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Analyse Power Consumption by Mobile Applications Using Fuzzy Clustering Approach

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ABSTRACT

With the advancements in mobile technology and its utilization in every facet of life, mobile popularity has enhanced exponentially. The biggest constraint in the utility of mobile devices is that they are powered with batteries. Optimizing mobile's size and weight is always the choice of designer, which led limited size and capacity of battery used in mobile phone. In this paper analysis of the energy consumption of some popular mobile apps is done using data mining technique. A large variety of mobile apps with differently functionality are executed on a smart phone. The power consumption of these apps is measured using Power Tutor. For holistic analysis these mobile apps are executed in different environment, which are created by varying the setting and internet facilities. Fuzzy Clustering approach is used to club the mobile apps based on similarity of the behaviour with respect to power consumption. Power consumption behaviour for each cluster and apps lying in overlapping zone is discussed in detail. The study gives the insight that power need of an app is dependent on the environment and code which can be used by app developers for creating an optimized energy app.

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1. INTRODUCTION

Building an eco-friendly society that is apt for living for our future generations is need of the day. In the current scenario scientist and researcher try to explore every opportunity to save energy and environment. The information technology has interwoven in every facet of life, developing a computing environment that is comparatively green, will make a remarkable change in saving the environment. The computing has two broad dimensions' hardware and software. Till date, the era focus was on hardware and its design aspects. The researchers are trying to curb the energy utilization by introducing new energy-saving power models of hardware and comparing the code in terms of energy it need.

Assessment of energy consumption is an important study that can help to reduce the environmental impact of modern Information and Communication Technology (ICT) tools usage. Today, for almost all e-applications, a mobile application is created. The modern high-end devices popularly known as smart phones have PC-like capabilities, with diverse functionalities such as voice communication, audio and video playback, short message, gaming and much more. The mobile applications executed on smart phones which are capable of handling data and image processing functionalities, consumes significant power thus increasing pressure on battery lifetime. The power consumption depends on smart phone, its features and mobile app [1]. The internal factor of an application includes coding, designing, functionality. The external factor includes CPU usage, RAM usage, LCD monitor brightness, Communication energy in the form of Wi-Fi and mobile data and also to a limit person using the application [2]. Advancement in hardware technology has enhanced the RAM, CPU and memory capacity leading to more computational capacities but increased load on the battery [3].

Wilke et al. [4] labels the mobile applications based on power consumption and found that an application consumes different power if used for various services

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like email handling when executed in different environments consume different power. Battery life depends on application type, the environment and network communication medium. A large number of tools are developed to measure the battery usage by the mobile app some of them are PowerTutor [5], GreenOracle [6], GreenScaler [7], TIDE [8] etc.

In this study, the mobile applications are labelled on power consumption. The apps energy consumption is measured varying the mobile setting to mine the power consumption pattern using data mining approach. A dataset of 200 test cases is created by executing 77 different applications in different environments. The power consumption of each test case was recorded and analysed using R-tool. This analysis helps to determine how each application's power need vary by changing execution environment. Clustering approach clubbed the mobile apps based on power usage namely low, medium and high. The fuzzy clustering algorithm is used as the boundaries of these clusters are not very rigid. The mobile apps that lie on the boundary of clusters have relatively equal membership in various clusters. This study will help to bring out the factors that can reduce the power usage, and a particular application can be transformed from the category of high power usage to medium and from medium power usage type to low.

This study will help to bring out the factors that can reduce the power usage, and a particular application can be transformed from the category of high power usage to medium and from medium power usage type to low. Section 2 discusses the related concepts and methodology followed in this paper is given in section 3. Fuzzy clusters are analysed in section 4 and paper is concluded in section 5.

2. RELATED WORK

Analysis and estimation of energy consumption by mobiles applications has attracted the researchers. Some recent works are referred in Table 1 which mainly focus on developing tools to measure the energy consumed and understand its trends using statistical tools [8-16]. The use of data mining can provide better insight to developer for creating an energy optimized application. The fuzzy clustering method is suitable to classify mobile applications as they have the gradual change in power consumption and cannot be partitioned into hard boundary clusters.

TABLE 1. Related Work on Energy Consumption by Mobile Apps

	Author	Technique used	Analysis
1	Dao et al. [8]	Developed a tool to identify applications which consumes more energy	Identified various factors That are involved in energy consumption and developed a tool that can filter the apps which need higher energy consumption
2	Bao et al. [9]	Statistical and Qualitative analysis of power management for different Android Applications	Analysis was done on the six activities namely Power Adaption, Power Consumption Improvement, Power Usage Monitoring, Optimizing Wake Lock, Adding Wake Lock, Bug Fix & Code Refinement
3	Li et al. [10]	Statistical Analysis of Android Power consumption by Android App using vLens	Study revealed application consumes 60% of the energy in idle state and network connectivity consumes maximum power among all the hardware components.
4	Liu et al. [11]	A tool GreenDroid was developed for automated problem diagnosis in Android Applications	Identified the magnitude of the problem and tried to fix it and also identified the causes and pattern for the energy problems
5	Balasubramanian et al. [12]	Studied the energy consumption for different network connectivity	Developed a protocol TailEnder, that minimizes the energy usage
6	Wilke et al. [4]	Proposed a process of comparing the mobile applications power consumption	Identified five steps to grade the mobile applications and use two tools
7	Sun et al. [13]	Experimental study of energy modeling in smartphones equipped with 802.11n/ac NICs	Analysed the real data traffic for You Tube and Google Play
8	Nucci et al. [14]	A new Android specific tool PETRA was developed for estimating energy consumption of Mobile Applications	Emphasis was given for estimating energy consumption of different components like sensor and network
9	Djedidi et al. [15]	Nonlinear autoregressive model with exogenous inputs (NARX) neural net for power consumption estimation	Simple to construct and train, less overhead and more accurate with absolute percentage error of 2.8%
10	Ahmad et al. [16]	Static code analysis based lightweight energy estimation (SA-LEE) framework	Reduced the estimation time and energy overhead associated with application runtime execution environment. The accuracy obtained is 82-88%

In fuzzy clustering approach for each object a degree of belongingness to all clusters is evaluated using soft computing approach, and membership value is assigned object for one or more clusters. In this paper FANNY, the fuzzy clustering method is used.

3. PROPOSED APPROACH

A large variety of mobile apps are available in the market, only sample applications are considered for this study. These applications cover popular apps and were categorised into six board categories based on their functionality [17]. PowerTutor is an android application that is used for recording the power and energy consumption of different mobile applications [5]. Along with total power, it also provides the breakup of power consumed by various components namely CPU, network, LCD usage.This application is used to measure the power that is consumed by each application in the mobile phone. The energy consumption apart from category depends upon its RAM requirement and communication media used for connectivity. The data was collected and analysed using R tool[2]. Fuzzy clustering was applied to the data gathered to form clusters of the applications that behaves similarly as far as power consumption is considered. The complete methodology adopted is shown in Figure 1.

3. 1. Identify the Applications The study is conducted on 77 unique Android applications frequently used by common users. 200 test cases were created by changing the working scenario. Different mobile applications were executed to find the applications that consume maximum power and also the factor that contributes to drainage of battery in a mobile phone. The applications with common functionality such as Wynk and Saavn (Music application) etc. were also considered for creating data set. Working Environment was varied by making Wi-Fi/Mobile data On/Off, Synchronization On/Off, download On/Off.

3. 2. Creating Dataset A smartphone with all the advanced features is considered for collecting the data set. Although battery power consumption also depends on the model of the smartphone but this study focus only on the software dimension of mobile apps and hence all analysis is done on a single phone. Each application was executed for five minutes over Wi-Fi and Mobile data alternately and power consumed was recorded for five times for each application, considering the average of all the values. Even the LCD and CPU utilization was also recorded. Some variants of the same application were taken like three music apps, three calling apps, in built tools, etc.

[2] https://www.r-project.org/

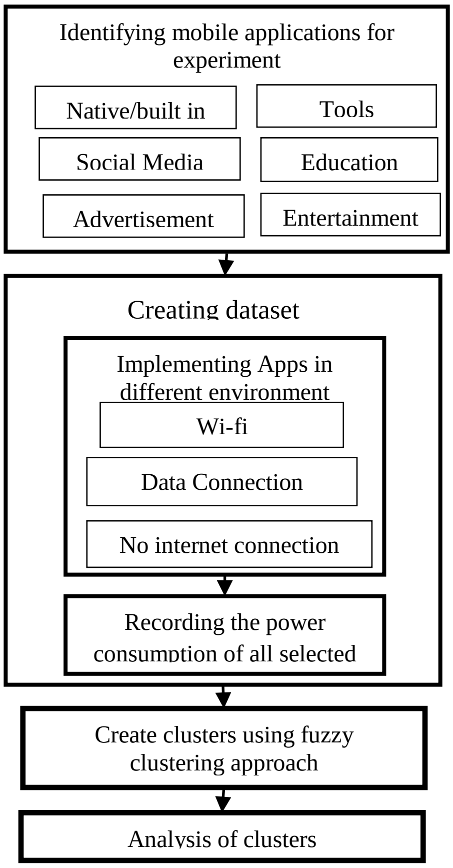

Figure 1. Steps adopted to label the mobile app on its power consumption pattern

The applications considered belong to six main categories namely:

Native/In-built This category contains applications do not require internet for execution like calculator, clock etc. This applications are inbuilt in every smartphone

Tools Contains the tool applications of Android and aids in all the processes like Polaris office, WPS office.

Entertainment applications act as a source of entertainment like multimedia or games.

Social Media Contains all the applications used for communication in any forms like texting, chatting.

Education Contains all the educational applications providing some knowledge through video, audio or graphics. Example- TOI, TED.

Advertisement- e-commerce websites that offer some form of service like food, clothes, travel. Example- Foodpanda, Myntra, Jugnoo.

200 test cases were designed by varying the execution environment like turning on/off of some critical features to see how much variation in energy consumption was found. Different cases of music app were created like just downloading, listening and downloading and only listening.

3. 3. Implementing Fuzzy Clustering Algorithm

R, an open source tool is used for implementing fuzzy clustering algorithms. The function used for the study is fanny () package represented as:

Fanny (x, k, memb.exp =2, metric=”euclidean”, stand=FALSE, maxit=500) where x: A data matrix.

k: the desired number of clusters to be generated determined using Silhottee coefficient.

memb.exp: The membership exponent (strictly larger than 1) used in the fit criteria.

metric: the metric to be used for calculating dissimilarities between observations.

Stand: Logical; if true the measurements in x are standardized before calculating the dissimilarities.

maxit: maximal number of iterations.

The average silhouette width for k = 3, 4 and 5 is 0.28, 0.23 and 0.19, respectively. The average silhouette width for k=3 is higher than values of other k’s like 4, 5 and so three clusters namely, High, Medium and Low is considered. The graphical representation of fuzzy clusters for given data set is shown below in Figure 2. The overlapping is observed between cluster 1 and 2 and between 2 and 3. The clusters formed are categorized into low, medium and high category. The various membership functions that resulted in the output are shown in Figure 3. The number of members of respective clusters and their average power consumption is given in Table 2. The average power justifies the nomenclature used. The applications identified at boundaries are provided in last two rows of Table 2.

3. 4. Validity of Cluster

Clustering is done on from distance similarity measures. The distance measure is defined on the space that contains 'n' objects in 'p' dimensional space.

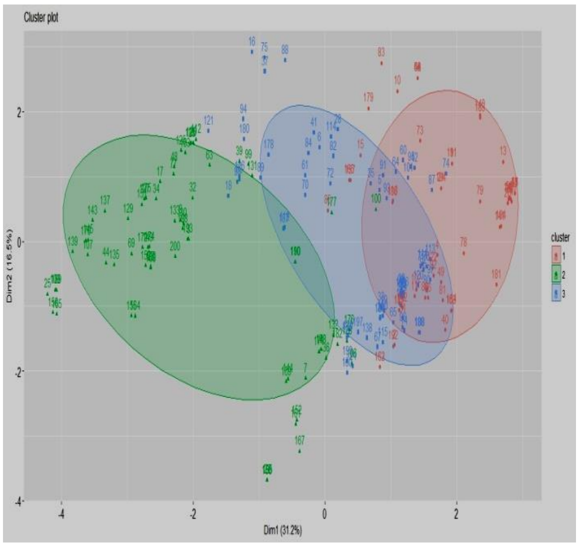

Figure 2. Graphical Representation of fuzzy clusters

```
> mem<-res.fanny$membership
> mem
          [,1]      [,2]      [,3]
 [1,] 0.5620549 0.1717445 0.2662006
 [2,] 0.4184127 0.2401618 0.3414255
 [3,] 0.2389913 0.3969986 0.3640102
 [4,] 0.4926032 0.1587092 0.3486876
 [5,] 0.2630049 0.2164959 0.5204992
 [6,] 0.2636284 0.2066893 0.5296822
 [7,] 0.1227620 0.6262341 0.2510039
 [8,] 0.1277090 0.6195143 0.2527767
 [9,] 0.6658019 0.1314513 0.2027469
[10,] 0.6414429 0.1296792 0.2288779
[11,] 0.4239801 0.1610818 0.4149381
[12,] 0.2277091 0.1771370 0.5951539
[13,] 0.6634275 0.1317491 0.2048234
[14,] 0.2795010 0.1712333 0.5492657
[15,] 0.6846913 0.1087877 0.2065210
[16,] 0.2022662 0.2055709 0.5921629
[17,] 0.1301580 0.5911513 0.2786907
[18,] 0.1943001 0.2586017 0.5470983
[19,] 0.1645691 0.3342379 0.5011930
[20,] 0.1234760 0.5821631 0.2943609
```

Figure 3. Fuzzy Membership Function

TABLE 2. Number of Applications in each category

Types of cluster	Number of members	Average Total power
Number of High clusters	71	861.04
Number of Medium clusters	71	511.70
Number of Low clusters	58	154.46
Overlapping clusters between High-Medium	18	686.37
Overlapping clusters between Medium-Low	13	351.08

This choice of distance is highly dependent on the type of data and the particular features a person is interested. Cluster validation is done to check the consistency and tendency of the data. It compares the output of clusters whether it fits with the data or not. Evaluation of fitness of clusters produced can be done by various Cluster validity indexes proposed in the literature [18]. Permutation test, 'permutest.betadisper' [19] available in R libraries is done to test if one or more group is dependent on other. It permutes model residuals to generate a permutation distribution of F under the Null hypothesis of no difference in dispersion between groups. The result of permutation test is given in Figure 4. As it can be seen from p-value the cluster constructed are valid, the behaviour pattern of each cluster is discussed in next section.

```
Permutation test for homogeneity of multivariate dispersions
Permutation: free
Number of permutations: 999

Response: Distances
           Df  Sum Sq Mean Sq      F N.Perm Pr(>F)
Groups      2 1233000  616500 12.153    999  0.001 ***
Residuals 197 9993411   50728
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pairwise comparisons:
(Observed p-value below diagonal, permuted p-value above diagonal)
             HIGH        LOW MEDIUM
HIGH              2.4600e-01  0.001
LOW    2.2225e-01             0.001
MEDIUM 2.3753e-07 4.7308e-04
> |
```

Figure 4. Permutation test for homogeneity of multivariate dispersions

4. CLUSTER ANALYSIS

In this section pattern observed in the three constituted clusters namely high, medium and low cluster are discussed in detail.

High The cluster 1 includes mobile apps with high battery need. The category wise distribution of application belonging to this cluster and average power consumption under different verticals is given in Table 4. On analysis, these applications which consume the maximum power various reasons were observed. Most of these applications are the ones with the prominent graphical interface like games, entertainment (media and video). Common examples members of this cluster are candy crush soda saga, candy crush saga, the clash of clans. Shopping sites consume high battery when synchronization is on since every second new offer are added, and also if one is browsing for some item he or she scrolls through a thousand items resulting in higher use of energy. Different test cases of various applications also consume different amounts of energy, such as video calling when done on WhatsApp consumes more energy than normal chatting.

Medium Cluster Medium is the second level category of the dataset. Table 5 contains those applications that consume average power that is neither very high nor very less. These applications have less media content or graphical display. They include the calling applications and the different texting applications. It was observed in the case of the music application, if one listens to music without downloading anything and switching off the LCD power, it consumes medium power and fall in the second category else it falls in 'high' cluster. These applications do not consume much battery of the mobile. In some cases, the same application can fall in both high and medium category depending upon the test case, like downloading or streaming videos falls in high whereas just listening or receiving calls falls in the medium category.

Low Cluster The third cluster contains all the applications consuming the least power.

TABLE 4. Energy Consumption by High Cluster

Category	Total test-cases	Avg. Power in mW	Avg. LCD Energy (J)	Avg. CPU Energy (J)	Avg. Comm. Energy (J)
Native/ Inbuilt	1	740.00	45.20	11.10	0.00
Tools	4	859.75	21.20	11.3	18.13
Entertainment	24	791.33	32.05	5.78	14.06
Education	15	915.87	41.23	5.30	12.97
Social Media	11	964.82	32.15	5.58	24.76
Advertising	16	850.75	32.79	4.83	26.02

TABLE 5. Energy Consumption by medium cluster

Category	Total test-cases	Average Power	Average LCD Energy	Average CPU Energy	Average Communication Energy
Native/ Inbuilt	9	556.11	20.90	4.72	2.67
Tools	16	501.56	18.56	8.50	4.97
Entertainment	6	484.50	22.78	9.13	0.00
Education	7	529.00	19.70	3.29	6.46
Social Media	23	492.83	20.42	5.42	5.91
Advertising	10	535.60	21.15	5.42	3.39

Most of these applications are in-built applications or system applications that have very less LCD or CPU value and do not require network connectivity like Wi-Fi or mobile data as in Table 6. These applications are default applications consuming least power and usually run on the system e.g., calculator, clock, weather, and camera. Educational applications such as Dictionary consume less power. Applications such as notes, recorder, FM radio, etc. consume negligible power. The least power is recorded for WhatsApp application when "only texting" was done.

Analysis of mobile apps lying in overlapping clusters 16 applications are found in the overlapping region. It is observed by making changes in the working environment some applications move from high cluster to medium cluster. Table 7 shows the applications which can be modified into a lower category by changing the environment. Like in the entertainment category if the songs are downloaded while listening and surfing then the power consumptionis high whereas if one listens to the music online instead of downloading, then it falls in low power consumption.

TABLE 2. High to medium shift of power consumption of applications

Category	Original Test Case	Original Cluster	Transformed Test Case	New Cluster
Entertainment : Music applications	Downloading and listening songs while surfing	High	Listening music	Low
Educational-Merriam-Webster	Mobile data enabled	High	Mobile data disabled	Medium
Tools-Camera360	Clicking pictures	High	Making videos	Medium

Similar behaviour was found in most of the music applications like saavn, gaana, wynk etc. Similarly, if music plays while the smartphone LCD is in off mode, then the power consumption shifted from medium to low category as shown in Table 8. In communication application hangouts when notification update is disabled then cluster moves to lower category.

TABLE 3. Medium to low shift of power consumption of applications

Category	Original Test Case	Original Cluster	Transformed Test Case	New Cluster
Entertainment: Music applications	Listening songs LCD on	Medium	Listening music	Low
Communication-Hangouts	Notification Update enabled	Medium	Notification Update disabled	Low

5. CONCLUSION

In this paper, a framework proposed for analysing power consumption pattern of various mobile applications. The focus is to understand energy management strategy, which include identifying the type of application and factors leading to the battery drainage. The entertainment and other apps that need network connectivity consume maximum battery life and the in-built app affect battery life the least. Type of smartphone and network service provider may also significantly vary the power consumption of a given app. To observe pattern of energy consumption of different mobile app irrespective of hardware on which they are executed and network services used for communication, a single smartphone and same network connectivity is considered for recording the observations. The purpose of this paper is to illustrate the utility of fuzzy clustering to classifying the mobile apps for power consumption perspective. It classified the mobile app into high medium and low category as per its power consumption. The fuzzy approach is used to find the applications whose category level can be reduced from high to medium by changing the setting of mobile. It can be seen similar applications are consuming the different amount of energy depending on the factors that are active at that time in this study all applications where executed for 5 minutes only. Similar music applications are consuming different energy depending on whether the song is downloaded or only listened. The LCD and CPU usage are also different for different cases. The study can help to classify the mobile application based on its features and provide an insight to the developer to build an energy efficient application.

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چکیده

با پیشرفت در فن آوری تلفن همراه و استفاده از آن در هر جنبه ای از زندگی، محبوبیت تلفن همراه به طور نمادین افزایش یافته است. بزرگترین محدودیت در استفاده از دستگاه های تلفن همراه این است که آنها با باتری شارژ می شوند. بهینه سازی اندازه و وزن تلفن همراه همیشه انتخاب طراح است، که منجر به اندازه محدود و ظرفیت باتری مورد استفاده در تلفن همراه می شود. در این مقاله، تجزیه و تحلیل مصرف انرژی برخی از برنامه های محبوب تلفن همراه با استفاده از تکنیک داده کاوی انجام می شود. طیف گسترده ای از برنامه های تلفن همراه با عملکرد متفاوت بر روی یک تلفن هوشمند اجرا می شود. مصرف برق این برنامه ها با استفاده از Power Tutor اندازه گیری می شود. برای تجزیه و تحلیل جامع این برنامه های تلفن همراه در محیط های مختلف اجرا می شوند، که با تغییر تنظیمات و امکانات اینترنت ایجاد می شوند. رویکرد خوشه بندی فازی برای برنامه های تلفن همراه بر اساس شباهت رفتار با توجه به مصرف انرژی استفاده می شود. رفتار مصرف برق برای هر خوشه و برنامه های موجود در منطقه همپوشانی به طور دقیق مورد بحث قرار می گیرد. این مطالعه بینش را نشان می دهد که نیاز به یک برنامه به محیط و کد بستگی دارد که می تواند توسط برنامه های توسعه دهنده برای ایجاد یک برنامه انرژی بهینه استفاده شود.

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