Application specific LTE TX Power Optimization using Predictive Modelling

Hinduja Ichapuram, Prasad R Rao, Maulik Patel, Diwakar Sharma and Tushar Vrind
Samsung Semiconductor India R&D, Samsung Electronics
Bangalore, India

***Abstract*—The ever changing nature of a UE's channel conditions pose a challenge to the existing closed loop power control technique. Today, most of the power control algorithms are highly dependent and controlled by the feedback and indications provided by the UE resulting in power hungry RF operations. This paper aims at deferring and optimizing LTE TX power for background data by reducing the RFIC's power consumption. Further, a predictive algorithm is used to determine and schedule TX at an optimal power level. This idea also finds application in low power distributed wireless sensor networks/IoT**

Keywords—LTE, power optimization, logistic regression, Predictive TX power

I. Introduction

There are existing proposals for intelligent hand off decisions based on radio channel conditions. This prediction is done by the eNodeB (eNB) and it relays information to the UE. The eNB in addition also has to maintain a huge data base that maps different location coordinates to differentiate signal fading characteristics**.** This paper aims at building intelligence in the user terminal (UE) which can predict low transmit (TX) power based on a training curve that is driven by factors like QoS(Quality of Service) Class Identifier, block error rate (BLER) and Path loss (PL) between eNB and UE. As per 3GPP release 8, the services having QCI more than 4, are Non-GBR. Non-GBR does not guarantee any minimum bit rate per EPS bearer. Non-GBR services are prone to congestion packet losses. The proposed idea is for the services which have QCI greater than 4 (Non-GBR) where in few seconds of delay is not time critical. Ex. Email, chat video streaming, Non-Conversational Video (Buffered Streaming), TCP based (chat, ftp, p2p, file sharing), Video (Live Streaming), Interactive Gaming, etc.

II. System model

Given a field scenario, eNB often requests the UE to reduce or increase its uplink power on basis of the radio channel condition, multiplexing and coding scheme (MCS) and number of resource blocks (NRB) allocated. During the initial phase our algorithm undergoes a training period wherein a profile is built on several parameters (MCS, PL, and NRB) for a given location. Post training, the UE would check the built power profile from the previous trials to find the probability of a TX power more optimal than eNB's request, within the affordable delay interval for a given QoS. Given that the uplink (UL) data of the application is delay tolerant (based on QoS) the UE may decide to defer its TX to the instance in the future where the TX power is likely to be low. The following system is modelled around the problem statement of taking a decision on whether to transmit according to what the eNB has requested or to delay SR request to a point where a successful TX can take place at a lower power. As SR request itself is not initiated by UE it does not have any implications on eNodeB side. However if SR request was already initiated and granted by eNodeB post which if the UE decides to delay the UL transmission then BSR is sent as 0 to eNodeB. SR is reinitiated by the UE based on the prediction algorithm wherein UL power is predicated to be lower than request UL power from the eNodeB. The location of the UE is calculated by fingerprinting three Observed Time Difference of Arrival (OTDOA) signals, or opportunistically using the Global Positioning System (GPS), eNB cell ID or Wi-Fi. Parameters from closed loop power equation (1) are used to model the input parameters for training.

$$P_{PUSCH}(i) = \min \{P_{CMAX}, 10\log_{10}(M_{PUSCH}) + P_{O\_PUSCH}(j) + \alpha(j) * PL + \Delta_{TF}(i) + f(i)\} \quad (1)$$

The signal profile parameters:
P_{Tx} [loc] - Power Transmitted by the UE
M_{PUSCH} [loc] - Number of Resource Blocks allocated
PL [loc] - Path loss observed
Δ_{TF} [loc] - MCS of the uplink data observed

The above data is collected per location (MCS [loc]) which forms the basic training set. Logistic regression determines whether to defer the transmission in time or to continue transmitting at eNB's requested power. Following are the input parameters to the logistic regression algorithm.

$$\Delta_{RB\,(t)} = M_{PUSCHprevious\_run\,(t+\Delta t)} - M_{PUSCHcurrent\_run(t)} \quad (2)$$

$$\Delta_{PL(t)} = PL_{previous\_run\,(t+\Delta t)} - PL_{current\_run\,(t)} \quad (3)$$

$$\Delta_{MCS(t)} = MCS_{previous\_run\,(t+\Delta t)} - MCS_{current\_run\,(t)} \quad (4)$$

A. Logistic Regression

Our goal is to estimate the weight vectors, given a set of supervised data [X] and the corresponding outcome [Y]. The weight vector [W] signifies the degree of importance of each input parameter.

$$XW^T = Y \quad (5)$$

$$X = [\Delta_{MCS}\ \Delta_{PL}\ \Delta_{RB}] \quad (6)$$

$$W = [w1\ w2\ w3] \quad (7)$$

$$Y = 0/1 \text{ , Do not defer transmission/defer transmission} \quad (8)$$

B. Training

Difference of closed loop power parameters eq. (2)-(4) between any two uplink TX transmission trials is computed and used in eq. (5) to compute the weight vector in eq. (7)

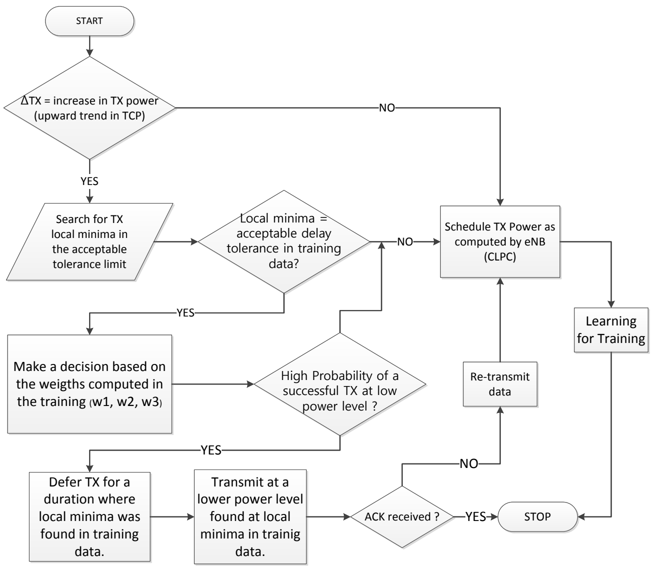

Figure 1 Proposed Prediction Algorithm

Fig.1, captures the algorithm which runs only if LTE UL data is a background data or delay insensitive in nature.

C. *Prediction*

X is computed by calculating the difference in MCS, PL and RB of the current scenario from the saved profile. The weight vector obtained from the training phase is then multiplied with X to obtain Y.

Fig.1, captures the algorithm which runs only if LTE UL data is a background data or delay insensitive in nature. The probability of a successful transmission at lower power is computed by the logistic regression eq. (8)

III. Prediction based LTE TX scheduling

Logistic regression model can schedule the SR request based on the output of the prediction algorithm, thereby applying a suitable delay proportional to QoS of the data. As shown in Fig.2, this intelligence can be applied at a data aggregator or MAC scheduler to control and defer the scheduling of SR and BSR for optimized TX power transmission.

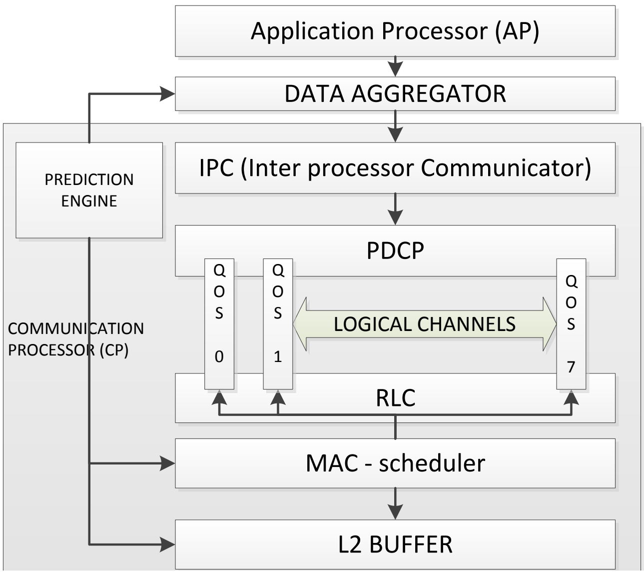

Figure 2 Prediction based Scheduling Request

A. *Optimized LTE Scheduling*

Buffer status request (BSR) scheduling can be optimized for LTE Delay insensitive high volume background traffic as shown in Fig.3, thus optimizing the TX power for the UE.

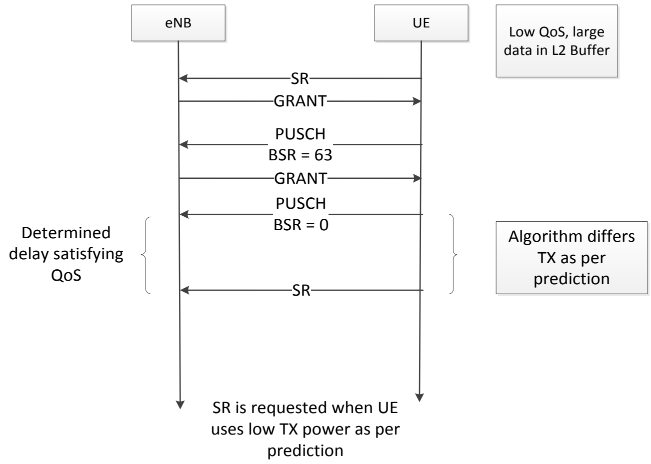

Figure 3 Optimized BSR Scheduling

B. *LTE SR (Scheduling Request)*

$$(10 * nf + [ns / 2] – N_{OFFSETsr})\%SR_{PERIODICITY} = 0$$

Parameters:
nf - System frame number
$N_{OFFSETsr}$ - Scheduling request observed
$SR_{PERIODICITY}$ = {5, 10, 20, 40, 80, 2, 1} - Scheduling request periodicity

An optimal $SR_{PERIODICITY}$ can be chosen by the algorithm based on its prediction for power efficient TX power transmission.

IV. Evaluation results

A. *Training Data*

Fig. 4 (a) denotes the input training set. Fig.4 (b) denotes the decision boundary obtained after training. A training accuracy of 76.85% was observed.

* denotes the difference [Δ_{MCS} Δ_{PL} Δ_{RB}] observed between uplink conditions, in the same geographic location.

* denotes the difference observed between the uplink conditions of two different geographic locations

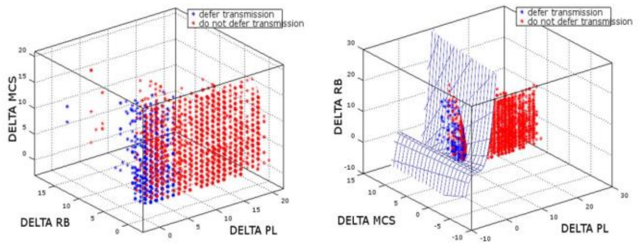

Figure 4 (a) Training Set (b) Decision Boundary

B. Prediction Phase

Two different scenarios were considered to check the prediction authenticity. Fig.5 (a) denotes saved profile being different from the channel conditions under which prediction is done. Predicted results show that the algorithm decided against deferring the transmission. Fig.5 (b) denotes saved profile being similar to channel conditions under which prediction is done. Table 1, captures the results where the prediction decided in favor of deferring the transmission at some instants.

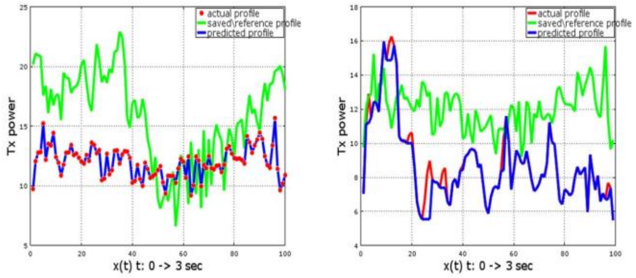

Figure 5 (a) Prediction Failures (b) Prediction Success

Based on the parameters given below Table 1, we were able to achieve an averaged gain of approximately 3dBm. Considering LTE ET PA which uses supply modulator and operating on HPM (High Power Mode) approximately using 1.8V for a TX output power of 23dBm could now be operated with supply modulator voltage of 0.15V lower than the normal scenario (1.8V – 0.15V = 1.65V) . The same number for LPM (Low Power Mode) is 0.05V. It requires implementation which may require additional memory of around 30KB. If the above mentioned time and memory is linearly interpolated then the user who takes one hour route daily would require memory of 1.17 MB. For a particular route, the data is written on the some memory location and weight vector is calculated. For the same route, the data is overwritten in next iteration and again weight vector is calculated for the iteration.

Training samples	3300- Do not defer,2800-Defer
Samples for prediction reference	100 samples averaged over 3000 samples
Memory consumed(bits)	(6000*18)*T/3(minutes) T- Duration of training

Table 1 Experiment details

V. Conclusion

A cross layer method to optimize LTE TX power for delay insensitive applications (Background Traffic) has been proposed. Logistic regression based prediction was used to find an optimal LTE TX power based on trained data for a specific geographical location. This idea will contribute to enhance the battery life of the DUT, use resource of the network efficiently. It finds a strong use case in IoT devices wherein battery life is very critical and data is delay insensitive in nature.

References

[1] Mobility Prediction Method for vehicular network using markov chains Arfah Hasbollah*, Sharifah H. S. Ariffin, N. Fisal

[2] Dowling, Martin. "Location aided wireless signal characteristic adjustment." U.S. Patent Application No. 10/74