Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Telecommunication Engineering Graduate Program

Master of Science
(In Telecom Network Engineering)
Thesis on

Traffic Modeling using Power Consumption of Base Station: The case of Ethio telecom

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A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Master Science in Telecommunication Network Engineering.

October, 2018

Addis Ababa, Ethiopia

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Thesis Title

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Approved by:

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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Place: Addis Ababa

Date of Submission: ________________

This thesis has been submitted for examination with my approval as a university advisor.

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Acknowledgement

I am highly thankful to Almighty God for giving me the strength, courage and grace with which I was able to successfully undertake my thesis. During the course of this study, I have received the assistance of many people to whom I am very grateful.

First and foremost, I want to thank my advisor, Dr. -Ing. Dereje Hailemariam, without his advice this work could not be transformed from the very beginning idea to the Master thesis that has resulted.

I would like also to thank Dr. Ephrem Teshale and Dr. Murad Ridwan for their kind, responsible and understanding advises during the process of this thesis. Without their continuous support, all this would have been not possible.

I must extend my gratitude to ethio-telecom employees, especially to Ato Teferi Bareto, Ato Mesfin Geremew, W/ro Tirufire Aberra and Huawei employee Ato Addis Berhanu as they were very cooperative in providing the necessary data for this work.

The last two years I spent a very difficult time so, it is the right time to thank everyone who are with me to pass that difficult time.

Finally, my utmost gratitude to all of my family member and friends who energetically helped me with mentally support. Last but surely above all, I would like to thank my father, his great belief in education that makes me work hard and envision more each time. I hope he is happy and see me with smile from heaven. This work is fully dedicated to my father.

Abstract

Wireless telecommunication networks have become fundamental to daily activities. The mobile telecommunication market in Ethiopia is grown significantly in the past few years. Recently there are about 67.5 million mobile subscribers served by 7,353 base stations. Now a day's optimizing the energy consumption of wireless telecommunications infrastructure has become a new challenge for the research community, governments and industries in order to reduce CO_2 emission and operational energy cost.

In view of the above problems, operators should have to have proper strategy to own energy efficient network. Studying the relationship between traffic load and power consumption at a Base Station (BS) could help to have proper strategy. The real time hourly data of the power consumption and traffic load have been obtained from servers where measurement is performed on a fully operated base stations. In this thesis, we analyze and model traffic load based on power consumption at a BS using MATLAB, R-studio and Excel.

The analysis show a direct relationship is obtained between base station traffic load and power consumption. According to the relationship, we develop a piecewise linear model for base stations serving GUL (GSM, UMTS and LTE) and GU (GSM and UMTS) technologies. This result can be input for energy saving techniques. This thesis also analyzes the power consumption data has lognormal distribution and the traffic load data has Weibull distribution.

Key words: - Base Station, Modelling, Power consumption, Mobile communication, Lognormal and Weibull distribution.

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List of Acronyms

Symbol	Description
Numbers (0-9)	
2G	2nd Generation Technology
3G	3rd Genration Technology
4G	4th Generation Technology
Letters (A-Z)	
	A
AIC	Akaike Information Criteria
	B
BIC	Bayesian Information Criteria
BS	Base Station
BSs	Base Stations
BSS	Base Station Subsystem
BTS	Base Transceiver Station
	D
DC	Direct Current
DF	Degree of Freedom
	E
ETC	Ethipoia Telecommunication Corporation
	G
Gbit	Giga Bit
GSM	Global System for Mobile Communictions

Symbol	Description
GU	GSM and UMTS
GUL	GSM, UMTS and LTE
	I
ICT	Information Communication Technology
	K
KW	Kilo Watt
	L
LL	Log Likelihood
LSM	Least Square Method
LTE	Long Term Evolution
	M
MATLAB	Matrix Laboratory
MCIT	Ministry of Communications and Information Technology
MLE	Maximum Likelihood Estimation
MS	Mobile Station
	N
NSS	Network Switching Subsystem
	O
OSS	Operation Support System

Symbol	Description
	Q
QoS	Quality of Service
	R
RU	Radio Unit
RRU	Remote Radio Unit
RMSE	Root Mean Square Error
	T
TEP	Telecom Expansion Program
	U
UE	User Equipment
UMTS	Universal Mobile Telecommunication System

1. INTRODUCTION

The focus of this section is to discuss the theoretical knowledge of wireless access network power consumption and daily traffic load variation; review papers to understanding what are the relationship between the traffic load and the power consumption of a Base Station (BS). Statement of the problem, objectives, methodology and main contribution of this thesis is also reviewed.

1.1. Background

The Information and Communication Technology (ICT) is an important sector where the total human being society which is experiencing transformation, catalyzed by it [1]. Telecommunication is a more dynamic and significant parts of ICT sector. It is one of the fastest growing industries in the world. Telecommunication network have changed the way people live, work and play. The unexpected increase in subscribers and demand for telecommunication services led to tremendous growth in telecommunication networks.

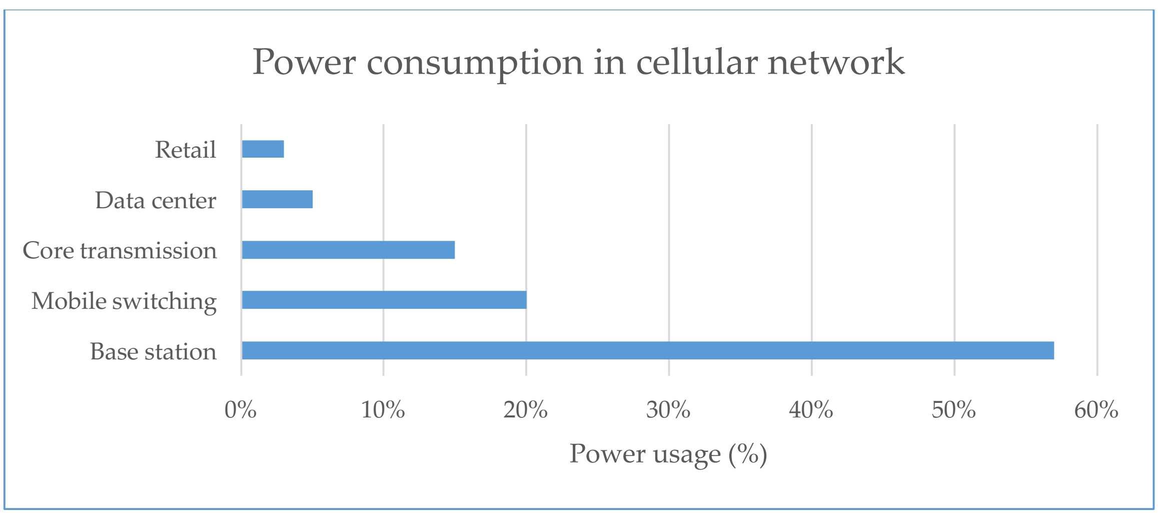


Figure 1: Breakdown of energy consumption in cellular networks [2].

As shown in Figure 1, Base Stations (BSs) consume the largest proportion of energy in cellular network.

A. Energy consumption breakdown in BSs

BSs (sometimes referred to as BS subsystem or access network) for commuting mobile traffic and signaling between User Equipment (UE) (end users to access the network) and network switching subsystem (to route call and data).

The total power consumption of a BS is composed of fixed (traffic independent) and traffic dependent parts. As shown in Figure 2, the fixed part, including air conditioning and power supply, accounts for around one fourth of total energy consumption. This amount of energy is wasted when no traffic is served by the BS.

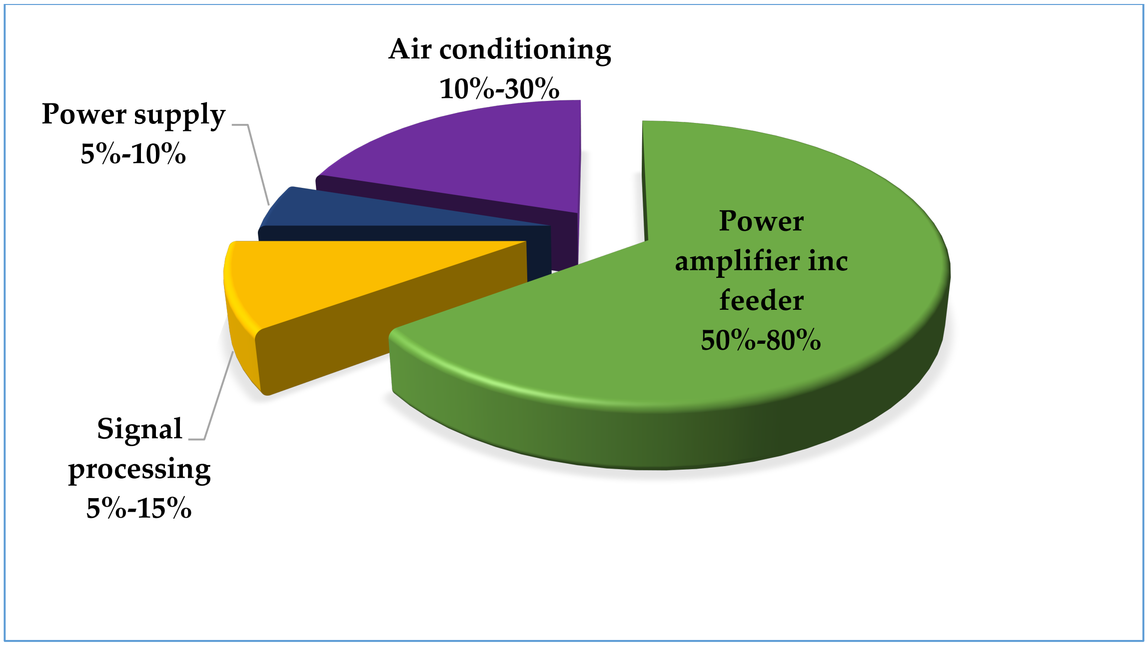


Figure 2: Power consumption distribution in BSs [3].

B. Traffic variation in BSs

It is evident that the mobile traffic level throughout a day or a week varies periodically with the living pattern of mobile users [4]. In the daytime on weekdays, people mostly concentrate in business areas in a city and are more likely to make phone calls. At night or on weekends, most people move to residential areas. Phone calls are generally less frequent at night than during the day but larger amount of cellular data is transmitted because more data-intensive applications such as social networking, web browsing, video streaming and video chatting are more likely to run. It has also been noticed that the maximum-to-minimum traffic ratio is larger for the observed real cases. The traffic variation thus creates opportunities for energy saving by turning off BSs appropriately.

Given that the traffic in a cellular network approximately fluctuates in such well-known daily and weekly behavior, it is feasible to adapt the level of active over-provisioning by switching some BSs to sleep mode to save energy without noticeable impact on Quality of Service (QoS) [5]. It should be noted that the traffic pattern in cellular networks has been influenced by different factors like time, human mobility, holiday, etc.

C. Energy saving techniques

BSs are the main targets of energy saving techniques because of their large share in energy consumption. It is now widely acknowledged that cellular networks will have greater economic and ecological impact [43], [48] – [49]. This issue has been recognized as a matter for both the planet and the wallet. For mobile operators, motivation and objective of "green" approaches are to gain extra commercial benefits, mainly by reducing operating expense related to energy cost.

There are various distinctive approaches to reduce energy consumptions in a mobile cellular network. Approaches in previous research can be broadly classified into the following five categories [31].

a) Improving energy efficiency of hardware components [9] – [14].
b) Turning off components selectively [15] – [20].

c) Optimizing energy efficiency of the radio transmission process [21] – [24].

d) Energy efficient planning and deploying heterogeneous cells [25] – [28].

e) Adopting renewable energy resources [29] - [30].

Table 1: Comparison of Green Cellular Network Approaches [31].

Approach	Example	Advantages	Limitation
Improved on hardware components	Improved power amplifier design	Largest reported savings, direct and intuitive	Certain upper limits for improvements, high cost for hardware replacement
Sleep mode techniques	Selectively turns radio transceiver or BSs to sleep mode	Easier and less costly for testing and implementation	Trade-off between performance and saving, current modeling not accurate enough
Optimization in radio transmission process	Cognitive radio transmission, cooperative relaying, channel coding and resource allocation for signalling	Low cost, various applications	Trade-off between performance and saving, errors due to uncertainly issues
Network planning and deployment	Mixed macro, micro, pico and femto cell deployments	Low cost to implement, user-oriented, high potential savings	Introduces new problems such as radio interference
Adoption of renewable energy resource	Adoption of renewable energy resources such as solar, wind, and water power in BSs	Long-term solution for off-grid BSs	High replacement cost and limited gain for existing on-grid BSs

While real-time traffic information is relatively difficult to obtain, knowing the daily traffic load variation helps to apply techniques enable BSs to switch to sleep mode to save energy and also used to plan energy efficient network; in traditional planning mostly designed to endure peak load and extreme conditions. As a result, the system is significantly under-utilized during non-peak hours, creating an opportunity for possible energy saving. So, in this thesis we are try to find the relationship between BSs power consumption and traffic variation which can be input for energy efficiency approaches 'b' and 'd' explained above.

1.2. Statement of the Problem

The demand for wireless communication is increased from time to time and to serve this demand the network elements specially the number of BSs are also increased. Usually the wireless network planned for full traffic load conditions, which encountered for limited time periods, the networks are underutilized most of the time and equivalent power resources are consequently wasted. Thus, it is essential to have proper energy saving techniques. So, in response to this problem, it is important to know the relationship between traffic load and BS power consumption.

Table 2 : Base Station and Customer base at ethio telecom [50]

No	Year	# of customer	# base station
1	2012	20.04M	3,100
2	2017	52.80M	7,353

1.3. Research Questions

(a) What are the power consumption and traffic load trends?

(b) What are the distribution of the measured power consumption and traffic load?

(c) Which is the relationship between traffic load and power consumption of base station?

1.4. Objectives

1.4.1. General Objective

The main objective of this study is to develop a model for BSs traffic load based on the power consumption, so that to find out the usage levels of the network. This modeling help us to implement proper energy saving technique.

1.4.2. Specific Objectives

The specific aims of the thesis are: -

- To show a different perspective on how to interpret power consumption data.
- To study the relationship between traffic load and power consumption.
- To develop a mathematical model for real time traffic based on base station power consumption.
- To compare different modeling technique and select the simplest and accurate one.

1.5. Literature review

Recently, the traffic variation and the power consumption of cellular networks has become a point of interest in research [32].

In [33], the rapid growth of mobile subscribes and number of BSs necessitate the need to study the relationship between traffic load and power consumption at BS in Ghana. The author in [33] took measurements of power and traffic load at fully operated BSs. It was found that linear relationship between cellular traffic load and BS Direct Current (DC) power consumption for different technologies. The Remote Radio Unit (RRU) is more energy efficient that the ground mounted RU. The analysis also find out that the second highest energy consuming device at a BS is air conditioner. Thus, replacing air conditioner with natural ventilation system and eliminating feeder cables can increased BS energy efficiency by 32%.

Oliver Arnold and et al. had proved that the wireless micro cells are potentially more energy efficient than conventional macro cells due to the high path loss component [34]. They develop power model for macro and micro BSs relaying on data sheet of several Global System for Mobile Communications (GSM) and Universal Mobile Telecommunication System (UMTS) BSs with focus on component level and apply the model on a traditional macro cell and a heterogeneous deployment. Heterogeneous deployments of both cells type can be used to optimize the energy consumption of a network.

Josip Lorincz et al. they developed linear power consumption model for BSs of both GSM and UMTS using measured data of total power consumption and traffic load on a fully operated BS sites [42]. Traffic load in mobile network significantly varies during a working or weekend days so, they figure out the influence of these variations on the BS power consumption.

As a summary, all the above studies quantified the relationship between traffic load and BS power consumption. Each author follows a different approach and data type to figure out the correlation between the variable in each of their studies. In addition, most of the studies focus for only single technology BSs like GSM, UMTS, etc. But, this study considers BSs which support GUL and GU technologies. The study first analyzed and identify the power affected by the traffic load and measure this power and the corresponding traffic load which later used to evaluate the relationship using proper tool.

1.6. Methodology

As shown in Figure 3, methodology of this thesis is described as follow. To reach the objectives and addressed the research questions the following methodology is used. The first one is literature review, where different academic research regarding the relationship between power consumption and traffic load will be reviewed; basic knowledge of linear modeling will be studied; lessons from common distribution types will be examined. The second part is collecting measured data of traffic load as well as base station power consumption: Operation Support System (OSS) is used as the data collection instrument. OSS have different interface out of this NetCo is used to measure the power consumption of base stations and M2000 is used to measure the traffic load. Analyze the measured data using MATLAB, R-studio and excel to get suitable distribution to the data and to model the traffic load based on the power consumption is the third part of the methodology. Finally, discussion will be set based on the result found and then we conclude.

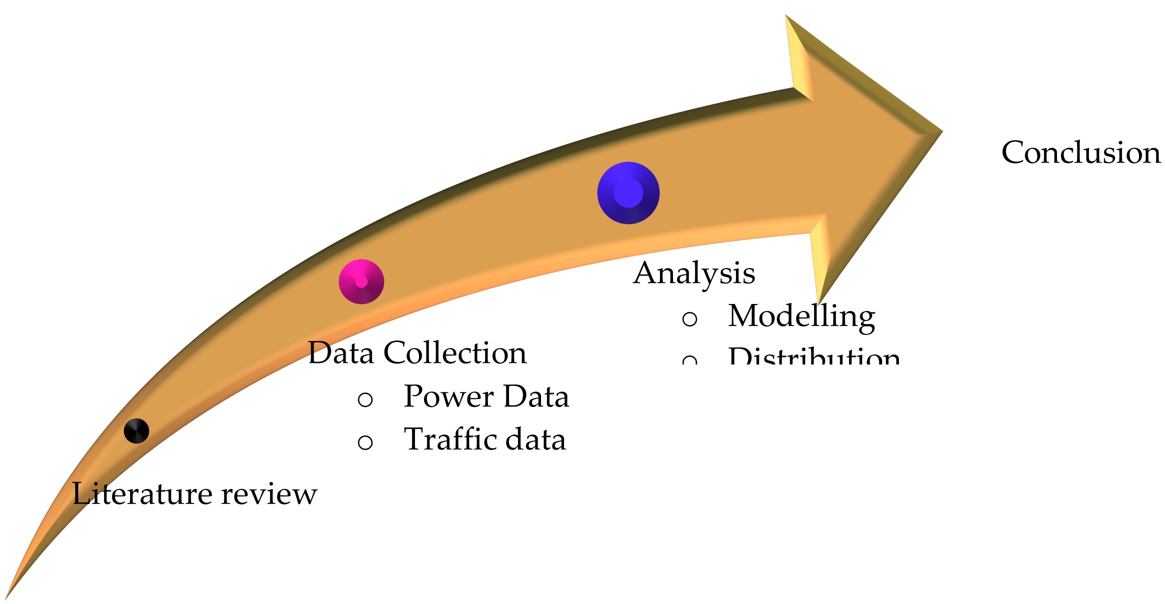


Figure 3 : Summary of Methodology

1.7. Scope and Limitation

1.7.1. Scope of the Thesis

This thesis is focusing to study the relationship between the traffic load and the DC power consumption of a base station since it is the major part of the consumption.

1.7.2. Limitations of the Thesis

This thesis has some limitations mainly due to fact that the study was done only on base stations which support GUL and GU technologies so base stations which serve other technologies are not included. Additionally, in this we will not consider the Alternating Current (AC) power consumption.

1.8. Contributions

The main contributions of this thesis are:

i. Propose a simple and accurate traffic load model using power consumption of a BSs which uses measurement data on fully operated wireless access networks and evaluated using different parameter.

ii. Identify distribution for both the traffic and power consumption data of a BSs which helps to improves the sensitivity and efficiency of the statistical tests on both variables.

iii. To show how the power consumption data of a BSs can be interpreted in detail to talk not only about the traffic load but also the demography of the area as well as the customer behavior to some extent.

1.9. Thesis layout

This thesis work is organized in four chapters. Chapter one introduces statement of the problem, objectives, methodologies and scope; and state of the art of linear modeling and probability distribution including the statistical parameter used to testing the model fitness discussed in chapter two. Chapter 3 discusses and reviews the result of all hypotheses testing and the findings discovered. Finally, summary of results, analysis, conclusion and recommendation for future work are included in Chapter 4.

2. SIMPLE REGRESSION MODEL

Linear regression is a frequently used method of exploring the relationship of variables and outcomes. Choosing a model, and assessing the fit of this model, are questions which come up every time one employs this technique. The parameters used to assess the fit of the model like F-test, R^2, t-test and p-value will be discussed, common types of probability distributions and the method used to identify the best distribution are also discussed in this section.

2.1. Introduction

The development of mathematical expressions which describe some behavior of a random variables is called modeling [35], [36]. When there is only one independent variable and one dependent variable in the model, then the model is termed as simple linear regression model. Regression analysis is the scientific method of fitting straight lines to patterns of data. In simple linear regression model, the variable of interest (the so-called "dependent" variable) is predicted from other variable (the so-called "independent" variable) using a linear equation. For a linear relationship, we can use a model of the form

$$Y = \beta_0 + \beta_1 * X + \mathcal{E} \qquad (1)$$

where Y is the dependent variable, X is the independent variable and $\mathcal{E}$ is the error term. The terms $\beta 0$ and $\beta 1$ are the regression parameters of the model. The parameter $\beta 0$ is termed as intercept term, the value of Y when X = 0 and the parameter $\beta 1$ is termed as slope of the line, the rate of change in Y per unit change in X.

The unobservable error component $\mathcal{E}$ accounts for the failure of data to lie on the straight line and represents the difference between the true and observed realization of Y. This difference has a statistical term which representing random fluctuations, measurement errors, or the effect of factors outside of our control [51]. We assume the distribution of the error terms are independence of the observed values and it is uniformly distributed random variable with mean zero and constant variance σ2.

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \mu))^2 \tag{2}$$

Where, σ2 is variance, which is a measurement of the spread between numbers in a data set, Yi is the value of the ith element, μ is mean of the Y and n is the number of elements.

Before we go to the analysis of the model it is better to know the requirement to choose a good regression model. These requirements are: -

(a) gathering useful data and making sure you know where it came from and how it was measured

(b) performing descriptive analysis on it to understand its general patterns and to spot data-quality problems

(c) applying appropriate data transformations if you see strong evidence of relationships that are nonlinear or noise that is non-normal or time-dependent

(d) fitting and refining and comparing models

(e) checking to see whether a given model's assumptions are reasonably well satisfied or whether an alternative model is suggested

(f) choosing among reasonable models based on the appropriate bottom-line accuracy measure, and

(g) deriving some useful insights from the whole process.

Using observed values of X and Y, we estimate β_0 and β_1 and make inferences such as confidence intervals and tests of hypotheses for β_0 and β_1. The determination of the statistical model depends on the determination of β_0, β_1 and σ^2. So, in order to know the values of these parameters, n pairs of observations (x_i, y_i) (i=1, ..., n) of the variable are collected and also used to determine these unknown parameters. Various methods of estimation can be used to determine the estimates of the parameters. Least squares error is one of the popular methods of estimation and this method is used in this thesis.

2.2. Least square method

The Least Square Methods (LSM) is probably the most popular technique in statistics used to determine a line of best fit by minimizing the sum of squares created by a mathematical function by squaring the distance between a data point and the regression line.

The simple linear regression model for n observations can be written as: -

$$Y_i = \beta_0 + \beta_1 * X_i + \mathcal{E}_i \quad (3)$$

Where i = 1,2,3, . . ., n. the intercept (β_0) and the slope (β_1) of the regression line. The least square method defines the estimate of these parameters as the values which minimize the sum of the squares between the measurements and the Regression line (model).

LSM uses a straight line in order to fit through the given points which is known as the method of ordinary least squares [51]. These line parameters can be calculated as shown below:

$$\mathcal{E} = \sum_{i=1}^{n} (Y_i - (\beta_0 + \beta_1 X_i))^2 \quad (4)$$

$$= \sum_{i=1}^{n} \left({Y_i}^2 - 2Y_i(\beta_0 + \beta_1 X_i) + {\beta_0}^2 + 2\beta_0\beta_1 X_i + {\beta_1}^2 \, {X_i}^2 \right) \tag{5}$$

(where Ɛ stands for "error" which is the quantity to be minimized). The estimation of the parameters is obtained using basic results from calculus and, specifically, uses the property that a quadratic expression reaches its minimum value when its derivatives vanish. Taking the derivative of Ɛ with respect to β_0 and β_1 and setting them to zero gives the following set of equations (called the normal equations):

$$\frac{\partial \mathcal{E}}{\partial \beta_0} = \sum_{i=1}^{n} (-2Y_i + 2\beta_0 + 2\beta_1 X_i) \tag{6}$$

$$0 = \sum_{i=1}^{n} (-Y_i + \beta_0 + \beta_1 X_i) \tag{7}$$

$$\sum_{i=1}^{n} (\beta_0) = \sum_{i=1}^{n} (Y_i) - \sum_{i=1}^{n} (\beta_1 X_i) \tag{8}$$

$$n\beta_0 = \sum_{i=1}^{n} (Y_i) - \beta_1 \sum_{i=1}^{n} (X_i) \tag{9}$$

$$\beta_0 = \frac{\sum_{i=1}^{n} (Y_i)}{n} - \frac{\beta_1 \sum_{i=1}^{n} (X_i)}{n} \tag{10}$$

$$\text{But, } \mu_x = \frac{\sum_{i=1}^{n} (X_i)}{n} \tag{11}$$

So, substitute Equation (11) to Equation (10) then,

$$\beta_0 = \mu_y - \beta_1 \mu_x \tag{12}$$

Where μ_x and μ_y are mean of the independent variable (X) and dependent variable (Y) respectively.

$$\frac{\partial \mathcal{E}}{\partial \beta_1} = \sum_{i=1}^{n} \left(-2X_iY_i + 2\beta_0 X_i + 2\beta_1 {X_i}^2\right) \tag{13}$$

$$0 = \sum_{i=1}^{n} -X_iY_i + \beta_0 \sum_{i=1}^{n} (X_i) + \beta_1 \sum_{i=1}^{n} {X_i}^2 \tag{14}$$

Now substitute (12) in to (14);

$$0 = \sum_{i=1}^{n} -X_iY_i + \left(\mu_y - \beta_1 \mu_x\right) \sum_{i=1}^{n} (X_i) + \beta_1 \sum_{i=1}^{n} {X_i}^2 \tag{15}$$

$$0 = \sum_{i=1}^{n} -X_iY_i + \mu_y \sum_{i=1}^{n} (X_i) - \beta_1 \mu_x \sum_{i=1}^{n} (X_i) + \beta_1 \sum_{i=1}^{n} {X_i}^2 \tag{16}$$

$$\beta_1 \left(\sum_{i=1}^{n} {X_i}^2 - \mu_x \sum_{i=1}^{n} (X_i) \right) = \sum_{i=1}^{n} X_iY_i - \mu_y \sum_{i=1}^{n} (X_i) \tag{17}$$

$$\beta_1 \sum_{i=1}^{n} X_i \,(X_i - \mu_x) = \sum_{i=1}^{n} X_i \left(Y_i - \mu_y\right) \tag{18}$$

$$\beta_1 = \frac{\sum_{i=1}^{n} X_i \left(Y_i - \mu_y\right)}{\sum_{i=1}^{n} X_i \,(X_i - \mu_x)} \tag{19}$$

So, the line with these parameters is termed as the line of best fit from which the sum of squares of the distances from the points are minimized.

2.3. Relation between variables

Regression analysis is the statistical tool that proves a quantitative assessment of the relationship between variables [52]. So, after solving the model, we have to verify the relationship between variables using the p-value and t-test.

2.3.1. P-value

Before running any statistical test, we must first determine our significance level. By definition, the significance level is the probability of making a wrong decision. Once we've chosen significance value, it is ready to conduct hypothesis test.

P-value stands for "probability value"; it indicates how likely a result occurred by chance alone and it ranges from 0 to 1. The confidence interval is the range of likely values for a population parameter, such as the population mean. If significance value equals 0.05, then our confidence level is 0.95. If we increase significance value, then we both increase the probability of incorrectly rejecting the null hypothesis and also decrease our confidence level.

If the p-value is less than the significant value then the result is statistically significant.

2.3.2. T-test

A t-test is a type of inferential statistic which is used to determine if there is a significant difference between the means of two groups.

A t-test can be found from t-table or calculated in excel by considering the degrees of freedom and p - value. Degrees of freedom are the number of values in a study that have the freedom to vary.

The t-value is the ration of variance between groups and variance with in groups. The larger the t score, the more difference between groups. The smaller the t score, the more similarity between groups.

$$t - value = \frac{Variance\ between\ groups}{Variance\ within\ groups} \tag{20}$$

$$= \frac{|\bar{x}_1 - \bar{x}_2|}{\sqrt{\frac{{S_1}^2}{n_1} + \frac{{S_2}^2}{n_2}}} \tag{21}$$

Where $\bar{x}_1$ and $\bar{x}_2$ are mean of both sample data, ${S_1}^2$ and ${S_2}^2$ are variance of both sample data n_1 and n_2 are the amount of both sample data.

When t-value is greater than the t-test value then the two variables have linear relationship.

2.4. Goodness of the model

Goodness-of-fit measures for linear regression are attempts to understand how well a model fits a given set of data. Models almost never describe the process that generated a dataset exactly, model approximate reality. However, even models that approximate reality can be used to draw useful inferences. So, a goodness-of-fit for the null hypothesis of a functional linear model can be verified using F-test and correlation coefficient.

2.4.1. F-test

The F-statistic is simply a ratio of two variances. Variances are a measure of dispersion, or how far the data are scattered from the mean. Larger values represent greater dispersion.

$$F - statistics = \frac{{S_1}^2}{{S_2}^2} = \frac{\frac{\sum_{i=1}^{n_1}(x_i - \bar{x}_1)^2}{n_1 - 1}}{\frac{\sum_{i=1}^{n_2}(x_i - \bar{x}_2)^2}{n_2 - 1}} \quad (22)$$

Where x_i is the i^{th} term of the random variable, $\bar{x}_1$ and $\bar{x}_2$ are mean of both the sample n_1 and n_2 are the total number of both data.

F-test is often used when comparing statistical model that has been fitted to a data set. It uses the p-value and the degree of freedom of the two samples as input to calculate it using excel or F-table.

When F-statistics is greater than the F-test (F-table) value then the goodness of the fit is good.

2.4.2. Coefficient of determination

R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination. The definition of R-squared is fairly straight-forward; it is the percentage of the response variable variation that is explained by a linear model. Or:

$$R - Squared = \frac{Explained\ Variation}{Total\ Variation} \quad (23)$$

In general, the correlation coefficient is a number that lies somewhere between -1 and +1, where -1 indicates a perfect negative linear relationship, +1 indicates a perfect positive linear relationship, and zero indicates no linear relationship.

Just to be clear: a correlation of zero between X and Y does not necessarily mean that there is no relationship, just that there is no linear relationship within the historical sample of data that is being analyzed, i.e., the model is no better for predicting Y. For example, if Y is always exactly equal to X squared, and you look at a sample of data in which X is symmetrically distributed on both sides of zero, then the graph of Y versus X looks like a parabola, and the correlation between X and Y can be zero even though Y can be perfectly predicted from X—it just can't be perfectly predicted using a linear equation.

2.5. Common distributions type

Data distributions are graphical methods of organizing and displaying useful information. The distribution of a statistical data set is a listing or function showing all the possible values (or intervals) of the data and how often they occur. When a distribution of numerical data is organized, they're often ordered from smallest to largest, broken into reasonably sized groups, and then put into graphs and charts to examine the shape, center, spread and outlier in the data.

a) Shape

The shape of a distribution might be considered symmetric, left/right skew, unimodal, bimodal or multi-modal. A bimodal distribution would have two high points rather than one. The shape of a distribution is sometimes characterized by the behaviors of the tails. A distribution can be said either to have no tails, or to have short tails. A normal distribution is usually regarded as having short tails, while an exponential distribution has long tails.

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.

b) Center

The center of a distribution can be explained by mean, median and mode. To find the center of a distribution in statistics, we generally have three options:

1. Mean: - the average of the data set.

2. Median: - the center of the data set.

3. Mode: - the frequently occurring value.

In left skewed graph mean < median < mode, in right skewed mode < median < mean and in symmetrical graph mean = median = mode.

c) Spread

The spread tells us the amount of variation with in the data set. The range is the largest value minus the smallest value in a data set. Note that this measure is based only on the lowest and highest extreme values in the sample.

d) Outlier

An outlier is a piece of data that is an abnormal distance from other points. In other words, it's data that lies outside the other values in the set.

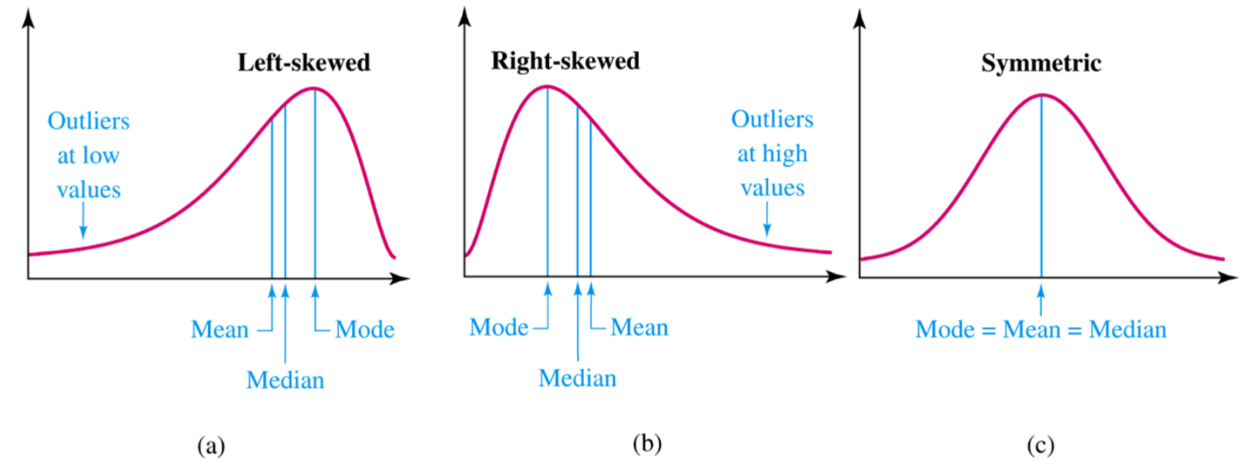


Figure 4: - (a) Skewed to the left (left-skewed) (b) Skewed to the right (right-skewed) (c) Symmetric distribution [53].

The world of statistics includes dozens of different distributions for categorical and numerical data; the most common ones have their own names. So, some of them will be discussed below:

2.5.1. Normal distributions

The normal distribution is the most widely known and used of all distributions. Its overall shape, when the data are organized in graph form, is a symmetric bell-shape. In other words, most (around 68%) of the data are centered around the mean, and as you move farther out on either side of the mean, you find fewer and fewer values.

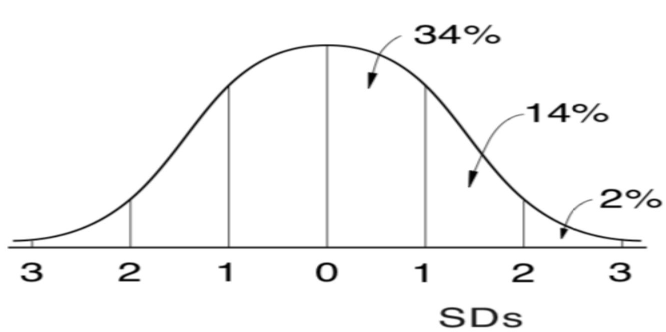


Figure 5: - Normal Distribution pdf (Bell Shape) [53].

For the mean = μ and standard deviation = σ the pdf of the distribution is:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}}\, exp^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{24}$$

2.5.2. Lognormal distributions

A random variable X is said to have the lognormal distribution with parameters $\mu \in R$ and $\sigma > 0$ if log (X) has the normal distribution with mean μ and standard deviation σ. The pdf of lognormal distribution is:

$$f_X(x) = \frac{1}{\sigma x\sqrt{2\pi}}\, exp^{\left(\frac{-(log(x)-\mu)^2}{2\sigma^2}\right)} \tag{25}$$

Only positive values are possible for the variable, and the distribution is skewed to the right. Two parameters are needed to specify a log-normal distribution. Traditionally, the mean μ and the standard deviation σ of log(x) are used.

2.5.3. Exponential distributions

The exponential distribution is one of the widely used continuous distributions. It is often used to model the time elapsed between events. We will now mathematically define the exponential distribution. Where λ is called the rate of the distribution and the pdf is:

$$f_X(x) = \begin{cases} \lambda\, e^{-\lambda x} & x > 0 \\ 0 & Otherwise \end{cases} \tag{26}$$

2.5.4. Gamma distributions

The gamma distribution is another widely used distribution. Its importance is largely due to its relation to exponential and normal distributions. Before introducing the gamma random variable, we need to introduce the gamma function.

Gamma function: The gamma function Γ(x) is an extension of the factorial function to real (and complex) numbers. Specifically, if $n \in \{1,2,3,...\}$ then

$$\Gamma(n) = (n-1)! \quad (27)$$

More generally, for any positive real number α, $\Gamma(\alpha)$ is defined as:

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx, \text{ for } \alpha > 0 \quad (28)$$

A continuous random variable X is said to have a Gamma distribution with a shape parameter α and rate of the distribution λ. X ~ Gamma (α, λ), where $\alpha > 0$ and $\lambda > 0$, its pdf is given by

$$f_X(x) = \begin{cases} \dfrac{\lambda^\alpha x^{\alpha-1} e^{-\lambda x}}{\Gamma(\alpha)} & x > 0 \\ 0 & \text{Else where} \end{cases} \quad (29)$$

Thus, we can see that Gamma (1, λ) = Exponential (λ).

2.5.5. Weibull distributions

The Weibull distribution is widely used for modeling the lifetimes of an electronic components.

A continuous random variable X is said to have a Weibull distribution with a shape parameter α and rate of the distribution λ. X ~ Weibull (α, λ), where $\alpha > 0$ and $\lambda > 0$, its pdf is given by

$$f_X(x) = \begin{cases} \lambda^{\alpha}\alpha x^{\alpha-1}e^{(-\lambda x)^{\alpha}}, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (30)$$

Thus, we can see that Weibull (1, λ) = Exponential (λ).

2.6. Parameter to select best distribution

After estimating the distribution for our data, we have to evaluate how good it is? Maximum Likelihood Estimation (MLE) is one of the parameter to accessing the quality of fit.

Probability: - What is the chance of observing particular data or sample given a specific model or population?

Likelihood: - Given observed data, what is the chance that a given reality or model is true?

2.6.1. Maximum Likelihood Estimation

A procedure to determine best parameters (reality) that fit given data or compare multiple models to determine the best fit to data.

What it does: -

1) Maximizes log-likelihood function to estimate parameters

2) Uses information theory to compare model fits.

Define the "Likelihood function" L:

$$\mathrm{L}(\theta/X_i) = \prod f(X_i/\theta). \tag{31}$$

Let observation X = (X1, . . ., Xn) be realized value of random variables. In addition, f(X/θ), will be used to denote the density function for the data where θ is scalar parameter to be determined. The likelihood of the true parameters being a certain value (given the data) is the same as the probability of observing the data (given some true parameter values). Maximization of the likelihood function is difficult in practice, so the method maximizes log-likelihood instead.

$$\mathrm{L}(\theta/X_i) = \prod_{i=1}^{n} f(X_i/\theta) \tag{32}$$

Addition is easier than multiplication during analysis so, the multiplication will be changed to addition by converting to logarithmic form and it becomes

$$\ln\left(\mathrm{L}(\theta/X_i)\right) = \sum_{i=1}^{n} ln\left(f(X_i/\theta)\right) \tag{33}$$

2.6.2. Kullback - Leibler information

Kullback – Leibler information can use information theory techniques to quantify the distance between model f and g(pdf).

$$\mathrm{L}I(\mathrm{f,g}) = \int f(x) ln\, \frac{f(x)}{g(x/\theta)} dx \tag{34}$$

Hirotugu Akaike showed that K – L information could be estimated based on the maximum log-likelihood and created "an information criterion" (AIC) – later Akaike Information Criterion.

$$AIC = -2ln[L(\theta/X)] + 2K \quad (35)$$

Smaller AIC value means a better model because the higher likelihood lead to low AIC. K is the parameter.

Adding parameters K increases model fit (maximum log-likelihood) but it also increases uncertainty in model prediction because the parameters themselves must be estimated with error. A tradeoff between bias (reduced with more K) and variance (increased with more K).

3. RESULT AND DISCUSSION

3.1. Analyze the Relationship Between Variables

3.1.1. The average traffic and power consumption of all BSs

The relationship between the traffic load and the power consumption of different base stations type is obtained. The data of power consumption of 25 different base stations and their respective traffic load were collected for 15 days from May 17, 2018 to May 31, 2018 on hourly basis. There were total 9000 sample values for both power consumption and traffic load.

The average daily traffic was calculated and it was found that the average traffic load is high during night time from 20:00 - 23:00 hrs and low after midnight from 02:00 - 04:00 hrs, which is shown in figure 1. The maximum traffic load is 36.24 Gbit and minimum traffic is 4.93 Gbit.

It was also found that the average power consumption of base station varies from 2.57 KW to 3.00 KW. The range of power consumption did not vary so much as the traffic load varied largely which is shown in figure 2. The highest power consumption was recorded between 20:00 to 22:00 hrs for each day whereas the lowest power consumption was recorded from 02:00 to 05:00 hrs.

The traffic load has maximum value of 36.24Gbit and corresponding power consumption is 3.00 KW during 21:00 to 22:00 hrs. Figure 3 shows the power consumption and traffic load generation for a single day. When the traffic load is high, the correlation between power consumption and respective traffic load is also high.

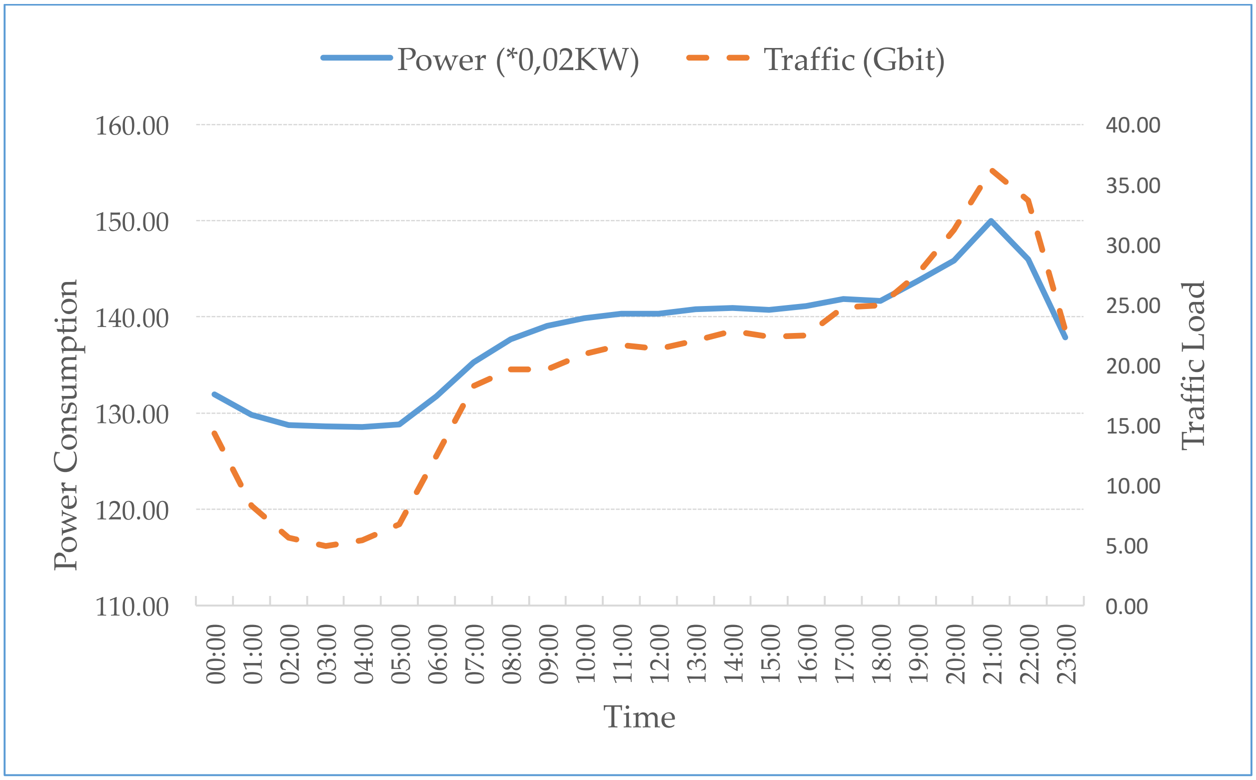


Figure 6: Average daily traffic Volume and power Consumption of Base Stations

3.1.2. Selecting the best distribution

The distribution of the measured data is shown in the below Figure 7 and Figure 8. In order to have the best distribution, we pick the distribution with highest maximum likelihood estimation value or minimum AIC or Minimum BIC. As can be seen in Equation (33) and Equation (35) AIC and LL have an inverse relationship so, these parameters can be used interchangeably to estimate a better distribution.

Table 3: Different distribution result for power data with selection parameters

	Lognormal	Weibull	Gamma	Normal	Exponential
LL	-51422.36	-53406.8	-51584.5	-52142.66	-68540.53
AIC	102848.7	106817.6	103173.0	104289.3	137083.1
BIC	102863.5	106832.3	103187.8	104304.1	137090.4

As can be seen in Figure 7 lognormal distribution fits to the power data better than the other distributions. The lognormal distribution parameters are seen in Table 4.

Table 4: Lognormal distribution parameter that fit to the power data.

	Estimate	Std. error
Meanlog	4.80	0.001436
SDlog	1.56	0.001015

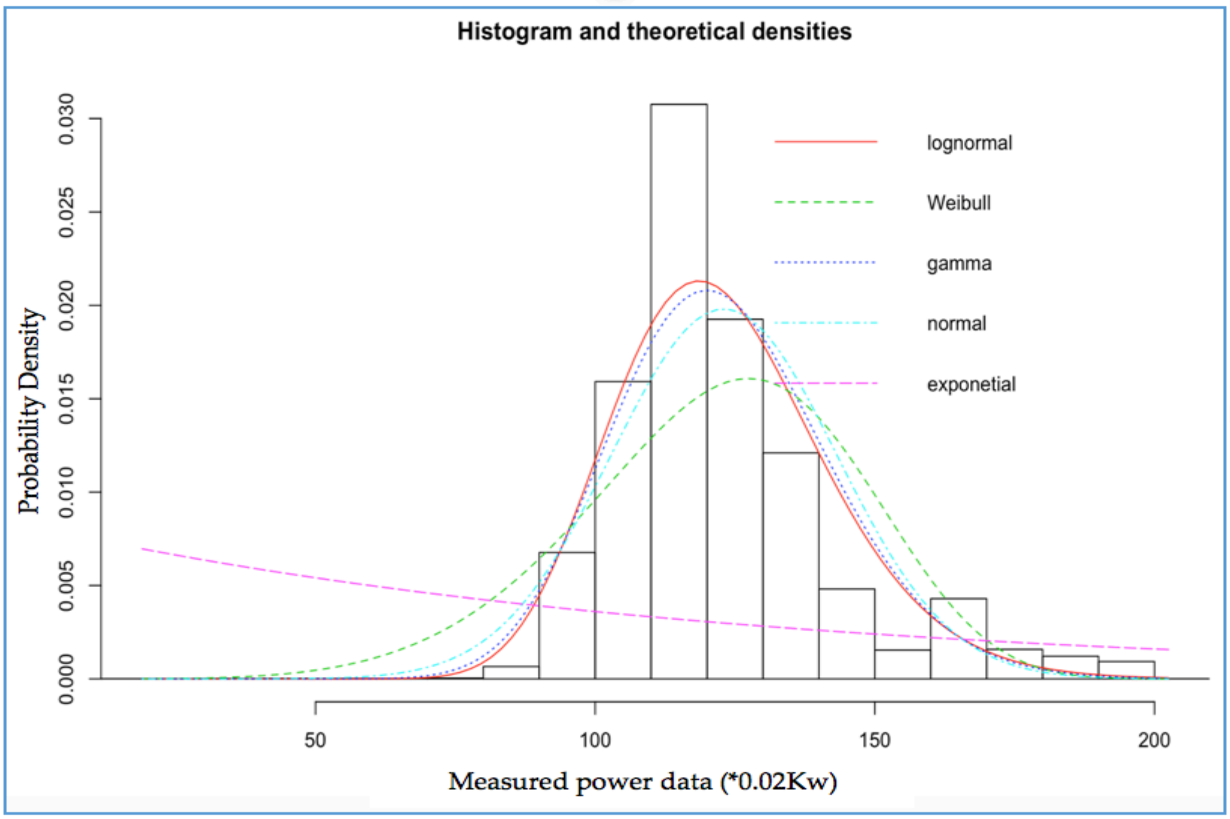


Figure 7: Power data with different distribution graphs

Table 5: Different distribution result for traffic data with selection parameters

	Lognormal	Weibull	Gamma	Normal	Exponential
LL	-48550.93	-47013.43	-47198.06	-48440.18	-48013.25
AIC	97105.87	94030.86	94400.11	96884.37	96028.50

	Lognormal	Weibull	Gamma	Normal	Exponential
BIC	97120.62	94045.61	94414.87	96899.12	96035.88

As can be seen in Figure 8 Weibull distribution fits to the traffic data better than the other distributions and its parameters are seen in Table 6.

Table 6: Weibull distribution parameter that fit to the traffic data.

	Estimate	Std. error
Shape	1.4328	0.010625
Scale	23.682	0.159840

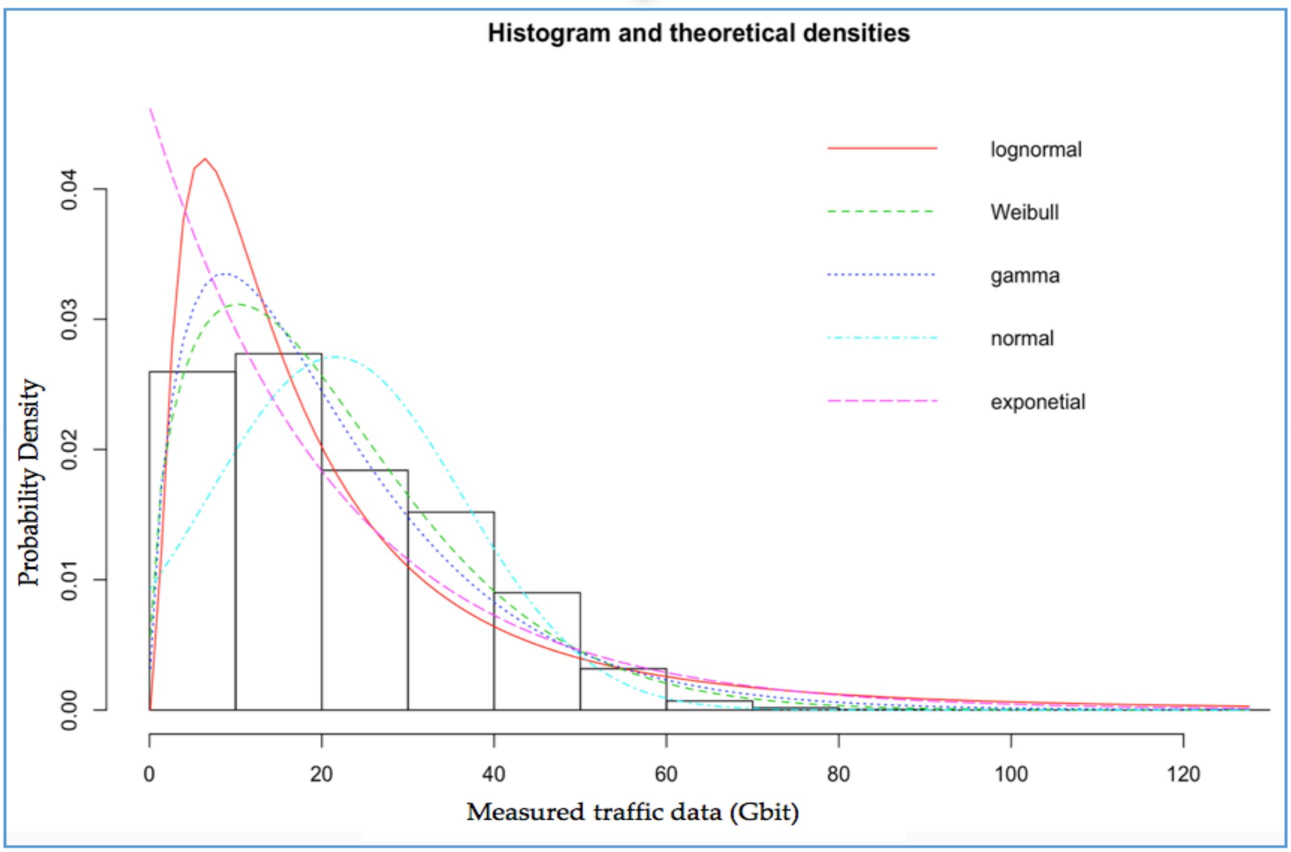
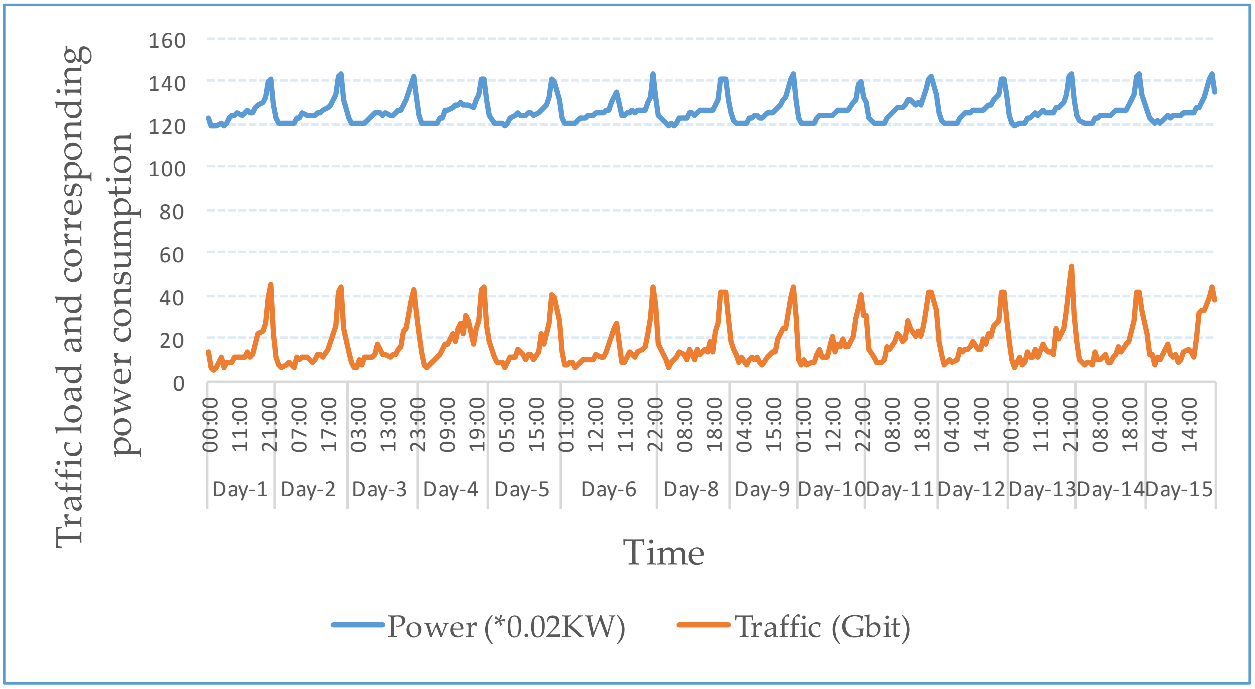


Figure 8: Traffic data with different distribution graphs

3.1.3. Relationship between BS power consumption and traffic load

It was also found that the power consumption and the traffic load of each base station differed not only in weekdays and weekends but also according to the morphology of the area. 25 sampled BSs are analyzed and some of this BSs data are discussed below without mentioning their name and location for security purpose.

I. Base Station # A



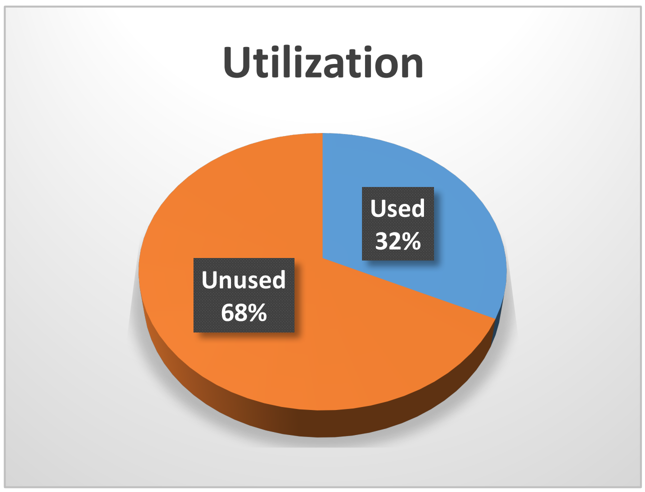
(13a)

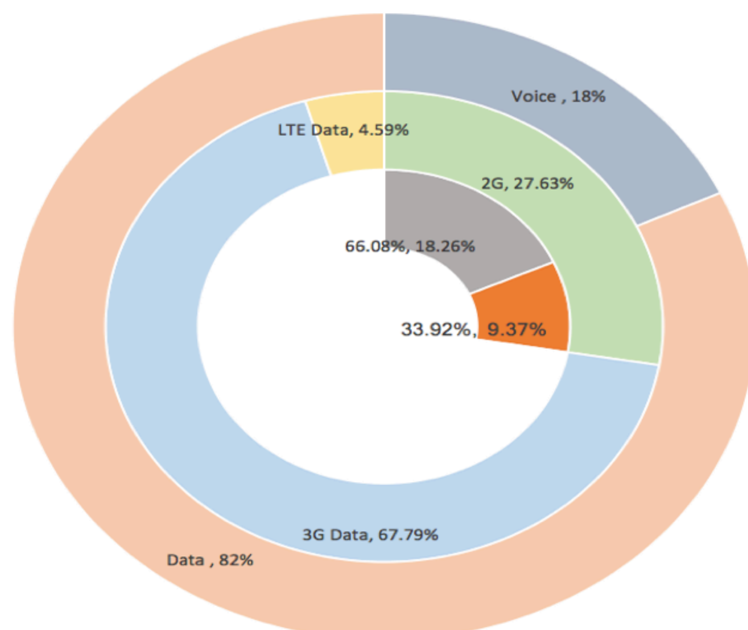
Figure 9: Base Station # A (9a) Power Consumption and Traffic load, (9b) utilization and (9c) Traffic share

The traffic pattern is a direct consequence of a daily power consumption pattern variation. It was observed that the increase in the power consumption of base station results in an increase in the traffic. Figure 9a shows the relationship between power consumption and traffic load for 15 days (1 holyday, 4 weekend and 10 weekdays), which clearly shows the correlation between power consumption and traffic load.

It was found that the traffic load and the power consumption is high during night time from 21:00 - 22:00 hrs and low from 02:00 - 05:00 hrs. The maximum traffic load is 54.01 Gbit and minimum traffic is 5.36 Gbit. The power consumption of base station varies from 2.38 KW to 2.88 KW. The BS utilization and traffic share is shown in figure 9b and 9c respectively. Since the lower traffic duration is long the utilization of the BS is about 32% and most of the traffic is data traffic generated from 3G technology.

(9b)





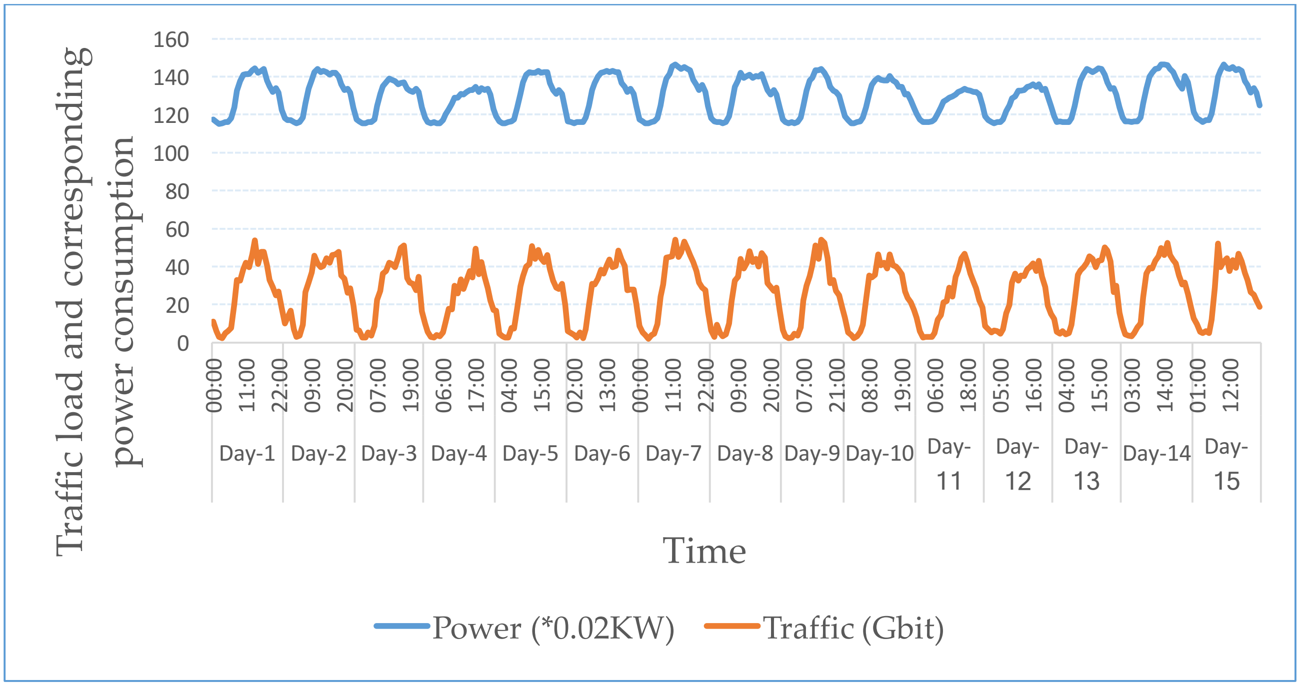
(9c)

All BS utilization calculated as shown in Equation (36)

$$Utilization\ (U) = \frac{1}{n}\sum_{i=1}^{n}\frac{T_i}{T_{Max}} \tag{36}$$

Where T_i is the instantaneous traffic, T_{Max} is the maximum traffic carried out by the BS and n is the number of collected data.

II. Base Station # B

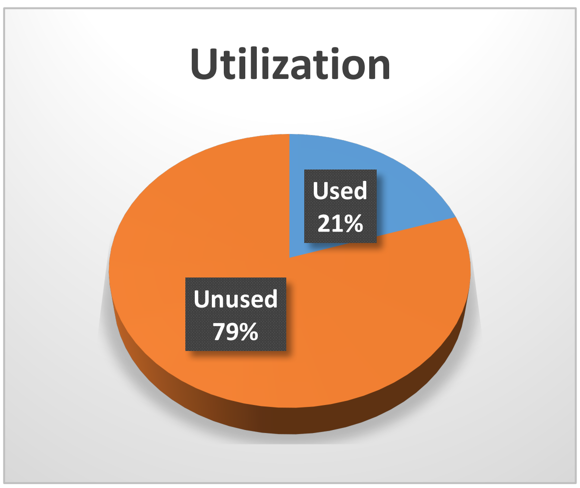


(10a)

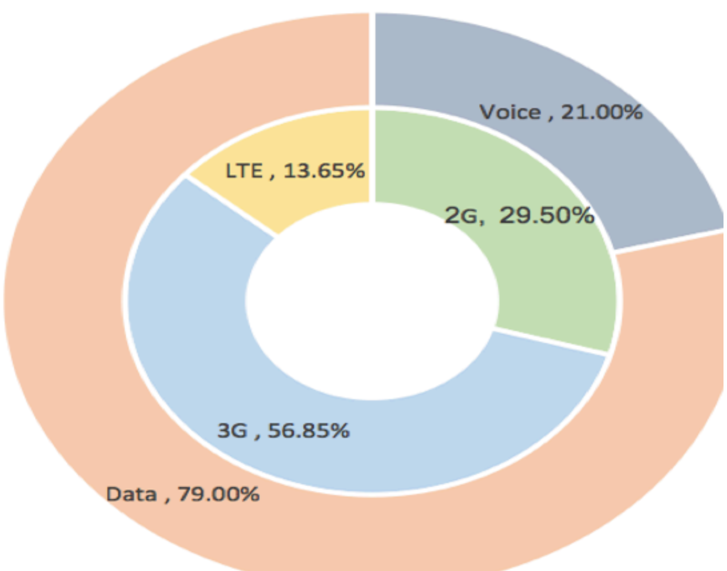
Figure 10: Base Station # B: (10a) Power Consumption and Traffic load, (10b) utilization and (10c) Traffic share

The traffic pattern is a direct consequence of a daily power consumption pattern variation. It was observed that the increase in the power consumption of base station results in an increase in the traffic. There is a direct correlation between the power consumption and respective traffic load. Figure 10a shows the relationship between power consumption and traffic load for 15 days (1 holyday, 4 weekend and 10 weekdays), which clearly shows the correlation between power consumption and traffic load.

It was found that the traffic load and the power consumption is high from 12:00 - 14:00 hrs and low from 02:00 - 05:00 hrs. The maximum traffic load is 54.12 Gbit and minimum traffic is 1.97 Gbit. The power consumption of base station varies from 2.30 KW to 2.93 KW. This BS utilization and traffic share is shown in Figure 10b and 10c respectively. Utilization of the BS is about 21% and most of the traffic is data traffic generated from 3G technology.

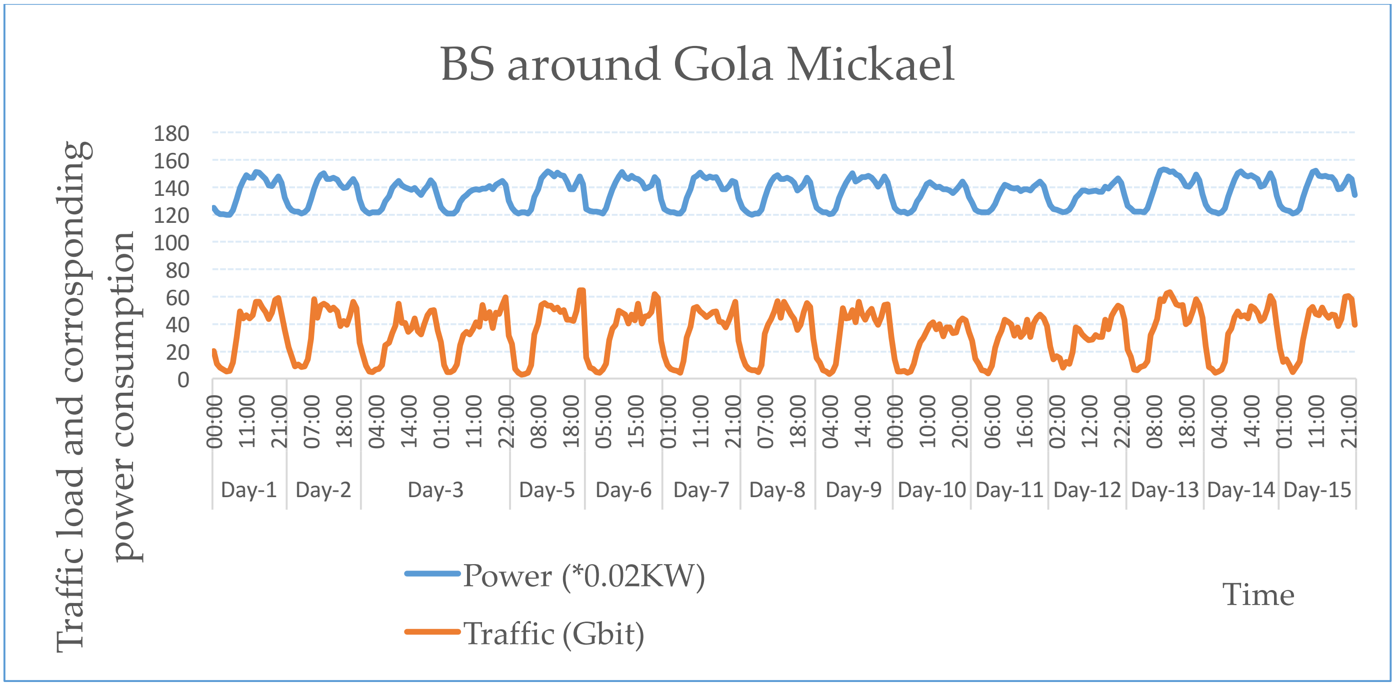


(10b)



(10c)

III. Base Station # C



(11a)

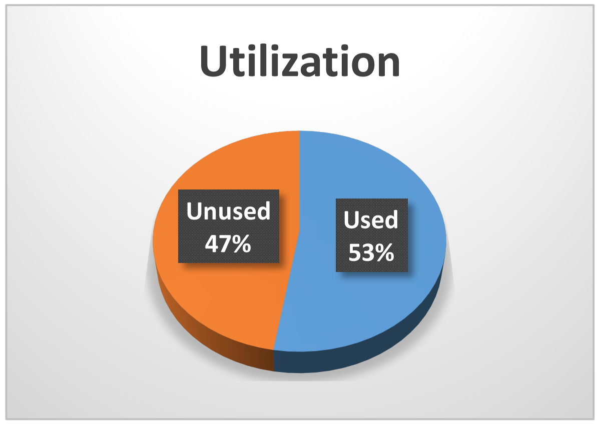
Figure 11: Base Station # C: (11a) Power Consumption and Traffic load, (11b) utilization and (11c) Traffic share

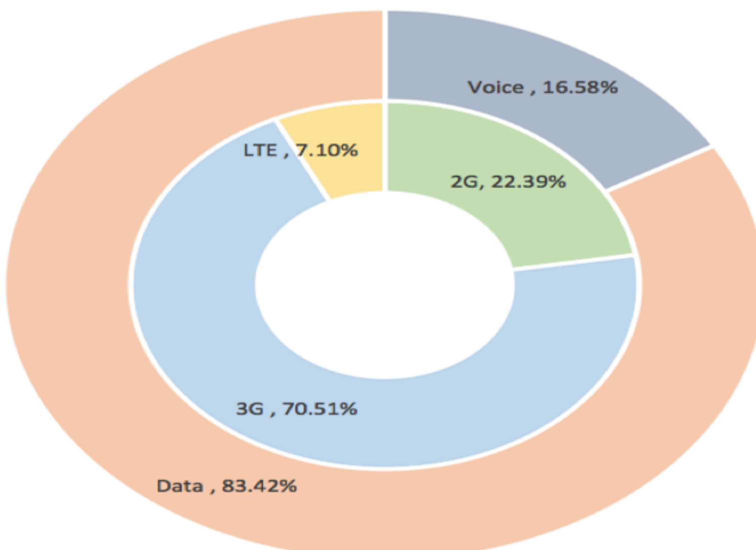
The traffic pattern is a direct consequence of a daily power consumption pattern variation. It was observed that the increase in the power consumption of base station results in an increase in the traffic. There is a direct correlation between the power consumption and respective traffic load. Figure 11a shows the relationship between power consumption and traffic load for 15 days (1 holyday, 4 weekend and 10 weekdays), which clearly shows the correlation between power consumption and traffic load.

It was found that the traffic load and the power consumption is high from 10:00 - 14:00 hrs and low from 02:00 - 05:00 hrs. The maximum traffic load is 64.51 Gbit and minimum traffic is 2.74 Gbit. The power consumption of base station varies from 3.08 KW to 2.40 KW. This BS utilization and traffic share is shown in Figure 11b and 11c respectively.

Utilization of the BS is about 21% and most of the traffic is data traffic generated from 3G technology.

(9b)

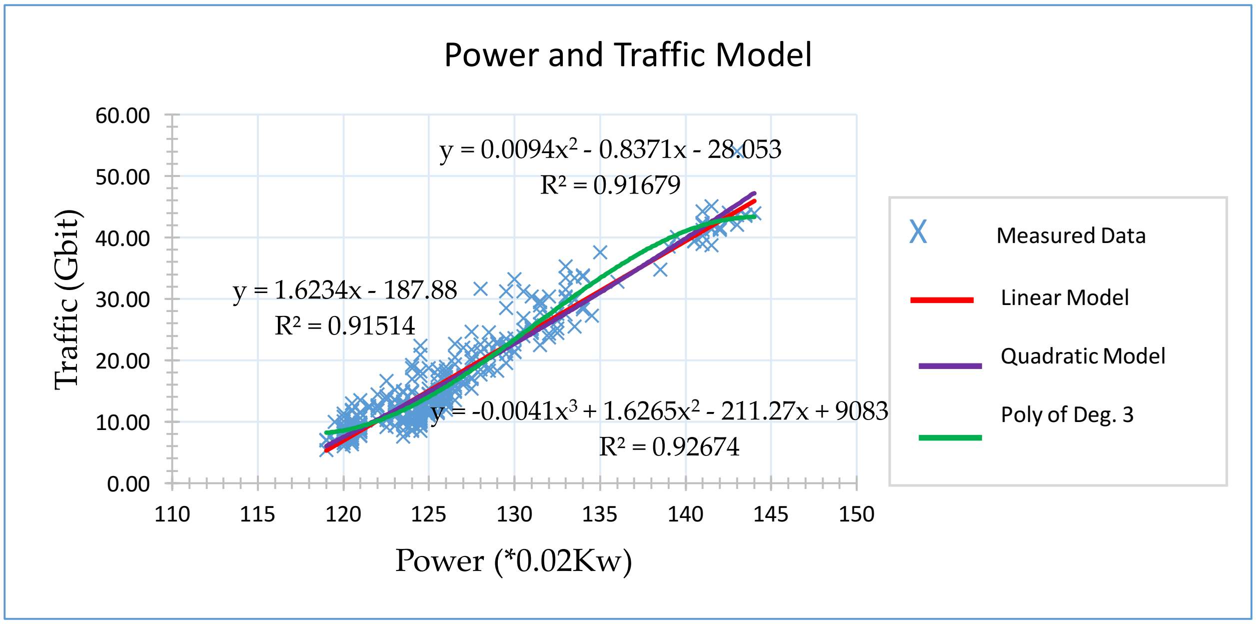




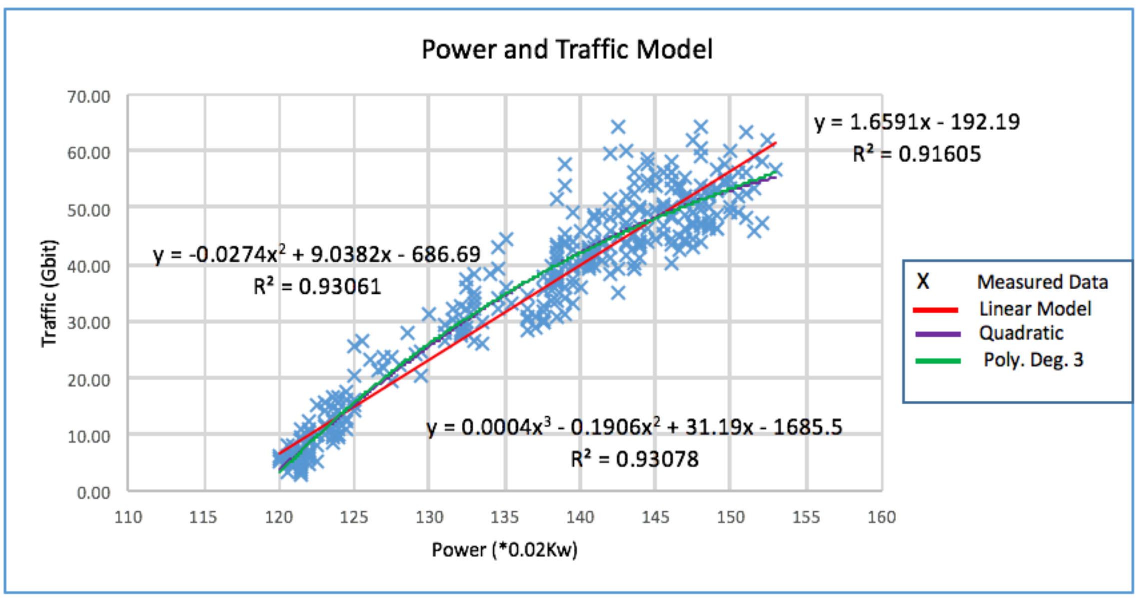
(9c)

3.1.4. Compare the Result with Standard and develop the model

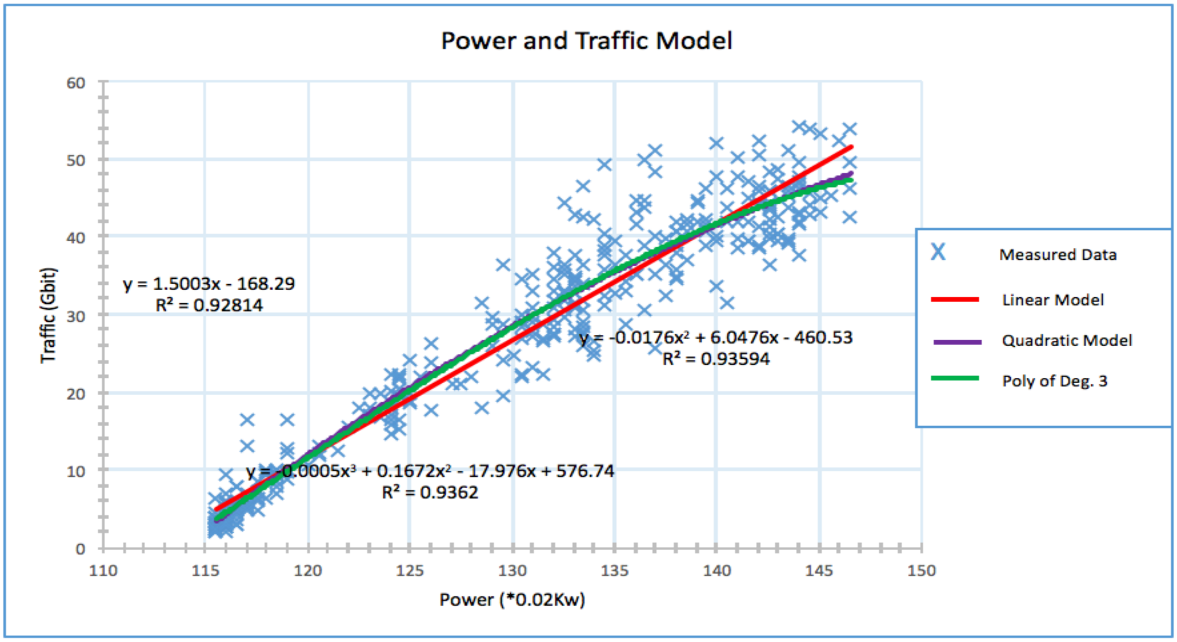
Even though traffic is influenced by different factors like time, human mobility, holiday, etc. we can model it using the power consumption of the BSs and it is the main purpose of this thesis. But first we have to compare different modeling types line linear, quadratic and polynomial of degree three and select the better one. So, those modeling types are comparison and analysis are shown in Figure 12a, 12b, 12c and Table 9.


Power and Traffic Model
y = 0.0094x² - 0.8371x - 28.053
R² = 0.91679
y = 1.6234x - 187.88
R² = 0.91514
y = -0.0041x³ + 1.6265x² - 211.27x + 9083
R² = 0.92674
Traffic (Gbit)
Power (*0.02Kw)
Measured Data
Linear Model
Quadratic Model
Poly of Deg. 3

(12a)


Power and Traffic Model
y = 1.6591x - 192.19
R² = 0.91605
y = -0.0274x² + 9.0382x - 686.69
R² = 0.93061
y = 0.0004x³ - 0.1906x² + 31.19x - 1685.5
R² = 0.93078
Traffic (Gbit)
Power (*0.02Kw)
Measured Data
Linear Model
Quadratic
Poly. Deg. 3

(12b)



(12c)

Figure 12: (12a) Base Station # A Power Consumption and Traffic load models, (12b) Base Station # B Power Consumption and Traffic load models and (12c) Base Station # C Power Consumption and Traffic load models.

The RMSE of those models can be seen in the Table 7.

Table 7 : Different model RMSE and % error

BS #	Model type	RMSE	% error
1	Linear	2.8590	5.29%
	Quadratic	2.8310	5.24%
	Polynomial of degree of 3	2.6563	4.92%
2	Linear	5.0839	7.88%
	Quadratic	4.6221	7.16%
	Polynomial of degree 3	4.6166	7.16%
3	Linear	4.1665	7.67%
	Quadratic	3.9349	7.27%
	Polynomial of degree 3	3.9270	7.26%

The linear model RMSE have no big difference with the other models because of its simplicity we choose the linear model.

In addition, different linear models also compared: Weighted Average and general (aggregated) model are also compared using RMSE as a comparison parameter and the general (aggregated) model have a minimum value.

In order to further increase the accuracy of our model we develop a piecewise model for which the modeling is done for different time frame.

So, first let as compare the weighted average and the aggregated models. To test the statistical model, we have to check the value of R squared. The coefficient of determination, R Squared is the number that indicates how well data fit a statistical model. It is also known as the coefficient of determination. 0% indicates that the model explains none of the variability of the response around its mean. In this study, the value of R square varies from 0.84669 to 0.93043 which indicates that our model explains good variability of the response data around its mean.

Table 8 : Sampled base stations with R Squared value

BS #	R Squared
1	0.91613
2	0.93043
3	0.88453
4	0.91116
5	0.84669
6	0.92228
7	0.89728
8	0.91588

BS #	R Squared
9	0.85243
10	0.88722
11	0.91462

Based on the measured traffic load and the power consumption obtained for each base station, the goal is to develop a linear traffic model as per power consumption. The developed model must express traffic load as a function of current power consumption of each base station.

When we implement the simple linear regression shown in Equation (1) our variables are Y is the traffic load and X is the power consumption of BSs.

Let the BS power consumption [KW] be independent variable X, while the traffic load [Gbit] is dependent variable Y. Then the coefficients of the regression line are: β1[Gbit] which represents the intercept and β2[Gbit/KW] which represents the slope of line. Calculations were performed by means of a function regression which is a part of Excel. The obtained results are shown in the Table 8.

Table 9 : Linear model of each base station

BS #	Slope	Intercept
1	1.7255	-190.47
2	1.5013	-168.43
3	1.4190	-161.42
4	1.8734	-206.38
5	1.7302	-185.71
6	1.8645	-205.09
7	1.3964	-148.48

BS #	Slope	Intercept
8	1.6595	-192.22
9	1.3189	-144.11
10	1.9379	-201.77
11	1.6089	-186.07
Weighted Average (WA)	1.6396	-180.92

So, the weighted average developed model is shown in Equation (37):

$$Y = 1.6396 * X - 180.92 \tag{37}$$

If we aggregated those BSs measured data and analyzed we get another model with a better RMSE.

$$Y = 1.1865 * X - 125.85 \tag{38}$$

Now we have both the weighted average and aggregation models what we left is to calculate the last modeling that is the piecewise modeling by dividing it in to three-time slots. From 00:00hr to 07:00hr when most of the low traffic data was seen, from 08:00hr to 18:00hr when the traffic is variation is slow and finally from 19:00hr to 23:00hr when the pick traffic is recorded.

So, after analysis we have found all the model as well as their corresponding RMSE and shown in Table 10, 11 and 12.

Table 10 : Summarization of different models and their RMSE for GUL new sites

No	Model Type		Equation	RMSE
1	Weighted Average model		Y=1.6396X-180.92	7.92Gbit
2	Agregated model		Y=1.1865X-125.85	6.07Bbit
3	Piecewise model	B/n (00:00 to 07:00)	Y=0.8230X-86.785	5.33Gbit
		B/n (08:00 to 18:00)	Y=1.0188X-103.66	
		B/n (19:00 to 23:00)	Y=1.1719X-120.65	

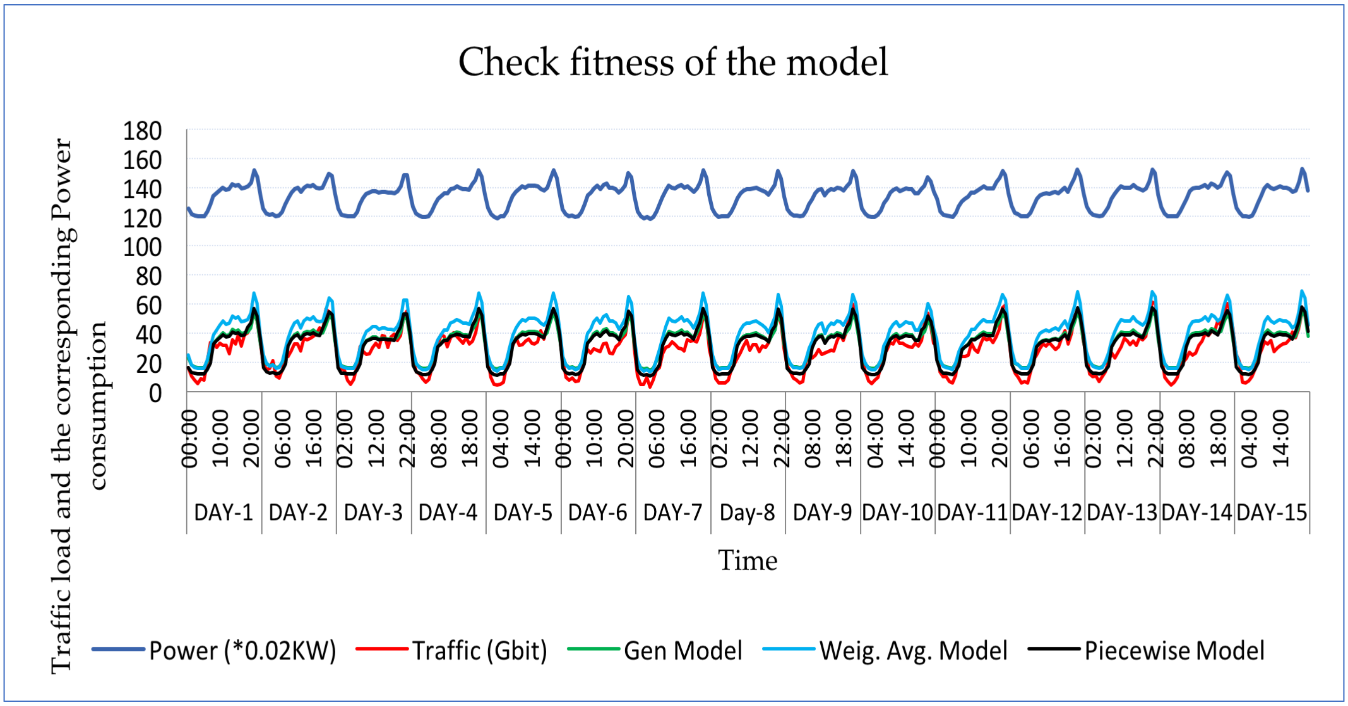
Table 11: Summarization of different models and their RMSE for GUL swap sites.

No	Model Type		Equation	RMSE
1	Weighted Average model		Y=1.257X-194.97	7.05Gbit
2	Agregated model		Y=1.052X-159.65	6.64Bbit
3	Piecewise model	B/n (00:00 to 07:00)	Y=0.7965X-119.85	6.24Gbit
		B/n (08:00 to 18:00)	Y=0.9866X-148.51	
		B/n (19:00 to 23:00)	Y=0.9620X-140.20	

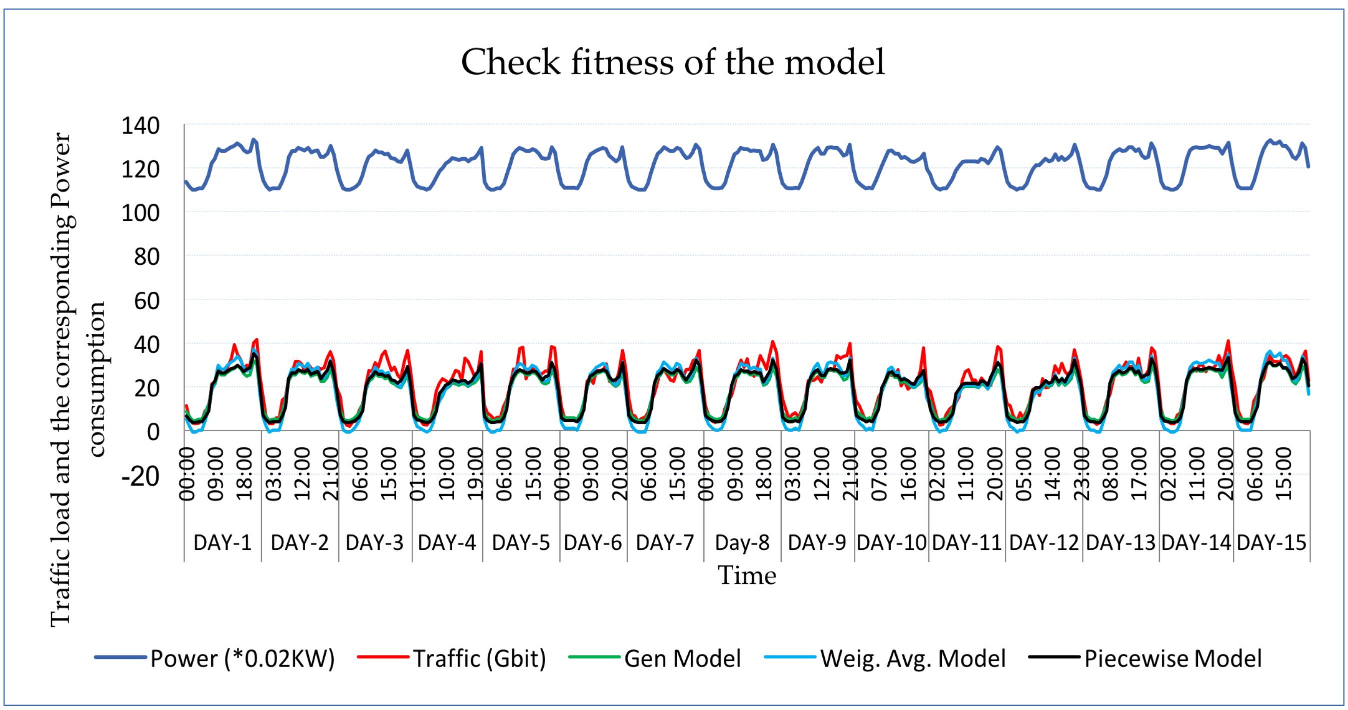
Table 12: Summarization of different models and their RMSE for GU sites.

No	Model Type		Equation	RMSE
1	Weighted Average model		Y=2.4659X-91.075	8.35Gbit
2	Agregated model		Y=1.6139X-52.996	6.15Bbit
3	Piecewise model	B/n (00:00 to 07:00)	Y=0.4731X-38.014	5.48Gbit
		B/n (08:00 to 18:00)	Y=0.6177X-49.112	
		B/n (19:00 to 23:00)	Y=0.5417X-36.695	

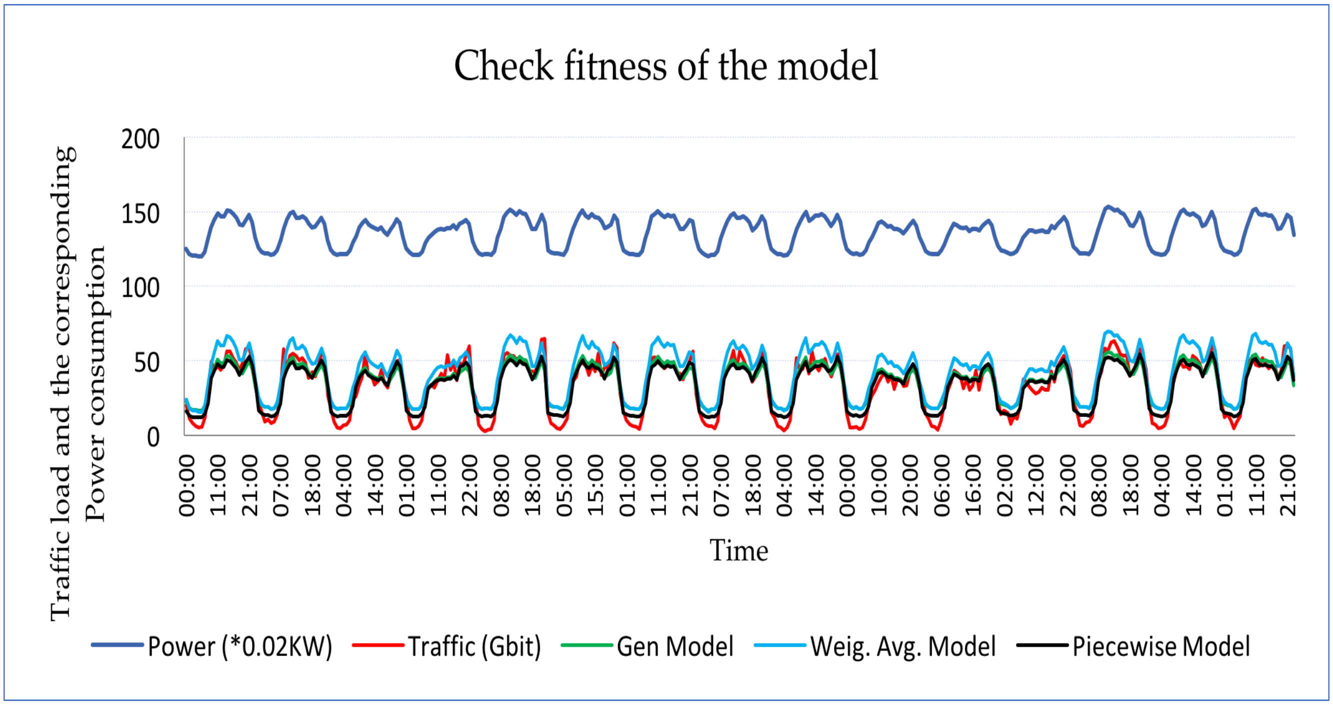
The fitness of those model can be seen from the below Figure 13 on sample BSs.



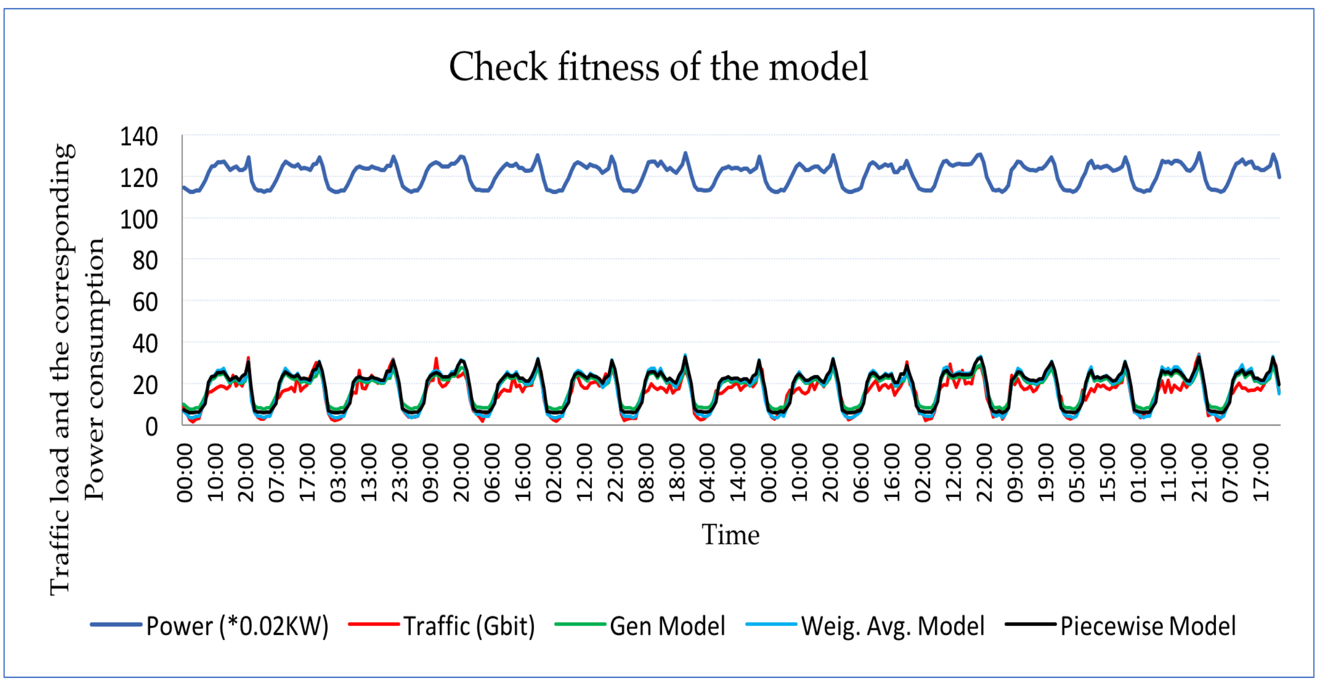
(13a)



(13b)



(13c)



(13d)

Figure 13: Different models checked in different Base Station to find the best fit model.

4. CONCLUSION AND RECOMMENDATION

4.1. Conclusion

Even though traffic is influenced by different factors like time, human mobility, holiday, etc. developing a model based on power consumption of the base stations is the main purpose of this thesis. Additionally, we investigate the distribution the traffic load and the power consumption at the BSs. Analysis have been performed on a fully operated BSs serving GUL and GU technologies.

9000 samples were taken from 25 base stations: 15 base stations serve GUL technologies sites (out of which 4 BSs are Swap sites) and the other 10 base stations serving only GU technologies and we obtain results which confirm that the power consumption of BSs varies in accordance with the traffic load in both BSs types. This is a consequence of the direct correlation which exists between the BS power consumption and the traffic load pattern as shown in Figure 6.

So, we develop a linear traffic model for each of the analyzed BSs. After finding the linear model we further analyzed it in order to get a better model with minimum RMSE, which make us develop a piecewise model for the low and high traffic load. This interdependency is important for further studies focused on improving the energy efficiency of already installed BSs.

We saw that the swap BSs power consumption is higher than that of the other BSs. (Its maximum power is about 4KW with the other BSs consume about 3KW). Additionally, we have found that lognormal distribution fit the power data better with mean = 4.80 ± 0.00143 and SD = 0.156 ± 0.001015359. For the traffic data, Weibull distribution fit better than the other distributions with a parameter: shape = 1.433 ± 0.0106 and scale = 23.682 ± 0.1598.

From the result of the study; it can be concluded that:

⇒ We develop for each of the analyzed BS types a linear piecewise traffic model. The proposed model has minimum RMSE when compared with the measurement data. This interdependence is important for future studies focused on improving the energy efficiency of already installed BSs.

⇒ We develop a suitable distribution type for the BS power data as well as for traffic load data. Which is helpful for further study on these data.

⇒ We have seen that the utilization of the BSs are below 50%, and most of the traffic recorded is due to the 3G data.

⇒ The range of traffic load is higher than the range of the power consumption, this fact we give us a room to play energy saving technique by turning on and off BSs.

⇒ The pick traffic load duration is at 21:00hr so, this fact will help for future planning work.

4.2. Recommendations

Based on the study this traffic model is an important input for those recommendations:

a) Most of the time energy efficiency is done during operation but considering energy efficiency during planning phase has very high advantage. In traditional planning pick hour traffic is considered while energy efficient planning considers daily traffic variation so, this study could be a good input [43] – [44].

b) Set base stations in sleep mode during low traffic is one of the energy efficiency strategy, so this model will help to identify the traffic level [45].

c) According to the result most of the time base stations are underutilization so, to improve the base station utilization and maximize revenue telecom operators can implement dynamic pricing [46], [47].

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Appendix 1: R – Code to find best distribution for our power data.

```
Pow1

p<-Pow1$X...Pow

summary(p)

normle<-fitdist(p,"norm",method = "mle")

normle

summary(normle)

plot(normle)

gammle<-fitdist(p,"gamma", method = "mle")

gammle

summary(gammle)

plot(gammle)

weimle<-fitdist(p,"weibull",method = "mle")

weimle

summary(weimle)

plot(weimle)

lnormle<-fitdist(p,"lnorm",method = "mle")

lnormle

summary(lnormle)

plot(lnormle)

expmle<-fitdist(p,"exp",method = "mle")

expmle

summary(expmle)
```

```
plot(expmle)

cdfcomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

denscomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

qqcomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

ppcomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

gofstat(list(lnormle,weimle, gammle, normle,expmle), fitnames=c("lognormal","Weibull", "gamma", "normal", "exponetial"))
```

Appendix 2: R – Code to find best distribution for our traffic data.

```
Tra1
t<-Tra1$X...Tra
summary(t)
normle<-fitdist(t,"norm",method = "mle")
normle
summary(normle)
plot(normle)
gammle<-fitdist(t,"gamma", method = "mle")
gammle
summary(gammle)
plot(gammle)
weimle<-fitdist(t,"weibull",method = "mle")
weimle
summary(weimle)
plot(weimle)
lnormle<-fitdist(t,"lnorm",method = "mle")
lnormle
summary(lnormle)
plot(lnormle)
expmle<-fitdist(t,"exp",method = "mle")
expmle
summary(expmle)
```

```
plot(expmle)

cdfcomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

denscomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

qqcomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

ppcomp(list(lnormle,weimle, gammle, normle,expmle), legendtext = c("lognormal","Weibull", "gamma", "normal", "exponetial"))

gofstat(list(lnormle,weimle, gammle, normle,expmle), fitnames=c("lognormal","Weibull", "gamma", "normal", "exponetial"))
```