Mobile Phone Charging: Power Statistics & Energy Consumption Pattern Analysis Using Developed "Powerstats" Android Application

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Abstract

Nowadays Mobile phones have become an essential part of life. The number of mobile phone users is also increasing rapidly; each person in a house has their handsets, leads to the rapid increase of mobile phone usages in every age group. This will ultimately lead to more electricity consumption required to charge a mobile phone. Mobile phone energy usage depends on factors such as Software energy use, equipment, devices, device contact with apps, wireless network, sensor network, etc. Hence, the paper presents a developed android application named "PowerStats" which gives the statistics of mobile phone charging patterns of users as per the i. Model of phones ii. Plugged in/out battery percentage iii. Plugged in/out timestamp iv. Voltage & v. Current. Based on these statistics, further analysis is done as I. The mobile phone charging patterns of users. II. The mobile battery and its consumption capacity. III. To show that electricity required to charge a group of mobile phones in a household is equivalent to Air Conditioners, on a large scale. IV. To predict the best classification algorithm for the collected dataset from the application.

Keywords: Power Statistic; Direct-Indirect charging; Machine learning; Supervised Learning; Smart Meter

Introduction

Mobile phones are a very valuable development because they have been the main device used in human life. The whole world is accepting and adopting the ways towards the advancement of technology. Surveys have consistently shown that people even prefer their mobile phones over television. In the past 20 years, global cell phone subscribers have risen from 12.4 million to more than 5.6 billion , accounting for around 70 % of the world 's population. According to the new statistics from GSMA Intelligence, there are 5.19 billion individual cell phone subscribers in the world today. Today smartphones are used at an annual rate of 8 percent, with well over 1 million new smartphones used every day on average. These statistics show the rapid increase in the usage of mobile phone users.

Statistics of Mobile Phone Users Worldwide

Figure 1 shows the maximum number of Mobile Phone Users rising around the world. South Korea leads with 71.5% of the population who are mobile users.

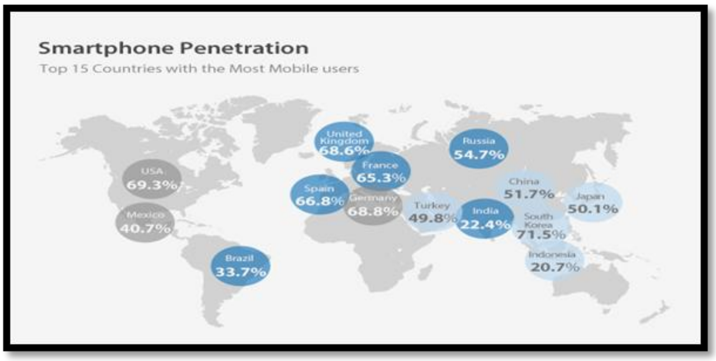


Figure 1: Mobile Phone Trends in 2020 - Stats & Facts Worldwide.

Source: https://www.vpnmentor.com/blog/vital-internet-trends/ (accessed on 3rd April 2020)

A mobile phone is a computer tool that is used to operate various operations, operate it software, wireless network interoperability, information exchange within a server and a network technology environment. It requires a battery as a power source. These batteries need 1 to 4 hours of charging which is not necessary as an average of 14 hours for a few hours of talk time. The mobile phone is often used in social networking, gaming, GPS applications, video sharing and another device connectivity. These specifications required the mobile system to process immensely. Ultimately, a lot of power energy is consumed during processing. Despite increasingly rising competition for machine power the approaches to this issue would not be applied regularly depending on the device's output. Today, electricity plays a critical function in everyday life. Since we use a lot of electrical energy-dependent appliances, it's pretty hard to live without electricity.

Factors Influencing Energy Consumption in Mobile Phones

Electronic products, in particular mobile phones, are powered by batteries that are small in size and so in performance. This means that effective energy conservation is of utmost importance in these appliances. Efficient energy usage requires a good view of when and how to utilize the electricity. Hence factors affecting the energy consumption are: A) Baseline cases: 1. Suspended device 2. Idle device and 3. Displays, B) Micro-benchmarks: 1. CPU & RAM 2. Flash storage 3. Network and 4. GPS

C) Usage Scenarios: 1. Audio and Video playback 2. Text messaging 3. Voice calls 4. Emailing and 5. Web Browsing.

Household Electricity Consumption of Appliances

The mobile phone users' population is increasing rapidly, and the demand for energy consumption & generation is also increasing. Rather than increasing the Energy production, supply and installations of utility centres the demand for energy can be adjusted. Figure 2 gives the percentage of energy usages of different electrical & electronic appliances. The graph even depicts the percentage of energy usages of electronic appliances (i.e. mobile phones) is almost equivalent to the percentage of energy usages of other electrical appliances.

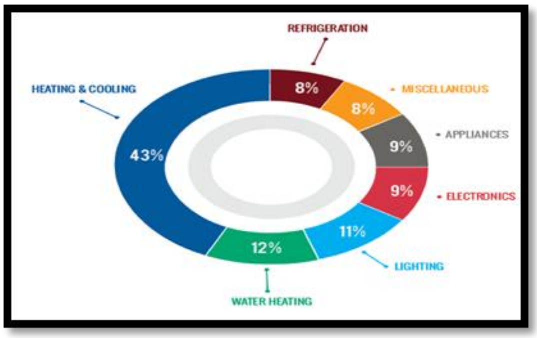


Figure 2: Household Energy Usage- Percentage of energy usages of appliances, Source: US Energy Information Administration

These statistics give the idea behind the proposed research work, as the Mobile Phone users are rapidly increasing and simultaneously the demand of energy to charge such a rising mobile usage population is also increasing.

The paper presents a new approach to deal with the energy consumption and power statistics of mobile phone charging. The research methodology is as follows:

1. Determine the best fit classification algorithm for the collected dataset. 2. To show that electric energy required to charge a mobile phone is equivalent to other electrical devices such as Air Conditioners, on a large scale. 3. To study and analyse: i. The mobile phone charging patterns of users and ii. The mobile battery and its consumption capacity. 4. Comparing the direct and indirect method of charging for the phone model, the usage of the battery in mAh(ampere-hour), the voltage needed to charge the cell, the time necessary to charge it fully, etc., and then, after evaluating the results, the result is determined:

The most efficient way of charging is determined which consume less energy or the best mode of charging is determined which keeps the long-lasting battery power w.r.t the model of the handset.

The format of the paper is as follows: section 2 and section 3 describes the related work, data summary and preparation; section 4 and section 5 is the proposed methodology, experimental results and section 6 is a Discussion, and section 7 is conclusion and future research directions.

Literature Review

In the past years, extensive research has been done to reduce energy consumption and discover the ways to manage the energy load. The different perspectives of the load minimization and the reason behind the maximum energy consumption has been found. The electrical devices lead to consumption of energy hence the study leads to further monitor the energy consumption patterns of these different electrical devices. So, different research cases exist to classify the above scenario.

Due to the increasing demand for electricity, researchers are focusing on alternative sources of reduction in energy consumption. The alternate ways introduced by researchers to reduce energy consumption are 1. Load Profiling 2. Peak Load Estimation 3. Demand – Response 4. Smart Grid

Some Existing Methods to Reduce the Energy Consumption:

1. Load Profiling: Smart Grid Technology field test financed by the USA for the Pacific North-West Grid Wise Testbed Project was obtained from the Pacific North-West National Laboratory (PNNL) Researcher; PNNL Energy was started in 2004. The initiative observed the energy consumption of 112 households in a bipartisan communication network for 15 minutes and ambient temperatures per hour. 96 data points per element are collected every day in every home, per 15 minutes at a data sampling scale. In order for data collected from each household to be transmitted and processed by a "intelligent meter profiling program," the transmitting ability of the telephone network and the control centre storage space will be significantly greater than the normal data collection. (Ambrosio et al. 2007)

2. Peak Load Estimation: Adequate power planning for substations and feeders relies largely on a reliable estimation of the potential peak demand for electricity. A conventional correlated peak load calculation is based on an analytical measure of high demand for variance, suggesting individual peak usage rates and diversification of supply across multiple inhabitants. (Sun et al. 2019)

3. The Demand Response (DR): Energy demand adjustments rather than supply modification have been introduced in programs. "Time of Use (ToU),' one of the DR's most well-known programs, encourages customers to shift their consumption pattern to less hours of energy consumption in return of incentives, also known as outsource hours. (Pabon et al. 2016)

4. Smart Grid: A broad repository of Smart Grid initiatives in Europe using project data to enable the study of trends and developments. The study discusses many facets of the Smart Grids framework to explain the state of the art of their operation, the evolving characteristics of the new electricity network and future developments. A core objective of the study is to explain how Smart Grid initiatives tackle and respond to the EU energy policy issues and to map out the major advantages and beneficiaries. Particular attention is paid to recognizing the most significant obstacles to innovation and potential approaches that may help to resolve them. (Liu et al. 2019)

Furthermore, the researchers concentrate on the other electronic devices apart from the larger ones such as cell phones and the power required to charge them, factors affecting power usage etc. The study described below relates to the same factor.

The current study work deals with the measurement of power use in terms of resource use across the specific cell phone variables. A system to identify and track the use of mobile apps for electricity. Approach to the measurement of the energy usage of the standard cellular device, the Openmoko Neo Free running mobile phone, has been decomposed into the main subsystems of the network in a large range of realistic scenarios. Specifically, it is suggested that power allocation, memory, touch screen, computer equipment, audio, data, and various network interfaces be broken down. The system's total energy model as a feature of major use scenarios. This offers a good foundation for working on future energy saving research on mobile devices. (Carroll and Heiser, 2010)

Considering the effect of application load on smartphone energy use, an energy-efficient timeline algorithm has been developed for specific program loads. Others looked at the relation between the energy expended while transmitting values and the bandwidth of the network. (Schulman et al. 2010)

Introduced a performance method for Wi-Fi & 3 G that would consider the effect of a good /bad connection on the electricity used by the cellular components installed in the device. (Ding et al. 2013)

Authors in Test the usage of connection capacity and transmission values on 802.11 networks. They concluded that mobile, device background, and OS are among the many variables that influence the optimum option of data transmission strategy. While cell phones are widely used in cloud technologies to form what is known while cell cloud computing, research has suggested energy saving techniques for mobile cloud technology. (Al-Ayyoub et al. 2015), (Bahwaireth et al. 2015) and (Rice and Hay, 2010)

In the same way, a thorough study of scalable and efficient mobile cloud storage was carried out, the writers proposed a system that assigns research to certain programs to be performed on a smart machine and transfers other activities to be performed on a server. (Fekete et al. 2013) and (Tawalbeh et al. 2015)

Methods for moving outsourced operations from a mobile unit to a remote network (e.g. cloud) have been implemented to reduce electricity consumption and local time of execution on a mobile device. (Carroll and Heiser, 2010) and (Jararweh et al. 2013)

Authors proposed a theoretical framework for a power-efficient software operated on a hypothetical wireless network. They can consider two factors for application, the size of the data and the timeline for fulfilment of the query. The empiric results of this empirical approach determine the position of the power-efficient system run for each device. Depending on the survey in question, it can therefore be argued that the unloading process may be used to minimize energy use in a cell phone device, but a number of considerations influence the performance of such a method, such as the nature of the devices, the size of the data and the internet connection. (Zhang, Weiwen, et al. 2013)

Energy usage is being evaluated for the unique features of two famous smartphone firms, namely Galaxy Note3 and Sony Xperia Z2. Calculations are rendered using software that calculates the power used in any aspect of the handset. The results gathered to provide more comprehensive information of these apps contribute to the overall power consumption of the device. (Tawalbeha et al. 2016)

A geographically dependent Wi-Fi scanning technique that identifies the closest Wi-Fi signal access points (APs) depending on the device's positioning data. This allows consumers to intelligently switch to the Wi-Fi device as they arrive at the closest Wi-Fi network AP. We will always meet the customer 's criteria for optimal connectivity in terms of bandwidth. It prevents long stretches of idleness and greatly reduces the number of unwanted Wi-Fi searches on a mobile computer. Our experiments and measurements demonstrate that our system effectively saves money for Wi-Fi phones and internet mediators. (Xia et al. 2015)

Measurement of the energy consumption properties of three popular mobile networking technologies: 3 G, GSM, and Wi-Fi. We note that the 3 G we GSM suffer more energy due to the remaining energy statistics after the transition has been completed. Based on these measurements, a method of energy consumed by the activity of the network has been developed for each device , i.e. TailEnder, a protocol that reduces energy use for growing smartphone applications. For systems that can tolerate a small delay, such as e-mails, TailEnder aims to popular the overall capital consumed by dealing on user-specific timelines. (Benkhelifa et al. 2015)

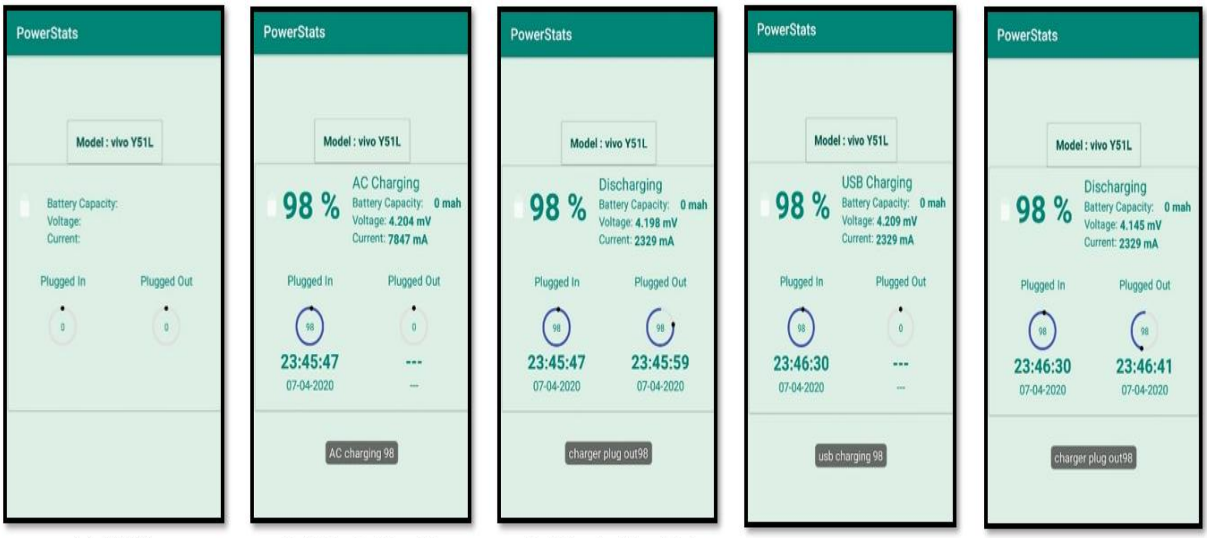
Paper clusters use domestic energy using smart metre data from the Danish town of Esbjerg. Methods of time series analysis and wavelets are used to allow the K-Means clustering method to compensate for auto data correlation and increase clustering efficiency. The results show the value of data awareness and we recognize sub-clusters of use in housing styles and allow K-Means to achieve adequate clustering by accounting for a temporary portion. The analysis also shows that the diligent pre-processing of data to compensate for the intrinsic structure allows improved clustering efficiency through the K-Means approach. (Alexander et al. 2018)

Data Summary and Preparation

This section introduces the proposed android application “PowerStats”, which is used to collect the dataset to do further analysis. Data Collection of Mobile Phones Charging Pattern is done using the developed “PowerStats” Android Application.

Data Collection and Pre-Processing

The Android Application- “PowerStats” is developed to collect the data from Users to analyze their charging patterns. Figure 3 shows the User Interface of the developed Android Application. The purpose of the application is to collect the dataset required to do further analysis of the proposed research study. The figure consists of different states of application: 1. Initial State: is the idle interface state of an application. 2. AC Charging Plugged In: is the state when the direct method of charging is used. 3. AC Charging Plugged Out: is the state when the charger is plugged out. 4. USB Charging Plugged In: is the state when the in-direct method of charging is used. 5. USB Charging Plugged Out: is the state when charger is plugged out.



1. Initial State | 2. AC charging Plugged In | 3. AC charging Plugged Out | 4. USB charging Plugged In | 5. USB charging Plugged Out

Figure 3: User Interface of "PowerStats" Android Application

This section introduces the electricity consumption data that will be analysed for the remainder of this paper. This paper analyses consumption patterns of 10 mobile phone users in the cities of Nagpur and Pune. The literature does not advise on the time length for analysing consumption patterns. The third week of December 2019 is selected, starting on Monday the 16th and ending of April, Thursday the 30th, with all days included. Table 1 shows the description of data in terms of various quantitative measures.

Table 1. Initial data description, comprising 8 distinct quantitative measures of the data applied

Data Description	Values
Country	India
Region	Region Maharashtra; Cities: Nagpur, Pune
Size	3,56,821 bytes
Missing Values	20 instances
Start Date	16 Dec 2019
End Date	30 April 2020
Length	2813 observations
Number of User's	10

Distributed System Architecture of Android Application "PowerStats"

The application is a Distributed System which is divided into 3 phases:

1. User Interface or Front End i.e. Android Application; 2. Interconnection between Sender & Receiver i.e. MongoDB Stitch Application; 3. Data Storage or Back End i.e. MongoDB Atlas. In this distributed system there is android mobile having an android application in which users basic charging information is collected. The interconnection is done using MongoDB Stitch Application which connects to the MongoDB Atlas cloud.

Components of Application: 1. Model (Company) name of Handset, 2. Plugged in/out battery percentage, 3. Plugged in/out timestamp, 4. Mode of Charging: AC or USB, 5. Battery Capacity mAh, 6. Voltage mV, 7. Current mA.

Figure 4 depicts the system architecture of android application (PowerStats) which has android interface, the interconnection between cloud and device is a Stitch React Native SDK and the storage is done on Atlas.

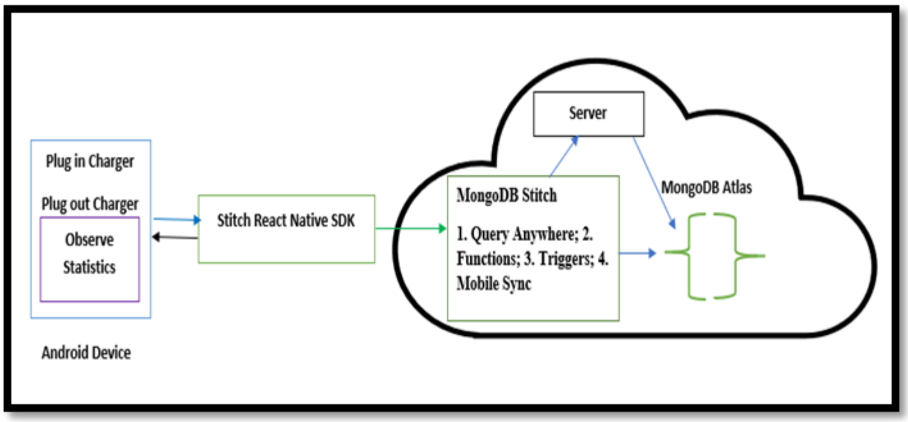


Figure 4: Architecture of System

Algorithm for "PowerStats" Android Application

Input: Plug In/Out battery charger, PlugInOutBattery().

Output: 1. Mode of Charging(Direct i.e. AC or Indirect i.e. USB); 2. Battery Percentage at Plug In/Out; 3. Timestamp at Plug In/Out; 4. Voltage; 5. Current 6. Battery Capacity.

Initialize: I, α, β**,** ϒ, θ, ψ, ω, status, batteryPct, timestamp, voltage, current, battery_capacity;

foreach item I € PlugInOutBattery(α) **do**

if (I== Plugged In) **then** status = Plugged In //**checks the status of battery**

return status

else if (I== Plugged Out) **then** status = Plugged Out

return status

else

return idle

end if

end for

foreach item I € PlugInOutBattery(β) **do**

if (I== AC charge plugged in) **then** (AC charge) **//checks the charging mode of battery**

return AC charge;

else If (I== USB charge plugged in) **then** (USB charge)

return USB charge

else

return null

end if

end for

foreach item I € PlugInOutBattery(ϒ) **do**

float batteryPct = level * 100 / (float)scale; **// formula to calculate battery percentage**

if (α == plugged in) **then** (store the plug-in time battery percentage) // **battery percentage at plug in/ out time**

return batteryPct

else if (α == plugged out) **then** (store the plug-out time battery percentage)

return batteryPct

else

return null

end if

end for

foreach item I € PlugInOutBattery(λ) **do**

if (α == plugged in) **then** (store the start timestamp) //**stores the timestamp**

return timestamp

else if (α == plugged out) **then** (store the end timestamp)

return timestamp

else

return null

end if

end for

foreach item I € PlugInOutBattery(θ) **do // voltage while charging**

float voltage = float.valueOf(sharedpreferences.getString("voltage", "00")) / 1000.0f

return voltage.

end for

foreach item I € PlugInOutBattery(ψ) **do // current while charging**

int current = int.valueOf(sharedpreferences.getString("current", "0")) / 100

return current.

end for

foreach item I € PlugInOutBattery(ω) **do // battery capacity while charging**

int battery_capacity = int.valueOf(sharedpreferences.getString("battery_capacity","0000"))
return battery_capacity.

end for

Data Pre-Processing

Data pre-processing is done to enhance the data consistency, increase efficiency and make ease in the mining process. This phase makes the data more efficient for further steps. Mostly the pre-processing is done to remove values with errors, imputing the null values, normalizing the values, dimensionality reduction, etc. Pre-processing features applied is: Imputing Missing Values - with Average or most frequent values.

Workflow of "PowerStats" Android Application

Figure 5 depicts the complete stepwise workflow of the Android Application. The figure consists of parameters which are checked to give the required results such as plugged in/out battery percentage, plugged in/out timestamp, charging mode, voltage and current required, model/handset of mobile, battery capacity of the phone.

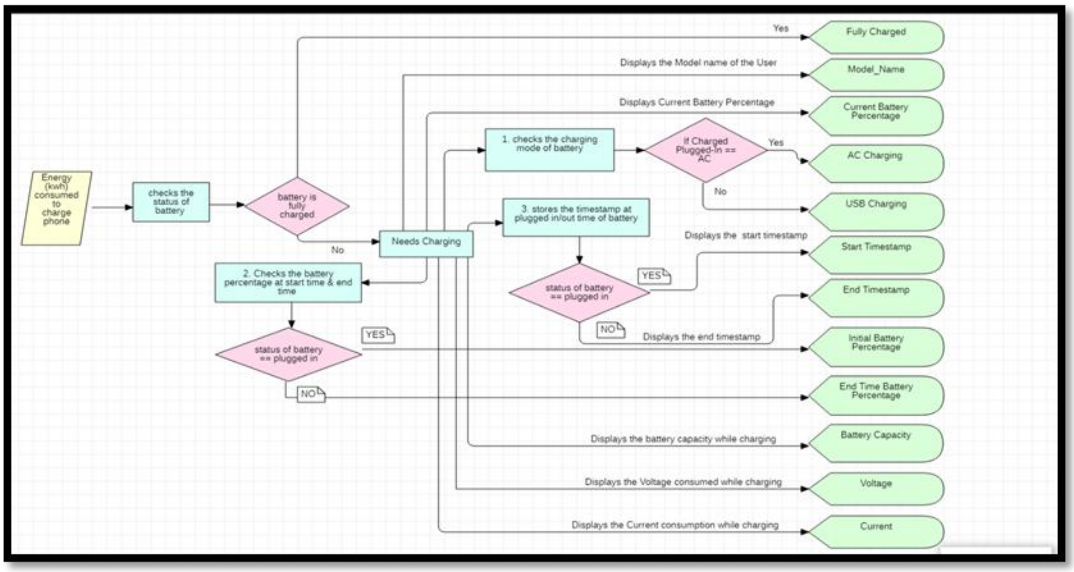


Figure 5: Flowchart shows the Workflow of the "PowerStats" Application

Comparative Analysis of : "Existing Mobile Battery Applications of Google Playstore" vs. "PowerStats"

There are more than 40 android applications related to mobile battery on Google Playstore. The applications with highest ratings and have some features to that of developed application "PowerStats" are considered for the comparative analysis.

Table 2 shows the specifications of the different Mobile based battery applications of playstore platform vs. the developed application "PowerStats".

Table 2: Comparative Specification of "Mobile Battery based Apps" vs. "PowerStats"

Android Applications → / Features ↓	**Battery**	**Green Battery - Power Saver Free, CPU better**	**Battery Charger with Battery Saver and Optimizer**	**AccuBattery**	**Ampere**	**Battery Doctor**	**Developed Application: "PowerStats"**
1. Displays battery information in	✓		✓			✓	✓

percent (%)							
2. Offers quality support for different Android devices.	✓	✓	✓	✓		✓	✓
3. Full support for all known screen resolutions	✓	✓	✓	✓		✓	✓
4. Battery Information in terms of: - Temperature - Voltage - Health Status - Technology	✓					✓ (in terms of temperature)	✓ (in terms of voltage)
5. Accurate – power available time remaining of phone.		✓				✓	
6. Track battery charge status	✓		✓			✓	✓
7. Battery charging history			✓				✓
8. Measure real battery capacity (in mAh)				✓			

9. Measure the charging and discharging current of your battery					✓		✓
10. Displays battery's timestamp (date & time) at the time of plugged in and plugged out.							✓
11. Displays battery percentage at the plugged in and plugged out time.							✓
12. Displays the mobile handset model name.					✓		✓
13. Displays the mode of charging (AC or USB mode).					✓		✓

Figure 6 shows the different mobile handsets and their battery percentage patterns w.r.t the power consumption. SM-A507 consumes more power and its battery charging percentage pattern lies between 0-90%. Similarly, lowest consumption of power is done by Vivo 1803 and its battery charging percentage pattern lies between 0-50%.

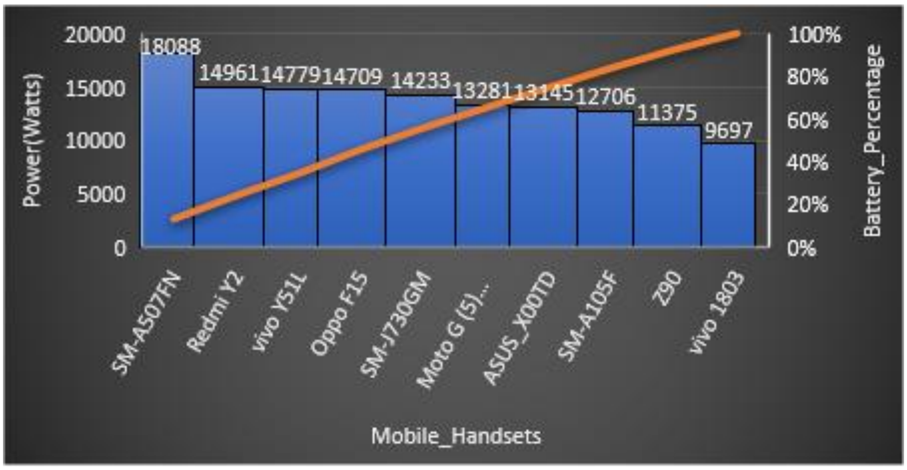


Figure 6 : Cumulative frequency graph of different handsets and their power consumption varying between the battery percentages

Dataset Validation

Methods Used to Validate the Collected Dataset. Figure 10 shows the Statistical Analysis of Data which is done using different methods such as 1. Nominal & Internal Scale Measurements Method 1.1 Range Check, 1.2 Type Check; 2. Physical or Mathematical Model-Based Method 2.1 Extreme Value check using statistics; 3. Statistical Method Spearman Correlation Coefficient. After performing the analysis on Sage Research Methods among various statistical method the Spearman Correlation Coefficient is most suitable for the dataset. Hence the Spearman Correlation Coefficient method is selected to find the dependent or independent variables among the dataset. Table 3 shows the various methods to perform data validation such as 1. Nominal & Interval Scale Measurements Method 2. Physical Or Mathematical Model-Based Method and 3. Statistical Method.

Table 3: Statistical Data Validation Table

Data Validation Techniques Attributes of Dataset	**Nominal & Interval Scale Measurements Method**		**Physical Or Mathematical Model-Based Methods**	**Statistical Method**
	1. Range Check **(Ensures the data**	**2. Type Check** **(Validates**	**3. Extreme value check using statistics**	**4. Spearman Correlation Coefficient**

<table>
<tr><td></td><td>lies within a specific range)</td><td>the data is of correct data type)</td><td>(determines “outlier”)</td><td></td></tr>
<tr><td>1. Age</td><td>(10-100)</td><td>Text</td><td>1. <10
2. >100</td><td rowspan="8">Aim of this Method: To check the dependency between the values of Voltage & Current.

Null Hypothesis H0: H_0: There is no [monotonic] association between Voltage and Current Values

There are two methods to calculate Spearman's correlation depending on whether:

1. your data does not have tied ranks or

2. your data has tied ranks. The formula for when there is no tied ranks is:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$
where di = difference in paired ranks and n = number of cases. The formula to use when there are tied ranks is:

$$\rho = \frac{\sum_i (x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_i (x_i-\bar{x})^2 \sum_i (y_i-\bar{y})^2}}$$
where i = paired score.

<table>
<tr><th>Method</th><th>COR(data1$Voltage, data1$Current)</th><th>COV(data1$Voltage, data1$Current)</th></tr>
<tr><td>Spearman Correlation</td><td>-0.016</td><td>-0.861</td></tr>
</table>
</td></tr>
<tr><td>2. Gender</td><td>(Male or Female)</td><td>Text</td><td>-</td></tr>
<tr><td>3. Profession</td><td>-</td><td>Text</td><td>-</td></tr>
<tr><td>4. Model_Name</td><td>-</td><td>Text</td><td>-</td></tr>
<tr><td>5. Start%</td><td>(0% - 100%)</td><td>Numeric</td><td>1. <0%
2. >100%</td></tr>
<tr><td>6. End%</td><td>(0% - 100%)</td><td>Numeric</td><td>1. <0%
2. >100%</td></tr>
<tr><td>7. Mode_of_charging</td><td>(AC or USB)</td><td>Text</td><td>-</td></tr>
<tr><td>8. Start_Timestamp</td><td>((16 Dec 2019 to 30 April 2020) i.e. (1576514603 – 155664</td><td>Date & Time</td><td>1. greater than 1576514603
2. less than 1556642</td></tr>
</table>

	2603)		603	<table><tr><td>**Coefficient**</td><td></td><td></td></tr></table>
9. End_Timestamp	((16 Dec 2019 to 30 April 2020) i.e. (1576514603 – 1556642603)	Date & Time	1. greater than 1576514603 2. less than 1556642603	Hence the Voltage & Current variables has no association and they are independent. As the -1<COR <1; and near to -1.
10. Voltage(mv)	(4000 mV-5000 mV)	Numeric	1. greater than 4000 2. less than 5000	
11. Current (milli ampere)	(500 mA – 2100 mA)	Numeric	1. greater than 500 2. less than 2100	
12. Battery_Capacity(mAh)	(1,900 mAh 5,500 mAh)	Numeric	1. greater than 1,900 2. less than 5,500	
13. Power(watts)	(100 watts – 1000 watts)	Numeric	1. greater than 100 2. less	

			than 1000	

Methodology

The theoretical mathematical structure for the study of the smart meter data is defined in this section. In Section 4.1 the concept of statistical learning begins, and a flow chart is presented illustrating the procedure employed in this paper. The literature review in Section 2 identified algorithms such as: KNN, SVM, Naïve Bayes, Random Forest, Neural Network as the most prevalent classification method for the large volume dataset.

Statistical Learning

Applying controlled or non-supervised learning will tip the statistical separation of data into smaller, more homogenic subsets. The differentiation between controlled and unsupervised learning is related to variations in the initial conditions of the problem. There are several established class names and comprehension of the identification characteristics of the class for supervised learning difficulties. This membership knowledge is used to create a mathematical function that maps observations into classes.

Figure 7 shows the flow of methodology used in the paper. The data is collected, pre-processed and classified using different methods, such as for imputing missing values average/most frequent method is used and for supervised learning different classification algorithms are used and the best-fit algorithm is determined.

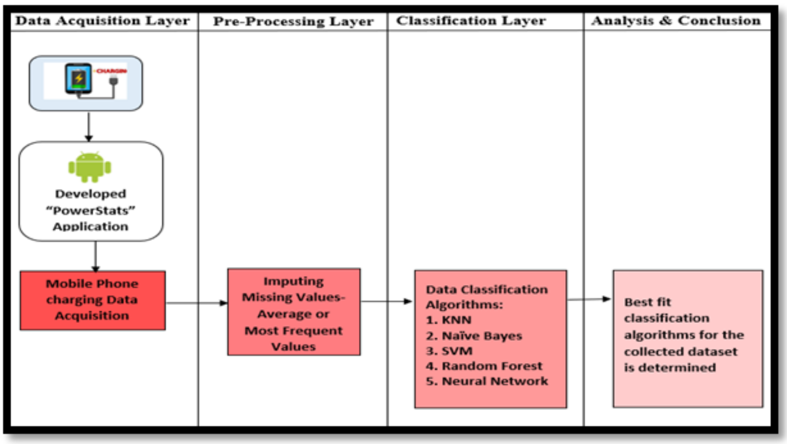


Figure 7: Methodology Flowchart

The classification is done using ORANGE tool. The classification is done using the different classification algorithms such as KNN, SVM, Naïve Bayes, Random Forest, Neural Network. Figure 8 depicts the workflow of supervised learning. The widget File has Training data and widget File1 has Testing data. Different learners are used to classifying the dataset. The Test & Score widget is used to give results and classification accuracy. The confusion matrix shows the number of classified and misclassified instances.

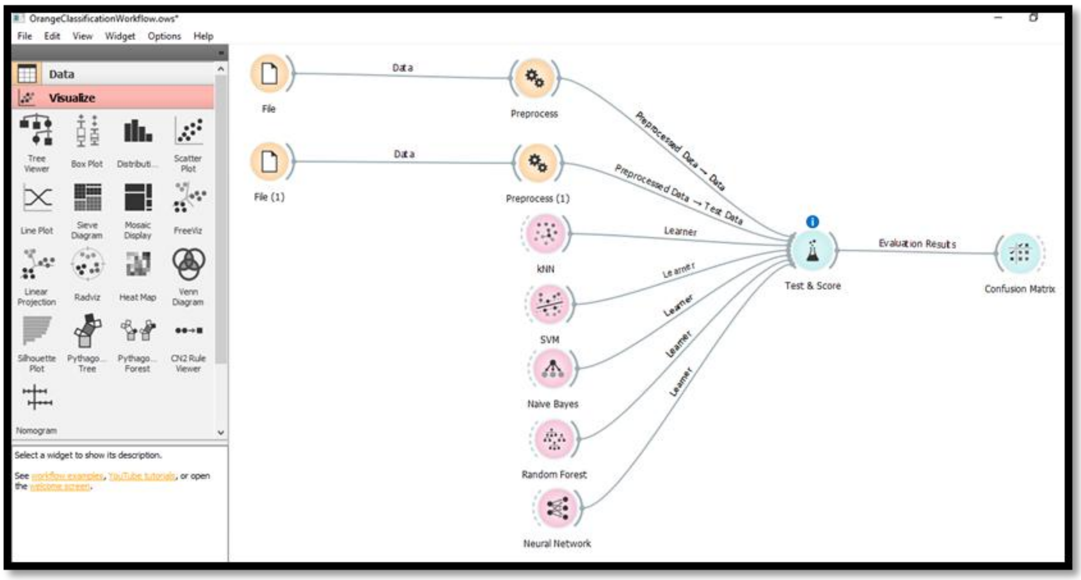


Figure 8: Workflow of supervised learning on ORANGE tool

Experimental Results

Supervised Learning Methods

The collected dataset from the “PowerStats” Android Application has gone through the phase of Pre- Processing and then done the Data Classification using various Classification Algorithm.

The Supervised Learning method is applied to the dataset in the following steps:

1. The dataset is split into Training and Testing data, in the ratio 50-50, 60-40, 70-30.

2. Different Classification Learners are applied to the Training data

3. The Classification Accuracy of both Training & Testing data is determined.

Hence the conclusion to predict the good classification algorithm for the dataset is done in two ways:

1. Maximum Correctly Classified Instances or 2. Least number of Misclassified Instances.

Table 4 depicts the comparative analysis of classification algorithms on the dataset collected based on factors such as 1. Training Set Size, and 2. Classification Accuracy.

Table 4: Comparative Analysis of Supervised Learners

Classification Algorithm	Train/Test Split ratio	Target Class (Mode of Charging)	Training Data		Actual Instances	Classification Accuracy of Training set	Test Data		Actual Instances	Classification Accuracy of Testing set
			Correctly Classified Instances	Misclassified Instances			Correctly Classified Instances	Misclassified Instances		
1. KNN	50-50 ratio	AC Charging	579	187	766	0.720 (72%)	522	189	711	0.531 (53.1%)
		USB Charging	432	207	639		225	471	696	
	60- 40 ratio	AC Charging	681	223	904	0.722 (72.2%)	252	321	573	0.514 (51.4%)
		USB Charging	537	246	783		326	226	552	
	70-30 ratio	AC Charging	795	255	1050	0.719 (71.9%)	163	264	427	0.518 (51.8%)
		USB Charging	620	299	919		274	142	416	
2. SVM	50-50 ratio	AC Charging	630	136	766	0.580 (58%)	651	60	711	0.512 (51.2%)
		USB Charging	185	454	639		70	626	696	
	60- 40 ratio	AC Charging	788	116	904	0.554 (54.4%)	532	41	573	0.512 (51.2%)
		USB Charging	147	636	783		44	508	552	
	70-30 ratio	AC Chargin	885	165	1050	0.538 (53.8%)	376	51	427	0.492 (49.2%)

		g								
		USB Charging	174	745	919		39	377	416	
3. Naïve Bayes	50-50 ratio	AC Charging	422	344	766	0.618 (61.8%)	240	471	711	0.515 (51.5%)
		USB Charging	446	193	639		485	211	696	
	60- 40 ratio	AC Charging	448	456	904	0.587 (58.7%)	130	443	573	0.498 (49.8%)
		USB Charging	543	240	783		430	122	552	
	70-30 ratio	AC Charging	505	545	1050	0.587 (58.7%)	138	289	427	0.504 (50.4%)
		USB Charging	651	268	919		287	129	416	
4. Random Forest	50-50 ratio	AC Charging	734	32	766	0.962 (96.2%)	482	229	711	0.513 (51.3%)
		USB Charging	614	25	639		205	491	696	
	60- 40 ratio	AC Charging	877	27	904	0.956 (95.6%)	301	272	573	0.488 (48.8%)
		USB Charging	758	25	783		254	298	552	
	70-30 ratio	AC Charging	1016	34	1050	0.960 (96%)	186	241	427	0.515 (51.5%)
		USB Charging	879	40	919		234	182	416	
5. Neural Network	50-50 ratio	AC Chargin	563	203	766	0.649 (64.9%)	666	45	711	0.512 (51.2%)

	g								
	USB Charging	349	290	639		54	642	696	
60- 40 ratio	AC Charging	556	348	904	0.646 (64.6%)	440	133	573	0.504 (50.4%)
	USB Charging	533	250	783		127	425	552	
70-30 ratio	AC Charging	671	379	1050	0.642 (64.2%)	267	160	427	0.474 (47.4%)
	USB Charging	593	326	919		133	283	416	

Comparative Analysis of Energy Consumption of Air Conditioners with Mobile Phones

Electricity Energy Usage Comparison in between Air Conditioner & Mobile Phone Charging- Considered a household Scenario where on an average there are 4 mobile phone handsets and 1 Air Conditioner.

Table 5 shows the data of energy consumption of household mobile phones as follows:

1. Number of Phones in a Household, 2. Model / Company of Handset, 3. The average number of times phones are charged in the time duration, 4. Average battery percentage at the plug in time in 137 days duration, 5. Average battery percentage at plug out time in 137 days duration, 6. Average Power Consumption per hour, 7. Total mobile charging power consumption of a household.

Calculation Steps:

1. The average number of times phones are charged in 137 days duration = Total number of times phones are charged / Total Number of Days

2. Average battery percentage at the plugin time in 137 days duration= Total number of times phones are plugged in battery percentage / Total Number of Days.

3. Average battery percentage at plug out time in 137 days duration= Total number of times phones are plugged out battery percentage / Total Number of Days.

4. Power (watts) = voltage (volt)* current (ampere)

5. Average Power Consumption/hour (watts/hour)= .total Power (watts)/total time (hours)

6. Total mobile charging power consumption of a household= Total addition of Average Power Consumption/hour (watts/hour)

Table 5: Comparative Energy Consumption Table of Mobile Phones Vs Air Conditioners

Households	Number of Phones	Model of Phones	Average number of times phones are charged in 137 days duration	Average battery percentage at plug in time in 137 days duration	Average battery percentage at plug out time in 137 days duration	Average Power Consumption per hour	Total mobile charging power consumption of a household
Household 1	3	1. Redmi Y2	1 time per day	47%	74%	180.46 watts/hour	563.46 watts/hour
		2. SM-A507FN	1 time per day	49%	73%	195.86 watts/hour	
		3.ASUS_X00TD	4 times per day	48%	74%	187.14 watts/hour	
Household 2	5	1. vivo 1803	2 times per day	46%	73%	127.49 watts/hour	795.5 watts/hour
		2. vivo Y51L	3 times per day	51%	72%	166.48 watts/hour	
		3. SM-A105F	1 time per day	50%	75%	168.59 watts/hour	
		4. Z90	1 time per day	49%	76%	132.95 watts/hour	
		5. Oppo F15	2 times per day	48%	72%	199.99 watts/hour	
Household 3	2	1. SM-J730GM	1 time per day	50%	79%	971.10 watts/hour	1121.67 Watts/hour
		2. Moto G (5) Plus	1 Time per day	49%	75%	150.57 watts/hour	

Figure 9 gives the comparative scenario of a household mobile phone charging energy consumption Vs different Split AC Type consumption. The power consumption is in terms of watts/hour. In Split AC Type 1 Ton 5 star, the mobile phone charging consumption on average is more than the AC consumption. Similarly, in 0.8 Ton 5 star and 1 Ton 3 star also; in other scenarios, the consumption is almost equal.

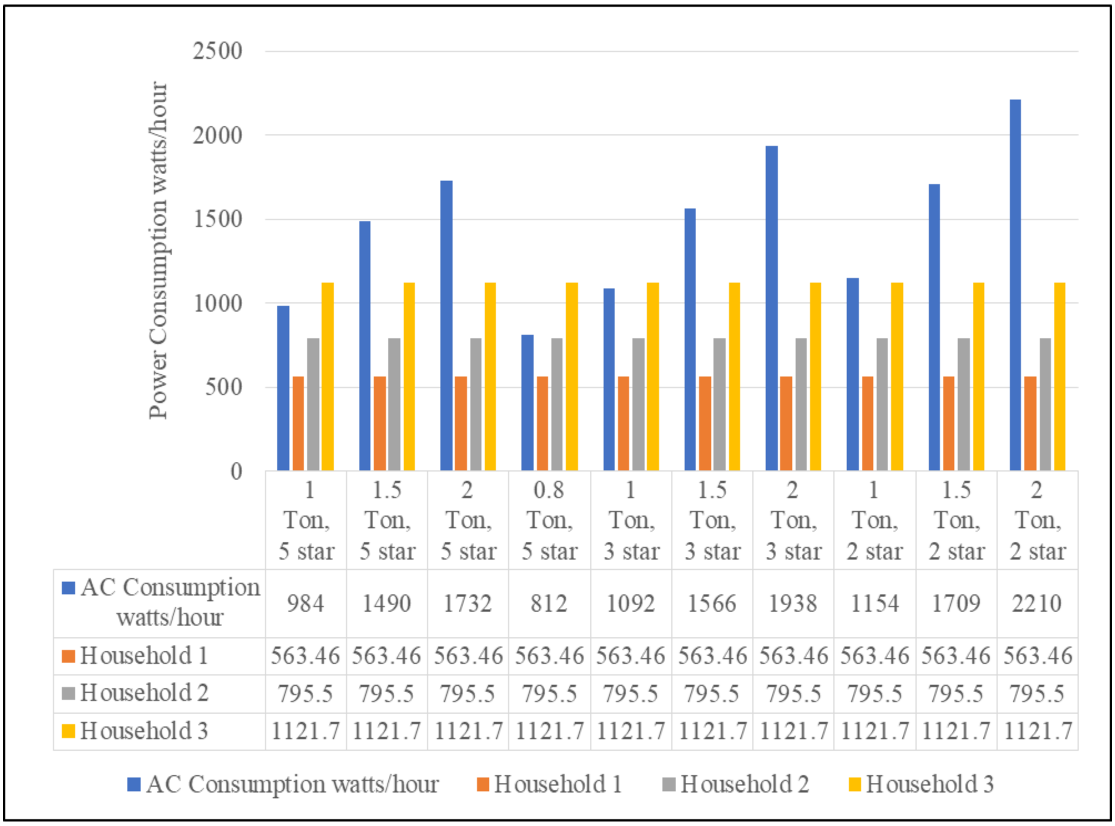


Figure 9: Generalised Household Energy Consumption Comparison Scenario

Determine the Most Efficient Mode of Charging

The most efficient way of charging is determined which consume less energy or the best mode of charging is determined which keeps the long-lasting battery power w.r.t the model of the mobile handset; as the mobile phone charging can be done in two ways: 1. Direct charging i.e. AC charging Mode. 2. Indirect charging i.e. USB charging mode, it involves 2 devices apparently more electric energy consumption.

Table 6 shows the Comparison between the Modes of Charging on the basis of the 1. Gender, 2. Profession, 3. Mobile Model Name, 4. New/Old Handset of Phone, 5. Average Battery lasting time.

Table 6: Comparative Table of Modes of Charging w.r.t Model of Mobile Handset

Sr. No.	Gender	Profession	Mobile Model Name	Mode of charging	Average battery lasting time	Conclusion
1	Male	Student	ASUS_X00TD	USB Charging	01:47:56 (1 hour 47 minutes)	USB charging mode is more suitable and has long lasting battery power. For ASUS_X00TD Model.
				AC Charging	01:41:17 (1 hour 41 minutes)	
2.	Female	Engineer	vivo Y51L	USB Charging	01:07:34 (1 hour 7 minutes)	AC charging mode is more suitable and has long lasting battery power. For vivo Y51L Model.
				AC Charging	03:22:53 (3 hour 22 minutes)	
3.	Male	Student	Z90	USB Charging	1:13:00 (1 hours 13 minutes)	AC charging mode is more suitable and has long lasting battery power. For Z90 Model.
				AC Charging	01:41:17 (1 hour 41 minutes)	
4.	Female	Student	SM-A105F	USB Charging	2:45:10 (2 hours 45 minutes)	AC charging mode is more suitable and has long lasting battery power. For SM-A105F Model.
				AC Charging	15:51:00 (15 hours 51 minutes)	
5.	Female	Engineer	vivo 1803	USB Charging	3:36:45 (3 hours 36 minutes)	AC charging mode is more suitable and has long lasting battery power. For vivo 1803 Model.
				AC Charging	16:16:00 (16 hours 16 minutes)	
6.	Male	Student	Redmi Y2	USB Charging	2:16:25 (2 hours 16 minutes)	AC charging mode is more suitable and has long lasting battery power. For Redmi Y2 Model.
				AC Charging	04:53:41 (4 hours 53 minutes)	
7.	Female	Engineer	SM-A507FN	USB Charging	3:20:15 (3 hours 20	AC charging mode is more suitable

					minutes)	and has long lasting battery power. For SM-A507FN Model.
				AC Charging	5:40:22 (5 hours 40 minutes)	
8.	Male	Engineer	SM-J730GM	USB Charging	2:50:12 (2 hours 50 minutes)	AC charging mode is more suitable and has long lasting battery power. For SM-J730GM Model.
				AC Charging	4:45:36 (4 hours 45 minutes)	
9.	Female	Student	Moto G (5) Plus	USB Charging	3:54:19 (3 hours 54 minutes)	AC charging mode is more suitable and has long lasting battery power. For Moto G (5) Plus Model.
				AC Charging	6:40:46 (6 hours 40 minutes)	
10.	Male	Engineer	Oppo F15	USB Charging	4:40:16 (4 hours 40 minutes)	USB charging mode is more suitable and has long lasting battery power. For Oppo F15 Model.
				AC Charging	2:25:45 (2 hours 25 minutes)	

Analysis of Charging Patterns of Users

To study and analyze :

i. The mobile phone charging patterns of users.

ii. The mobile battery and its consumption capacity.

Figure 10 shows the average plug in and plug out battery percentage of different mobile handsets. The plug-in time varies between 0-50% and plug out time in between 70-100%.

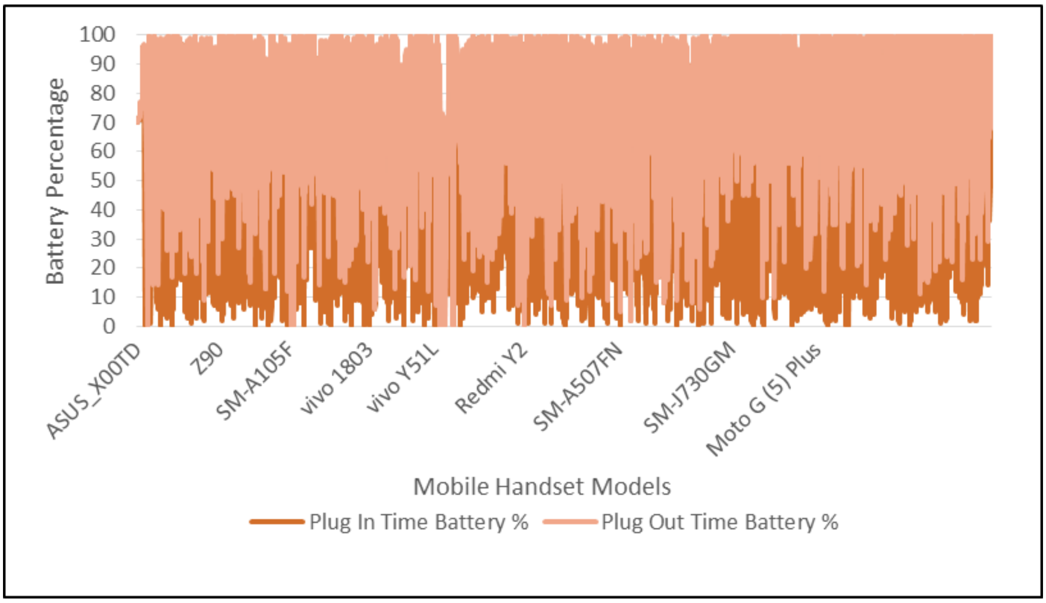


Figure 10: Comparative Plug In & Plug Out battery percentage with the mobile handsets

Discussion

The Random Forest & KNN algorithm has classified maximum number of correct instances or least misclassified instances; hence Random Forest & KNN are the best fit classification algorithms of the dataset. (Table 5) The electricity required to charge a group of mobile phones in a household is almost equivalent to run an Air Conditioner in the same household. (Figure 9) Hence; the Mobile phone Usage are directly proportional to the increasing Energy consumption and the other electric devices such as Air Conditioners are not only responsible. The best mode of charging is determined on the average long-lasting battery charging capacity; the best mode depends on the mobile handsets. On an average Direct Charging (AC) Mode is most efficient way to do the charging of phones to keep the battery power long lasting. (Table 6). The study and analysis of collected dataset gives more interesting results such as: 1. The plug-in time varies between 0-50% and plug out time in between 70-100%.(Figure 10) and 2.

Conclusion and Future Research Directions

The research shows the impact of increasing population of mobile users on power consumption and gives the thorough comparison of different mobile phone charging methods. The results also show the comparative scenarios of power consumption between Air Conditioners and Mobile Phones. On the basis of the results the conclusion is that the power consumption required to charge a group of mobile phones is equivalent to other electrical appliances like Air Conditioners.

In future work, the research can be done on different geographical part as the temperature, humidity varies as per the different environment and landmarks, and these variables affects the electricity consumption, hence the results may vary according to the region and its respective climate. And to give new horizons to the research, the researchers can also include the varying temperature, seasons, humidity while doing the analysis.

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Author's Note

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