Approximating and Predicting Energy Consumption of Portable Devices

Tehseen Ullah, MS; Ameer Hamza Siraj, PhD; Umer Mukhtar Andrabi , PhD, Alexey Nazarov, Professor

Moscow Institute of Physics and Technology, Innapolis University

Abstract

Over the recent years we have witnessed a significant surge in the usage of mobile and portable devices such as mobile phones, laptops, smart watches, smart handheld devices etc. The usage of these equipment has reached a point where they have become a tool that helps us to manage our daily tasks, related to education, work or entertainment. However, considering the global energy consumption, research is being conducted to estimate the energy contribution of these devices. Although various studies are available about the share of energy consumption of such type devices, but there are no concrete studies characterising the growing share of energy consumption by most portable devices. This fact leads us to consider a key aspect in the mobility provided by these devices and to approximate and predict the energy consumption of portable devices. Our research is based on the limited capacity of energy stored in these devices, for which we want to define a data collection process about the applications that our devices use, to accurately approximate the amount of energy used and generate a model that allows us to predict energy consumption.

Index Terms—Energy efficiency, Process metrics, Power consumption, resources utilization.

Introduction

Over the years, we have seen various technological advancements , which has led to a tremendous increase in the usage of portable devices such as laptops, smartphones, and various other kinds of smart devices. These devices have become part of our daily life as they help us to simplify and streamline many of our daily tasks ranging from educational tasks to entertainment. Although the power of such devices has been greatly improved at the levels of processing and information storing capacities, still there lies many limitations in terms of storage and energy consumption. Thus it is obvious that devices which are powerful enough to process multiple, computationally expensive tasks and run multiple applications consume more energy. Therefore it is obvious that the increase in computational capabilities will result in higher energy consumption.

As portable computing devices are being used across different domains and sectors such as in offices, schools as well as for commercial and entertainment purposes, their contribution towards global energy consumption has been increased significantly. There is no complete study available in this field of research to date that fully document and cover the subject of rapidly increasing segment of portable devices and share of energy consumption in the future. Such studies demand a complete analysis of energy consumption in these computationally expensive devices. This tracking and analysis of energy consumption will also help in more efficient use of energy as well as Monitoring its impact over the environment.

Considering the scope and relevance of the topic it is necessary to take up the research that will help us to build tools to estimate energy consumption approximations and monitor the impact of the applications executed by the user on the consumption of electrical energy stored in these mobile and portable devices. To do this, we have carried out a series of experiments so that we can make an estimation and simultaneously collect the data of resource utilisation such as the use of CPU, GPU, RAM and other processing units to predict the energy consumed by certain applications running on a device.

Methods and Materials

APPROXIMATING ENERGY CONSUMPTION
In this section, we will describe the general research that has been carried out in order to estimate and approximate energy consumption. Over the past few years, significant amounts of power has been consumed by portable devices on daily basis due to the increase in the computational capabilities of these devices. Devices such as mobile phones, laptops, Ipads and other electronic gadgets have become part of our daily life. A study in 2007 has been conducted on telecommunication infrastructure that revealed that nearly 0.12% of total global electricity is being consumed by these devices[18]. As we can see even though its a small number but that is just used by only telecommunication devices around the world. Moreover, research suggests that approximately 0.14% of the total global CO2 emission was due to these devices. As portable devices are getting popular by every passing day and their number is increasing continuously, it is important to raise mindfulness about the impeding ecological impacts, contribution of ozone-depleting substances and increasing demands for energy. All this has urged a large number of organizations to reconsider their needs. This has persuaded companies such as Nokia, Intel, Ericsson, Google, Microsoft, and others to develop guaranteeing energy-saving practices in their products and also motivates a large number of researchers to analyze

Results

Results in Approximation
We conducted different experiments and found the difference between information collected from those experiments, and found out the information loss between each the experiments. We assume that the information gathered on 15 seconds intervals is our required baseline information that we need, but if we would have collected that information more frequently, we would have spent more energy on the collecting process. We took out the impact of data collector and collected only the information that we needed for our experiments. We did the same for all of the experiments, with the assumption that we collected the right information in 15 seconds interval and normalized the data collected in 15 seconds interval with the data we collected with the intervals more than 15 seconds. We used 3 different metrics namely MAE (Mean Absolute Error), MSE(Mean Squared Error) and The area under the curve difference, to find the information loss between two intervals.

Table 2 represents the information loss of different intervals. It can be seen from the table that information loss between big intervals is higher. We concluded that collecting information after every 120 seconds is the best interval concerning information loss because during that interval we do not lose much information as compared to any of the other intervals.

B. Results in Prediction
From our results, we can see good custom accuracy due to our custom loss function with our optimized hyper parameters. We can see that our neural network model has higher performance with α = 1 for both loss functions. Since a large α does not give great results, we decided to continue working with α = 1 and came up with more metrics that can help evaluate the model's performance, in order to choose the best suited coefficient c as well to see how much the coefficient c in the loss function affects our neural network model.

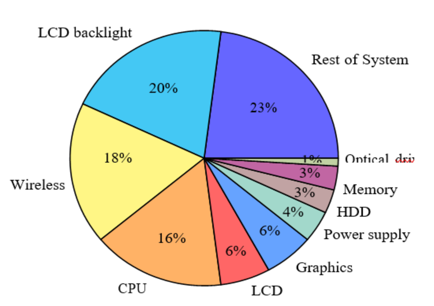
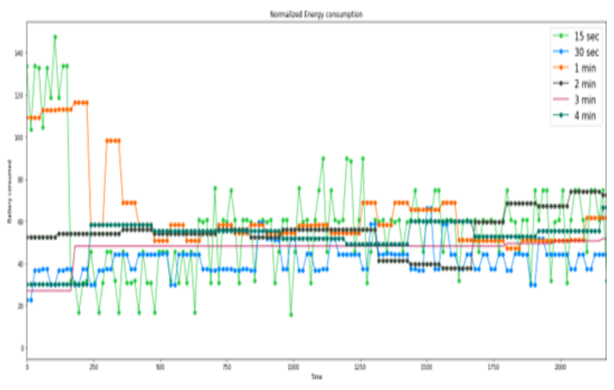


Fig. 1. Power consumed by different components of laptop [12]



Model	Specification	Energy consumption when WNIC off(W)	Energy con- sump-tion Idling with WNIC on (W)	Energy con- sump- tion when stream-ing through WNIC (W)
HP pavilion dv4t	4GB RAM, 2GHz processor	30	31	32
Dell Inspiron1525	3GB RAM, 2GHz processor	21	24	36
Compaq Presario C300	2GB RAM, 2GHz processor	28	30	34
Dell Inspiron1440	4GB RAM, 2.2GHz processor	18	19	24
Aspire 4730Z	2GB RAM, 2GHz processor	27	29	31
Dell InspironXPS M1310	2GB RAM, 1.6GHz processor	36	39	48
Hp pavilion dv2000	2GB RAM, 2GHz processor	64	71	72
Fujitsu Siemens AMILO M7440	512 MB RAM, 1.73GHz processor	29	31	35
Lenovo ThinkPad X60	512 MB RAM, 1.6GHz Processor	21	25	28

Chart 1. LAPTOP POWER STUDY.

best results for loss$_2$function		
hyper parameters	in-sample data	out-of-sample Data
α = 1,c = 30	0.814	0.819
α = 1,c = 100	0.803	0.805
α = 1.5,c = 3000	0.686	0.686
α = 2,c = 3000	0.688	0.689
α = 2.5,c = 3000	0.744	0.745

best results for loss$_1$function		
hyper parameters	in-sample data	out-of-sample Data
α = 1,c = 10	0.837	0.841
α = 1,c = 300	0.835	0.838
α = 1,c = 3000	0.836	0.840
α = 1.5,c = 10	0.792	0.795
α = 1.5,c = 300	0.821	0.826
α = 1.5,c = 3000	0.789	0.792
α = 2,c = 30	0.744	0.745

Error between two lines			
Interval(seconds)	MAE	MSE	CurveArea (W)
30	25.399	997.32	59571.73
60	23.012	899.55	79235.22
120	21.817	713.112	19692.80
180	22.92	842.41	3152.47
240	22.50	831.657	13888.36

Chart 2. ERROR BETWEEN EXPERIMENTS WITH RESPECT TO INFORMATION COLLECTED DURING 15 SECONDS EXPERIMENT.

Discussion

It is difficult to say how valid the results are for a neural network since it is difficult to assess it accurately due to floating point values of battery energy consumption. We need to come up with new metrics to evaluate the efficiency of our model. So far, we could identify suitable parameters for our loss function. At the moment, it is necessary to establish whether the difference between the actual and predicted values is significant and what difference can be considered acceptable and normal, and we can't figure that out by using standard metrics.

Conclusions

From this research, we can conclude that we have been able to obtain a parameter that allows us to set an information sampling interval so that we spend a moderate amount of energy, at a constant time interval. it also allows us to have an acceptable precision, to simulate and predict the energy consumption of the applications used, and based on the results, we can measure the impact of the future energy consumption of different devices. It is important to highlight that our prediction model is still in an early stage of development and requires the incorporation of additional features, which provide us with more details on the use of resources, such as network usage, I/O operations, or GPU usage.

Contact

Tehseen Ullah
Moscow Institute of Physics and Technology, Moscow ,Russian Federation
Email: tehseen@phystech.edu
Phone: +79017359737

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