T G.729 codec is due to the fact that ITU-T G.729 codec provided better QoE and could sustain variations in RTTs better than the ITU-T G.711 codec. The proposed method in case of the ITU-T G.711 codec tried to maintain higher QoE levels by making higher number of handoffs to the network interface that provided higher QoE. The results presented in this section validates that:

1. Our passive probing method based on HMMs can be used by any MN incorporating multi-homed mobility management protocol such as M-MIP for efficient QoE prediction for all network interfaces simultaneously. Our method eliminates the need for active probing mechanism. Instead, it uses signaling mechanisms such as BU/BA packets for accurate QoE prediction. We showed that the average prediction accuracy of approximately 97% was achieved.

2. Our method incorporating HMMs and RL can be used by any MN for seamless roaming in HANs. Our results clearly validate that our method reduce the average number of handoffs by approximately 65% compared to the state-of-the-art methods.

4.4 Discussion

Developing metrics for users’ QoE prediction is an active area of research. Recently, several methods for QoE measurement and prediction were proposed [67, 60]. For example, the ITU-T E-Model [59], PESQ [68], PSQA [51], Menkovski et. al [69], and CaQoEM [3]. In this paper, we considered QoE as the function of the ITU-T E-Model [59] as it is the most widely used metric for users’ QoE prediction in both industry and academia. The E-Model outputs the mean opinion score as a non-linear function of delay, packet
loss and numerous other parameters including codec-type, mean loss burst length and advantage factor. This parameter however, does not consider user QoE ratings over time and is limited to VoIP applications. We believe, capturing users’ QoE over time can help build robust and more realistic models. As part of the future work, we would like to incorporate SCaQoEM [70] for users’ QoE estimation. We can then try to integrate PRONET with SCaQoEM for highly adaptive handoffs for various applications used under varying context.

We would also like to integrate mechanisms for users ratings collection on-the-fly, once the MN goes through the handoff. This way the MN can optimize the reward function based correct/incorrect actions taken by it based on direct users’ feedback. Finally, in this paper, we considered two network interfaces (WLAN and CDMA2000). In the future, a MN may incorporate several other network interfaces such as Bluetooth and ZigBee. Thus, as mentioned in section 3, for each network interface, a new HMM will have to be learnt. Similarly, for Q-learning, new states and actions for the new network interface will have to be incorporated. However, this can easily be integrated within our system.

As mentioned previously, QoE prediction and provisioning is a challenging task. Till date, nearly all methods [25, 6, 26, 27, 28] treated these problems independently [26, 20]. Therefore, lacking either of the two crucial functionalities without which an efficient system for QoE provisioning cannot be realized. To the best of our knowledge, ours is the first paper to integrate QoE prediction and proactive QoE provisioning capabilities into a mobility management protocol. In all, the results presented in the previous subsection clearly validate our methods for efficient QoE prediction and proactive QoE provisioning in HANs. We showed that the HMMs trained using passive probing (thereby, eliminating the need for additional probe packets) i.e., using the BU/BA messages exchanged using between the MN and the HA can be used for accurate QoE prediction with high accuracy. Further, compared to the state-of-the-art methods, using Q-learning, a large number of handoffs can be reduced significantly.

5 Conclusion

This paper proposed, developed and validated a novel method for QoE prediction using HMMs and M-MIP based passive probing mechanism. Our results based on simulations and experimental studies conclude that HMMs trained using OWD or RTT delay calculated using BU and BA packets are suitable to accurately estimate and predict QoE for
VoIP applications. Our method achieves an average prediction accuracy of 97%. The highlight of our approach is that it learns QoE states automatically and quickly by considering finite state spaces compared to the state-of-the-art.

This paper also proposed, developed and validated a novel reinforcement learning based method for proactive QoE-aware handoffs in HANs. We demonstrated that our method reduces a number of vertical handoffs by 60.65% compared to \( M^4 \) and a naive method while maintaining desired QoE. As an immediate future work, we will incorporate our methods on mobile devices running Android operating system and on other resource constraint devices such as Raspberry Pi.

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