Estimating the end-to-end energy consumption of IoT devices along with their impact on Cloud and telecommunication infrastructures

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Abstract. Information and Communication Technology takes a growing part in the worldwide energy consumption. One of the root causes of this increase lies in the multiplication of connected devices. Each object of the Internet-of-Things often does not consume much energy by itself. Yet, their number and the infrastructures they require to properly work have leverage. In this paper, we combine simulations and real measurements to study the energy impact of IoT devices. In particular, we analyze the energy consumption of Cloud and telecommunication infrastructures induced by the utilization of connected devices, and we propose an end-to-end energy consumption model for these devices.

1 Introduction [2 col]

2 Related Work [1 col]

3 Use-Case [1 col]

3.1 Application Characteristic

3.2 Cloud Infrastructure

4 System Model [2 col]

The system model is divided in two parts. First, the IoT and the Network part are models through simulations. Then, the Cloud part is model using real servers connected to watt-meters. In this way, it is possible to evaluate the end-to-end energy consumption of the system.

4.1 IoT Part

In the first place, the IoT part is composed of several sensors connected to an Access Point (AP) which forms a cell. This cell is model using the ns-3 network simulator. Consequently, we setup between 5 and 15 sensors connected to the AP using WIFI 5GHz 802.11n. The node are placed randomly in a rectangle of 400m2 around the AP which corresponds to a typical real use case. All the cell nodes are setup with the default WIFI energy model provided by ns-3. The different energy values used by the energy model are provided on Table 1. These energy were extracted from previous work[1,2] on 802.11n. Besides, we suppose that the energy source of each nodes are unlimited and thus each of them can communicate until the end of all the simulations.

As a scenario, sensors send 192 bits packets to the AP composed of: **1)** A 128 bits sensors id **2)** A 32 bits integer representing the temperature **3)** An integer timestamp representing the temperature sensing time to store them as time series. The data are transmitted immediately at each sensing interval I varied from 1s to 60s. Finally, the AP is in charge of relaying data to the cloud via the network part.

Table 1. Simulations Energy Parameters

(a) Wifi

Parameter	Value
Supply Voltage	3.3V
Tx	0.38A
Rx	0.313A
Idle	0.273A

(b) Network

Parameter	Value
Idle	1W
Bytes (Tx/Rx)	3.4nJ
Pkt (Tx/Rx)	192.0nJ

4.2 Network Part

The network part represents the a network section starting from the AP to the Cloud excluding the server. It is also model into ns-3. We consider the server to be 9 hops away from the AP with a typical round-trip latency of 100ms from the AP to the server. Each node from the AP to the Cloud is assume to be network switches with static and dynamic network energy consumption. The first 8 hop are edge switches and the last one is consider to be a core switch as mention in [3]. ECOFEN [4] is used to model the energy consumption of the network part. ECOFEN is a ns-3 network energy module dedicated to wired network. It is based on an energy-per-bit model including static energy consumption by assuming a linear relation between the amount of data sent to the network interface and its power consumption. The different energy values used to instantiate the ECOFEN energy model for the network part are shown in Table 1(b) and come from previous work [5].

4.3 Cloud Part

Finally, to measure the energy consumed by the server, we used real server from the large-scale test-beds Grid5000 (G5K). In fact, G5K has a cluster called Nova composed of several nodes which are connected to watt-meters. In this way, we can benefit from real energy measurements. The server used in the experiment include an Intel Xeon E5-2620 processor with 64 GB of RAM and 600GB of disk space on a Linux based operating system. This server is configured to use KVM as virtualization mechanism. We deploy a classical Linux x86_64 distribution on the Virtual Machine (VM) along with a MySQL database. We used different amount of allocated memory for the VM namely 1024MB/2048MB/4096MB to highlight its effects on the server energy consumption.

The sensors requests are simulated using another server. This server is in charge to send hundred of requests to the VM in order to fill the database. Consequently, it is easy to vary the different requests characteristics namely: **1)** The number request, to virtually add/remove sensors **2)** The requests interval.

5 Evaluation [3 col]

5.1 IoT/Network Consumption

In a first place, we start by studying the impact of the sensors position on their energy consumption. To this end, we run several simulations in ns-3 with different sensors position. The results provided by Table 2 show that sensors position have a very low impact on the energy consumption and on the application delay. It has an impact of course, but it is very limited. This due to the fact that in such a scenario with very small number of communications spread over the time, sensors don't have to contend for accessing to the Wifi channel.

Table 2. Sensors send interval effects

Sensors Send Interval	10s	30s	50s	70s	90s
Sensors Power Consumption	13.51794W	13.51767W	13.51767W	13.51767W	13.51761W
Network Power Consumption	10.44178W	10.44167W	10.44161W	10.44161W	10.44161W
Average Appplication Delay	17.81360s	5.91265s	3.53509s	2.55086s	1.93848s

Previous work [2] on similar scenario shows that increasing application accuracy impact strongly the energy consumption in the context of data stream analysis. However, in our case, application accuracy is driven by the sensing interval and thus, the transmit frequency of the sensors. Therefore, we varied the transmission interval of the sensors from 1s to 60s. Some of these results are proposed on Table 2. In case of small and sporadic network traffic, these results show that with a reasonable transmission interval the energy consumption of the IoT/Network if almost not affected by the variation of this transmission interval. In fact, transmitted data are not large enough to leverage the energy consumed by the network.

The number of sensors is a dominant factor that leverage the energy consumption of the IoT/Network part. Therefore, we varied the number of sensors in the Wifi cell to analyze its impact. The Figure 1 represents the energy consumed by each simulated part according the the number of sensors. It is clear that the energy consumed by the network is the dominant part. However, since the number of sensors is increasing the energy consumed by the network will become negligible face to the energy consume by the sensors. In fact, deploying new sensors in the cell do not introduce much network load. To this end, sensors energy consumption is dominant.

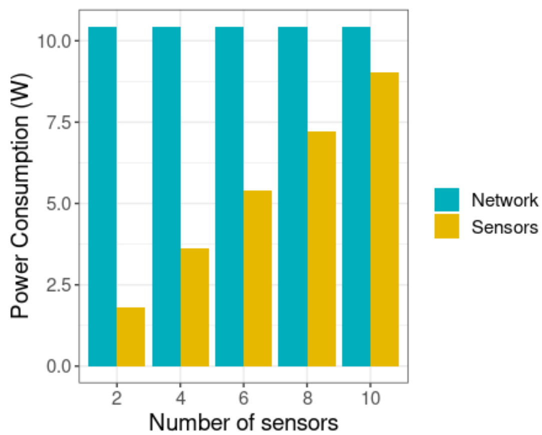


Fig. 1. Analysis of the variation of the number of sensors on the IoT/Network part energy consumption.

5.2 Cloud Energy Consumption

In this End-To-End energy consumption study, cloud account for a huge part of the overall energy consumption. According a report [6] on United States data center energy usage, the average Power Usage Effectiveness (PUE) of an hyperscale data center is 1.2. Thus, in our analysis, all energy measurement on cloud server will account for this PUE.

In a first place, we analyze the impact of the VM allocated memory on the server energy consumption. Figure 2 depict the server energy consumption according to the VM allocated memory for 20 sensors sending data every 10s. Note that horizontal red line represent the average energy consumption for the considered sample of energy values. We can see that at each sensing interval, server face to peaks of energy consumption. However, VM allocated memory do not influence energy consumption. In fact, simple database requests do not need any particular huge memory access and processing time. Thus, remaining experiments are based on VM with 1024MB of allocated memory.

Next, we study the effects of increasing the number of sensors on the server energy consumption. Figure 3(a) present the results of the average server energy

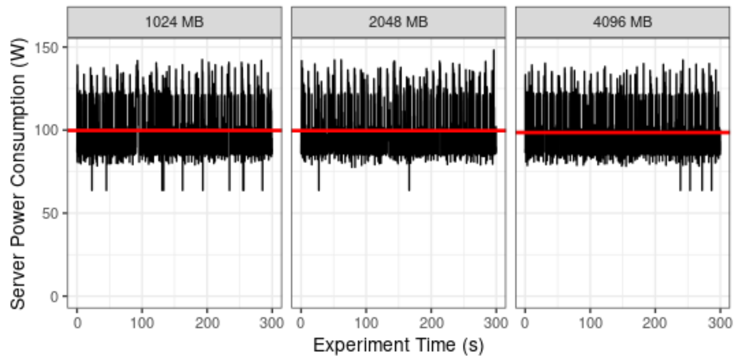
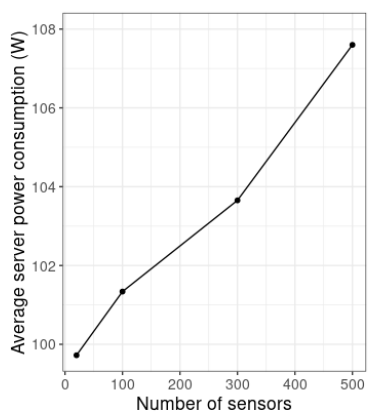
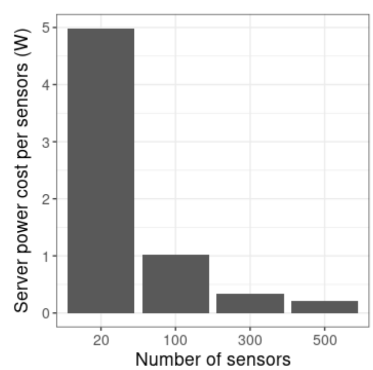


Fig. 2. VM size impact on the server energy consumption using 20 sensors sending data every 10s

consumption when varying the number of sensors from 20 to 500 while Figure 3(b) present the average server energy cost per sensors according to the number of sensors. These results show a clear linear relation between the number of sensors and the server energy consumption. Moreover, we can see that the more sensors we have per server, the more energy we can save. In fact, since the idle server energy consumption is high, it is more energy efficient to maximize the number of sensors per server. As shown on Figure 3(b), a significant amount of energy can be save when passing from 20 to 300 sensors per server.



(a) Average server energy consumption



(b) Average sensors energy cost on server

Fig. 3. Server energy consumption for sensors sending data every 10s

A last parameter can leverage server energy consumption namely sensors send interval. In addition to increasing the application accuracy, sensors send interval increase network traffic and database accesses. Figure 5.2 present the impact on the server energy consumption of changing the send interval of 50 sensors to 1s, 10s and 30s. We can see that, the lower sensors send interval is, the more server energy consumption peaks occurs. Therefore, it leads to an increase of the server energy consumption.

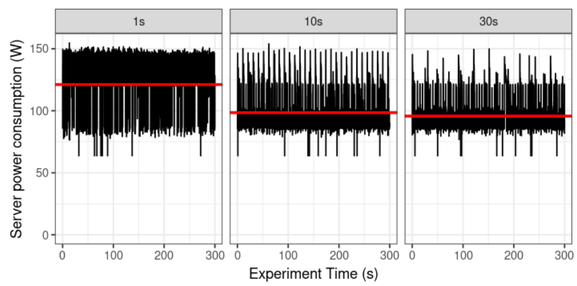


Fig. 4. Server energy consumption for 50 sensors sending request at different interval.

5.3 End-To-End Consumption

To have an overview of the energy consume by the system, it is important to consider the end-to-end energy consumption. The Figure 5.3 represents the end-to-end system energy consumption while varying the number of sensors. It is important to see that, for small-scale systems, the server energy consumption is dominant face to the energy consumed by the sensors. However, since we are using a single server, large-scale sensors deployment lead to an increasing consumption of energy in the IoT part. On the other side, network energy consumption is stable regarding to the number of sensors since the system use case do not required large data transfer. Thus, it is important to remember that, to save energy, we should maximize the number of sensors handle by each cloud server while keeping reasonable sensors request intervals.

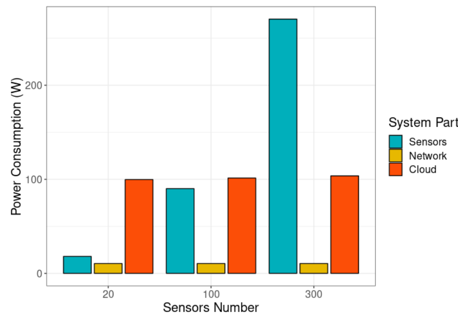


Fig. 5. End-to-end network energy consumption using sensors interval of 10s

6 Discussion [1 col]

7 Conclusion [1 col]

8 References [1 col]

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