REAL-TIME NON-INTRUSIVE APPLIANCE LOAD MONITOR
Feedback System for Single-point per Appliance Electricity Usage

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Abstract: External single-point appliance load monitoring gives detailed information about appliance electricity use without expensive or intrusive installation. This is vital for a wide distribution of practical solutions. Current research has focused on improving the load disaggregation algorithms, whereas consumers would benefit most from a good feedback system, even if the energy usage estimates are not perfect. A good feedback system can motivate consumers to save energy from 10% to 15%. In an ongoing project on energy efficient living at the University of Oulu, we have developed a real-time application using a non-intrusive appliance load monitoring algorithm. The algorithm is based on thresholding, kNN-classifier, and on-and-off event matching. Accuracy of the developed system is in line with other similar work and provides a real-time operation. In a test setting, events were detected with 96.1% accuracy and the total energy estimate differed from the actual consumption by 11.3%. With such a solution, consumers can easily see the energy used by different appliances and can make energy saving decisions because they can see the effects of their actions immediately. This kind of technologies will play a key role if ever increasing energy saving targets set by international contracts are to be met.

1 INTRODUCTION

Climate change is already happening and represents one of the greatest environmental, social and economic threats facing the planet. For example, in US households consume 21% of nation's energy producing 20% of CO_2 emissions, as well as use half of the publicly supplied water (Froehlich et al., 2009).

It is stated in an European Union directive that Member States shall aim to achieve an overall national energy savings target of 9% by the year 2016 (Commission et al., 2006). Therefore, developing a technology for making consumers aware of their energy consumption habits is of great importance if this goal is to be reached. This among other investments in energy saving technology and renewable energy production could also have a positive impact on the financial status of the countries involved. In this sector, there is an abundance of possibilities for European countries to aim at the top of competition as providers of clean future technologies.

In an ongoing project here in the Department of Computer Science and Engineering of University of Oulu in association with Tokyo University of Agriculture and Technology, we have been developing an interactive context-aware sensor-based feedback and control system to support energy efficient housing. The aim of the system is to motivate inhabitants to be aware of their energy consumption habits and make decreasing energy costs easier. In a long run, this leads to a more efficient use of energy resources for living in the whole society.

Typically, consumers are unaware of their energy consumption such as electricity consumption of different household appliances. It is common to get an electric bill only a few times a year. This kind of feedback as such is not helpful, especially because the consumers only see the total energy used. To motivate consumers to actually save energy, they must be made aware of the energy consumption amounts of certain appliances or appliance groups. They must also be made aware of the times when those appliances are used and the amount of energy those appliances are using. With this kind of accurate information, especially if the information is real-time, it is easier to make energy saving decisions. Raw energy consumption statistics might not be as motivating as seeing the same figures in price estimates. According to Matthews (Matthews et al., 2008), a reduction of 10 to 15% might be possible with feedback related to elec-

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tricity consumption. With a real-time system showing the disaggregated per appliance consumption figures, the potential savings may even increase.

Appliance load monitoring refers to techniques that measure individual appliance electrical loads either directly or indirectly. For consumer applications, indirect estimation of electrical loads is usually the most practical way if several appliances are to be monitored. Typically, such a system's development focuses on providing an even better accuracy of disaggregation of individual appliances from a total load measured at the breaker panel or the main cord, compared to previous research. This allows users to see which appliances have used the most energy and help them to make better energy saving decisions in the future. Having this information in real-time provides even more useful feedback to the users, and most importantly, they can see the effects of their actions immediately and react accordingly.

We use single-point sensing of aggregated appliance power consumption to determine individual appliance consumption. Noise and the lack of resolution in the measurements make the use of machine learning and pattern recognition techniques (Bishop, 2006) a rational choice to address this problem.

Here in the Department of Computer Science and Engineering of University of Oulu, we have developed a low cost system that is operating in real-time and is able to infer which appliances or appliance groups are turned on or off during operation. It works by feeding real-time measurement data to the event detection algorithm. It also calculates estimates of energy consumption of each appliance or appliance group in both energy used and price in Euros. With this system, the consumers can see in real-time how the use of different appliances affects the energy usage figures and cost. They can then make informed decisions to save energy where possible and see the effects of their decisions immediately. The developed prototype system uses only one sensor to make installation very easy and as non-intrusive and as cheap as possible. These features make it a practical solution for wide deployment.

The article is ordered as follows: in Section 2, a background for non-intrusive appliance load monitoring in general is briefly discussed. In Section 3, methods used in the developed real-time system are presented. Experiments run with the system are then presented in Section 4 and the specifics of the developed Real-Time Appliance Load Monitor software are discussed in Section 5. Finally, Section 6 concludes the article.

2 LOAD DISAGGREGATION METHODS

Groundwork for non-intrusive appliance load monitoring (NIALM) research was done in the 80's and early 90's. Pioneer work of the field was presented in (Hart, 1992). In this breakthrough article the methods still used today in NIALM systems are described. Recently methods such as detecting the electromagnetic interference (EMI) of appliances (Gupta et al., 2010) have been developed but they tend to be expensive compared to the extra value they offer over traditional lower cost sensor based approaches. In the next sections the most commonly used methods are introduced.

2.1 Steady State Methods

Steady state analysis of power consumption data refers to the methods where the power value changes from a nearly constant value to another (Najmeddine et al., 2008) when a certain appliance turns on or off. In fundamental frequency steady state analysis, step changes in power consumption, both active and reactive power, are recorded and can be used as signatures. In our test setting, there are four different appliances forming the aggregate consumption: a TV, a fridge, a water boiler, and a coffee maker. A sample recording from our test setting can be seen in Figure 2. The step changes in the graph are detected and the magnitude of those changes are used as signatures by the classifier. In this case, the feature space is two dimensional and is presented in Figure 1 using the four aforementioned appliances.

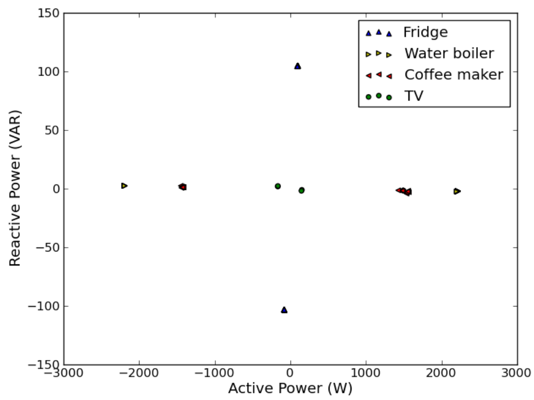


Figure 1: Feature space of the appliance signatures from a test setting.

Power consumption values should be normalized to take account of voltage fluctuations. This is because power line voltage and current can fluctuate $\pm 10\%$ so that the measured power figures can vary as much as about ±20%. Equation 1 can be used to calculate the normalized power values. The optimal value for β in the equation is different for different types of appliances, but typically, a value of two is used (Hart, 1992).

$$P(t)_{Norm} = (\frac{230}{V(t)})^{\beta}P(t). \tag{1}$$

In addition to fundamental frequency signatures explained above, current harmonics can be used as signatures as well. This is because most appliances are not strictly linear and therefore produce detectable currents on the odd harmonic frequencies that differ from one appliance type to another. It might be possible, e.g., to differentiate between two small appliances that are too difficult to differentiate based only on power changes (Hart, 1992).

The found events are finally matched so that when a switch-off event of some appliance is found, the previous unmatched switch-on event of the same appliance is matched with it. The operation time of the appliance can then be determined from the time difference in timestamps of the events. The energy consumption estimate can be calculated based on the magnitude of change in the power value of the switch-off event (Pihala, 1998). The process is illustrated in Figure 2. In the figure, dP_1 and dP_3 are from one appliance and dP_2 and dP_4 are from another. The algorithm matches those corresponding events and estimates the energy used.

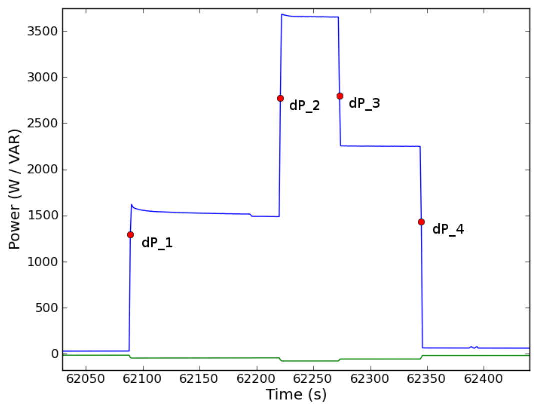


Figure 2: Event matching in real-time appliance load monitor.

2.2 Other Methods

If higher frequency data is available, it is also possible to use transient state signatures to aid identification of appliances. Transients are of different shapes, depending on the mechanism they are produced (Leeb et al., 1995). Other transient classification criteria are their size, duration, time constants, or parametric values in models of waveforms (Hart, 1992). Transients are only detectable during switch-on events and provide therefore less information than steady state methods. Switch-off events do not produce transients; thus, only switch-on events can be detected with transient methods (Hart, 1992).

A novel method to detect appliance use with a single sensor has been developed by Gupta (Gupta et al., 2010). It makes use of the electromagnetic interference (EMI) signals that are unique to each appliance. Others have used magnetic sensors, light intensity sensors, and microphones (Kim et al., 2009) to aid appliance identification. Also, a thermal camera has been used (Ho et al., 2011) in trying to estimate appliance usage.

All the above methods require more expensive and complex sensing hardware than the steady state fundamental frequency measurements. For practical domestic solutions, they might not yet be sensible options.

3 METHODS FOR THE REAL-TIME APPLIANCE LOAD MONITOR

In this work, we focus on providing a real-time, low cost, and non-intrusive load monitoring system for consumer households. This has influenced the selection of the used hardware and load disaggregation algorithms.

Single point sensing was chosen to minimize intrusiveness of the system. The sensor we are using is Plogg[1]. It is a type of sensor that is plugged into an electric socket. This kind of sensor allows the development of a prototype system that can be later used as a basis for a system capable of monitoring a whole household. The sensor has a maximum sampling rate of 1Hz. This is enough if fundamental frequency steady state signatures are used, but does not allow the use of harmonics or transients as signatures.

Consumption values are fetched from the sensor every second. These consumption values are normalized according to Equation 1 to minimize distortion of voltage and then fed to the event detection algorithm. The event detection algorithm finds step changes in the consumption data and extracts the steady state signatures of those step changes. The event detection algorithm is presented in Algorithm 1. The real-time version of the algorithm differentiates from the offline version that was presented in (Hart, 1992) in one way. To operate in real-time, event signatures must be re-

[1] http://www.plogginternational.com/

Algorithm 1: Event detection algorithm for the Real-Time Appliance Load Monitor. In the algorithm, representation c stands for current sample, ws for window size, bl for baseline, th for threshold, and ls for the last stable baseline index.

```
while True do
  bl ← average(data[ls : (ls + ws)])
  if max|bl − data[ls : (ls + ws)]| < th then
    break
  end if
  ls ← ls + 1
end while
while application running do
  if eventstarted = 0 then
    if |data[c] − bl| > th then
      eventstarted ← timestamp
      continue
    else
      bl ← average(data[ls : c])
    end if
  else
    if (c − eventstarted) ≥ ws then
      avg ← average(data[(c − ws) : c])
      if max|avg − data[(c − ws) : c]| < th then
        if avg − bl > th then
          eventqueue ← (eventstarted, avg − bl)
          ls ← c
        end if
        eventstarted ← 0
      end if
    end if
  end if
end while
```

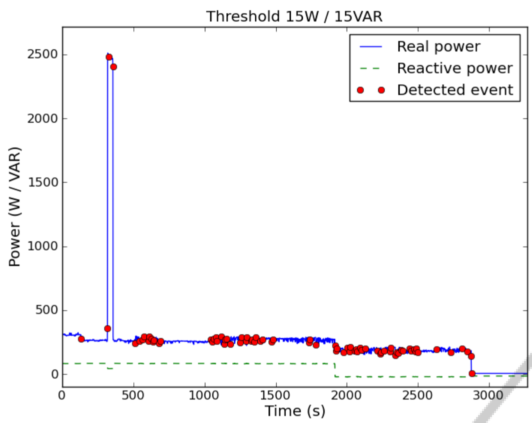
corded right after the event has occurred. In comparison, the offline version takes averages of each steady states and uses the difference of two consecutive steady states as signatures. Switch-on events therefore are different in these two algorithms as we do not have time to take the average of the whole on-cycle to calculate the switch-on signature. These signatures along with timestamps are then fed to a classifier that has been trained on data from the appliances or appliance groups that we are interested in. The classifier then identifies to which appliance the signature belong. It uses k-nearest neighbor algorithm (Duda et al., 2000) that finds the data point's nearest neighbors in training data in the feature space using Euclidean distance as a distance metric. The class for the data point is then chosen based on the majority vote of the nearest neighbors' classes. K's value of three was chosen based on the validation dataset to account for the greater variance compared to the offline algorithm and noise in the data while maximizing performance.

4 EXPERIMENTS

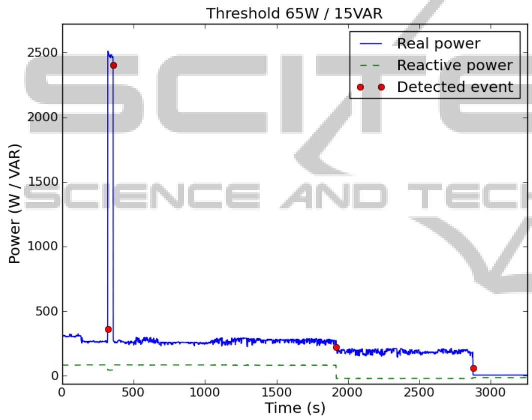
A test environment was built in the coffee room of our department. One Plogg sensor was installed so that every appliance in the test setup drew its power from the socket where the sensor was plugged. In addition to that, an individual sensor was installed to each test appliance to obtain accurate reference data. There were four test appliances in the setup: a fridge, an old CRT TV, a water boiler and a twin coffee maker.

Test data were collected for a total of 27 days 11 hours. The collected data were then analyzed with an offline version of the software using the same load disaggregation algorithm as the real-time version of the software. A previously collected dataset with only one appliance in the setting at a time was used as training data. A minimum of seven on/off event pairs was collected for each appliance's training dataset. As fine tuning the algorithm was not the main research topic, the tests were only run with one set of configuration values. Threshold values of 65W/15VAR were used for the event detection triggering. A window length of three seconds was used for finding a new stable steady state after an event. These values were determined by experimenting with training data. In other work (Hart, 1992), 15W/15VAR has been used as a threshold. In this case, the measurement noise from TV made it impossible to use such a low threshold value. Thus, a higher threshold was selected based on the training data. Real power was found to more susceptible to noise than reactive power so higher threshold value was used for real power than for reactive power. A window size of three seconds was used (Hart, 1992). The effect of the threshold value used can be seen in Figure 3. With 15W/15VAR (3(a)) threshold there are tens of false events detected whereas with 65W/15VAR (3(b)) threshold only real events are detected.

From the tests, two performance measures were determined: first, energy use estimate, and second, event detection accuracy of each appliance. The test results are presented in Tables 1 and 2. The event detection accuracy is tabulated as a confusion matrix. The confusion matrix is based on the first two parts of the six part test data. As seen from the results, the event detection accuracy is excellent, whereas the energy consumption estimates could be better. A total of 382 events were detected in the analyzed dataset. Of those events, 367 of those events were correctly classified, which makes the overall event detection accuracy of 96.1% for the system. Energy consumption estimate accuracy varied from one appliance to another. The largest error is seen with the TV. It was noted that the hot plates of the coffee maker some-



(a) Event detection with threshold with 15W/15VAR



(b) Event detection with threshold 65W/15VAR

Figure 3: Effect of threshold value selection on event detection.

times triggered an event that was classified to an event caused by the TV. The hot plates also account for most of the error in the coffee makers energy estimate. The coffee maker was sometimes left on for long periods of time and the hot plate consumption was not detected by the system. The total energy estimate was 11.3% lower than the actual consumption. Ignoring the TV, the overall energy estimate was 2.6% higher than the actual total consumption. The results are in line with other work in the field (Pihala, 1998).

The TV used in the test setting is extremely noisy and makes detection of other appliances harder. In Figure 3(a), this phenomena can be seen. The false events affect the energy estimates and also the detection accuracy, especially regarding the TV. Nevertheless, the appliance class detection accuracies of the other appliances remain high. The noise also makes it harder to accurately detect other appliances as finding a stable steady state before and after events is harder. Also, the threshold value for event detection must be raised to avoid false alarms and therefore small appliances are undetectable. Additionally, one simultaneous event of two appliances was detected in the analyzed dataset. This was falsely classified as the algorithm does not take account for the possibility of simultaneous events.

Table 1: NIALM system energy consumption estimates.

Appliance	True consumption	Estimated consumption	Error-%
Twin coffee maker	10.54 kWh	8.24 kWh	-21.9%
Water boiler	20.59 kWh	22.11 kWh	+7.3%
CRT TV	13.90 kWh	5.44 kWh	-60.9%
Fridge	18.28 kWh	20.36 kWh	+11.4%
Total	63.31 kWh	56.14 kWh	-11.3%
Total without TV	49.42 kWh	50.70 kWh	+2.6%

Table 2: NIALM system confusion matrix for the event detection algorithm. Each row represents the actual appliance class. Each column represents the predicted appliance class.

	Twin coffee maker	Water boiler	CRT TV	Fridge	No event
Twin coffee maker	55	0	0	0	1
Water boiler	1	111	0	0	0
CRT TV	0	0	13	0	0
Fridge	0	0	3	188	2
No event	0	0	8	0	-

5 REAL-TIME APPLIANCE LOAD MONITOR

An application capable of showing the users in real-time the use of electrical appliances, called Real-Time Appliance Load Monitor, was developed. The base of the application was the NIALM algorithm, as described in Section 3. The application shows the current power consumption and also the total energy used while the application was running. In addition to this, for each appliance or appliance group, the application shows information of the current state of the appliance, its name, estimated consumption, total energy used and the cost of the energy used by the appliance. All detected events are shown in a text area at the bottom of the application. A screenshot of the developed application running on a Linux desktop computer can be seen in Figure 4.

The total power consumption value is shown at the top of the application in watts. This value is the raw data from the sensor on any given moment rounded to the nearest integer value for clarity. Below the power consumption value, a total energy used while the application was running is shown in kilowatthours (kWh). The value can be fetched directly from the sensor. An estimation of the cost of the total energy used is also shown next to the total energy used figure. A price of 0.12€per kWh is used as an estimate. In the list of appliances, are all appliances that the system knows of.

In the appliance or appliance group section, there are five columns. In the first column, the current ap-

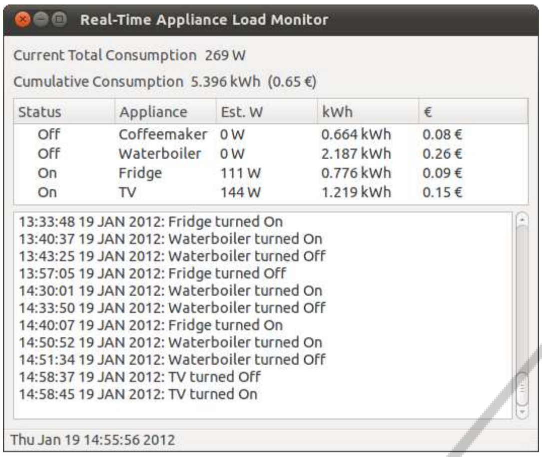


Figure 4: Graphical user interface of the developed software.

pliance state is shown. If the state is unknown, i.e. no events of that appliance have yet been seen, a dash is shown. When an event regarding a certain appliance is detected, the Status column of that appliance is updated accordingly to either On or Off, depending on the event. In the second column, the appliance name is shown. The third column shows an estimate of the appliance's current consumption. The fourth column shows the energy use estimate of the corresponding appliance. This column is updated every time an appliance is turned off. The value is calculated based on the real power magnitude in the off-event signature and the time from the switch-on event. This value can then be used to calculate the price estimate in the last column.

6 CONCLUSIONS

To meet the energy saving targets set by governments, it is vital to motivate average consumers to make energy saving decisions. Feedback for energy use has been found to be an effective way to decrease energy use. Therefore, a need for a cheap solution for a wide deployment of energy usage feedback systems in households exists. A prototype application for providing feedback about individual appliance use in real-time to consumers was presented. The system was tested in a real test environment and was observed to give accurate appliance use statistics on average. Events were correctly identified 96.1% of the time and the total energy estimate was within 11.3% of the real consumption.

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