Applicability of Different Models of Burstiness to Energy Consumption Estimation

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Abstract

The advent of internet use through mobile devices using WLAN has pushed the research of energy consumption quite aggressively to find a better solution that will lead to a longer battery life. There are quite a few ways to reduce the energy consumption of a mobile device e.g. rate adaptation, sleeping, battery recovery effect, different queuing algorithms etc. Most of these techniques deals with by adapting some method at the device end. However, in this paper we will look at the power consumption issue from the network or data source point of view. We will first show what kind of network traffic causes a reduced power consumption in the mobile device and then we will approach for a traffic model that fits best to that kind of traffic. Through our experiment we have found that bursty traffic consumes less power in the mobile device compared to the smooth data traffic. Having figuring out the traffic nature, we have used an On/Off model to capture the burstiness of data traffic. Our aim here is to model this bursty traffic using traffic modelling techniques so that the model can be used in data sources in the internet to send data traffic to the mobile devices in such a way that the energy consumption will be reduced.

KEYWORDS: Poisson Model, Self-Similar Model, On/Off model, Smooth Traffic, Bursty Traffic, Mobile Power Consumption, Nokia Energy Profiler, Bandwidth Controller.

1 Introduction

Since the last couple of decades, a number of different portable devices have been connected to the internet. This trend is growing fast, leading to billions of users with internet connection on their portable devices all over the globe. Although there are quite a few different technologies to connect to the internet for these devices e.g. 3G, yet the WLAN technology remains as one of the popular choices. The reason behind this is that it offers faster data rates. Moreover it is accessible mostly free of charge in organizational or personal domain. However, despite of being one of the popular technologies, it also incurs the most crucial problems for the portable devices, which is the power consumption. While the RF communication for usual mobile phone activities, display and the memory have the greatest impact on the power consumption of such devices, using a WLAN interface increases the power consumption in few orders of magnitude [5]. As a result it has become a critical issue to manage this kind of power consumption in an efficient way for portable devices.

A lot of studies have been conducted to improve the battery life of a mobile device mostly dealing with the techniques at the device end [5, 11]. However, in this paper we will look into the internet traffic model that can lead to a better understanding of power consumption using the WLAN technology and model the data traffic accordingly. There are basically two different types of IP traffic source, one with smooth traffic and the other with the bursty traffic. These two can be considered as the extreme cases as most of today's traffic falls in between them. The smooth traffic can be modelled with the Poisson traffic model which uses the Poisson distribution. Nevertheless researches [4, 13] have shown that this model is not good enough for the bursty internet traffic. In longer time scale this model smooths out the burstiness and makes the bursty traffic to look like random noise. Whereas the self-similar model scales the bursty traffic very well, as it has the similar characteristic on any scale. Having said that, the self-similar model is quite complex in reality while a simple On-Off model [14, 17] can be very useful to capture the burstiness in the IP traffic.

The goal of this paper is to find a suitable model for IP traffic that gives the best performance in terms of energy consumption. A proper model for IP traffic can be found through measurements taken by test environment using tools such as Nokia Energy Profiler. Eventually this will lead us to estimate the power consumption in terms of IP traffic model and hence to improve power consumption in portable devices by applying traffic shaping at the source.

2 Overview of Traffic Models

In this section we will look into the high level overview of different traffic models starting from the oldest one, the Poisson model. Next we will look into the Self-similar model which is recognized to be the most appropriate model to capture today's internet traffic. Finally, we will look into the simple On/Off model which is very attractive to capture the bursty nature of internet traffic.

2.1 Poisson Model

The Poisson traffic model was introduced in the context of telephony by A.K. Erlang and is the oldest traffic model still in use. It has a nice memoryless property that is very attractive from the analytical point of view. There are two basic assumption in this model:

1. The packet arrivals are independent of each other

2. The packet inter-arrival times are exponentially distributed

The mean arrival rate λ is the only parameter in Poisson model. The packet inter-arrival times are exponentially distributed with a mean $1/\lambda$. Also the number of packet arrivals on any time interval (t) follows a Poisson distribution with a mean $t\lambda$ [18]. The memoryless property of the poisson model signifies the fact that the future behaviour of the model will have no relationship with the past, present or distant behaviour. Another important property of the Poisson model is that, the superposition of all the independent poisson stream generates a new Poisson stream having the rate parameter as the summation of all the rates of the independent streams. These two properties have made the Poisson model an excellent choice as an analytical model for the traditional telephony system. Having said that, the memoryless property of this model does not allow it to reflect the bursty traffic which is more common in the traditional data driven network or the internet [9]. The reason behind this is that the Poisson model supports only short-range dependent process while the traffic burstiness can be characterized by the long-range process or by the heavy-tail distribution processes. The term short-range dependence refers to such a process where the correlation between values in different times decreases rapidly as the time difference increases. In other words, the correlation among values decreases exponentially as the time difference increases. The long-range dependence refers to the processes where there is non-negligible correlation between values despite the high time difference. In other words, the correlation between values decreases much more slowly than an exponential function as the time difference increases. Since Poisson model can not capture the long-tail nature of the bursty traffic, in fine scale bursty traffic appear bursty, but in coarse scale bursty traffic just looks like random noise.

Several studies have been carried out to show that Poisson model is not suitable for today's internet traffic [4, 13]. It was very good for older telephony system with traffic of low variability. Low variability also implies that no or nominal burstiness. However, internet traffic is of high variability which the Poisson model is unable to capture.

2.2 Self-Similar Model

The self-similar traffic model is built around the self-similarity phenomenon presented in the data traffic. The term self-similarity refers to a phenomenon where a certain property of an object is exactly or approximately similar to a part of itself [10]. The similarity still holds with different orders of magnitude or different scales on a dimension. In other words, the phenomena is invariant with space and time. This self-similar nature of traffic modelling allows traffic to look the same in a long range interval. That means the correlation never vanishes with longer time scales. This behaviour of self-similar process is completely opposite to the Poisson process where the correlation among data traffic smooths out with longer time scale and the process becomes memoryless. Nonetheless, it is this fractal [10] behaviour that makes the self-similar model to capture the burstiness of internet traffic.

There are several properties of a self-similar process which can be summarized as follows [9] -

1. It is a stochastic process that shows the *Long Range Dependence*.

2. The distribution is *fractal* like, which means that the process shows the same characteristic at any scale.

3. Mathematically the self-similar process is described by a parameter called the *Hurst Parameter* [7]. This parameter defines the degree of self-similarity.

4. It has a slowly decaying variance which is the most salient feature of the self-similar process from the statistical point of view.

Several studies have shown that the internet traffic follows the Self-similar model [9, 15] and the mathematical model for Self-Similarity can be found here [12, 18]. Although, the self-similar model captures the internet traffic most accurately, the complexity of this model with several parameters to be considered makes it difficult to analyse and computationally expensive to use.

2.3 On/Off Model

A model is generally said to be good when it is simple, accurate and easily applicable to both mathematical analysis and computer simulations. And when it comes to find a good model to capture the scaling/bursty behaviour of the internet traffic, the On/Off model is generally used by most of the people e.g. [14, 19, 20]. The properties that have made the On/Off model to be the most widely used data traffic model are as follows -

1. The model is capable of capturing the burstiness of data traffic efficiently.

2. The model is very simple to apply as compared to the Self-Similar model that has a greater number of parameters.

3. Having a smaller number of parameters, the model is easier to analyse.

The On/Off model can be considered as a finite state machine having only two states - On state and Off state. On state refers to an active state where some process is going on whereas the Off state refers to a situation where no process is running. The state transitions between On and Off states is depicted in Figure 1. The model starts initially at the Off state as it is assumed that no process is running initially. The model remains in the Off state until a new activity is started, e.g. until a new packet arrives. The state transfers from Off state to On state as soon as a new packet arrives and also the on-timer is started. The model remains in the On state as long as the packets keep coming within the on-timer interval and the on-timer gets restarted every time a new packet

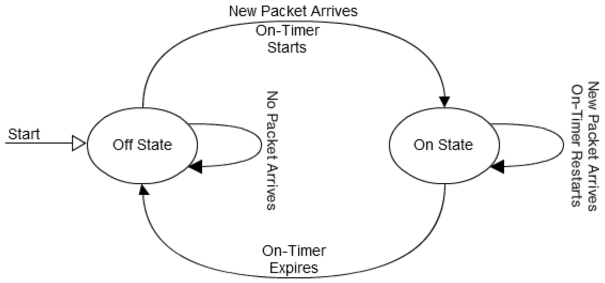

Figure 1: On/Off model state transition Diagram

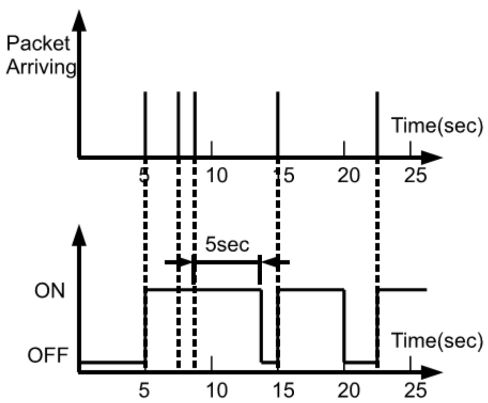

Figure 2: On/Off state transition with 5 sec on-timer [17]

arrives. If there is no new packet coming during the whole duration of an on-timer period, the model falls back to the Off state. Figure 2 shows the On/Off state transitions as a time series plot where the on-timer is set to 5 seconds.

The total amount of time spent in On state is called the On period. Similarly, total amount of time spent in Off state is called Off period. The On period refers to a traffic burst where some packets have arrived. The longer the On period is, the longer is the traffic burst. And in this context, the most important parameter in the On/Off model is the on-timer. The choice of an on-timer is clearly case specific as it is heavily dependant on how the packets arrive. If we select the on-timer to be too large in a situation where the traffic burst is short and the gap between any two traffic burst is also small, then the model will almost always be in On state and will fail to capture the bursty nature of the data traffic. Similarly, if we choose the on-timer to be too small, then it may not be able to capture one whole burst of data into a single On period which will also fail to capture the traffic burstiness accurately. Hence, while applying the On/Off model in some application, the on-timer value needs to be chosen carefully by analysing the application characteristics.

3 Experimental Setup

In this paper we will look at two different traffic scenarios and the associated power consumption in the mobile devices. The first traffic scenario appears when the data is being transferred to the mobile device continuously, without any break, in a constant rate. This scenario is referred as smooth traffic. The other scenario appears when the data is being transferred at a relatively higher bandwidth for a shorter period of time. In other words, data is being transferred in a higher rate but in a discrete manner. This scenario is referred to as bursty traffic. In either case, the average data transmission rate will be same.

To achieve such traffic scenarios, we have developed an experimental environment. The environment basically consists of three core components.

1. An Apache web server running on Windows 7 platform

2. Nokia Energy Profiler measuring software running on Nokia 5530 handset

3. Bandwidth Controller software running in the server machine

Firstly, we have used an Apache [1] web server that will host our dummy website. Having our own server allows us to limit the transfer rate from the server machine. The dummy website contains nothing but a downloadable link for a content. The web server is given a private IP address and thus the website is accessible only from the local network. Therefore, to download the content, the mobile device has to be connected in the same local network. Again, the rate limiting in the server, which is also the source for our traffic, is important here because we want to measure the power consumption at a same average data rate for the two different traffic scenarios.

Secondly, we have used a Nokia phone which runs the Nokia Energy Profiler [3] software to measure the power consumption on the device. This software not only measures the power consumption of the device as the transmission takes place but also measures the data transfer rate to the device concurrently.

Finally, we have used the Bandwidth Controller [2] software to limit the transmission rate in such a way that the server is able to generate two different traffic scenarios while keeping the average transmission rate same. Using this software, there are two different ways to limit the rate at which the server is allowed to send traffic. And it follows from the software behaviour that these two different ways to limit transmission rate generates the traffic in two different manner. One generates the smooth traffic while the other generates the bursty traffic that we need for our power consumption measurement.

4 Measurement

We perform the measurements at two different data rates for both smooth and bursty traffic scenarios. We have collected power consumption data for a data rate of 50KBps and 100KBps which are shown in Figure 3 to Figure 6. The yellow line in the graphic represent the power consumption in the mobile device whereas the green line corresponds to the bit rate received by the mobile. The lightly yellow shaded region is used to calculate the average power consumption which is shown by the horizontal white line in the shaded area with the average power consumed shown on top of it.

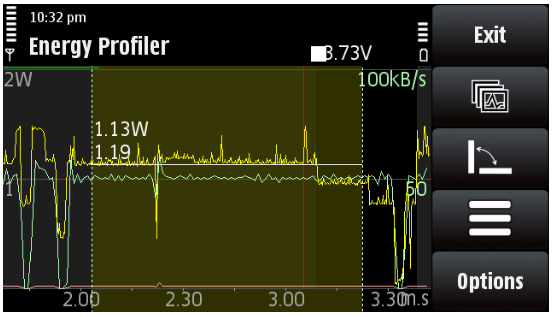

Figure 3: Power Consumption for Smooth Traffic at 50KBps Data Rate

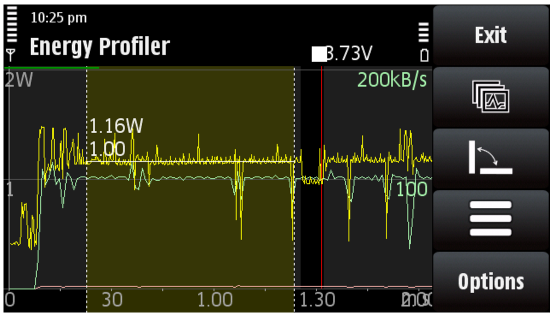

Figure 5: Power Consumption for Smooth Traffic at 100KBps Data Rate

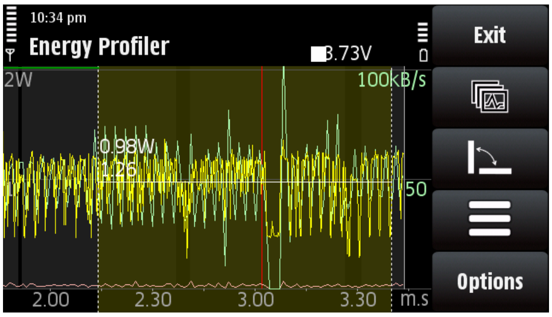

Figure 4: Power Consumption for Bursty Traffic at 50KBps Data Rate

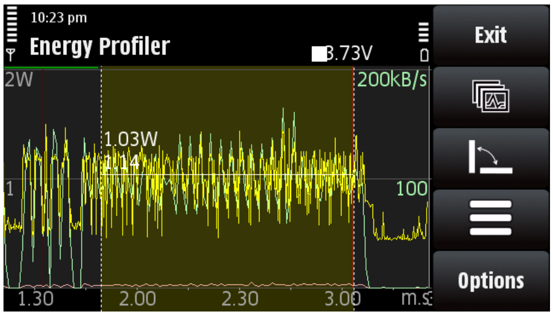

Figure 6: Power Consumption for Bursty Traffic at 100KBps Data Rate

Following our measurement it is evident that there is a subtle difference in power consumption between the two different traffic scenarios. Both in the 50KBps and 100KBps data rate cases there is about 0.15W reduced power consumed for the bursty data traffic compared to the smooth data traffic. And this gives us an opportunity to model the bursty data traffic so that the model can be applied to the server/source end to achieve a reduced power consumption in the mobile devices.

5 Model Fitting

In this section we investigate our measurements to find a suitable model for the acquired data traffic trace. Figure 4 and Figure 6 shows the traffic that gives the better performance in terms of power consumption. Now, these are bursty traffic and following the discussion about different traffic models we have to choose between self-similar and on/off model to capture this burstiness in the traffic. Considering the pros and cons among these two models we prefer the On/Off model for its simplicity and easier analysis criteria. Nonetheless, we have carried out further analysis on the power consumption of the mobile device to show that the On/Off model fits well for this data traffic.

It is enough if we can show that our traffic trace has the similar kind of On-period and Off-period as it is with the On/Off model, then we are ready to fit this model. Now, if we look at the power consumption graph of both the bursty and smooth traffic shown in Figure 7 and Figure 8 respectively, we find that the bursty traffic shows a very nice On/Off property. If we compare Figure 7 with the Figure 2, the similarity among these two graphs are easily visible. And because of this similarity, this bursty traffic can be easily modelled using the On/Off traffic model.

For the case of smooth traffic, we can barely find any off states in the Figure 8. It follows from the behaviour of the smooth traffic that the data packets are continuously arriving at the destination thus showing only the On state. Theoretically, it is still possible to model this phenomena using On/Off model. However, there will be negligible or no impact of on-timer in this case as almost all the time the model will be in On state. But in this paper our goal is to model the bursty traffic, not the smooth traffic. So we can overlook this without harming our work.

Here we are choosing the power consumption graph instead of the bit rate graph to model the data traffic. This is because of the fact that the bit rate graph only gives the bit rate received at any certain point, not gives any idea how the packets are arriving in the device. On the other hand, the power consumption graph shows the value of around 0.4W which is the normal operating power consumption of the experimental device. Whenever there is a new packet to be received, the power consumption goes high up over 1.0W and remains there until all the packets in that burst are being processed. This phenomena gives us an excellent opportunity to map this high power consumption as On state and the low power consumption as the Off state. This leads us directly to model this traffic behaviour using the On/Off model.

To analyse the potential saving in power consumption using the On/Off model in the mobile devices we define the following terms -

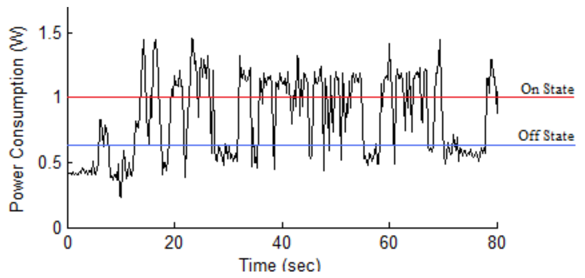

Figure 7: Power Consumption for Bursty Traffic at 100KBps Data Rate

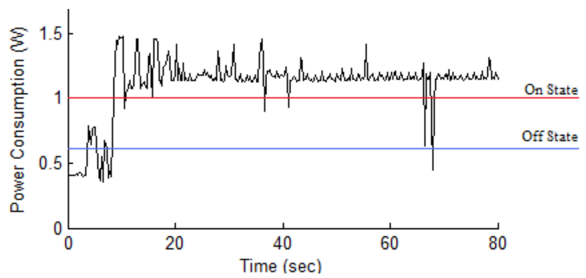

Figure 8: Power Consumption for Smooth Traffic at 100KBps Data Rate

- *Average On Power (P_{on})* - The average amount of power consumed by the device while it is in On state.
- *Average Off Power (P_{off})* - The average amount of power consumed by the device while it is in Off state.
- *On Time (T_{on})* - Total amount of time spent in On State.
- *Off Time (T_{off})* - Total amount of time spent in Off State.

Finally we calculate the Total Power Consumed (P_{Tot}) using the following formula -

$$P_{Tot} = P_{on} * T_{on} + P_{off} * T_{off}$$

Table 1 presents the comparison in power consumption between the two traffic scenarios at 100KBps data rate using the On/Off model. From Table 1 we can see that there is about 14W less power consumed for the bursty traffic case. Also it is noticeable from Table 1 that the average On power consumption and the average Off power consumption are almost the same in both smooth and bursty traffic cases. However the bursty traffic scenario spends much more time in the Off state as compared to the smooth traffic case. And this causes the mobile device to consume less power.

Table 2 reflects the same outcome as Table 1 emphasizing the fact that bursty traffic consumes less power by depicting a saving of 28W. Here the content was same as with the 100KBps case. Comparing Table 1 and Table 2 we can see that the average On power and Off power in both the cases are almost the same. However, the time required in the 50KBps case is much longer compared to the 100KBps case. Hence the device consumes more power at 50KBps data rate.

Criteria	Bursty Traffic	Smooth Traffic
P_{on} (Watt)	1.18	1.18
P_{off} (Watt)	0.56	0.50
T_{on} (sec)	96.25	128.50
T_{off} (sec)	46.50	2.50
P_{Tot} (Watt)	139.09	153.11

Table 1: Power consumption comparison between two traffic scenarios using On/Off model at 100KBps data rate

Criteria	Bursty Traffic	Smooth Traffic
P_{on} (Watt)	1.16	1.17
P_{off} (Watt)	0.52	0.35
T_{on} (sec)	133.75	170.25
T_{off} (sec)	38.00	7.25
P_{Tot} (Watt)	174.58	202.54

Table 2: Power consumption comparison between two traffic scenarios using On/Off model at 50KBps data rate

6 Conclusion

In this paper we have shown a new approach to model data traffic to reduce power consumption in the mobile device while using the WLAN technology. Our method presented here shows how the data traffic to a source can be modelled or shaped in order to get better power usage in the mobile device. We have shown that bursty data traffic is more suitable in this regard and we have modelled this traffic using the On/Off traffic model. However, there is a lot that needs to be done to find the optimal parameters for this model to be applied efficiently at the server end. It is evident from our experiment that there is a potential amount of power saving possible for the mobile devices using WLAN if this traffic model is adopted by the servers.

Future work will include more test cases with varying data rates in varying environmental conditions, e.g. lightly loaded wireless medium or heavily loaded wireless medium. Also the impact of the size of the content on amount of power saved needs to be examined. Finally the model will be tested in a real life application.

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