Data Driven techniques to analyse Power Consumption

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Overview:

- Load Forecasting and Monitoring are intelligent solutions which can be utilized to devise scheduling strategies to optimize power consumption.
- Granular level data can be obtained by using smart technology (sensors, actuators, etc.) installed at convenient locations. This method of installing sensors locally is both costly and time consuming.
- Non Intrusive Load Monitoring(NILM) is thus a solution to the aforementioned problem. Previous studies have investigated the usage of side channel information including EMF signals to detect and track appliance usage.
- Fluctuations in the EMI caused by Switch mode power Supply devices can be also observed in the Light intensity if sampled at a very high rate. These fluctuations may be useful in characterizing appliances.

Methods and Datasets:

- **Load Prediction:**

EnFuse Panel Meters
Electricity usage

Firefly Environmental
Light, Temperature, Humidity, Sound, Pressure, Vibration

Datasets:

- Power Consumption**:** Power Consumption Data every minute, Scaife-Hall
- Temperature: Outdoor temperature every 5 minutes, Intelligent work space

Parameters:

- Time of week indicator
- Piecewise linear and continuous outdoor air temperature

Model : Multidimensional linear regression model

- **Frequency Analysis of the flicker produced in a bulb:**

FireFly Sensor
Light Intensity

NI-9215
Data Acquisition (100kHz)

NI-9215
Data Acquisition (100MHz)

Experiment:

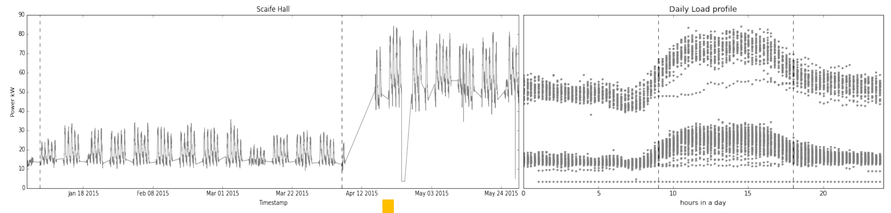
- Sampling rates(fs): 30kHz, 500kHz
- Measured Light intensity of a 13W CFL bulb
- Instruments used: Vacuum Cleaner, Blender, Fan.

Method:
Short time Fourier Transform of the data with

- Window length - fs/60Hz (~ Power of 2)
- % Overlap – 50%

Results:

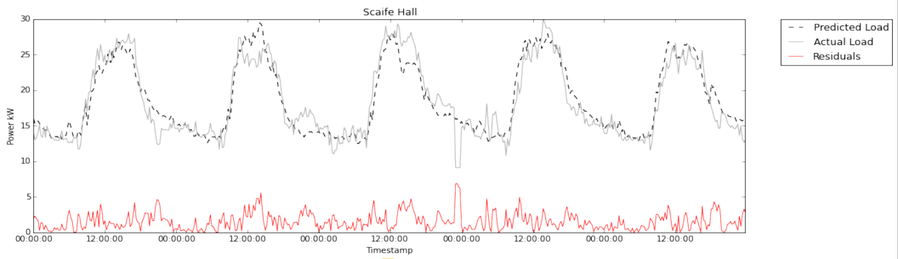
Power Consumption Prediction[1]:



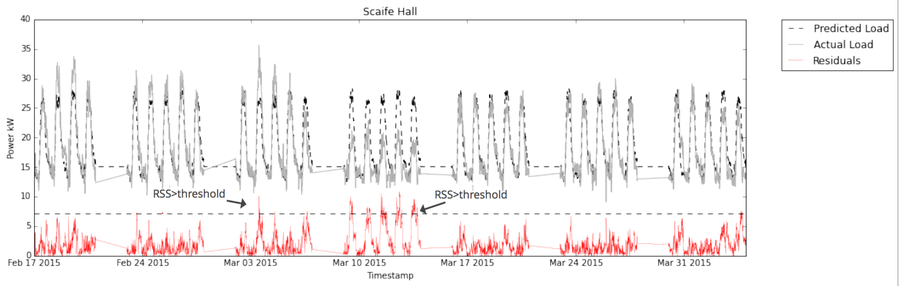
$$\hat{L}_o(t_i,(T(t_i))) = \alpha_i + \sum_{j=1}^{j=6} \beta_j T_{c,j}(t_i) \quad (1)$$

$$\hat{L}_u(t_i,(T(t_i))) = \alpha_i + \beta_\mu T(t_i) \quad (2)$$

- 15 min intervals
- Occupancy time: **9am – 7pm**



RSS k-fold cross validation
Threshold: **7.12kW**



Conclusions:

- The timestamps corresponding to error > threshold are compared with the CMMS dataset provided by CMU FMS to detect any anomalies.
- So far there haven't been any high correlations and mostly correspond to PM(Preventive Maintenance)
- The model has a few limitations:
  - It does not take into consideration holidays, exam days and drastic weather changes.
  - It also does not take into consideration the addition/removal of meters which may increase/decrease the measured power consumption.
  - Availability of data

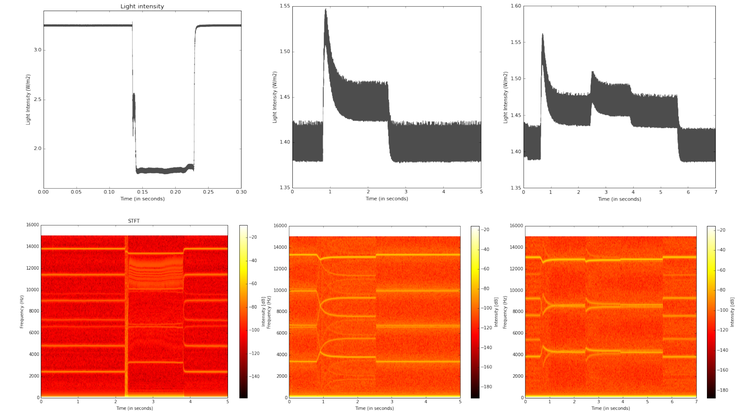
References:

[1]: Mathieu, Kallaway, D.S., and Kiliccote. "Quantifying Changes in Building Energy Use, With Application to Demand Response." IEEE Trans Smart Grid (2011): n. pag. Web.

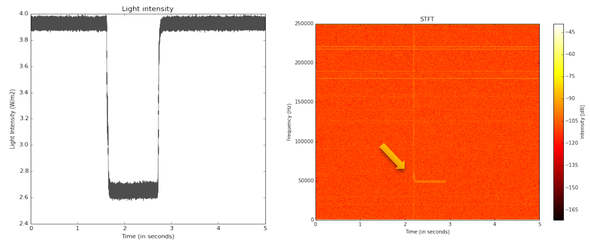
Results:

Time Domain frequency Analysis:

- Sampling @ 30kHz



- Sampling @ 500kHz



Conclusions:

- As seen in the above figures, there are features being observed corresponding to appliances but they are not distinct.
- These features were also not observable while shifting to another circuit on the same phase.
- While sampling at a higher rate(>100kHz), the features corresponding to the Electromagnetic interference produced due to SMPS in the CFL bulb is observed in the frequency analysis of Light intensity.
- This might open future avenues in this area of analyzing Light in appliance monitoring.

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