Smart meter led probe for real-time appliance load monitoring

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***Abstract*—Non-intrusive load monitoring of domestic appliances has received steady interest in the last twenty years, first because of interest from energy companies interested in usage statistics for power balancing and, more recently, in order to assist users in tuning their habits for reduced power consumption. We discuss how this concept can be used in real-time with a cheap, easy-to-install device based on Arduino to monitor the usage of domestic appliances and thus the activities of persons inside their home. The device is presented, complete with free software and hardware, and a proof-of-concept web-based user interface is depicted that is able to discriminate very simple activities.**

***Index Terms*—Arduino, energy meter, NIALM, AIDL, appliance usage detection**

I. Real-time non-intrusive appliance load monitoring

Load monitoring of domestic appliances has received steady interest in the last twenty years, both due to the attention by energy companies interested in using statistics for power balancing and, more recently, in assisting users in tuning their habits for reduced power consumption. Home automation networks for smart energy [1] have the potentiality to become the main energy management tools to reduce residential energy consumption, but often they require a common communication infrastructure among the household appliances. Whereas new appliances could be manufactured with the necessary communication and control systems, existing appliances would need to be modified. This aspect leads to the need for a non-intrusive, low cost and easy-to-install electrical end-use appliance load monitoring system for buildings.

The term Non-Intrusive Appliance Load Monitor (NIALM) was introduced in the early nineties [2] to identify the technique for disaggregating the entire electric load of domestic houses into major end uses. The main idea of NIALM systems is to obtain appliance-specific time and power draw characteristics by disaggregating the information collected at the main breaker level (or at a circuit breaker level) [3]. In order to do this, a hardware installation (sensor and data acquisition system) that can detect the selected features, is required. Commercially available off-the-shelf sensors exist on the market, such as The Energy Detective (TED) [1], Brultech ECM-1240 Energy Monitor [2], Blueline PowerCost [3], Wattvision [4], and Sequentric [5]. These solutions use two main hardware approaches. The first one is based on the Current Transformers (CTs) clamped around the main incoming wires from the utility service provider inside the breaker panel. The second one is based on a smart meter front-mounted infrared LED that reads electricity usage in real time via optical readers and transmits wirelessly or on powerline to a paired receiving devices in the home. These devices provide the information with a typical sampling rate up to 1 Hz and a sensitivity up to 1 Watt.

NIALM algorithms suitable for such sensors have been detailed in several publications [4]–[6] showing how to detect step changes in power and how to match these changes with the appliances being turned on or off. These algorithm are evolutions of the original NIALM method developed by MIT [2], where a cluster analysis algorithm is applied to the two-dimensional signature space of real and reactive power of the appliance's load. In [5], authors propose an extension of the MIT method in order to recognize additional "macroscopic" signatures such as spikes in power draw, typical of appliances like heat pumps, dishwashers, or refrigerators. Another interesting NIALM technique is the one developed in [6] based on conventional power meter systems complemented by optical sensors that continuously monitor the overall real power per second.

Following the approach proposed in [6], we present an inexpensive hardware solution based on optical sensors applied to the most recent smart meters. Our solution infers the domestic electric consumption from the readings of the smart meter's led flashes and, using a Finite State Machine (FSM), it recognizes the most common appliances, e.g. ovens, used in domestic activities. Smart meters are currently deployed on national scales [7], thus constituting an ideal data collection gateway for NIALM solutions. We chose to implement a smart meter led probe also because using such an inexpensive device makes easier the installation and maintenance of the system. The proposed solution is based on an open source

[1]http://www.theenergydetective/

[2]http://brultech.com/products/ECM1240/
[3]http://www.bluelineinnovations.com/powercost-series
[4]http://www.wattvision.com/
[5]http://sequentric.com/

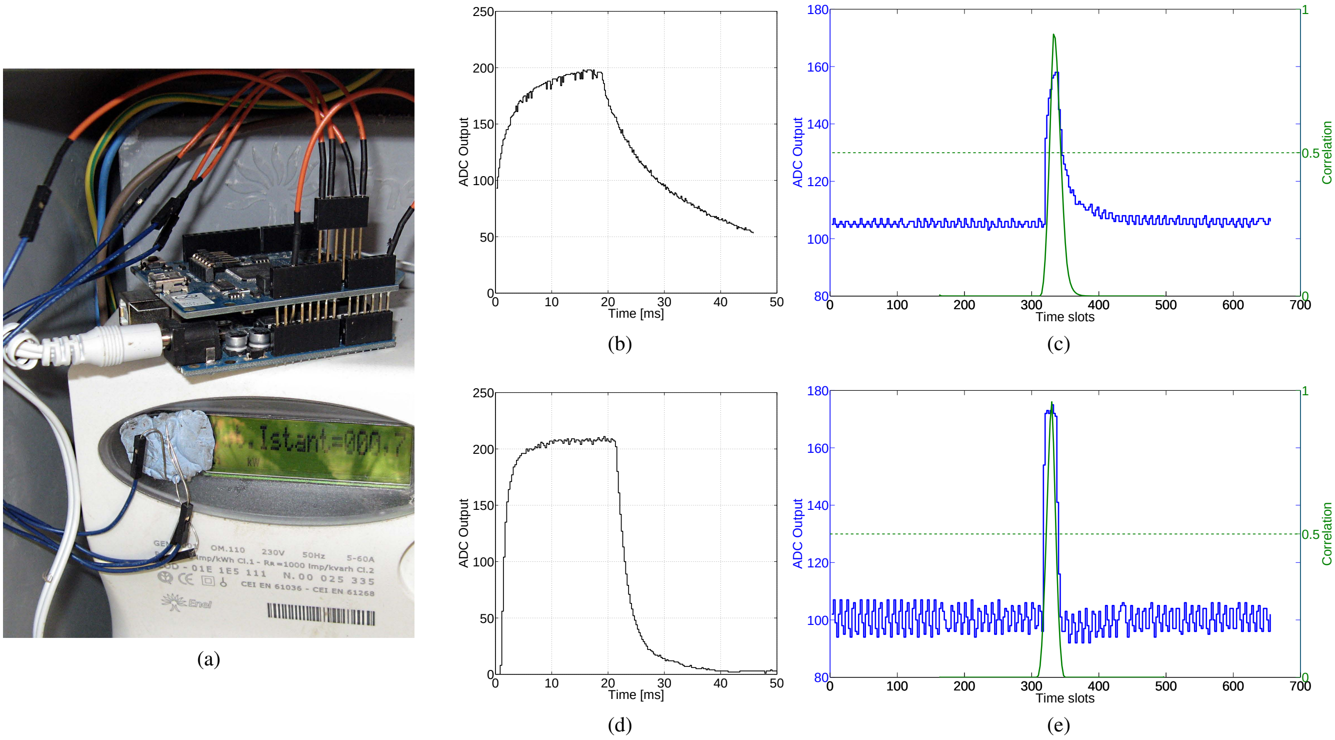


Fig. 1: (a) The proposed solution installed in test house using blue-tack to connect photoresistors. (b,d) The responses of the photoresistors used in the proposed system. (c,e) The correlator output superimposed to the photoresistors' responses.

and open hardware system, built upon the Arduino [6] platform. We embrace the open source and hardware principles in order to offer a system easily modifiable to suit the user needs and to be used as the basis for new products. Many authors based their work on this kind of platform to perform appliance load monitoring by means of standalone plugload meters [8], [9], wireless sensor networks [10], and dedicated microcontrollers [11], offering different levels of connectivity [12]. We focused on the non-intrusiveness of the system developing a single device easy to install and embedding a light webserver in order to avoid dedicated software infrastructures to get real-time information about the energy consumption and the usage of domestic appliances.

The ability of recognizing in real-time the usage of domestic appliances becomes relevant in the more complex scenario of the activity recognition in smart environments. The device proposed in this work aims at being the core component of an Ambient Assisted Living [7] (AAL) system [13] to be deployed in smart homes. Domestic appliances, like ovens, washing machines, or hair dryers, are used in typical Instrumental Activities of Daily Living (AIDL) [14], like feeding, doing laundry, or grooming. Monitoring these tasks is important to determine the level of independence of people, in particular elderly living alone. As a preliminary result, we show the ability of the system in recognizing the usage of a domestic oven that is strictly connected with the IADL (Instrumental activities of daily living) "preparing meal" of the feeding category. Using a simple web interface, a caregiver can remotely monitor this activity. The presented system is released with open source license and it is available in [15].

[6]http://www.arduino.cc
[7]http://www.aal-europe.eu

II. The Proposed Solution

The smart meter currently deployed by Enel in about 27 million houses in Italy [7] provides real-time information regarding the active and reactive power consumption of an house by means of two LEDs blinking one time per Wh and one time per Varh consumed respectively. When there is no consumption in the active or reactive power for more than twenty minutes, the corresponding LED remains on until the next activation. The proposed system gathers this information by means of two photoresistors (Figure 1a) connected to the analog inputs of an Arduino board in order to detect the LEDs blinking.

Blink detection passes through three phases. In the first phase, every 2.5 ms, if the power of the signal recorded by the sensor in a sliding window of 225 ms (equal to 90 periods of 2.5 ms) exceeds a small threshold (10% of the maximum ADC output), covariance is computed respect to three prototype responses. Each response is a 20-ms rectangular blink passed through a 1-pole filter with time constants of 5, 12 and 30 ms in order to account for different photoresistors found on the market. The three prototypes allow for a good match of photoresistors having response times in the range from 0 to 50 ms, and a reasonable match for slower devices.

In the second phase, for each prototype response, if covariance turns out to be positive, then correlation is computed. If correlation exceeds a threshold of 0.5, then a blink has been detected.

In the third phase, the correlation is tracked and its maximum value is stored. An envelope detector is applied to guard against cross-interference form the other blinking led. The envelope detector decays with a time constant of 128 blinks.

Figures 1b and 1d show the responses of the two different photoresistors used (with response time of 20 and 2 ms respectively) when a blink occurs (one Wh or Varh consumed). Figures 1c and 1e show the output (green line) of the implemented correlator applied to the response of the corresponding photoresistor. In the figures, the output of the correlator is superimposed to the response for clarity. Using a correlation window of 90 time slots of 2.5 ms, we obtain a significant output after 45 time slots. We chose a short correlation window in order to save memory and CPU time, loosing a non-significant amount of accuracy. Furthermore, since the smart meter's LEDs blink faster when the grid consumes more power, setting a longer correlation window would introduce an upper limit to the maxim power that can be read by the system.

As stated in [2], domestic appliances like ovens, washing machines, or hair dryers behave as FSMs. This kind of devices are very useful to infer IADLs. For this reason we chose to implement an FSM embedded on the proposed Arduino platform in order to recognize as proof-of-concept one of these devices, in particular a microwave oven. The FSM has been implemented reflecting the states changing of a typical microwave oven (Figure 2). It passes through intermediate phases (going up and going down) between two cyclic up/down states. This cycle is repeated until the appliance is turned on. When the oven is turned off the FSM returns to the idle state.

The proposed FSM is composed by 5 states; namely idle, going up, up, going down, and down. The initial state is the idle state and there are two inputs that affect the state of the FSM: the difference between the last measured power and the current power ΔP and the current power P. The FSM changes its state according to thresholds in ΔP and P (that correspond to the power consumption of a particular model of microwave oven), and when a significant change in reactive power is measured. The following section shows the performance obtained by the proposed solution in recognizing the chosen appliance.

III. Monitoring performance

The proposed solution has been tested in a real house. In this residential house lives a family composed by three persons. We monitored the power consumption of the entire house for six months. Figure 2a shows the web interface created to monitor in real-time the active and reactive power consumed in the house (green and blue lines, respectively). This simple visualization could give to the reader some useful information such as the power consumed by the house even in absence of activities (i.e. the power consumed during the night). More in general, we are able to discriminate when the house is uninhabited or not.

A. Qualitative Analysis

As a proof-of-concept, we tested the proposed power monitoring solution to infer when the electrical microwave oven was on. The graphical interface is able to put an orange marker M when the microwave oven is turned on, while a green M when it is turned off. Figure 2b shows how the electrical power consumption changes when the microwave oven is turned on. The active power increases of about 1500 watt and oscillate every 20 seconds and this behavior is captured by the FSM that correctly marks the appliance usage.

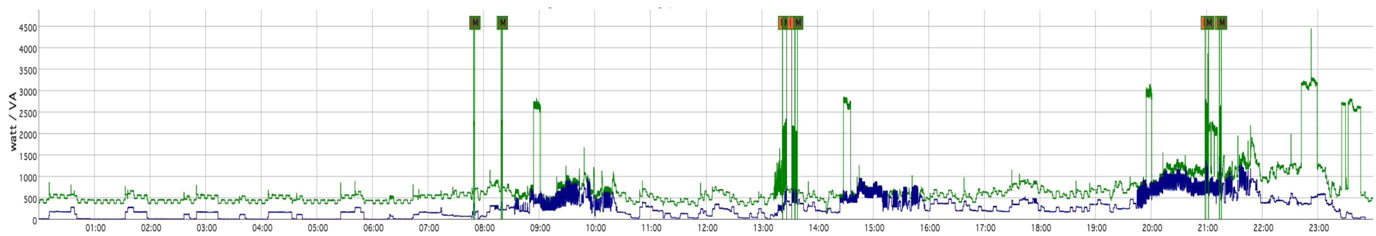
As highlighted in Figure 2c, sometimes the FSM infers that the microwave oven has been turned on later, or it marks that the microwave oven has been turned off before the real usage. This happens when simultaneous to the microwave oven even other appliances are turned on/off. However, in order to infer the IADL activities and the behavior of the users, the exact instant which the user turns on/off the appliance is non influential. Therefore, in the following analysis we will mark these cases as correctly identified by the FSM.

B. Quantitative Analysis

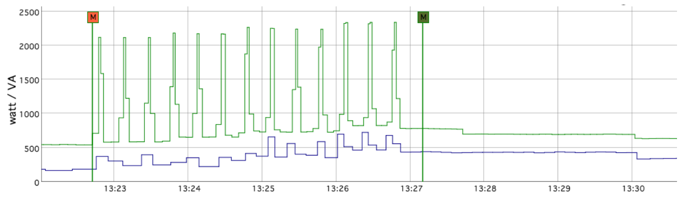
During the six mouths the microwave oven has been used only 168 times for a mean time of about 3 minutes. As a consequence, in this period, the microwave oven was turned on for about 500 over more than 259000 minutes. Therefore, since the use of the microwave oven is a spurious event, a fair analysis requires the use of a statistic that take into account the True Positive (TP – the system realizes on and the microwave oven is turned on), the False Negative (FN – the system realizes off and the microwave oven is turned on), and the False Positive (FP – the system realizes on and the microwave oven is turned off). The performance results will be then evaluated measuring the true positive rate (also called sensitivity or recall), and the positive predicted value (also called precision). The recall relates to the test's ability to identify a correctly condition (i.e. the number of correct results divided by the number of all returned results), while the precision represents the number of correct results with respect to the number of results that should have been returned. Precision and recall are then defined as:

$$\text{Precision} = \frac{\sum TP}{\sum TP + \sum FN} \qquad \text{Recall} = \frac{\sum TP}{\sum TP + \sum FP}$$

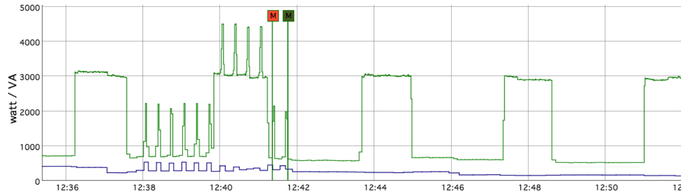
We achieved a recall of about 95% and a precision of about 84%. This means that in 95 percent of cases the system infers that the microwave oven is on when it was really turned on, while some times (16 percent of cases) the system didn't recognize it. In order to measure the overall accuracy we evaluated the F_1-measure and G-measure. Indeed, they consider both the precision and the recall of the test to compute the scores. The F_1-measure can be interpreted as a weighted



(a) Example of the reactive (blue line) and the active (green line) powers during a day long



(b) Changes of the electrical power when the microwave oven is turned on



(c) Delay in distinguishing that the microwave oven was turned on

Fig. 2: Long term monitoring of the electrical power consumed in the house

average (harmonic mean) of the precision and recall, while the G-measure represents their geometric mean.

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad G = \sqrt{\text{Precision} \cdot \text{Recall}}.$$

The experimental F_1-measure and G-measure of the proposed system reach about 89% and 87%, respectively.

IV. Conclusions and Future Works

In this paper we present a NIALM system able to provide real-time data thanks to a cheap, easy-to-install device based on Arduino. The proposed system embed a FSM that detects the usage of a domestic appliance chosen as proof-of-concept in order to recognize the associated activity of the user. The device is presented, complete with free software, hardware, and a web-based user interface. Results show that it is possible to discriminate when the microwave oven is used (therefore the associated IADL) simply observing the cumulative power consumed by the house. Indeed, in the 95% of cases the system infers that the microwave oven is on when it was really turned on, while in the 16% of cases the system didn't recognize the "preparing meal" activity. In future works, we plan to extend the capabilities of the proposed system implementing a more complete set of recognized appliances. Integrating learning techniques, would be possible to automatically set up the correct thresholds for ΔP and P to be used with FSMs.

Acknowledgment

This work was supported by the EU Commission in the framework of the GiraffPlus FP7 project (Contract no. 288173).

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