Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor

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REDD: A Public Data Set for Energy Disaggregation Research

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Introduction

• Smart Grid
  – Optimal management and improved control of energy
• Smart Grid Meters
  – Building’s overall energy consumption (aggregate usage)
• Most of the time, aggregate usage details are not enough
  – Need ‘per device energy consumption details’ to improve energy saving
  – Room heater vs. Washing machine.
Measuring Disaggregate Energy Usage

- Distributed Direct Sensing
- Single-Point Sensing
- Intermediate Sensing Methods
Measuring Disaggregate Energy Usage

• Distributed Direct Sensing
  – Sensor at each device
  – Senses and controls the device
  – Labels the device connected
    • Solves the problem of differentiating devices with similar power consumption.
  – Installation and maintenance
  – Costly
Measuring Disaggregate Energy Usage

• Single-Point Sensing
  – Single Sensor (plug and play)
  – Non-Intrusive Load Monitoring (NILM)
  – Classification using pattern matching
  – Training the system – installation complexity
Measuring Disaggregated Energy Usage

• Intermediate Sensing Methods
  – Smart breaker device
    • Inside home’s circuit breaker panel
  – Circuit by circuit analysis of energy consumption
  – Circuit may feed only one appliance
    • Depends of home’s circuit layout
  – Fresh installation and comparatively costly
  – Maintenance
Challenges in Recognizing Appliance Activity

• Appliance with similar current draw
• Appliances with multiple settings
• Parallel appliances activity
• Environment noise
• Load Variation
• Load appliance cycle
Artificial Neural Network

Basic element – neuron
Artificial Neural Network

Multi-Layered ANN
Artificial Neural Network

Example:
Artificial Neural Network

• Advantages
  – Handles any type of data
  – No need of prior understanding of appliance
  – Easily extensible
  – Automated learning process
  – Error feedbacks
  – Handles multiple simultaneous appliance

• Disadvantage
  – Training process
RECAP:
RECognition of electrical Appliances and Profiling in real-time
System Design
Data Acquisition System

Energy Monitoring Data Acquisition System
RECAP

1. Generation Application Signature
   - Application Profiling
   - Unique Application Signature

2. Training and Recognition
Appliance Profiling

• Appliance Classification
  – Resistive
    • Example: kettle, toasters
  – Inductive
    • Example: transformers
  – Capacitive
    • Example: capacitor bank
  – Predominance
    • Example: electric fan
Appliance Profiling

- Resistive
Appliance Profiling

- Inductive
Appliance Profiling

• Capacitive
Appliance Profiling

- Real power (Active)
- Reactive Power
- Apparent power

- Power factor = $P_{\text{load}} / P_{\text{resistive}}$
Appliance Profiling

\[ S = P + j Q \]
\[ Pf = \frac{P}{|S|} \]

- **S** - Apparent power
- **Q** - Reactive power
- **P** - Active power
- **Pf** - Power factor
- **|S|** - Real part of apparent power
Unique Application Signature

• Parameters
  – Real power
  – Power factor
  – Peak current
  – RMS current
  – Peak voltage
  – RMS voltage

• Additional factors
  – Signature length
  – Sampling frequency
Unique Application Signature

- Signature -> Power Frequency
- Example power signatures
## Signature Database

<table>
<thead>
<tr>
<th><strong>Captured Parameters</strong></th>
<th><strong>Environmental</strong></th>
<th><strong>Physical</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Signature ID (SID)</td>
<td>SID</td>
<td>Appliance ID (AID)</td>
</tr>
<tr>
<td>Real Power</td>
<td>Device Location</td>
<td>Type</td>
</tr>
<tr>
<td>Power Factor</td>
<td>Temperature</td>
<td>Model</td>
</tr>
<tr>
<td>RMS Current</td>
<td>Humidity</td>
<td>Make</td>
</tr>
<tr>
<td>RMS Voltage</td>
<td></td>
<td>Power Rating</td>
</tr>
<tr>
<td>Peak Current</td>
<td></td>
<td>Voltage Rating</td>
</tr>
<tr>
<td>Peak Voltage</td>
<td>User ID (UID)</td>
<td>Frequency Rating</td>
</tr>
<tr>
<td>Sampling Rate</td>
<td>Name</td>
<td></td>
</tr>
<tr>
<td>Timestamp</td>
<td>Confidence Rate</td>
<td></td>
</tr>
<tr>
<td>State: [startup, steady, shutdown, off]</td>
<td>Association</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Contributor</strong></th>
<th><strong>Energy Meter</strong></th>
<th><strong>Signature Property</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>User ID (UID)</td>
<td>Meter ID (MID)</td>
<td>SID (Primary key)</td>
</tr>
<tr>
<td>Name</td>
<td>Device Type</td>
<td>AID</td>
</tr>
<tr>
<td>Confidence Rate</td>
<td>Accuracy</td>
<td>MID</td>
</tr>
<tr>
<td>Association</td>
<td></td>
<td>UID</td>
</tr>
</tbody>
</table>
Training and Recognition
Training and Recognition

- Feedback mechanism (user input)
- Initial weights are random
- $W_n = W_0 - (\delta \times Lr)$
Training and Recognition

• Automatic training program (ALP)
  – *Uses generated signature to create training data set*

• More neuron -> long training time

• Less neuron -> poor results

• 6 input neuron, 6 hidden neuron

• Activity function (output 0 to 1) – Sigmoid function (S shaped) ex: \[ S(t) = \frac{1}{1 + e^{-t}}. \]
Experimentations

- ZEM-30 ZigBee Energy Monitor
Experimentations

- 3 main appliances with high power consumption
  - Along with lower consuming devices
  - Duration: a week
  - 95% accuracy
Experimentations

• Appliance with similar power consumption and power factor
  – Electric fire – microwave and kettle
Experimentations

• Increase in signature length -> increase in training time

• With Pentium 4 machine
  – Training time < 1 minute up 15 appliance

• Training subset of appliance in order of 15 or less
Use Cases

- Real-time energy awareness
- Enabling load shifting
- Personalized energy bill
Critiques

- Unique Signature State Information (USSI) database
- Experiment is done on a very small scale
- Value of the parameter $Lr$?
- No evidence of the time required for the system to train itself (BHARAT SINGHVI)
Reference Energy Disaggregation Data Set (REDD)
REDD

- **Frequency of Measurement**
  - 15kHz monitoring
  - 2 phases of current and one phase of voltage

- **Real power / Reactive power**
  - AC waveform

- **Use of External Features**
  - UTC time stamps & geographical information

- **Supervised / Unsupervised Training**
  - Supervised information

- **Training / Testing Generalization**

- Evaluation metrics
Hardware setup

• Wireless plug monitoring system (Enmetirc)
  – Power strips
  – Router
  – Information @ 1Hz

• Circuit level data – eMonitor
  – Current Transformers (CTs) in Circuit breaker panel

• AC waveform
  – CTs (TED) in power main (can sense power change of 0.5 watts)
  – Pico TA041 Oscilloscope probe – voltage measure (sense deference of about 7mV)

• NI-9239 Analog to digital convertor (A/D)
  – 25bit resolution with 70μV
Hardware setup

REDDBox
Software System

- Stores readings locally
- Sends processed information to a central database
REDD hardware and software system

http://redd.csail.mit.edu/

- username: redd
- password: disaggregate_the_energy
Critiques

• No mapping between the appliance and the phase (BHARAT SINGHVI)

• Calculations, leading to extraction of power and reactive power, from the voltage and current information, present in the data result, do not match with the provided information about power.

• How is it different from other disaggregation datasets like BLUED, UMASS Smart Home Data Set, Tracebase etc
Thank You