LWA Rate Adaption by Enhanced Event-Triggered Reporting

Yi-Bing Lin, *Fellow, IEEE*, Ying-Ju Shih, Hung-Chun Tseng and Ling-Jyh Chen

***Abstract*—Unlicensed spectrum has been utilized to open up additional capacity to support LTE service. LTE and WLAN Aggregation (LWA) is a perfect solution that satisfies this need. In 2017, Taiwan has deployed the first commercial LWA service. The deployed LWA network reuses and is nicely merged with the existing individual LTE and WLAN networks. To provide appropriate WLAN transmission bandwidth, the UE periodically measures the WLAN quality and reports the results to the eNB (the LTE base station). The eNB then decides if the transmission rate should be adapted. We investigate the performance of periodical reporting and then propose the enhanced event-triggered reporting to improve the performance of WLAN transmission rate adaption. We suggest how to select appropriate frequency to minimize the network traffic of periodical reporting. We also show that enhanced event-triggered reporting outperforms periodical reporting. Our solution utilizes the standard 3GPP protocols and does not modify the mobile phone's software.**

***Index Terms*—Long Term Evolution (LTE), Wireless Local Area Network (WLAN), LTE and WLAN Aggregation (LWA), Measurement Report, Unlicensed Spectrum, Wi-Fi**

I. Introduction

In the recent years, mobile users and mobile data traffic have been dramatically increased, the telecom operators are seeking solutions to support more users and wider bandwidth including device-to-device communications [18, 19], Licensed Assisted Access (LAA) [22], and LTE and WLAN Aggregation (LWA) [7]. Both LAA and LWA utilize unlicensed spectrum to open up additional Long Term Evolution (LTE) service capacity. Since most wireless data is consumed indoors, unlicensed spectrum is particularly suited to indoor deployments, which is a key market for mobile operators. By utilizing Wireless Local Area Network (WLAN) to carry LTE traffic, LWA is a palatable way to bring LTE and WLAN together [1, 2, 14]. LWA cleverly uses the well-established Wi-Fi protocols and coexistence mechanisms to carry LTE traffic to offer exceptionally fast data speeds. In 2017, we (Chunghwa Telecom) have deployed the first commercial LWA service in the world [3]. We also consider integrating LWA with mobile edge computing [20, 21] to enhance the radio bandwidth for edge computing.

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Figure 1 illustrates a simplified LWA network architecture. The LWA-supported User Equipment (UE, Figure 1 (1)) accesses the LTE network through the eNB (LTE base station; see Figure 1 (2)), and sends packets to external networks through the Evolved Packet Core (EPC; see Figure 1 (3)). To implement LWA, the Wi-Fi APs (Figure 1 (4)) are connected to the eNB, and every downlink data stream from the EPC to the UE can be split at the eNB into two branches targeting at either LTE or WLAN.

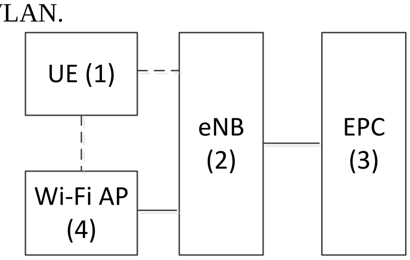


Figure 1. A simplified LWA network architecture.

One important issue about LWA is to detect the quality of WLAN, and provide the appropriate transmission rate to the UE. To maintain WLAN transmission quality such as low packet loss rates, the eNB adapts the transmission rate dynamically according to Wi-Fi AP's channel quality. To do so, 3GPP R13 [4, 6, 9, 15] has proposed two feedback mechanisms (which are followed by subsequent 3GPP releases): Xw-based feedback from the Wi-Fi AP and UE-based feedback from the UE. Since a typical legacy Wi-Fi AP does not provide Xw feedback, most studies consider the UE-based feedback mechanism. In [5], Lopez-Perez et al. used the periodical Packet Data Convergence Protocol (PDCP) LWA status report [6] to estimate the packet transmission delay over the WLAN channel. The delay over LTE channel can also be estimated by the Radio Link Control (RLC) status reports. Then the eNB sends the packet to the UE through the path with lower delay. However, this method may incur high computing complexity because the eNB needs to estimate the transmission delay of each packet before transmission. In addition, this method may need to record the transmission path of each unacknowledged PDCP packet, which consumes extra system memory. In [7], Lin et al. proposed a simple scheme for the eNB to adapt the LTE to WLAN transmission ratio based on a predefined LTE-to-WLAN Ratio table. In this approach, the eNB estimates the WLAN channel quality based on the received WLAN signal strength indicator (RSSI) in the measurement reports periodically sent from the UE. The eNB then adapts the transmission rate based on the received RSSIs. This approach may waste the uplink radio resource and incur extra signaling load [8].

To resolve the above problems, we propose the enhanced event-triggered reporting approach. To the best of our knowledge, no researchers have proposed event-triggered reporting approach for LWA transmission rate adaption. In this approach, the UE sends a WLAN measurement report to the eNB only when it detects the RSSI change. Two pre-defined tables are built. The WLAN RSSI range table built in the UE consists of several WLAN RSSI ranges. The WLAN transmission rate table built in the eNB consists of several WLAN RSSI ranges (same as those saved in the UE) and their corresponding transmission rates. The UE triggers report sending according to the WLAN RSSI range table. Based on the received report, the eNB determines new transmission rate. As compared with periodical reporting, enhanced event-triggered reporting is optimal in the sense that it only generates necessary measurement report traffic. However, building the WLAN RSSI range table in the UE is not a trivial task. We will show that the table can be built without modifying the UE software. LWA is also affected by metrics such as system load and capacity of backhaul links. These metrics determine the upper bound transmission rate for downlink, and are typically used in network planning to select appropriate eNB and Wi-Fi APs. For example, if the backhaul link is 500Mbps, then the operator will select the eNB and Wi-Fi APs such that the maximal net transmission rate is no more than 500Mbps. Our approach is independently exercised without being affected by these metrics.

This paper is organized as follows. Section II describes WLAN RSSI measurement for switching APs (i.e., for mobility) based on the event-triggered mode, and for transmission rate adaption based on the periodical mode. We also point out potential problems of periodical reporting. Section III proposes enhanced event-triggered reporting for transmission rate adaption to mitigate the problems of periodical reporting. Section IV conducts analytic analysis to model periodical reporting. Section V uses the analytic results and measurements to validate the simulation experiments. Our study suggests how to select appropriate frequency to minimize the network traffic of periodical reporting. We also show that enhanced event-triggered reporting outperforms periodical reporting.

II. WLAN RSSI MEASUREMENT REPORTING

This section describes how WLAN RSSI measurement reports are used for UE mobility (i.e., switching between APs) and WLAN transmission rate adaption.

A. *Event-triggered Reporting for UE Mobility*

According to 3GPP TS 36.331 [9], the eNB can configure a UE to perform WLAN measurement and report the measurement results. There are 2 trigger modes of WLAN measurement reporting. Periodical reporting is typically used to adapt WLAN transmission rate of the serving Wi-Fi AP as we described in Section I. Event-triggered reporting is typically used in the mobility procedure to determine if the UE should connect to a Wi-Fi AP, switch to another AP or disconnect from the AP. When event-triggered reporting is configured, the UE sends a measurement report when one of three events occurs. Event W1 is triggered at a UE to notify the eNB only when LWA is not activated, and the UE detects a suitable Wi-Fi AP (i.e., the RSSI of the AP is better than a threshold THR_1). Then the eNB may activate LWA for the UE. Events W2 and W3 are triggered only when the UE is connected to a Wi-Fi AP (the serving AP). Event W2 is triggered if the RSSI of the serving AP becomes worse than a threshold THR_3 and the RSSI of a neighbor Wi-Fi AP becomes better than a threshold THR_4. Event W3 is triggered to notify the eNB that the RSSI of the serving AP becomes worse than a threshold THR_2, and the eNB may invoke the LWA deactivation procedure.

Figure 2 depicts the RSSI changes of two Wi-Fi APs (AP 1 and AP 2) during an observation period. In the beginning, the UE is not connected to any AP. At T_1, the RSSI of the AP 1 becomes larger than THR_1. Therefore, the UE sends a W1-triggered (measurement) report to the eNB. The eNB then activates LWA by sending the LWA setup configuration to the UE. After successful WLAN association, AP 1 becomes the serving AP for the UE. At T_2, the RSSI of AP 1 drops below THR_3 and the RSSI of AP 2 is larger than THR_4. The UE sends a W2-triggered report to the eNB. The eNB then invokes the WLAN mobility procedure to transfer the UE from AP 1 to AP 2. When the RSSI of the serving AP 2 is smaller than THR_2, the UE sends a W3-triggered report to the eNB at T_3. Then the eNB sends the LWA release configuration to the UE, and LWA is deactivated after T_3.

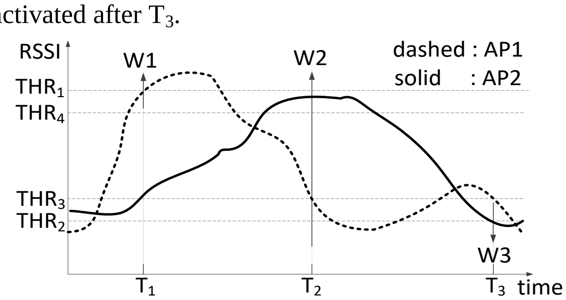


Figure 2: Triggering for events W1, W2, and W3.

In general, $THR_1 \geq THR_4 > THR_3 > THR_2$. From the above description, it is obvious that no event can trigger the UE to send a measurement report when the signal of the serving WLAN becomes better.

B. Periodical Reporting for WLAN Transmission Rate Adaption

WLAN transmission rate adaption is performed at the Radio Resource Management layer (RRM) of the eNB. The RRM uses a WLAN transmission rate table (TR; see Table 1) to determine the transmission rate to the UE. In this table, $THR_{Lm} > THR_{L(m+1)}$ and $Rate_m > Rate_{m+1}$, where $1 \leq m < M$. Note that Infinity (INF)$\gg THR_{L1}$ represents a very large value. Also, $THR_{LM} = THR_2$ and $THR_{L(M-1)} > THR_1$.

Suppose that the UE sends a measurement report to the eNB with an RSSI such that THR_{Lm}<RSSI<$THR_{L(m-1)}$, then the RRM will instruct the PDCP layer to schedule the received packets and transmit them to the UE with the rate $Rate_m$. For the TR table used in the ITRI LWA eNB [7], $M = 6$, where $THR_{L1} = -50$ dBm, $THR_{L2} = -55$ dBm, $THR_{L3} = -60$ dBm, $THR_{L4} = -65$ dBm, $THR_{L5} = -70$ dBm, and $THR_{L6} = THR_2 = -75$ dBm. The transmission rates are $Rate_1 = 312$ Mbps, $Rate_2 = 248$ Mbps, $Rate_3 = 185$ Mbps, $Rate_4 = 156$ Mbps, $Rate_5 = 134$ Mbps, and $Rate_6 = 117$ Mbps, respectively.

Table 1: WLAN TR table

WLAN RSSI Range	Transmission Rate
THR_{L1} - INF	$Rate_1$
THR_{L2} - THR_{L1}	$Rate_2$
…..	…..
$THR_{L(m+1)}$ - THR_{Lm}	$Rate_{(m+1)}$
…..	…..
THR_{LM} -$THR_{L(M-1)}$	$Rate_M$

When the UE is configured in the periodical reporting mode, it periodically sends the measurement reports, and the eNB uses the received RSSI to search the TR table to determine the transmission rate for the UE. Periodical reporting incurs two problems. First, the UE repeatedly sends the measurement reports to the eNB even if the RSSI does not change, which wastes the wireless bandwidth as well as computation resource at the eNB. This effect becomes serious if the reports are frequently sent. Second, the eNB cannot immediately detect the RSSI change until it receives the next report. This effect becomes serious if the reports are infrequently sent. We will investigate these two problems in Section IV.

A better way to detect the RSSI change is to download the first column of the TR table to the UE, and when the UE detects the RSSI change, it triggers to send the measurement report to the eNB. Unfortunately, the event-triggered reporting mechanism defined in 3GPP does not allow the UE to report the situation when the RSSI of the serving AP becomes better than a threshold (e.g., THR_1 in Fig. 2). In the next section, we propose a novel setup in event-triggered reporting to detect the situation when the RSSI of the serving AP becomes better.

III. Enhanced Event-triggered Reporting for Transmission Rate Adaption

From the description of event-triggered reporting, the events defined in the 3GPP LWA specifications cannot be used to adapt the transmission rate of the serving AP for the following reason. After the LWA is activated for a UE, there is no event to report when the serving AP's RSSI becomes better than a threshold. To resolve this issue, we propose a novel yet simple setting for Wi-Fi APs and the UE, which allows W2 to detect when the serving AP's RSSI becomes better. Our approach is called enhanced event-triggered reporting, which only slightly modify the RRM of the eNB.

In this approach, W2 is used to increase the transmission rate of the serving AP, and W3 is used to decrease the transmission rate. In WLAN, every Wi-Fi AP is identified by a service set identifier (SSID) and a basic service set identifier (BSSID). The idea is to configure every Wi-Fi AP in the LWA with two identities, where SSID1/BSSID1 is the serving AP identity (called the first identity) for normal LWA operations (activation, deactivation, mobility) and SSID2/BSSID2 is used as the identity to "pretend" that the serving AP is a neighbor AP. That is, SSID2/BSSID2 (called the second identity) is used to represent "AP 2" in Figure 2 to trigger W2 for rate adaption at the serving AP. In the reminder of this section, we use AP 1 to represent the serving AP with the first identity, and AP 2 as the "neighbor AP", which is the serving AP with the second identity. Let $RSSI_x$ be the RSSI of AP x. Then $RSSI_1 = RSSI_2$ in our example.

Suppose that an LWA eNB physically connects to two APs, i.e., AP 1 and AP 3 where the first identity of AP 3 is SSID3/BSSID3. After a UE is connected to AP 1 with its first identity, the RSSI change rules are downloaded to the UE as follows. After LWA activation, the eNB sends the RRCConnectionReconfiguration message with the MeasConfig information element to the UE, which specifies the measurements to be performed by the UE. MeasConfig has 3 major parameters: measurement objects (MOs), reporting configurations (RCs) and measurement identities (MIs). An MO indicates the object (i.e., the AP specified by its identity) on which the UE will perform measurements. The format of an MO is "SSID/BSSID". In our example, there are three MOs, one for AP 1 (the serving AP), one for AP 2 (the serving AP pretending a neighbor AP), and one for AP 3 (the real neighbor AP). Therefore, the measObjectToAddModList element of MeasConfig includes the following MOs:

MO_1: SSID1/BSSID1, MO_2: SSID2/BSSID2,
MO_3: SSID3/BSSID3,

where MO_1 represents the first identity of AP 1, MO_2 represents the second identity of AP 1, and MO_3 represents the first identity of AP 3.

An RC specifies the reporting criteria such as the reporting trigger mode, the periodical reporting period, or the triggering conditions of an event. In our example, the reportingConfigToAddModList element of MeasConfig specifies $2M$ RCs, which implement the WLAN RSSI range table. The first $M-1$ RCs specify the W2 events for increasing the transmission rates:

RC_1: W2(INF,THR_{L1}), RC_2: W2(INF,THR_{L2}), …,
RC_{M-1}: W2(INF,$THR_{L(M-1)}$)

The M-th RC specifies the W2 event for switching from AP 1 to AP 3:

RC_M : W2(THR_3,THR_4)

The next $M-1$ RCs specify the W3 events for decreasing the transmission rate:

RC $_{M+1}$: W3(THR$_{L1}$), RC $_{M+2}$: W3(THR$_{L2}$), …, RC $_{2M-1}$: W3(THR$_{L(M-1)}$)

and the last RC specifies the W3 event for LWA deactivation:

RC$_{2M}$: W3(THR$_2$)

A measurement identity (MI) links an MO to an RC, which is included in the measurement report as a reference number of the measurement configuration. In our example, the MeasIdToAddModList element in MeasConfig configures 2M MIs, where the first $M-1$ of them specify the relationship between MO$_2$ and RC$_1$-RC$_{M-1}$:

MI$_1$: (MO$_2$, RC$_1$), MI$_2$: (MO$_2$, RC$_2$), …, MI $_{M-1}$: (MO$_2$, RC $_{M-1}$),

For $1 \le m \le M-1$, MI$_m$ configures a W2 event to detect when to increase the WLAN transmission rate. Specifically, we set INF as the threshold for AP 1, and THR$_{Lm}$ as the threshold for AP 2. When the serving AP's RSSI becomes larger than THR$_{Lm}$ (i.e., RSSI$_1$=RSSI$_2$≥THR$_{Lm}$), this event is triggered because RSSI$_1$ is always smaller than INF and RSSI$_2$≥THR$_{Lm}$. Then the eNB uses RSSI$_2$ to search the WLAN TR table, which results in selection of the transmission rate Rate$_m$. The M-th MI links MO$_3$ to RC$_M$:

MI$_M$: (MO$_3$, RC$_M$)

When RC$_M$ is met, it means that RSSI$_1$ < THR$_3$ and RSSI$_3$>THR$_4$, and the eNB will switch AP 1 to AP 3. The last M MIs link MO$_1$ to RC $_{M+1}$-RC$_{2M}$:

MI $_{M+1}$: (MO$_1$, RC $_{M+1}$), MI $_{M+2}$: (MO$_1$, RC $_{M+2}$), …, MI$_{2M}$: (MO$_1$, RC$_{2M}$)

For $1 \le m \le M-1$, MI$_{M+m}$ configures a W3 event to detect when to decrease the WLAN transmission rate. When RC$_{M+m}$ ($1 \le m < M$) is met, RSSI$_1$<THR$_{Lm}$, and the eNB will selects the transmission rate Rate$_{m+1}$. When RC$_{2M}$ is met, RSSI$_1$<THR$_{LM}$ =THR$_2$, and eNB deactivates the UE from the LWA mode.

After the WLAN RSSI range table and the mobility criterion are established at the UE, it starts event-triggered reporting, and the eNB will receive one or more measurement reports triggered by the configured events. To support enhanced event-triggered reporting, the RRM of the eNB is slightly modified. First, when the MO of a W2 event is the second identity of AP 1, the RRM increases the transmission rate instead of switching the AP. Second, for a W3 event, if the received RSSI$_1$ > THR$_2$, then the RRM decreases the transmission rate instead of deactivating LWA.

Note that our experiments as well as commercial operation do not use LTE signal strength to determine transmission rate because the variation of the LTE signal strengths is small. This is due to the fact that LTE utilizes the licensed band, which is seldom interfered by other base stations, and the pure LTE's throughput can be stably kept. On the other hand, the Wi-Fi RSSI dramatically changes from -30 dBm to -75 dBm [7]. Therefore, changing the LWA transmission data rate is based on the Wi-Fi RSSI value. If the LTE RSSI is not stable, we can also change the transmission rate via LTE based on the LTE RSSI strength.

IV. Modeling Periodical Reporting

Consider the timing diagram in Figure 3. At time τ_0^* and τ_n^*, the changes of the serving AP's RSSI measured by the UE are larger than a threshold. Therefore, when the eNB receives the WLAN measurement reports sent by the UE at τ_1 and τ_{n+1}, it changes the WLAN transmission rate based on the RSSI range table. Let $t_1 = \tau_n^* - \tau_0^*$ be a random variable that represents the time interval between the previous RSSI change and the next RSSI change.

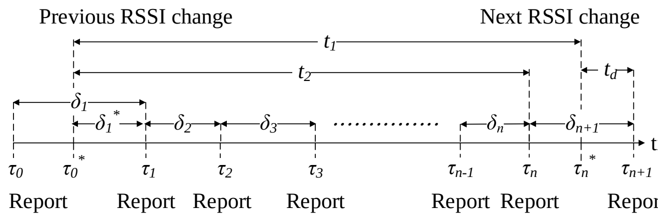


Figure 3. The timing diagram for RSSI changes and the periodical reporting.

Assume that t_1 has the density function $f_1(t_1)$ and the Laplace Transform $f_1^*(s) = \int_{t_1=0}^{\infty} f_1(t_1)e^{-st_1}dt_1$. For t_1 with the Gamma distribution, we have

$$f_1(t_1) = f_1(t_1, \alpha, \beta) = \frac{\beta^{\alpha} {t_1}^{\alpha-1} e^{-\beta t_1}}{\Gamma(\alpha)} \tag{1}$$

where α is the shape parameter and $1/\beta$ is the scale parameter. The Gamma distribution is considered because it is widely used in modeling the transmission delay and cell residence times of moving UEs in telecommunications networks [10, 16]. From the statistics of commercial operation, we also found that the RSSI change can be appropriately modeled by a Gamma variable or a sum of Gamma variables. The Laplace transform of (1) is

$$f_1^*(s, \alpha, \beta) = \frac{\beta^{\alpha}}{(s+\beta)^{\alpha}} \tag{2}$$

From the frequency-domain general derivative of Laplace transform, we have

$$\int_{t_1=0}^{\infty} {t_1}^n f_1(t_1) e^{-st_1} dt_1 = (-1)^n \left[\frac{f_1^{*(n)}(s)}{\mathrm{d}s^n}\right] \tag{3}$$

From (2) and (3), we have

$$\int_{t_1=0}^{\infty} {t_1}^n f_1(t_1, \alpha, \beta) e^{-st_1} dt_1 = \frac{\Gamma(\alpha+n)\beta^{\alpha}}{\Gamma(\alpha)(s+\beta)^{\alpha+n}} \tag{4}$$

Equations (2) - (4) will be used in the derivation of this section. In Figure 3, after the previous RSSI change occurs, the i-th measurement report is sent at τ_i. For $i \ge 1$, let $\delta_i = \tau_i - \tau_{i-1}$ represent the time interval between two measurement reports. A typical δ_i period is either a fixed interval or is Exponentially distributed. This section considers both cases.

A. Exponential δ_i and General t_1

Let δ_i be i.i.d. random variables with the Exponential density function

$$f(\delta_i) = \gamma e^{-\gamma \delta_i} \tag{5}$$

Let random variable N represent the number of measurement reports sent from the UE to the eNB between the previous RSSI change and the next RSSI change. For the derivation purpose, we express $\Pr[N=n]$ for an arbitrary t_1 distribution, and $\Pr[N=n,\alpha]$ for Gamma t_1 where α is the scale parameter in (1).

Theorem 1. For Exponentially distributed δ_i, if t_1 has a general distribution, then

$$\Pr[N=n]=\left[\frac{(-\gamma)^n}{n!}\right]\left[\frac{f_1^{*(n)}(s)}{\mathrm{d}s^n}\right]\Bigg|_{s=\gamma}$$

For Gamma t_1, $\mathrm{E}[N]=\mathrm{E}[t_1]/\mathrm{E}[\delta_i]$.

Proof. Since δ_i is Exponentially distributed, for any interval t_1, N has a Poisson distribution with the probability

$$\Pr[N=n,t_1]=\frac{(\gamma t_1)^n e^{-\gamma t_1}}{n!}$$

and

$$\Pr[N=n]=\int_{t_1=0}^{\infty}\Pr[N=n,t_1]\,f_1(t_1)dt_1$$

$$=\left(\frac{\gamma^n}{n!}\right)\int_{t_1=0}^{\infty}{t_1}^n f_1(t_1)e^{-\gamma t_1}dt_1 \quad (6)$$

For $n\geq 0$, substitute (3) into (6) to yield

$$\Pr[N=n]=\left[\frac{(-\gamma)^n}{n!}\right]\left[\frac{f_1^{*(n)}(s)}{\mathrm{d}s^n}\right]\Bigg|_{s=\gamma} \quad (7)$$

From (4), for Gamma t_1, we have

$$\Pr[N=n,\alpha]=\frac{\beta^\alpha\gamma^n\,\Gamma(\alpha+n)}{(s+\beta)^{\alpha+n}(n!)\,\Gamma(\alpha)}\Bigg|_{s=\gamma}$$

$$=\left[\frac{\Gamma(\alpha+n)}{\Gamma(\alpha)(n!)}\right]\left(\frac{\beta}{\gamma+\beta}\right)^\alpha\left(\frac{\gamma}{\gamma+\beta}\right)^n \quad (8)$$

From either (7) or (8), we have

$$\Pr[N=0,\alpha]=\left(\frac{\beta}{\gamma+\beta}\right)^\alpha \quad (9)$$

For Gamma t_1, the expected number $\mathrm{E}[N,\alpha]$ of the measurement reports between two RSSI changes is

$$\mathrm{E}[N,\alpha]=\sum_{n=1}^{\infty}n\left[\frac{\Gamma(\alpha+n)}{\Gamma(\alpha)(n!)}\right]\left(\frac{\beta}{\gamma+\beta}\right)^\alpha\left(\frac{\gamma}{\gamma+\beta}\right)^n$$

$$=\left[\frac{1}{\Gamma(\alpha)}\right]\left(\frac{\beta}{\gamma+\beta}\right)^\alpha\left\{\sum_{n=1}^{\infty}\left[\frac{\Gamma(\alpha+n)}{(n-1)!}\right]\left(\frac{\gamma}{\gamma+\beta}\right)^n\right\} \quad (10)$$

$$=\left[\frac{1}{\Gamma(\alpha)}\right]\left(\frac{\beta}{\gamma+\beta}\right)^\alpha \mathrm{S}(\alpha)$$

where $\mathrm{S}(\alpha)=\sum_{n=1}^{\infty}\left[\frac{\Gamma(\alpha+n)}{(n-1)!}\right]x^n$ and $x=\frac{\gamma}{\gamma+\beta}$. We elaborate on $\mathrm{S}(\alpha)$ as

$$\mathrm{S}(\alpha)=x\left\{\sum_{n=1}^{\infty}[n(n+1)\ldots(n+\alpha-1)]x^{n-1}\right\}$$

$$=x\left[\sum_{n=1}^{\infty}\frac{d^\alpha}{dx^\alpha}(x^{n+\alpha-1})\right]$$

$$=x\left\{\frac{d^\alpha}{dx^\alpha}\left[\frac{1}{1-x}-(1+x+x^2+\cdots+x^{\alpha-1})\right]\right\}$$

$$=x\left\{\frac{d^\alpha}{dx^\alpha}\left[\frac{1}{1-x}\right]\right\}=\frac{\Gamma(\alpha+1)x}{(1-x)^{\alpha+1}}$$

$$=\left\{\frac{\Gamma(\alpha+1)}{\left[1-\left(\frac{\gamma}{\gamma+\beta}\right)\right]^{\alpha+1}}\right\}\left(\frac{\gamma}{\gamma+\beta}\right) \quad (11)$$

Substitute (11) into (10) to yield

$$\mathrm{E}[N,\alpha]=\left[\frac{1}{\Gamma(\alpha)}\right]\left(\frac{\beta}{\gamma+\beta}\right)^\alpha\left[\frac{\Gamma(\alpha+1)\left(\frac{\gamma}{\gamma+\beta}\right)}{\left(1-\frac{\gamma}{\gamma+\beta}\right)^{\alpha+1}}\right]$$

$$=\left[\frac{1}{\Gamma(\alpha)}\right]\left(\frac{\beta}{\gamma+\beta}\right)^\alpha\left[\frac{\Gamma(\alpha+1)\left(\frac{\gamma}{\gamma+\beta}\right)}{\left(\frac{\beta}{\gamma+\beta}\right)^{\alpha+1}}\right]$$

$$=\frac{\alpha\left(\frac{\gamma}{\gamma+\beta}\right)}{\left(\frac{\beta}{\gamma+\beta}\right)}=\frac{\alpha\gamma}{\beta}=\frac{\mathrm{E}[t_1]}{\mathrm{E}[\delta_i]}$$

which is independent of the variance of the t_1 distribution. **Q.E.D.**

In Figure 3, $t_d=\delta_{n+1}-t_1+t_2$. Now we prove that if δ_n is Exponentially distributed, then t_d and δ_1^* have the same Exponential distribution.

Theorem 2. Suppose that $t_1\geq\delta_1^*$. If δ_i is Exponentially distributed i.i.d. random variable, then for Gamma t_1 distribution, both δ_1^* and t_d have the same distribution as δ_i.

Proof. We prove by induction. In Figure 3, we have $t_2<t_1$ and $\delta_{n+1}+t_2-t_1=t_d>0$. Let $t_{j,1}$ be the t_1 period for the *j*-th RSSI change, i.e., $t_{j,1}$ is the interval between the arrivals of the *j*-th RSSI and the (*j*+1)-th RSSI changes. Let $\delta_{j,1}^*$ be the δ_1^* period for the *j*-th RSSI change, $\delta_{j,i}$ be the δ_i period and $t_{j,d}$ be the t_d period. Clearly, $t_{j,d}$ is $\delta_{j+1,1}^*$ for the (*j*+1)-th RSSI change. Suppose that the hypothesis is true for the (*j*-1)-th RSSI change. That is, $\delta_{j,1}^*$ has the same Exponential distribution as δ_i. Now we prove that the hypothesis is also true for the *j*-th RSSI change, i.e., $\delta_{j+1,1}^*$ ($t_{j,d}$) has the same distribution as δ_i.

Let $f_d(t_{j,d})$ be the density function of $t_{j,d}$ under the condition that $N\geq 1$. That is, $t_{j,2}=\delta_{j,1}^*+\delta_{j,2}+\cdots+\delta_{j,n}$ and $t_{j,2}\leq t_{j,1}\leq t_{j,2}+t_{j,d}$. From the hypothesis, $\delta_{j,1}^*$ has the same Exponential distribution as $\delta_{j,1}$, and $t_{j,2}$ has the *n*-stage Erlang density function expressed as

$$f_2(t_{j,2},n,\gamma)=\frac{\gamma^n {t_{j,2}}^{n-1}e^{-\gamma t_2}}{(n-1)!} \quad (12)$$

Let $f_d(t_{j,d},n)$ be the density function of $t_{j,d}$ when $N=n\geq 1$. Then we have

$$f_d(t_{j,d},n)=f_d(t_{j,d})\Pr[N=n] \quad (13)$$

From (1), (5) and (12), $f_d(t_{j,d},n)$ is expressed as

$$f_d(t_{j,d},n)$$

$$=\int_{t_{j,1}=0}^{\infty}\int_{t_{j,2}=0}^{t_{j,1}}f_1(t_{j,1})f_2(t_{j,2},n,\gamma)f(t_{j,1}-t_{j,2}+t_{j,d})dt_{j,2}\,dt_{j,1}$$

$$= \gamma e^{-\gamma t_{j,d}} \int_{t_{j,1}=0}^{\infty} \int_{t_{j,2}=0}^{t_{j,1}} f_1(t_{j,1}) e^{-\gamma t_{j,1}} \left[\frac{\gamma^n t_{j,2}{}^{n-1}}{(n-1)!}\right] dt_{j,2}\, dt_{j,1}$$

$$= \left(\frac{\gamma^{n+1} e^{-\gamma t_{j,d}}}{n!}\right) \int_{t_{j,1}=0}^{\infty} t_{j,1}{}^n f_1(t_{j,1}) e^{-\gamma t_{j,1}} dt_{j,1} \quad (14)$$

Substitute (6) into (14) to yield

$$f_d(t_{j,d}, n) = \gamma e^{-\gamma t_{j,d}} \Pr[N = n, \alpha] \quad (15)$$

From (13) and (15), we have

$$f_d(t_{j,d}) = \gamma e^{-\gamma t_{j,d}} \quad (16)$$

Therefore, the hypothesis is true for $t_{j,d}$ ($\delta_{j+1,1}^*$). **Q.E.D.**

From (16), $\mathrm{E}[t_d, \alpha]$ is expressed as

$$\mathrm{E}[t_d, \alpha] = \int_{t_1=0}^{\infty} t_d f_d(t_d) dt_d = \frac{1}{\gamma} = \mathrm{E}[\delta_i] \quad (17)$$

which is independent of the variance of the t_1 distribution.

We expect that when an RSSI change occurs, it is detected by the next measurement report with a delay t_d. If t_d is large such that before the next measurement report arrives at the eNB, $J \geq 1$ RSSI changes occur. Then these measurement reports except for the last one are not detected, which will be investigated later. For an RSSI change, let t'_d be t_d such that $J = 0$, then the RSSI change is detected with the delay t'_d. We derive $\mathrm{E}[t'_d]$ as follows.

Theorem 3. If δ_i is Exponentially distributed, and t_1 has a general distribution. Then

$$\mathrm{E}[t'_d] = \frac{1}{\gamma} + \frac{\left.\frac{f_1^*(s)}{\mathrm{d}s}\right|_{s=\gamma}}{1 - f_1^*(\gamma)}$$

Proof. We note that $\mathrm{E}[t'_d] = \mathrm{E}[t_d | J = 0]$, where

$$\mathrm{E}[t_d | J = 0] \Pr[J = 0] = \int_{t_1=0}^{\infty} \int_{t'_d=0}^{t_1} t'_d \gamma e^{-\gamma t'_d} f_1(t_1) dt'_d dt_1$$

$$= \int_{t_1=0}^{\infty} f_1(t_1) \left[\frac{1 - e^{-\gamma t_1} - \gamma t_1 e^{-\gamma t_1}}{\gamma}\right] dt_1$$

$$= \frac{1 - f_1^*(\gamma)}{\gamma} + \left.\frac{f_1^*(s)}{\mathrm{d}s}\right|_{s=\gamma} \quad (18)$$

The probability $\Pr[J = 0]$ is expressed as

$$\Pr[J = 0] = \int_{t_1=0}^{\infty} \int_{t'_d=0}^{t_1} \gamma e^{-\gamma t'_d} f_1(t_1) dt'_d dt_1$$

$$= 1 - f_1^*(\gamma) \quad (19)$$

Therefore, from (18) and (19), we have

$$\mathrm{E}[t'_d] = \mathrm{E}[t_d | J = 0] = \frac{1}{\gamma} + \frac{\left.\frac{f_1^*(s)}{\mathrm{d}s}\right|_{s=\gamma}}{1 - f_1^*(\gamma)} \quad (20)$$

Q.E.D.

From Theorem 2, (17) shows that $\mathrm{E}[t_d, \alpha]$ is independent of the t_1 distribution. On the other hand, from Theorem 3, (20) indicates that $\mathrm{E}[t'_d]$ is affected by the second and higher moments of the t_1 distribution.

When $N = 0, \delta_i > t_1$, and there may be more than K RSSI changes occurring in δ_i. Let $t_{1,k}$ be the k-th t_1 preiod in δ_i, where $k \geq 1$. Note that the δ_i period starts at τ_i, which is a random observer of $t_{1,1}$. Let $t_{1,1}^*$ be the residual life of $t_{1,1}$, and

$$T_{1,k} = t_{1,1}^* + \sum_{j=2}^{k} t_{1,j} \quad (21)$$

For $k \geq 1$, let $\Pr[K \geq k, \alpha]$ be the probability that there are no less than k RSSI changes in δ_i. Then $\Pr[K \geq k, \alpha] = \Pr[\delta_i \geq T_{1,k}, \alpha]$. Let $r_{1,1}(t_{1,1}^*)$ be the density function of $t_{1,1}^*$. Then from (1) and the residual life theorem, we have

$$r_{1,1}(t_{1,1}^*) = \left\{\frac{1}{\mathrm{E}[t_1]}\right\} \left[1 - \int_0^{t_{1,1}^*} f_1(t_1) dt_1\right] \quad (22)$$

From (3), the Laplace transform of (22) is

$$r_{1,1}^*(s) = \left(\frac{1}{\mathrm{E}[t_1]s}\right) [1 - f_1^*(s)] \quad (23)$$

For $k \geq 1$, let $f_{1,k}(T_{1,k})$ be the density function of $T_{1,k}$. From (21), (3) and (23), and the convolution rule of the Laplace transform, $f_{1,k}^*(s)$ is

$$f_{1,k}^*(s) = \left(\frac{1}{\mathrm{E}[t_1]s}\right) [1 - f_1^*(s)][f_1^*(s)]^{k-1} \quad (24)$$

We derive $\Pr[K = k]$ and $\mathrm{E}[K]$ as follows.

Theorem 4. If δ_i is Exponentially distributed, then for an arbitrary t_1 distribution,

$$\Pr[K = k] = \begin{cases} 1 - \dfrac{1 - f_1^*(\gamma)}{\mathrm{E}[t_1]\gamma} & \text{for } k = 0 \\ \left(\dfrac{1}{\mathrm{E}[t_1]\gamma}\right) [1 - f_1^*(\gamma)]^2 [f_1^*(\gamma)]^{k-1} & \text{for } k \geq 1 \end{cases}$$

and $\mathrm{E}[K] = \mathrm{E}[\delta_i]/\mathrm{E}[t_1]$.

Proof. We first use (24) to derive $\Pr[K \geq k]$ as follows. Clearly, $\Pr[K \geq 0] = 1$. For $k \geq 1$, we have

$$\Pr[K \geq k] = \int_{T_{1,k}=0}^{\infty} \int_{\delta_i = T_{1,k}}^{\infty} f_{1,k}(T_{1,k}) f(\delta_i) d\delta_i\, dT_{1,k}$$

$$= \int_{T_{1,k}=0}^{\infty} f_{1,k}(T_{1,k}) e^{-\gamma T_{1,k}} dT_{1,k}$$

$$= \left(\frac{1}{\mathrm{E}[t_1]s}\right) [1 - f_1^*(s)][f_1^*(s)]^{k-1}\Big|_{s=\gamma}$$

$$= \left(\frac{1}{\mathrm{E}[t_1]\gamma}\right) [1 - f_1^*(\gamma)][f_1^*(\gamma)]^{k-1} \quad (25)$$

$\Pr[K = k]$ can be directly derived as follows:

$$\Pr[K = k] = \Pr[K \geq k] - \Pr[K \geq k + 1]$$

From (25), we have

$$\Pr[K = k] = \begin{cases} 1 - \dfrac{1 - f_1^*(\gamma)}{\mathrm{E}[t_1]\gamma} & \text{for } k = 0 \\ \left(\dfrac{1}{\mathrm{E}[t_1]\gamma}\right) [1 - f_1^*(\gamma)]^2 [f_1^*(\gamma)]^{k-1} & \text{for } k \geq 1 \end{cases} \quad (26)$$

If t_1 has the Gamma distribution, then (26) is rewritten as

$$\Pr[K=k,\alpha]=\left(\frac{\beta}{\alpha\gamma}\right)\left[1-\left(\frac{\beta}{\gamma+\beta}\right)^{\alpha}\right]^2\left(\frac{\beta}{\gamma+\beta}\right)^{(k-1)\alpha} \quad (27)$$

The expected value of K is expressed as

$$\begin{aligned}\mathrm{E}[K]&=\sum_{k=1}^{\infty}\left(\frac{k}{\mathrm{E}[t_1]\gamma}\right)[1-f_1^*(\gamma)]^2[f_1^*(\gamma)]^{k-1}\\&=\left\{\frac{[1-f_1^*(\gamma)]^2}{\mathrm{E}[t_1]\gamma}\right\}\sum_{k=1}^{\infty}k[f_1^*(\gamma)]^{k-1}\\&=\frac{1}{\mathrm{E}[t_1]\gamma}=\frac{\mathrm{E}[\delta_i]}{\mathrm{E}[t_1]}\end{aligned} \quad (28)$$

Q.E.D.

Equations (26) and (28) show that $\Pr[K=k]$ is affected by the t_1 distribution but $\mathrm{E}[K]$ is only affected by $\mathrm{E}[t_1]$.

B. General δ_i and Exponential t_1

Let δ_i be i.i.d. random variables with a general density function $f(\delta_i)$ and t_1 has the Exponential density function

$$f_1(t_1)=f_1(t_1,1,\beta)=\beta e^{-\beta t_1}$$

Then the RSSI changes are random observers of the inter-arrival times δ_i of measurement reports. We derive $\Pr[K=k]$ and $\mathrm{E}[K]$ as follows.

Theorem 5. If t_1 is Exponentially distributed, then for an arbitrary δ_i distribution,

$$\Pr[K=k]=\left[\frac{(-\beta)^k}{k!}\right]\left[\frac{f^{*(k)}(s)}{ds^k}\right]\Bigg|_{s=\beta}$$

For a fixed δ_i,

$$\Pr[K=k]=\frac{\left(\frac{\beta}{\gamma}\right)^k e^{-\frac{\beta}{\gamma}}}{k!}$$

and $\mathrm{E}[K]=\mathrm{E}[\delta_i]/\mathrm{E}[t_1]$.

Proof. Similar to the derivation for (6), the probability that there are k RSSI changes between two measurement reports is

$$\Pr[K=k]=\left[\frac{(-\beta)^k}{k!}\right]\left[\frac{f^{*(k)}(s)}{ds^k}\right]\Bigg|_{s=\beta} \quad (29)$$

If δ_i is a fixed value, then its density function can be considered as a delayed delta function with the Laplace transform

$$f^*(s)=e^{-\frac{s}{\gamma}} \text{ and } \frac{df^{*(k)}(s)}{ds^k}=\left(-\frac{1}{\gamma}\right)^k e^{-\frac{s}{\gamma}}$$

Therefore, (29) is rewritten as

$$\Pr[K=k]=\frac{\left(\frac{\beta}{\gamma}\right)^k e^{-\frac{\beta}{\gamma}}}{k!} \quad (30)$$

and

$$\mathrm{E}[K]=\frac{\beta}{\gamma}=\frac{\mathrm{E}[\delta_i]}{\mathrm{E}[t_1]} \quad (31)$$

Q.E.D.

The t_d density function, $\mathrm{E}[t_d]$ and $\mathrm{E}[t'_d]$ are derived as follows.

Theorem 6. If t_1 is Exponentially distributed, then for a fixed δ_i,

$$\mathrm{E}[t'_d]=\frac{1}{\beta}-\left(\frac{1}{\gamma}\right)\left(\frac{e^{-\frac{\beta}{\gamma}}}{1-e^{-\frac{\beta}{\gamma}}}\right)$$

Proof. Since t_1 is Exponentially distributed, the RSSI changes are random observers of δ_i. From (22)

$$f_d(t_d)=\left\{\frac{1}{\mathrm{E}[\delta_i]}\right\}\left[1-\int_0^{t_d}f(\delta_i)d\delta_i\right] \quad (32)$$

For a fixed δ_i, (32) is rewritten as

$$f_d(t_d)=\begin{cases}\gamma \text{ for } 0\le t_d<\dfrac{1}{\gamma}\\ 0 \text{ for } t_d\ge\dfrac{1}{\gamma}\end{cases}$$

and

$$\mathrm{E}[t_d]=\int_{t_d=0}^{\frac{1}{\gamma}}t_d f_d(t_d)dt_d=\frac{1}{2\gamma} \quad (33)$$

Now we derive $\mathrm{E}[t'_d]$ as follows.

$$\begin{aligned}\mathrm{E}[t_d|J=0]\Pr[J=0]&=\int_{t'_d=0}^{\frac{1}{\gamma}}\int_{t_1=t'_d}^{\infty}\beta t'_d e^{-\beta t_1}\gamma dt'_d dt_1\\&=\int_{t'_d=0}^{\frac{1}{\gamma}}\gamma t'_d e^{-\beta t'_d}dt'_d=\frac{\gamma\left(1-e^{-\frac{\beta}{\gamma}}-\frac{\beta}{\gamma}e^{-\frac{\beta}{\gamma}}\right)}{\beta^2}\end{aligned} \quad (34)$$

and

$$\begin{aligned}\Pr[J=0]&=\int_{t'_d=0}^{\frac{1}{\gamma}}\int_{t_1=t'_d}^{\infty}\beta e^{-\beta t_1}\gamma dt'_d dt_1\\&=\int_{t'_d=0}^{\frac{1}{\gamma}}\gamma e^{-\beta t'_d}dt'_d=\left(\frac{\gamma}{\beta}\right)\left(1-e^{-\frac{\beta}{\gamma}}\right)\end{aligned} \quad (35)$$

Therefore, from (34) and (35)

$$\begin{aligned}\mathrm{E}[t'_d]&=\mathrm{E}[t_d|J=0]\\&=\left[\frac{\gamma\left(1-e^{-\frac{\beta}{\gamma}}-\frac{\beta}{\gamma}e^{-\frac{\beta}{\gamma}}\right)}{\beta^2}\right]\left[\left(\frac{\gamma}{\beta}\right)\left(1-e^{-\frac{\beta}{\gamma}}\right)\right]^{-1}\\&=\frac{1}{\beta}-\left(\frac{1}{\gamma}\right)\left(\frac{e^{-\frac{\beta}{\gamma}}}{1-e^{-\frac{\beta}{\gamma}}}\right)\end{aligned} \quad (36)$$

Q.E.D.

Now we derive $\Pr[N=n]$ and $\mathrm{E}[N]$.

Theorem 7. If t_1 is Exponentially distributed, then for an arbitrary δ_i distribution,

$$\Pr[N=n]=\left(\frac{1}{\mathrm{E}[\delta_i]\beta}\right)[1-f^*(\beta)]^2[f^*(\beta)]^{n-1}$$

and for a fixed δ_i, $\mathrm{E}[N]=\mathrm{E}[t_1]/\mathrm{E}[\delta_i]$.

Proof. If $N=n\ge 1$, then the Laplace Transform of the t_2 distribution is

$$f_2^*(s)=\left(\frac{1}{\mathrm{E}[\delta_i]s}\right)[1-f^*(s)][f^*(s)]^{n-1} \quad (37)$$

From (37)

$$\Pr[N\ge n]=\int_{t_2=0}^{\infty}\int_{t_1=t_2}^{\infty}f_1(t_1)f_2(t_2)dt_1\,dt_2$$

$$= \left(\frac{1}{\mathrm{E}[\delta_i]\beta}\right)[1 - f^*(\beta)][f^*(\beta)]^{n-1} \quad (38)$$

Therefore, $\Pr[N = n]$ is derived from (38) as

$$\Pr[N = n] = \left(\frac{1}{\mathrm{E}[\delta_i]\beta}\right)[1 - f^*(\beta)]^2[f^*(\beta)]^{n-1} \quad (39)$$

If δ_i is a fixed value, then for $n > 0$,

$$\Pr[N = n] = \left(\frac{\gamma}{\beta}\right)\left[1 - e^{-\frac{\beta}{\gamma}}\right]^2 e^{-\frac{(n-1)\beta}{\gamma}} \quad (40)$$

and

$$\mathrm{E}[N] = \frac{\gamma}{\beta} = \frac{\mathrm{E}[t_1]}{\mathrm{E}[\delta_i]} \quad (41)$$

Q.E.D.

Equations (39) and (40) show that $\mathrm{E}[N]$ is independent of the variance and higher moments of the δ_i distribution, while $\Pr[N = n]$ is affected by the δ_i distribution.

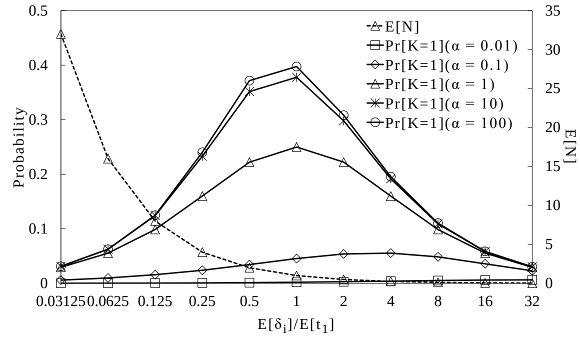
V. PERFORMANCE EVALUATION

We have actually implemented periodical reporting and enhanced event-triggered reporting in the ITRI eNB. This section conducts simulation experiments and measurements of ITRI eNB to investigate the performance of both periodical and event-triggered reporting. The analytic analysis described in Section IV is partially validated by the measurements. The simulation methodology can be found in [11-13], and the simulation experiments are validated by both analytic analysis and the measurements. For Pr[K=1], $\mathrm{E}[t_d']$ and $\mathrm{E}[N]$, the discrepancies between the simulation experiments and the analytic analysis are less than 0.07% for Exponential δ_i and 0.06% for fixed δ_i. In [7], the UE is configured with fixed δ_i=1024 ms, and E[t_1]=5 seconds. In the measurements, we obtain $\mathrm{E}[N] = 4.870$. The analytic result computed by using Equation (41) is $\mathrm{E}[N] = 4.883$, which is consistent with the measurement.

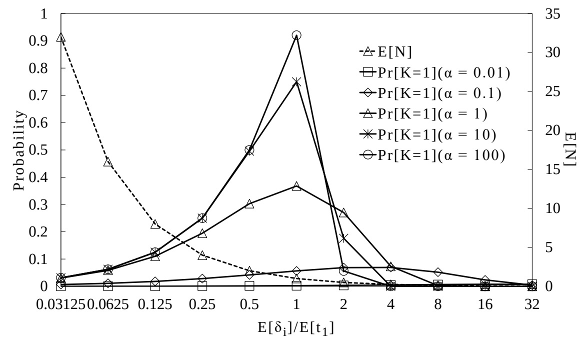
To achieve good performance, the δ_i value should be chosen such that $\mathrm{E}[N]$ is small, $\mathrm{E}[t_d']$ is small, and Pr[K=1] is large. Figures 4 and 5 show the performance of these output measures for periodical reporting. In these figures, t_d' and δ_i are normalized by E[t_1], where t_1 has the Gamma distribution with different variances, and δ_i is either fixed or Exponentially distributed. Figure 4 plots the $\mathrm{E}[N]$ and the Pr[K=1] curves against $\mathrm{E}[\delta_i]$ (normalized by E[t_1]). The figure shows that when $\mathrm{E}[\delta_i]$ increases, Pr[K=1] increases and then decreases. When δ_i is small, it is likely that K=0. Therefore, increasing δ_i will decrease Pr[K=0] and the probability that K=1 increases. When δ_i is large, it is likely that more than one RSSI changes occur in a δ_i period. Therefore, increasing δ_i will decrease Pr[K=1]. The maximal Pr[K=1] occurs when $\mathrm{E}[\delta_i] \approx \mathrm{E}[t_1]$.

We also observe that Pr[K=1] decreases as α decreases (the variance of the t_1 distribution increases). When the variance of t_1 increases, there are more short t_1 periods (where K=0) and more very long t_1 periods (where $K \geq 2$), and Pr[K=1] decreases. When $\alpha \geq 1$, the maximal Pr[K=1] occurs at $\mathrm{E}[\delta_i] \approx \mathrm{E}[t_1]$. When $\alpha < 1$, the maximal Pr[K=1] occurs when $\mathrm{E}[\delta_i] > \mathrm{E}[t_1]$.

From Theorems 1 and 7, $\mathrm{E}[N]$ is a decreasing function of $\mathrm{E}[\delta_i]$. The non-trivial result is that when $\mathrm{E}[\delta_i] \leq \mathrm{E}[t_1]$, $\mathrm{E}[N]$ significantly decreases as $\mathrm{E}[\delta_i]$ increases. On the other hand, when $\mathrm{E}[\delta_i] > \mathrm{E}[t_1]$, $\mathrm{E}[N]$ is insignificantly affected by $\mathrm{E}[\delta_i]$.

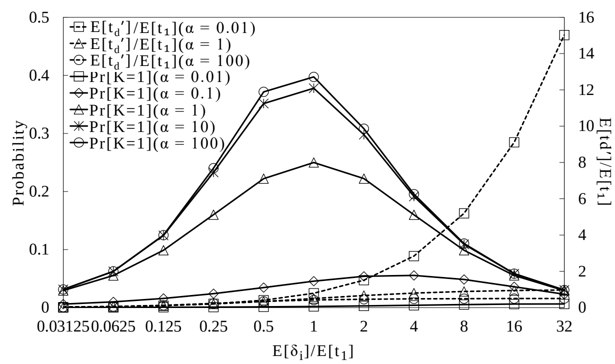


(a) Exponential δ_i

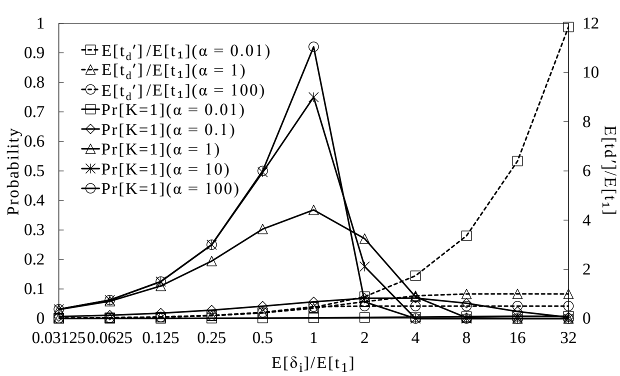


(b) Fixed δ_i

Figure 4. Pr[K=1] and E[N] against δ_i



(a) Exponential δ_i



(b) Fixed δ_i

Figure 5. Pr[K=1] and $\mathrm{E}[t_d']$ against δ_i

In periodical reporting, we should select $\mathrm{E}[\delta_i]$ such that $\mathrm{E}[N]$ is small and Pr[K=1] is large. From the curves in Figure 4, $\mathrm{E}[\delta_i] \approx \mathrm{E}[t_1]$ should be chosen so that Pr[K=1] is maximized and $\mathrm{E}[N]$ is sufficiently small.

Figure 5 shows that $\mathrm{E}[t'_d]$ increases as δ_i increases. When $\mathrm{E}[\delta_i] \leq \mathrm{E}[t_1]$, $\mathrm{E}[t'_d]$ insignificantly increases as $\mathrm{E}[\delta_i]$ increases. When $\mathrm{E}[\delta_i] > \mathrm{E}[t_1]$, $\mathrm{E}[t'_d]$ is more significantly affected by $\mathrm{E}[\delta_i]$. We also observe that $\mathrm{E}[t'_d]$ decreases as α decreases (the variance of t_1 increases). When the variance of the t_1 distribution increases, much more short t_1 than long t_1, and more t_1 will fall in a δ_i period, which results in a smaller t'_d. In periodical reporting, we should select $\mathrm{E}[\delta_i]$ such that $\mathrm{E}[t'_d]$ is small and Pr[K=1] is large. Based on our observation in Figure 5, $\mathrm{E}[\delta_i] \approx \mathrm{E}[t_1]$ should be chosen.

For $\mathrm{E}[N]$, both Exponential and fixed δ_i have the same performance. When $\mathrm{E}[\delta_i]/\mathrm{E}[t_1] < 2$, Pr[$K$=1] for fixed δ_i is larger than Exponential δ_i . On the other hand, when $\mathrm{E}[\delta_i]/\mathrm{E}[t_1]>2$, the result reverses. When $\mathrm{E}[\delta_i]/\mathrm{E}[t_1]<2$, $\mathrm{E}[t'_d]$ for fixed δ_i is smaller than Exponential δ_i. On the other hand, when $\mathrm{E}[\delta_i]/\mathrm{E}[t_1] > 2$, the result reverses. The above results show that when $\mathrm{E}[\delta_i]/\mathrm{E}[t_1]$ is small, fixed δ_i yields better performance and should be selected; otherwise, Exponential δ_i should be selected.

Based on the above discussion about Figure 5, $\mathrm{E}[\delta_i] \approx \mathrm{E}[t_1]$ should be chosen so that Pr[K=1] is maximized and $\mathrm{E}[t'_d]$ is sufficiently small. For Exponential δ_i, when α=1 and $\mathrm{E}[\delta_i] = \mathrm{E}[t_1]$, we have Pr[$K$=1] = 0.249958, E[$N$] = 1.00066, and $\mathrm{E}[t'_d] = 0.49995\mathrm{E}[\delta_i]$. When $\alpha = 100$, Pr[K=1] = 0.397383, E[N] = 0.999684, and $\mathrm{E}[t'_d] = 0.419364\mathrm{E}[\delta_i]$. For fixed δ_i, when α=1, and $\mathrm{E}[\delta_i] = \mathrm{E}[t_1]$, we have Pr[$K$=1]=0.367938, E[$N$] = 1.00024, and $\mathrm{E}[t'_d] = 0.418015\mathrm{E}[\delta_i]$. When α=100, Pr[K=1] = 0.920444, E[N] = 0.999979, and $\mathrm{E}[t'_d] = 0.481936\mathrm{E}[\delta_i]$.

In enhanced event-triggered reporting, Pr[K=1] = 1 , $t'_d = 0$, and $N = 1$, which is optimal as compared with periodical reporting. When α=1 and $\mathrm{E}[\delta_i] = \mathrm{E}[t_1]$, the event triggered reporting can save 36% redundant measurement reports and increase the accuracy of the RSSI change detection by 26% without RSSI change detection delay. In our approach, an extra overhead comes from using fake neighbor AP. The Wi-Fi bandwidth consumed by the fake neighbor is about 1.121% [17]. This overhead is small and acceptable in commercial operation. As for downloading the triggering rules, it is merely a one-time overhead. We have conducted experiments to measure the message exchange time of the RRC Connection Reconfiguration message pair for the measurement configuration (the time between when the eNB RRM issues "RRCConnectionReconfiguration" message and when the UE reports "RRCConnectionReconfigurationComplete" message). The average time of 1000 measurements is 37.7058 ms when $M = 1$ (i.e., no enhanced event-triggered reporting) and 38.414916 ms when $M = 6$. Our measurements indicate the enhanced event-triggered reporting incurs negligible overhead.

VI. Conclusion

LWA utilizes periodical reporting to adapt the WLAN transmission rate. How to select an appropriate period for sending measurement reports is an important issue that will affect the LWA performance. In this paper, we conducted the measurements, analytic analysis and the simulation experiments to provide guidelines for selection of appropriate frequency to minimize the network traffic of periodical reporting.

We then proposed enhanced event-triggered reporting, a novel approach to enhance 3GPP event-triggered reporting to increase/decrease the WLAN transmission rate. This approach fully explores the LWA transmission capacity by detecting the WLAN radio bandwidth in real time. We showed that enhanced event-triggered reporting incurs little extra overhead, and therefore outperforms periodical reporting. Our solution utilizes the standard 3GPP protocols and does not modify the mobile phone's software. This work is pending US, China and Taiwan patents. In the future, we will investigate the event-triggered reporting method in the dense network. For example, we can use reporting events to request the UE to report the nearby Wi-Fi AP in the same and adjacent frequency channels to detect congestion. We will also investigate the LWA rate adaption when LTE signal is unstable.

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