# Modeling the Impacts of WiFi Signals on Energy Consumption of Smartphones

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**Abstract.** In this paper, we explore the impacts of the WiFi signal strengths under normal signal conditions on the energy consumption of smartphones. Controlled experiments are conducted to quantitatively study the phone energy impacts by normal WiFi signals. As the experimental results show, the weaker the signal strength is, the faster the phone energy dissipates. To quantitatively describe such impacts, we construct a time-based signal strength-aware energy model. The energy modeling methods proposed in the paper enable ordinary developers to conveniently compute phone energy draw by utilizing cheap power meters as measurement tools. The modeling methods are general and able to be used for phones of any type and platform.

**Keywords:** WiFi environment · Phone energy consumption · Signal strength Modeling method

## 1 Introduction

With the incredible popularity of smartphones all over the world, the energy consumption problem of smartphones has gained growing attentions. Constrained battery capacity of smartphones is a pain spot that users have to face while enjoying various energy-consuming applications. Thus, it is significantly important to understand and then optimize the energy consumption of smartphones.

WiFi connection, being the prime way for smartphone users to access the Internet, is a major source of smartphone energy consumption [1, 2]. With the WiFi switch being on, it is experienced by many smartphone users that a phone's energy drains in various rates under different WiFi environments, even if the phone keeps the same application state (e.g. running no applications) and with the same hardware settings in all the environments. As reported by prior works, WiFi environments have notable impacts on smartphones' energy draw [3]. For instance, poor signal condition obviously inflates energy drain [4–6].

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This paper is concerned with the impacts of normal WiFi environments on smartphone energy consumption. We conduct a couple of experiments to investigate the impacts of normal rather than weak signal strengths on phone energy draw, and construct a time-based energy model to describe the impacts. We empirically investigate the impacts of WiFi signal strengths on the energy dissipation of smart phones, and propose energy models to depict these impacts. It is noteworthy that although the model created in this paper is phone-type dependent, however, the method to create the models could be applied to any phone. Our modeling methods require a cheap power meter as a measurement tool and the model parameters are also easily available, thus enabling ordinary developers to analyze phone energy draw in a convenient manner.

This work primarily has the following two contributions:

(1) Empirically study the quantitative relationship between the signal strength and the phone energy consumption under normal WiFi signal environments.
(2) Propose a novel time-based phone energy model considering the WiFi signal impacts, and facilitate ordinary developers to compute mobile energy consumption in a simple way.

The rest of the paper is organized as follows. Section 2 presents our research questions and methodology, and details our method of measuring the phone energy consumption. Section 3 elaborates how WiFi signal strengths impact phone energy draw using some experiments, and proposes a time-based energy model. Section 4 discusses the causes of the impacts observed in the experiments. We discuss the related works in Sect. 5 and conclude in the last section.

## 2 Methodology

### 2.1 Research Questions

In this paper, we investigate the impacts of WiFi signal strengths on energy consumption of smart phones while maintaining basic network communications. To exclude the energy consumption interference of various applications and non-WiFi radios, we only study the phone in basic state – a state in which Bluetooth/GSM/3G radios are disabled, the screen is off, the phone runs no applications while keeping the WiFi switch on. To exclude the interference from other WiFi hotspots or devices, we perform the experiments with only one WiFi AP during the night hours, when


**Fig. 1.** Power meter

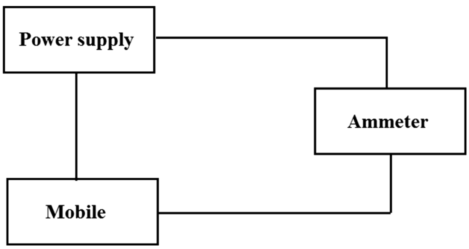


**Fig. 2.** Power measurement

interference is minimum. *In our experiments, we measure the total energy consumption of the smartphone in the basic state*. The energy draw is not only due to the WiFi NIC but also other phone components including CPU, screen and so on.

By performing experiments, we explore the following research questions:

Q1: How does WiFi signal strength impact the energy consumption of a smart phone?

Q2: What energy model can be constructed to indicate this impact?

### 2.2 Measurement of Energy Consumption

Figure 1 shows the power meter used in our experiment, which consists of a power supply with adjustable stabilized voltage and a current meter. The sampling rate of the power meter is 2 current samples per second. Its resolution is 10 mV/1 mA which enables sample collection with a very fine granularity, 10 mW, as required in [7].

To measure the overall system power of a smart phone, we unload the battery of the phone and connect the phone to the power meter as illustrated in Fig. 2. During all these measurements, the voltage value U is adjusted to a constant. By reading the current value $I$, we can get the power drain value $P$, i.e. U * $I$, of the phone.

To measure the overall energy consumption of a smart phone during any $t$ seconds, we collect all the current samplings using the above power meter. Because the sampling rate is 2 samples per second, the sampling duration $t$ consists of $2t$ sampling periods and each period is 0.5 s. The overall energy consumption of the smart phone within $t$ seconds is calculated as follows:

$$E(t) = \Sigma_{i=1}^{2t} \mathrm{U} I_i * 0.5 = 0.5\mathrm{U}\Sigma_{i=1}^{2t} I_i. \quad (1)$$

## 3 Impact of WiFi Signal Strength

In this section, we conduct experiments to investigate the impact of WiFi signal strength on phone energy, so as to get answers to research questions Q1 and Q2. The signal strength is measured in RSSI (Received Signal Strength Indicator) level.

### 3.1 Energy Data Collection

The smart phone under measurement, in this experiment, is Samsung Galaxy GT-S7898 phone running on Android 4.1.2. *During the measurement, we keep the phone in basic state by turning off all the applications and keep the WiFi switch on*. We use an AP set on a PC to transmit WiFi signals. To control the WiFi signal strength, we adjust the distance between the AP and the smart phone. The RSSI level is measured using a software tool named *Wirelessmon* [8] running on a laptop. The laptop is placed at a spot where to measure phone energy, the corresponding WiFi signal strength at that spot can be collected easily. As depicted above, while collecting the phone energy data in different spots, we use the same experimental settings except for the phone-AP distance, so as to exclude the impacts of external factor as much as possible.

We adjust the phone-AP distance, ranging from 0.5 m to 4 m with the interval 0.5, by placing the phone at eight different spots. At each spot, we monitor the total energy consumption of the phone for a period of time (for instance, 30 s). Table 1 lists the results acquired at the end of 30 s. The first column shows the eight phone-AP distances measured in meters. The second column denotes the signal strengths, measured in RSSI levels, at each spot. The last column represents the total energy consumption (Joule) of the phone within 30 s under each RSSI level.

**Table 1.** Distance, RSSI and energy consumption in 30 s

| Distance (m) | RSSI (dBm) | Energy consumption (J) |
|---|---|---|
| 0.5 | −38 | 36 |
| 1 | −40 | 40 |
| 1.5 | −42 | 44 |
| 2 | −44 | 48 |
| 2.5 | −46 | 51 |
| 3 | −47 | 55 |
| 3.5 | −48 | 62 |
| 4 | −49 | 70 |

To visualize the above results, we use Fig. 3 to demonstrate the total energy consumption of the phone within 30 s under eight RSSI levels. We make the following observation from the graph in Fig. 3: with the signal strength increased (e.g., from −49 dBm to −38 dBm), that is, with the phone-AP distance decreased (e.g., from 4 m to 0.5 m), the energy consumption of the phone can be reduced obviously (e.g., from 70 J to almost half, namely 36 J).

At each measurement spot, we measure the energy consumption of the smart phone during 30 s by utilizing the methodology described in part B of Sect. 2. The stabilized voltage U of the power meter is set to a constant of 4.2 V. With the power meter, we can log 60 current values within 30 s. And then, we can calculate the corresponding energy values along the time according to Eq. (1).

Figure 4 plots the phone energy consumption (Joule) sampled along 30 s under four RSSI levels mentioned above. Eight types of scatterplots are made by different point types and point colors. *For example, under the RSSI level of −40 dBm, the scatterplot consists of 60 black and square sampling points*. We can make the following observation from the graph in Fig. 4:

(1) Under a given signal strength (i.e., RSSI level), the total energy draw of the phone increases with the time in a near-linear trend.
(2) During each sampling period, under a higher signal strength (i.e. higher RSSI value), the total energy draw of the phone is lower.

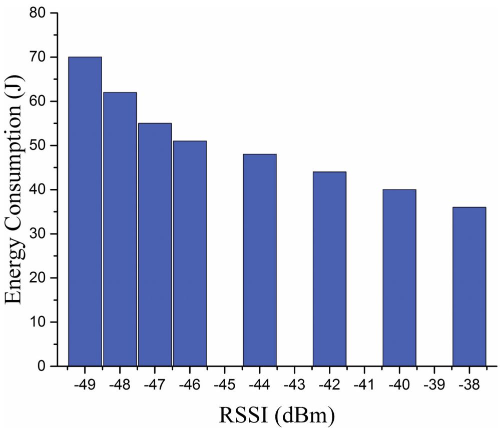


**Fig. 3.** Energy consumption in 30 s vs RSSI.

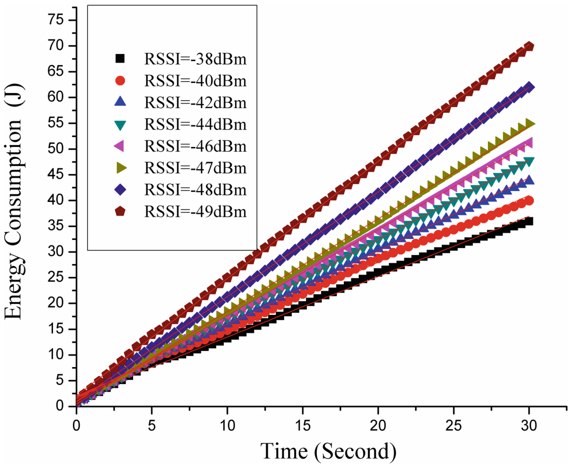


**Fig. 4.** Energy consumed along with time

## 3.2 Energy Model

This subsection aims at introducing a simple measurement-time based model for estimating the energy consumption of smart phones as a function of the WiFi signal strength. We use three curve fitting approaches compared with each other to develop a model that is able to match well the energy consumption with RSSI and time values exhibited in Fig. 4, and the detailed steps are as follows:

(1) Create linear regression models of energy consumption vs time under given RSSI levels: For each given RSSI level, Fig. 4 illustrates a curve fitting process of the energy consumption with the time, and the corresponding linear regression equation is in accordance with the following formula.

$$E(t) = \beta_1 t + \beta_0 \tag{2}$$

where *E(t)* is the total energy consumption of the phone within the time period *t;* $\beta_0$ and $\beta_1$ being two model parameters.

(a) Determine $\beta_0$ value: Under the RSSI level of −38 dBm, we set up a linear regression model for energy draw vs time, shown in Column 2 Row 2 in Table 2, by utilizing the statistical values of the 60 black points plotted in Fig. 4. As the model demonstrates, the parameter $\beta_0$ is fitted to 1.76.

(b) Determine $\beta_1$ value: For the other RSSI levels of −40 dBm to 49 dBm, we use the energy values vs time plotted in Fig. 4, together with $\beta_0$ value of 1.76, to create seven linear regression models, as shown from Row 3 to Row 9 of Column 2 in Table 2.

(c) Validate models: To evaluate the model predicted data deviation from the experimental data, we perform three GoF (Goodness of Fit) tests, namely SSE (Sum of Squared Errors), R-square value and RMSE (Root Mean Squared Error). The SSE and RMSE tests are based on affinity to zero, while the R-square value should approximate to one. Suppose that $\boldsymbol{y_i}$, $\boldsymbol{\hat{y}_i}$ and $\boldsymbol{\bar{y}}$ $(0 \leqslant i \leqslant 60)$ represent experimental data, model predicted data and average experimental data, respectively, and $v$ denotes the difference between the number of experimental data and the number of adjustable parameters, then the three test methods are formulated as the following formulas 3–5 [9].

$$\mathrm{SSE} = \sum\nolimits_{i=1}^{n} (y_i - \hat{y}_i)^2. \tag{3}$$

$$\mathrm{R-square} = 1 - \frac{SSE}{\sum\nolimits_{i=1}^{n} (y_i - \bar{y})^2}. \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{SSE}{v}}. \tag{5}$$

Table 2 shows the three GoF test results from Column 3 to 5: RMSE values are close to zero, R-square values are close to one, and the results from the three tests are consistent with each other. It is observed that our models are able to predict

**Table 2.** RSSI, energy model and GoF test results

| RSSI | Energy model | SSE | R-square | RMSE |
|---|---|---|---|---|
| −38 dBm | $E_1(t) = 1.173t + 1.76$ | 0.56 | 0.99 | 0.21 |
| −40 dBm | $E_2(t) = 1.311t + 1.76$ | 8.78 | 0.98 | 0.56 |
| −42 dBm | $E_3(t) = 1.421t + 1.76$ | 8.36 | 0.99 | 0.52 |
| −44 dBm | $E_4(t) = 1.532t + 1.76$ | 5.54 | 0.99 | 0.30 |
| −46 dBm | $E_5(t) = 1.629t + 1.76$ | 8.75 | 0.98 | 0.55 |
| −47 dBm | $E_6(t) = 1.735t + 1.76$ | 8.86 | 0.98 | 0.58 |
| −48 dBm | $E_7(t) = 1.995t + 1.76$ | 6.75 | 0.99 | 0.42 |
| −49 dBm | $E_8(t) = 2.291t + 1.76$ | 6.94 | 0.99 | 0.48 |

experimental data very well using the error analysis methods SSE, R-square value, and RMSE. Therefore, under a given RSSI level, the following model of energy consumption with time is reliable:

$$E(t) = \beta_1 t + 1.76. \tag{6}$$

In (6), the value of depends on the value of RSSI level, as shown at the Column 1 and 2 in Table 2.

(2) Create regression model of $|RSSI|$ vs $\beta_1$: Fig. 5 illustrates three curve fitting methods of the absolute value, $|RSSI|$, with the parameter $\beta_1$, where the eight $|RSSI|$ values (namely 38, 40, 42, 44, 46, 47, 48 and 49) are derived from Column 2 in Table 1, and the eight $\beta_1$ values (from 1.173 to 2.291) are derived from Column 2 in Table 2. Accordingly, we set up the linear regression, quadratic linear regression and logarithmic linear regression models for $\beta_1$ with $|RSSI|$, and Fig. 6 compares the GoF tests of the three models to select the best one for explaining the relationship between the $|RSSI|$ and $\beta_1$. From Fig. 6 we can see that the quadratic linear regression model has the largest value of R-Square, and the SSE and RMSE values are smaller than the other two methods. Thus, we can get the quadratic relation as follows:

$$\beta_1 = 0.009|RSSI|^2 - 0.7|RSSI| + 14.87. \tag{7}$$

(3) Create the target energy model: By substituting the value of $\beta_1$ from (7) into (6), we can get the energy model with time and RSSI levels as follows:

$$E(RSSI, t) = \left(0.009|RSSI|^2 - 0.7|RSSI| + 14.87\right)t + 1.76. \tag{8}$$

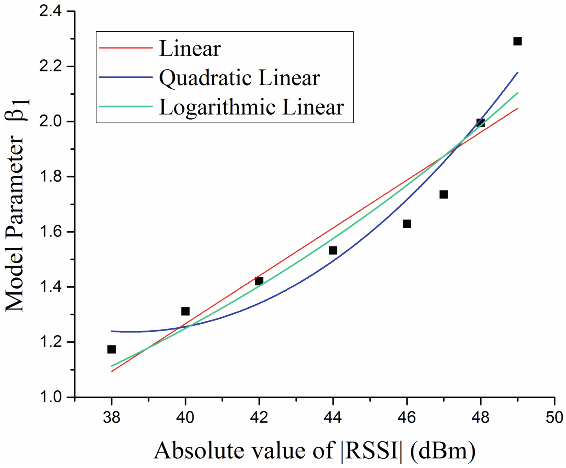


**Fig. 5.** $|RSSI|$ vs energy model parameter $\beta_1$

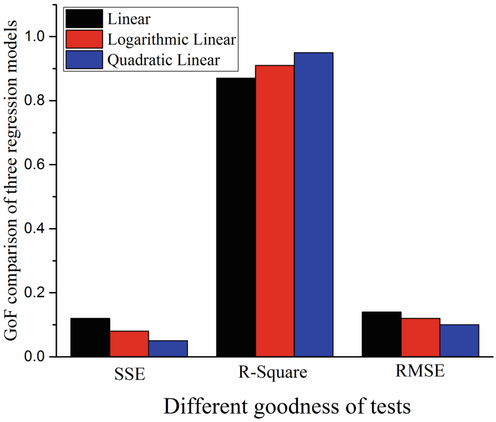


**Fig. 6.** Different goodness of tests for three models

The energy model (8) is a function of WiFi RSSI level and time. The model can simply but reliably estimate the impact of WiFi signal strength on phone energy at real time. We can set the part concerned RSSI in (8) to zero, and |RSSI| equals 78. It reviews that when the RSSI level is below −78 dBm the phone energy draws quickly while above −78 dBm the impact decreases but still exists, which proves the conclusion drew in (5). Further, Eq. (8) can be transformed to:

$$E(RSSI, t) = [0.009(|RSSI| - 38)^2 + 1.26]t + 1.76 \tag{9}$$

The formula (9) illustrates that in the normal WiFi environment, i.e. when the RSSI level ranges from −78 dBm to −38 dBm, the energy consumption decreases as the WiFi signal strength gets improved.

## 4 Discussions

When exploring the impact of WiFi signals on phone energy, we focus on good signals, whose RSSIs are over −50 dBm, rather than weak signals. We observed that the phone energy draw goes up with the decline of the signal strength under good signal conditions. The increment of energy drain could be caused by the rate adaptation at the physical layer with the changed signal strength, even if neither data re-transmission nor re-association with AP is triggered by the good signals.

## 5 Related Work

A major fraction of the energy consumption in smartphones comes from the WiFi radio [6]. The impact of WiFi signal strength on phone energy consumption has been studied in some previous works. For example, Gupta et al. [4] measure the phone energy draw under poor signal strength and dynamic power control. Ding et al. [5] propose a signal strength-aware model by systematically breaking down the impact of poor WiFi signal strength on phone energy drain. Sun et al. [6] are concerned with phones' energy consumption in active power states, and propose energy models based on the application layer throughput. Sun et al. [6] claim that signal strength alone cannot always capture the dynamics of the wireless channel. The works in [4–6] focus on phone energy drawn by NICs and model the energy without considering time as an input parameter. Our research on signal strength distinguishes from the above ones as follows: we study the phone energy under good signal strength condition, where the energy is consumed by the whole phone rather than by the NIC; we construct the signal strength-aware energy model based on measurement time together with signal strength.

Energy consumption of mobile phones are also influenced by such network factors as packet types, packet amounts, network channels and so on. Packet-driven phone energy draw in WiFi networks have been reported in some prior works. For instances, Sun et al. [6] and Zhang et al. [10] study the impact of TCP and UDP packets on phone energy consumption. Khan et al. [11] and Xu et al. [12] investigate the impact of packet size and amount on phone energy draw. Prasad and Balaji [3] create a phone energy model considering network channels.

## 6 Conclusions and Future Work

We investigated, in this paper, the impacts of normal WiFi signals on the energy consumption of smartphones by a detailed measurement. Experiments were conducted on the phone in basic state at night to minimize interferences. We empirically studied the impact of good signal strength on the phone energy draw, and created a signal-strength aware model based on measurement time to depict the impact, by comparing three regression methods. Our research results confirm the following experience of many phone users: higher signal strength implies lower energy drain even under normal WiFi signal conditions. The modeling method proposed in this paper enable developers to conveniently analyze the phone energy draw in WiFi environments, because the method only requires cheap power meter as a measurement tool and the model parameters are also easily available.

Although the models proposed in this paper is phone-type dependent, the method to create the models could be applied to any type of phones. In order to improve our model methods, we plan to collect more experimental data on more types of phones. We look forward to study the impacts of other WiFi environmental factors on the phone energy, and then create energy models with the most prominent influencing factors.

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