Enhancing IoT Devices Power Consumption Using Machine Learning Algorithms

Mohamed H. Elgazzar
IoT Senior Solutions Architect, Vodafone International Services, Cairo, Egypt
elgazzarm@acm.org

Abstract

IoT is a leading technology that is employed in different businesses such as security, automotive, retail, healthcare, smart cities, etc. Some applications of IoT requires that the IoT devices are placed far from any power supply and depends only on batteries. For example, the IoT devices that detects the water leakage in the water pipelines must be put underground and away from any power source. So, it is important for such IoT devices to reduce the power consumption in order to make the battery live longer. This work presents a methodology for enhancing the power saving of the IoT devices by enhancing its location and distribution using machine learning approaches. The results showed that using the random forest algorithm provided 83% accuracy for the IoT devices placement to enhance the power saving.

Keywords: *IoT, Power Saving, Machine Learning, IoT Device Placement*

1. Introduction

IoT is one of the fast growing technologies that is employed in different businesses and work environments. A major challenge that faces the deployment and integration of the IoT devices and sensors is the power consumption of the IoT devices. For example, battery drain is a serious problem when GPS sensors are usedin small devices. This is well testified by the number and varietyof works that try to mitigate it [1]. Lots of the IoT devices are located away from power sources either for application limitation or physical location. An example of the application limitation is the water leakage detection where the IoT devices are located underground beside the water pipelines so that it is hard to reach a power supply. In other applications, the locations of the IoT devices on a building such as shopping malls are away from power sources due to the early old design of the building that did not consider the IoT devices or due to safety restrictions. In both cases, the IoT devices are located away from the power sources and depend only on the battery. In such applications, it is crucial to reduce the power consumption of the IoT devices in order to let them live for longer durations.

The power consumed by the IoT devices depends on many factors. One of the most important factors is the signal strength which is the transmitter power output as received by the reference antenna at the distance from the transmitting antenna [2]. Increasing the distance between the devices implies increased power consumption in order to communicate with the receiving device. Also, the interference can impact the transmission of the devices if they are located in the interference range of the IoT device.

In this paper, a methodology is developed using machine learning algorithms in order to provide recommendation of the best locations of the IoT devices that reduces the power consumption. The remainder of the paper is organized as follows: Section 2 discusses the related works on reducing the power consumption of IoT devices. Section 3 describes the proposed methodology. Section 4 provides the experiments, section 5 is the conclusion and section 6 is the acknowledgement section.

2. Related Work

In this section, the previous work that is related to reducing the power consumption of the IoT devices is discussed: In [3], the power consumption in smart farms where farmers collect and transfer important environmental parameters in an automated way is discussed. This might lead to increased productivity of the farms. However, the power consumption of the IoT devices that are allocated in the field are depending on batteries which drain quickly. In this work, a study of the impact of CPU usage on packet loss and battery drain during data transmission is presented and a design for an efficient data transmission platform for smart farms that takes into consideration CPU usage, signal strength and battery life. The results achieved are promising, however, it does not take into consideration the location and distribution of the IoT devices in the farm as a way of reducing the power consumption.

In [4], A Secured Smart Energy Controller (SSC) with an Autonomous Intelligent Ambient Control System is presented in this work as an Internet of Things (IoT) solution, This controller is capable of turning present Home Automation System (HAS) into smart establishment. According to the authors, The SSC system has been proven to save energy, approximately: 50% energy savings in lighting and 30% energy saving in air-conditioner. The SSC consists of Master, Slave, web server, and mobile smart device.

In [5], an approach that helps in reducing the power consumption driven by the IoT device information. The proposed approach allows the IoT device to send its data to the CoAP (Constrained application protocol) server only if its current reading is different from the old one. The work presented in [5] used the Intel Lab Data to conduct experiments using the proposed approach on real-world sensor readings. The experiments have shown that the proposed approach allowed device lifetime extension by 33% to 155% with respect to the standard CoAP protocol and device lifetime extension by 8% and 14% with respect to the dynamic tuning approach.

In [6], a methodology is developed to reduce the power consumed by M2M devices is proposed via instructing some M2M devices to sleep. The novelty of this work is the use of the data generated on the CDRs in the power saving by calculating a factor of QoS and presenting the C-Analyzer to analyze the CDRs and instruct the M2M devices to standby to save the power.

In [7], a model for real-time power management for M2M usingintelligent learning is proposed. The proposed system is modeledinto three components: 1) the device 2) the user and 3) the queue.The power management aims at reducing power consumption insystems by selectively placing components into lower-powerstates. Thus, at run time, the power manager observes the userrequests arrival, the state of the device's buffer, the power state,and the activity level of device. When all user requests areserviced, the power manager can choose to place the device into alower-power state. This choice is based on a policy from aproposed model relies on average number of requests serviced in atime unit.

In [8], a framework is introduced to enable fast and accurate power estimation for Application Specific Integrated Circuit (ASIC) designs. The proposed framework in this work trains machine learning models with design verifications test benches for characterizing the power of reusable circuit building blocks. The trained model can then be used to generate detailed power profiles of the same blocks under different workloads.

In [9], PRIMAL framework is introduced that provides fast power estimation for application specific integrated circuits. This reached to less than 1% error rate in the power estimation.

Although the enhanced power consumption of those works, the impact of the placement/locations of the IoT devices is not studied in any of those researches. Also, the use of the machine learning algorithms is not investigated in order to enhance the location of the IoT devices.

3. Proposed Work

A. Motivation

Smart cities are defined as a one application connecting variety of day to day features like transportation, power and buildings in smart and effective manner [10]. The location of the IoT devices impacts the transmission between them. In setup of the IoT devices might include communication between all the IoT devices to exchange data or just communication with a main device (cluster head) and the cluster head is responsible of communicating with the backend application. The destination between the IoT devices and the cluster head impacts the signal strength of each IoT device (the longer distance requires higher signal strength and hence higher power consumption). On the other hand, if the IoT devices are not correctly placed on suitable distance to the cluster head or to each other, interference might occur. So that, the distribution of the IoT devices have to be distributed so that the devices are not too close or too far (either out of communication range or more power consumption required).

Figure 1 shows a floor map of a shopping mall and the distribution of the IoT devices on it. The IoT devices are symbolled as bold circle. The IoT device marked "1" has two circles around it. The inner one is the transmission range of the IoT device and the outer circle is the interference range. The IoT device can communicate with the IoT devices in the inner circle (transmission range) and the IoT device in the outer circle (interference range) cannot receive packets correctly. IoT device marked "2" cannot communicate with device "1" as it is out of its coverage. In the case of clustered IoT devices, all the devices have to be in the transmission range of the cluster head or the router as it is the responsible node for communicating with the backend application. Any device out of the transmission range of the router or the cluster head will not be able to transmit the data to the backend application. So that, as the number of the IoT devices in the floor increases, they have to be adequately placed so that they are in the transmission range of the cluster head and using the minimum signal strength and hence the power used.

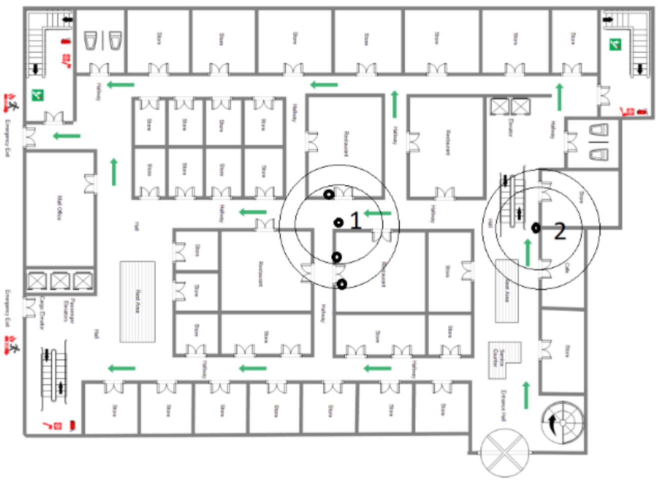

Fig. 1. IoT device distribution in a shopping mall

B. Proposed Architecture

The proposed system attempts to recommend the best location of the IoT devices using the machine learning algorithms. The proposed system consists of four stages: a) *Generation:* In this stage, the data set is generated which includes different locations of IoT devices on different floors with different signal strength (impacts both transmission and interference ranges). The dataset include the power consumption resulted from that device physical distribution. b) Train a machine learning model using the generated data set. By doing that we have a trained model that can be used to evaluate other IoT device distributions. Stage 1 and 2 constitutes phase 1 which is the phase of training the model. c) generate different random locations of the IoT devices based on floor map image d) Enter the generated locations to the trained model and the output is the recommendation of the location of IoT devices. Stage 3 and 4 constitutes phase 2 which results of the recommendation. Figure 2.a shows the phase 1 of the training part:

Fig. 2.a Training a model on (Phase 1)

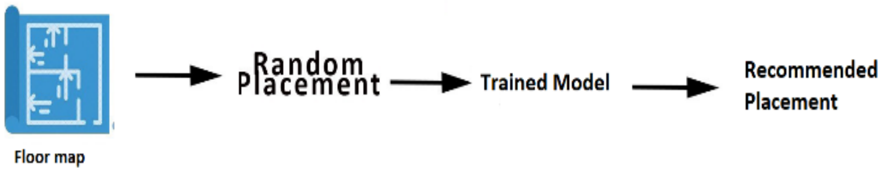

Fig. 2.b Phase 2 of generating IoT devices distribution recommendation

In phase 2, the floormap is analyzed and the corners are determined by using “Harris Corner Detection” algorithm. This algorithm generates the corners in the floormap and this is used to generate random placements of the IoT devices on those corners. After detecting the corners, the IoT devices are randomly placed on the corners to generate new IoT device placements with different transmission/interference ranges. This is repeated to get different distributions. Those distributions are then fed to the previously trained model in order to classify them into one of the three categories based on the previously learnt data.The proposed algorithm is shown in figure 3.

```
readcount_of_dataset;
counter = 0;
While ( counter<count_of_dataset) {
        sample = generate_simulator()
        append_dataset_file (sample, file_ds.txt)
        counter++;}
train_ml(train, test, file_ds.txt);
readfloormap;
array corners = harris_corners(floormap);
randomize();
rand_num = generate_random_num();
counter = 0;
while (counter <rand_num){
        IoT_placement =
generate_IoT_device_distribution()
Power_consumption_class[counter] = ML_run(train,
test, IoT_placement();}
sort(Power_consumption_class);
print (Power_consumption_class[0]);
```

Fig. 3 IoT device distribution in a shopping mall

C. Dataset Description

The Cooja simulator is used to generate the dataset. The dataset is generated by organizing different setups of the IoT device distribution/placement and recording the power consumed. Figure 4 shows a screenshot of Cooja simulator while simulating IoT network.

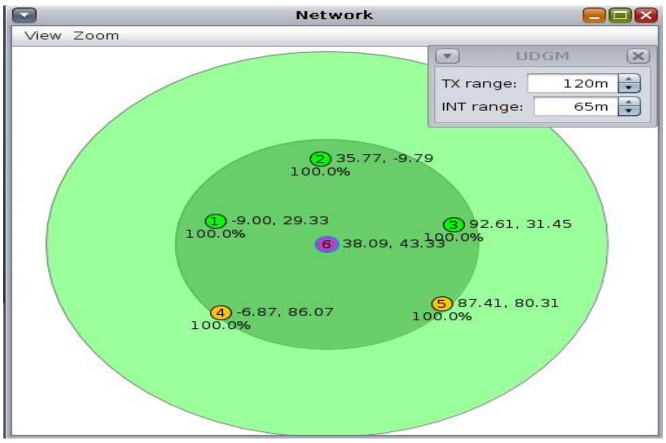

Fig. 4 IoT device distribution in a shopping mall

The dataset record consists of thirty fields. The first nineteen features describe the distances between each pair of the IoT devices and the distances between the IoT devices and the router. The next six features describe the types of the IoT devices. The next two fields are the transmission range and the interference range. The last field is the class of the IoT device distribution based on the power consumption. The power consumption. The consumed power is divided into three categories 1) High, 2) Medium, and 3) Low. Figures 4, 5, and 6 shows snapshots of the dataset. In this research, the number of the IoT devices are restricted to be six IoT devices in order to ease the generation of the dataset.

x1x2	x1x3	x1x4	x1x5	x1x6	x2x3	x2x4	x2x5	x2x6
49.44	59.91	25.02	77.1	36.55	78.44	24.42	59.8	41.96
83.96	117.46	103.1	63.89	57.21	86.98	118.89	120.35	61.7
85.36	67.75	46.43	94.78	51.64	97.72	50.76	64.42	47.63
69.85	86.77	123.77	129.21	64.48	131.48	82.51	137.23	68.66
94.4	130.42	66.76	121.97	79.61	156.72	112.4	93.58	83.42
100.9	62.68	115.31	97.38	24.2	147.91	109.1	179.19	89.9
44.6	60.56	45.05	22.97	32.16	43.65	65	58.32	31.32
33.93	36.42	45.36	37.95	24.99	48.34	20.7	32.48	24.28
165.72	69.55	146.94	135.45	97.1	126.61	65.11	118.35	68.68
150.25	218.8	199.11	89.78	110.4	154.22	199.08	134.87	104.78

Fig. 5 Screenshot of the dataset (distances between IoT devices)

rx4	rx5	typen1	typen2	typen3	typen4	typen5	typeofR
30.27	40.83	1	1	2	2	2	3
61.48	61.65	2	2	1	1	1	3
48.77	45.6	1	1	2	2	1	4
68.45	72.03	2	2	1	1	2	3
40.01	44.17	2	2	2	1	1	3
91.16	93.07	1	1	1	2	2	4
33.72	32.86	1	2	1	2	1	4
23.53	13.6	2	1	2	1	2	3
67.01	98.03	2	2	2	2	2	3
107.48	37.83	1	1	1	1	1	4

Fig. 6 Screenshot of the dataset (IoT device types)

TR	IR	Class
50	100	2
70	120	2
60	110	2
80	130	2
90	140	2
100	150	2
40	90	2
30	80	2
110	160	1
120	170	3

Fig. 7 Screenshot of the dataset (Transmission/Interference ranges and the power consumption class)

4. Experiments

The experiments are done using the dataset generated from the Contiki/cooja simulator. Contiki is an operating system for resource-constrained devices in the Internet of Things. Contiki-NG contains an RFC-compliant, low-power IPv6 communication stack, enabling Internet connectivity. The system runs on a variety of platforms based on energy-efficient architectures such as the ARM Cortex-M3/M4 [11]. Contiki contains cooja simulator which simulates nodes of contiki nodes [12]. The dataset consists of 223 different IoT devices physical distribution with different types and transmission/interference ranges. The dataset generated from the cooja simulator is used with different machine learning algorithm in order to train and test the model. So that, it can be used to recommend the best placement of the IoT devices from a floor map. The implementation is done using python programming language. The classifications used in the experiments are 1) Naïve Bayes, 2) 3) KNN, 4) Support Vector Machine (SVM), 5) Decision Tree and 6) Random Forest. The dataset is divided to train and test sets using different test ratios and the model is built and tested to check the accuracy of determining the power consumption category based on the IoT placement and attributes passed in the dataset. Building the model (training and testing) allows it to specify if any other IoT devices placement will fall in which power consumption category (classes in the dataset).

a. Experiment 1: Naïve Bayes

The experiment run using the naïve bayes algorithm using A) 0.9 training and 0.1 testing. B) 0.7 testing and 0.3 training. The accuracy of the test was the least as the results was 65% and 61% respectively. This is due to the fact that the naïve bayes algorithm treats the features independently.

b. Experiment 2: KNN

In this experiments, the KNN algorithm is used with both K-5 and K=7 where K is the number of neighbors used in the experiment. Both experiments are done using 0.1 testing and 0.9 training. The results showed that with K=5 the accuracy was 75% and reduced to 70% when increasing the number of neighbors to 7.

c. Experiment 3: SVM

In this experiment, the SVM is used with both split ratios A) 0.9 training and 0.1 testing B) 0.8 training and 0.2 testing. This experiment showed a bit higher accuracy. The accuracy obtained are 76% and 70% respectively.

d. Experiment 4: Decision Tree

In this experiment, the decision tree algorithm is used with the same split ratios used in experiment 3. The results was a bit higher than the results reached in experiment 3 (78% and 70% respectively).

e. Experiment 5: Randome Forest

In this experiment, the Random Forest algorithm is used. The higher accuracy is reached in this experiment, the higher accuracy is 83% with the split ratio of (0.9 training and 0.1 testing).

The detailed results of the experiments are shown in table 1 showing the algorithms used, train and test ratios, and accuracy obtained.

Table 1. The results of the experiments

Algorithm	Split Ratio	Accuracy
Naïve Bayes	0.1 testing, 0.9 training	65%
Naïve Bayes	0.3 testing, 0.7 training	61%
KNN (K-5)	0.1 testing, 0.9 training	75%
KNN (K=7)	0.1 testing, 0.9 training	70%
SVM	0.1 testing, 0.9 training	76%
SVM	0.2 testing, 0.8 training	70%
Decision Tree	0.1 testing, 0.9 training	78%
Decision Tree	0.2 testing, 0.8 training	70%
Random Forest	0.1 testing, 0.9 training	83%
Random Forest	0.2 testing, 0.8 training	71%

5. Conclusion

The machine learning algorithms can be used to enhance the power consumption of the IoT devices by enhancing the placement of the IoT devices. This can be used in the placement of the IoT in different applications specially where the IoT devices are away from power sources. In this experiment, a methodology is developed to build a trained model that can classify the IoT devices distribution based on their power consumption (classes). The classes are three classes 1) low, 2) medium, and 3) high. The second phase of this, is to generate random different IoT devices placements based on the given floor map. The different placements are passed to the trained model to classify those IoT devices placements. The output is sorted and the one that classified low is returned to the user as the recommended placement. The limitation of the implementation is that the limited number of IoT devices. The results showed that the Random Forest algorithm provided83% accuracy for the IoT devices placement to enhance the power saving which is the highest accuracy among the machine learning algorithms used.

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