Exploring Techniques for Monitoring Electric Power Consumption in Households

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***Abstract*—Recent works in ubiquitous computing have addressed analysis of electric power for energy conservation by detailing and studying consumption of electrical appliances. We contribute with an approach to develop techniques for fingerprinting and monitoring consumption of electric power in households. The approach builds on previous works and employs three phases: feature extraction of attributes such as real power and current harmonic contents, event detection and pattern recognition. A load library is foreseen that stores appliance characteristics as corpus data for training and recognition. We report early findings achieved using a high definition sensor directly applied to the loads showing promising results but also challenges in event detection (smaller state transitions, challenges in detecting and pairing switch on and off events). These studies are important in order to be able to address opportunities of identifying and monitoring directly at the appliance level or sensing the total load of the network. Future applications include monitoring and detailing of loads in a "balance sheet" and context aware service with advice tips for energy users.**

Keywords- ubiquitous computing; load monitoring; fingerprinting; pattern recognition; energy awareness

I. INTRODUCTION

In ubiquitous computing, measuring electric power consumption has been pursued for energy conservation and also as a means to recognize user activities [1]. Power measurement and analysis can be done at whole-house level as demonstrated in [2] and [3], on selected plugs as shown in [4] or by placing sensors near electrical devices [5]. The current state is that several electrical appliances can be identified either by using measurement from the main power entry point or with sensors placed near the appliance. While researches successfully showed a way to finger print appliances switching on and switching off, less explored activities are beyond these simple operations such as the analysis of specific uses of the device. Appliances can have nominally the same instantaneous power usage and yet perform quite different operations. Such variety of operations can be possibly tracked by utilizing different attributes with a state of the art sensor that monitors electrical parameters such as active power, power factor, harmonic distortion, crest factor and energy consumption.

In this paper, we discuss techniques for appliance identification and monitoring system that uses measurement data received from sensors installed in customer premises for applications in energy awareness and power quality monitoring. Two techniques, namely, device fingerprinting and balance sheet application are being developed, which are foreseen to provide detailed information about residential electric power consumption in a near-real-time processing environment.

This paper is organized as follows: a review of related work is presented in Section II; the two techniques being developed are introduced in Section III; Section IV discusses device fingerprinting in detail and Section V presents preliminary findings; Section VI explains the balance sheet application. Finally, Section VII concludes the paper, pointing out major problems and further improvements.

II. RELATED WORK

Earlier researches conducted on nonintrusive appliance load monitoring system (NIALMS) were based on the principle that the waveform of a total site load changes in predictable manner as appliances are individually turned on and off [7].

One of the pioneering researches on load identification was made in the US at Massachusetts Institute of Technology [6]. An algorithm was developed for two-state appliances and a recorder was installed next to the existing energy meter, with sampling rate of 2 kHz, to record step changes in real and reactive power (ΔP, ΔQ). The time stamped edge data are then stored for semi-automatic identification by employing a library of load models and finding a possible match. The main limitations of this work were inability to detect edges (events) for appliances that are always in continuous operation and to distinguish between appliances with similar power consumption profiles.

Another study, in Finland, at VTT Technical Research Center implemented a 3-phase power quality monitoring energy meter and it developed its own load identification algorithm that required a prior manual set up for the naming of appliances and building a signature library (the manual set up is a one-time intrusive activity in which signatures are observed and named as appliances are manually turned on and off) [7]. The system utilized fundamental frequency signatures (ΔP, ΔQ) for edge detection and load identification.

 ISBN: 978-1-61208-100-7

Subsequent studies put into practice supplementary methods such as higher-order current harmonics and transients to be used as additional parameters in load identification [8]. Higher harmonics studies showed that evaluating power consumption data at higher frequencies helps to disaggregate certain loads that have overlapping consumption profiles at fundamental frequency. Another advanced approach presented in [9], in addition to the parameters at higher harmonics, used phase shift between the fundamental input current and the source voltage for load identification.

The study on transients was based on the principle that appliances can be identified by their unique load transient shapes [8]. Events detected from the aggregate power stream are matched to previously recorded and defined transient signatures. However, the test results for the sampled devices indicate that similar transient patterns can be achieved only for switch-on transitions.

On the pattern recognition aspect, an algorithm for identifying the type of domestic appliances based on fuzzy logic theory is proposed in [10]. It identifies an electric load by comparing its transient with a database of known transients and selecting the closest match. The algorithm was tested on a few sample waveforms and it is stated that promising results were obtained.

Other researches of interest in this field include - load monitoring system developed in Germany using existing energy meters fitted with optical sensors, appliance identification algorithm based on Dynamic Time Warping for micro grids and NIALMS based on Integer Programming, which are presented in [11], [12] and [13] respectively.

III. FINGERPRINTING AND CONSUMPTION BALANCE SHEET CALCULATION

The device fingerprinting concept is based on the fact that different appliances exhibit different operational electrical characteristics. Fingerprinting adds the capability to monitor appliances individually or at least in categories, which in turn provides the possibility for near-real-time monitoring of appliances' energy consumption and thus the corresponding energy cost.

The BeAware project fingerprinting research is aimed at exploring various electrical characteristics of household appliances that have the potential to be used in load identification techniques. On the other hand, the balance sheet feature provides the aggregate energy consumption report and more importantly, the respective share of categories of appliances that are not directly monitored by the sensor.

Before commencing the development of the fingerprinting and balance sheet applications, an extensive series of measurements on various household appliances was conducted. The primary objectives were to obtain a technical load classification and to examine the operating behaviors of different loads using the measurement results.

It was observed that most appliances fall in one of the four major classes: resistive load, electronic load, motor driven load or general inductive load. From an operation point of view, appliances can also be divided as:

- Short-cyclic, long-cyclic or continuously-operating depending on their ON cycle time
- Mono-mode or multi-mode depending on the number of sequences of tasks they perform
- Two-state or multi-state depending on the number of distinct switch-on states they possess

In addition, closer studies were performed on switch-on, switch-off and steady-state characteristics, duty cycle and current harmonic contents of individual appliances.

IV. DEVICE FINGERPRINTING APPLICATION

The device fingerprinting process is depicted in Fig. 1. It consists of three steps - feature extraction, event detection and pattern recognition [14]. The load library stores appliance signatures that are used for matching purpose during pattern recognition stage.

A. Feature extraction

Different attributes such as real power, current harmonic contents and power factor are extracted from voltage and current waveforms. Feature extraction is performed by a sensor installed in the customer premise.

For this particular work, TOPAS 1000 power quality analyzer [20], a product of LEM NORMA GmbH, Austria, was used for feature extraction. It is capable of measuring harmonics up to 50^{th} order. The unit has 8 electrically isolated analogue inputs that can be used for current and voltage measurement. Each channel is equipped with a 16-bit analogue-to-digital converter. Sampling of all channels is synchronous based on a common clock signal. The sampling rate is synchronized with the line frequency and is typically 6400 Hz on a 50 Hz line.

B. Event detection

Changes in the extracted features are detected and classified as events based on static or dynamic thresholds. The information obtained from the event detection stage is required for:

- Triggering the appliance identification (pattern recognition) stage
- Computing the appliance's duration of operation (length of time it was connected)
- Estimating the energy consumed in that period

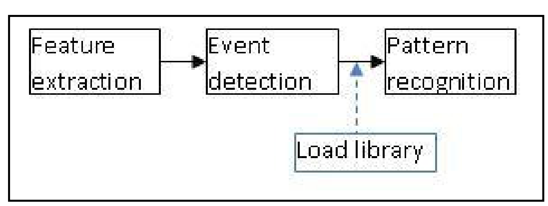

Figure 1. Fingerprinting process.

There are several ways in which events can be defined. 'For example, events can be changes in the average real power exceeding a certain threshold, the appearance of a known start up transient shape or any other suitable condition' [14]. It is possible to select a single method or to have a combination of different methods for detecting events.

After selecting a suitable method, it is necessary to define an appropriate threshold. Previous works such as [3], [6], [7] and [15] utilized changes in average real and/or reactive power for detecting events based on static thresholds. For instance, in [15] changes are classified as events if they exceeded 200 W. Opting for a static threshold presents its own challenges: choosing a large setting means it will not be possible to detect the operation of small appliances and on the contrary, a small setting means the system becomes too sensitive for appliances with large power consumptions.

The event detection technique in our work will employ a dynamic threshold, which allows the detection of events for different appliances over a wide range of real power consumption. The advantage is that the threshold adjusts itself according to the power consumption level of the appliance connected to the sensor, which avoids the need for equipment-specific settings.

The other challenge in event detection is the need to distinguish between genuine events and fluctuations that normally occur during the operation of majority of appliances. Fig. 2 shows the load curve of a sample desktop computer during a half hour operation. In this particular example, only the switch-on and switch-off transitions (marked with bold arrows) shall be classified as events.

C. *Pattern recognition*

At this stage, a set of averaged steady-state load features, captured after the occurrence of a corresponding event, is processed to find its match from a load library using pattern recognition. A study conducted on load monitoring techniques compared the performance of four different training classifiers in noise free (laboratory) as well as real world situations [16]. The tested classifiers were – Gaussian Naïve Bias, 1-Nearest Neighbor (1-NN), AdaBoost and Decision Tree. One of the conclusions of the study indicates that 1-NN algorithm, which is a specific instance of the *k*-NN algorithm (*k*=1), has a decent performance in classification tasks when applied in load monitoring. For the sake of its simplicity and adequate performance, it was studied in further detail so as to explore its applicability in the BeAware fingerprinting process.

The nearest neighbor algorithm was originally suggested in [17] and nowadays it is among the most applied classification methods. Its operation is based on comparing a new record with a set of training records in order to find the ones that are similar to it [18]. The training phase of this algorithm consists of storing the training records and their class labels.

Every record with n attributes represents a point in an n-dimensional space. When given a new record, the k-NN algorithm searches the space for the k training records that are nearest to the new record and then predicts the label of the new record using the class labels of these nearest neighbors.

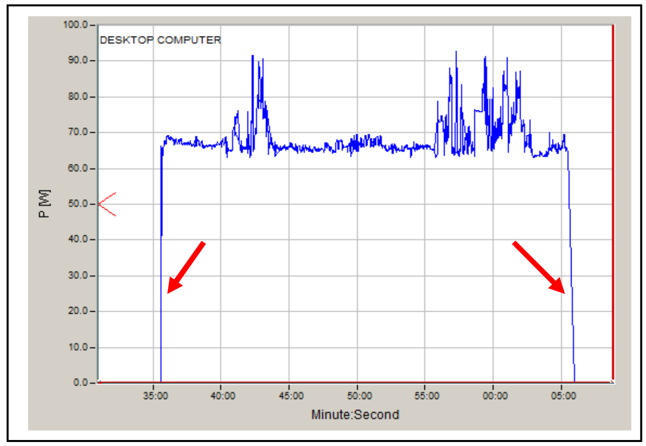

Figure 2. Events and fluctuations during an appliance operation.

In this algorithm, nearness is defined in terms of a distance metric such as Euclidean distance. For any two records consisting of n continuous attributes or two points in an n-dimensional space, $\mathbf{p} = (p_1, p_2... p_n)$ and $\mathbf{q} = (q_1, q_2... q_n)$, the Euclidean distance $\mathrm{d}(\mathbf{p},\mathbf{q})$ is defined as –

$$\mathrm{d}(\mathbf{p},\mathbf{q}) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{1}$$

After calculating the distances between the new record and the respective training records, the resulting values are sorted and k nearest neighbors are selected. A training record will qualify as nearest neighbor if its distance from the new record is less than or equal to the k^{th} smallest distance.

The next step is to provide a classification decision for the new record based on the class labels of the selected k nearest neighbors. Generally, two methods exist: *unweighted voting*, in which the class label most frequent among the neighbors is simply selected as the class label of the new record without considering the preference of the neighbors, and *weighted voting*, in which more weight is given to the neighbors that are closer to the new record.

A common weighting scheme is to give each neighbor a weight of ***1/d***, where ***d*** is the distance to the neighbor. Thus, the nearer neighbors will have more influence on determining the class label than the more distant ones. After weighting the neighbors, the sum of weights of neighbors with the same class label is calculated. Finally, the class label corresponding to the neighbors with the largest sum of weights is selected as the class label (identity) of the new record.

If the features of records, for instance $x_1, x_2... x_n$ of $\mathbf{x}$, are on different scales then it is necessary to remove scale effects. A common way to do this is to transform the records by applying *Z-score standardization*, in which a raw feature

 ISBN: 978-1-61208-100-7

value x_{ij} is transformed using the mean and standard deviation of all feature values, given by the relationship:

$$\frac{x_{ij} - \mu_j}{\sigma_j} \tag{2}$$

where x_{ij} is the j^{th} feature of the i^{th} record, μ_j is the arithmetic mean and σ_j is the standard deviation of all the j^{th} features. The distance calculated using these transformed values is called *standardized Euclidean distance*. For the i^{th} record $\mathbf{x_i}$ and new record $\mathbf{y}$, the standardized Euclidean distance can be written as:

$$d(x_{ij}, y_j) = \sqrt{\sum_{j=1}^{n} (1/\sigma_j^2) * (x_{ij} - y_j)^2} \tag{3}$$

Since the j^{th} mean cancels out when computing the differences between the corresponding feature values, the standardized Euclidean distance is in effect the normal Euclidean distance with a weight attached to the respective squared differences, which is the inverse of the j^{th} variance ($1/\sigma_j^2$).

In order to apply this pattern matching technique in the fingerprinting process, all measured appliances are modeled as records using their steady-state attributes and stored in a load library. Another important aspect is the accuracy of pattern recognition; validation of the classification accuracy is usually performed by using *k-fold cross validation* (also possible with *leave-one-out cross validation* at k=1). The result obtained will be indicative of the classification accuracy for the particular dataset, which is characterized by its number of attributes, size of instances (records) and number of class label types.

D. Load library

The basis for the pattern recognition phase is the preparation of a load library that shall consist of known appliance signatures. Taking into account the parameters that will be measured and transmitted by the sensor, a given appliance can be characterized by the following average values - active power (P), power factor (PF), crest factor (CF), total harmonic distortion (THD_I), fundamental power factor (FPF) and 3rd harmonic, 5th harmonic and 7th harmonic currents.

It is planned to create a large load library using appliance samples, which will be collected during the project trial phase. The information that will be stored in the load library also provides the opportunity to monitor the performance of an individual appliance; for instance, to track any degradation in its efficiency through time.

V. PRELIMINARY FINDINGS

Preliminary tests were done for the event detection and pattern recognition stages using measurement data collected from a number of household appliances during the measurement period, which are listed in Table I.

For the event detection part, an algorithm with dynamic threshold was developed, which detects events using criteria that are defined based on standard deviation of a stream of active power measurement. For test purpose, accumulated active power values (recorded at one second interval) were simulated as incoming data.

The tests done on the available two-state appliances resulted in the correct detection of 87.50% of the total possible *switch-on events* and 90.63% of the total *switch-off events*.

The following points were observed from the event detection tests –

- Switch-on events belonging to appliances with large starting current (such as refrigerators) were not detected. Besides, the falling edge of such an initial spike can be wrongly detected as a switch-off event. Hence, an improvement is needed to search for the first stable transition point.
- In the case of multi-state appliances (such as a fan operating at different speeds), improvement is needed to detect smaller state transitions (other than the two large switch-on and switch-off events, intermediate transitions can possibly occur due to user selection or automatic settings).
- By observing the number of switch-on and switch-off event pairs (especially if they occur within a short period of time as in the case of microwave oven), it is possible to substantiate the output of the pattern recognition algorithm.

TABLE I. APPLIANCES LIST WITH PARTIAL PARAMETER VALUES

	Appliance name	**P [Watt]**	**PF**	**THD_I**
1	Coffee maker	2079.16	0.99	1.24
2	Space heater	1196.09	0.99	0.91
3	LCD PC monitor	33.93	0.51	156.92
4	LED lamp	16.33	0.47	178.93
5	Desktop computer	110.35	0.77	81.60
6	CRT television	84.14	0.76	79.42
7	CRT PC monitor	88.49	0.76	83.19
8	Vacuum cleaner	1119.10	0.96	24.56
9	CFL	14.37	0.57	110.75
10	Table fan	26.80	0.61	12.04
11	Freezer	334.27	0.68	10.23
12	Incandescent lamp	60.83	0.99	1.35
13	Refrigerator	99.50	0.73	8.16
14	Laptop	23.36	0.37	233.61
15	Dishwasher - wash cycle	76.81	0.89	6.17
16	Fluorescent lamp	53.78	0.52	9.42
17	Cloth washer- spin cycle	420.85	0.79	47.04
18	Toaster	754.30	0.99	2.03
19	Halogen lamp	53.88	0.99	1.43
20	Microwave oven	796.87	0.73	27.92

 ISBN: 978-1-61208-100-7

The pattern recognition stage was also tested with the available appliance samples using the nearest neighbor approach explained in the previous section. By removing one appliance record from the load library at a time, the classification capacity was checked for the available records, which yielded an *overall accuracy* of 62.30%.

The respective values for active power (P), power factor (PF) and total harmonic distortion (THD_I) are provided for selected samples from each appliance type in Table I. These three attributes are among the eight parameters used for defining a given sample during recognition phase.

This test is equivalent to a first-time classification, i.e., without prior knowledge about the appliance nature except the availability of other records from the same family of appliances in the load library. For instance, if there are 3 coffee maker records in the load library, one will be removed temporarily and a possible match is searched for this record from the library. It is expected that subsequent re-classifications of the same set of appliances using data acquired from new measurements will have a much improved accuracy owing to the fact that the data obtained from these new measurements will closely match with the respective steady-state features already available in the load library. This is assuming that newer measurements are conducted while the appliance is operating under *normal condition* and also assuming that there is *no degradation* in the performance of the appliance through time.

The first-time classification itself can be improved by increasing the size of the load library via the collection of more appliance samples during the project trial phase. Furthermore, it is planned to improve the overall reliability of the system by modeling the operation of more complex appliances, such as those with multiple states and those performing sequences of tasks, using other techniques such as Hidden Markov Model in conjunction with the nearest neighbor algorithm.

VI. BALANCE SHEET FOR LOAD DISAGGREGATION

The device fingerprinting application relies on information received from the sensor, which at present is designed for precise measurement at socket outlet level. This calls for the development of a supplementary technique to keep track of the consumption that is not directly monitored. The balance sheet application is designed to serve this purpose, i.e., to compute the power consumption of the loads that are not monitored individually and thus disaggregate their consumption and provide their respective energy cost.

Such inaccessible loads are directly connected to the electric supply network, which include significant domestic loads such as electric Heating, Ventilation and Air Conditioning (HVAC). The parameters proposed to estimate these permanently connected loads are electrical consumption and external factors (temperature, season and time of day).

A. Electrical consumption

Electrical consumption share of an unidentified load is calculated by the balance sheet from the aggregate consumption data and individual consumption shares of plugged-in devices. For plugged-in devices, the sensor records and transfers consumption readings of each appliance. The calculated consumption share of an unidentified load is cross-checked with the offline range of consumption profile for common significant household appliances. The reference offline consumption profile is developed from the data gathered during the project trial phase.

When a match is obtained, the system will keep on checking for external factors or indicators to ensure the reliability of the estimation. The proposed external, non-electrical parameters used for load identification are temperature, season and time of day data during operation. Evaluating as many applicable parameters as possible will allow the system to provide a more accurate estimate for load identification. Even if a match is not found from the offline reference, the system still checks for the availability of external parameters indicating the load type. If no related external factor exists, then the load is labeled as anonymous load together with its calculated consumption share from the balance sheet.

B. External factors

The proposed external factors, temperature, season and time of day, are essential parameters to consider for implementing a probabilistic approach in order to estimate significant loads. However, experimental study results are required on each parameter to confirm the relation with electrical consumption. In this project, an indoor temperature reading device will be installed at the base station, which is a measurement gateway installed at each household, and the temperature data will be analyzed with electrical consumption data of significant loads. In addition, outdoor temperature measurement will also be provided as an input to the system.

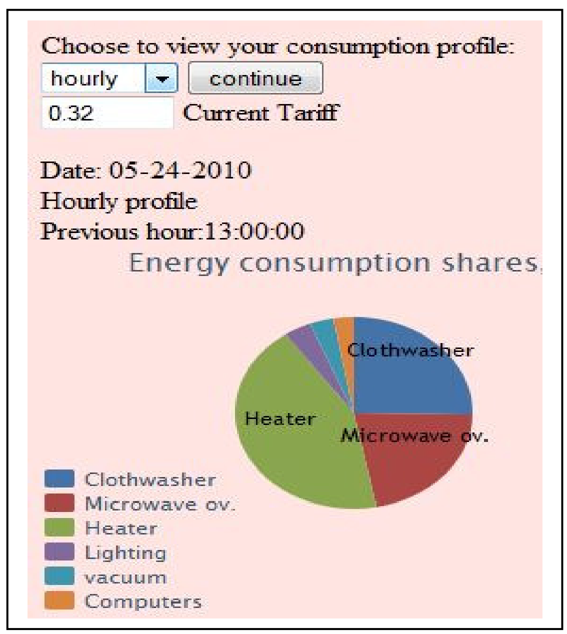

Figure 3. Snapshot of part of the balance sheet model.

Even if the applicability of the parameters is not verified yet using probabilistic approach, practical assumptions were considered for the model balance sheet so as to simulate the load identification. For instance, temperature reading is expected to have inverse relationship with electrical heating system consumption. Air conditioners are likely to operate during the summer season and there is a common time of the day for certain residential appliances to be used.

The model balance sheet developed is a dynamic web page presenting graphically (with a pie chart) consumption shares and cost shares of plugged-in as well as directly connected loads. After estimating or identifying the permanent loads as well as receiving the outputs of the device fingerprinting algorithm for plugged-in devices, their individual consumption is used in the balance sheet calculation. The percentage shares are finally calculated from the individual shares and the total household energy consumption. These percentages are given as inputs to the pie chart, which accordingly displays the consumption shares as shown in Fig. 3.

VII. CONCLUSION

Given the rapid developments in sensor and communication technologies, systems for analysis of electrical power are of great interest to ubiquitous computing for application in energy conservation or recognition of user activities. Different approaches have been documented in the literature about monitoring the total load and trying to fingerprint individual loads by utilizing different parameters from simple instantaneous power through optical interfaces to more sophisticated sensing. We proposed an approach that opens the possibility to integrate sensors also at the plug level as a new commercial solution and also utilizing advanced analysis based on various electrical attributes.

The approach comprises three phases: feature extraction, event detection and pattern recognition. In feature extraction, detailed characteristics are extracted such as active power, power factor and harmonic contents. In event detection, changes in extracted features are detected for triggering appliance identification, computing duration of operation and the energy consumption. The pattern recognition phase starts with a given set of averaged steady-state load features, captured after the occurrence of a corresponding event, and is then processed to find a match from a load library using pattern matching techniques.

The approach has been experimented using a high definition sensor (power quality analyzer) and has resulted in promising findings as well as certain challenges. Some issues were encountered in identifying state transitions of appliances with complex operations and detecting switch-on and switch-off events of certain types of appliances. The pattern recognition phase in this work is implemented using the nearest neighbor approach and it can also be enhanced by employing other techniques such as HMM.

The preliminary results are promising showing satisfactory success rates even with small number of samples in the load library. Such a sensor-based system is foreseen to be applied in real time analysis and monitoring of loads at socket outlet level as well as at whole-house level. This allows the accurate tracking of different appliances followed by the identification of other significant loads from the remaining unknown consumption, thereby enabling the creation of a "balance sheet" of electric power consumption for a specific household.

A fully developed working system needs to overcome a number of problems that include production of hardware and refinement of techniques presented here including collection of a database of load signatures. In addition to appliance monitoring and detailing of loads in a "balance sheet", future applications in the BeAware project [19] will include the development of context aware services with advice tips for energy consumers that are triggered when specific situation arises, for example, when users open too many times or for too long the refrigerator door. Research will have to explore which situations can be exploited in order to provide such services through the utilization of advanced monitoring techniques.

ACKNOWLEDGMENT

This work has been co-funded by the European Union through the 7th Framework ICT Programme in the BeAware Project 224557.

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