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Abstract—Appliance load monitoring systems are designed to disaggregate the power load of a building in order to estimate the nature of individual loads, providing a real-time fine-grained recognition of active appliances. Monitoring nonintrusively appliances’ contributions to a given load enables a wide range of applications, ranging from electricity bill decomposition to accurate electricity user profiling. This work demonstrates a real implementation of such appliance load monitoring system. An intuitive graphical user interface is proposed to drive the system setup for profiling appliances’ signatures and for visualising the monitoring output.

I. INTRODUCTION

Electricity represents 41% of the total energy used in the Unites States [1]. However, the efficiency of the current electrical system is poor, mainly due to the impossibility to monitor in real-time consumers’ consumption, preventing both accurate electricity usage profiling important for the electricity providers and immediate feedback to users for awareness. Subsequently, about one third of electricity is wasted [2]. Recent advances in wireless communication are changing the deal, allowing near real-time transmission of electricity readings to both electricity providers and electricity consumers. The lengthy and expensive integration of smart meters, part of the grand plan to modernize the electric grid [3], as well as the quick and cheap installation of home electricity monitors are paving the way to an efficient electrical system and high energy savings.

II. APPLIANCE LOAD MONITORING AS ENABLERS FOR ENERGY EFFICIENCY

The installation of smart meters and electricity monitors provides readings of a building power load. Feedback based on raw data to the user is however not sufficient for concrete action; home occupants may realise their consumption is too high compared to previous periods or to similar users, but they may not know how to react. Appliance load monitoring (ALM) systems have been designed to disaggregate the power load of a building in order to estimate the nature of individual loads, providing a real-time fine-grained recognition of active appliances. Monitoring nonintrusively appliances’ contributions to a given load is the enabler for acquiring the valuable information from a power flow, opening a wider range of applications and feedback to users and utilities, ranging from electricity bill decomposition to accurate electricity user profiling.

III. DEMONSTRATION OF APPLIANCE LOAD MONITORING

This work presents implementation details of the RECAP appliance load monitoring system, and its integration within an intuitive graphical user interface used to drive the system setup and to visualise the load monitoring output.

A. Architecture

The demonstration of appliance load monitoring that is presented is built following the architecture shown in Figure 1. A PC-class storage unit receives data from a single electricity monitor clipped to the live wire of a power strip, replacing the electric fuse box, where a set of appliances are plugged. We use the ZEM-30 electricity monitor from Episensor, which provides a large number of electrical measurements, ranging from real power, power factor, RMS current, and RMS voltage to peak current and peak voltage of the total load [5]. Data is stored on the PC-class machine into a database for further use by RECAP. A PC-class processing unit accesses the data and runs RECAP to disaggregate the power load. Interaction with users is done via the graphical user interface.

B. RECAP processing and user interfacing

The Recognition and Profiling of Appliances (RECAP) system is an intelligent system developed at CLARITY designed to recognise appliance activities in real-time, using a neural network machine learning technique [4]. As with similar systems, RECAP requires an initial one-off procedure where home appliances are successively profiled for recording their power footprints or signatures. Once the signatures recorded, RECAP trains its neural network to tune the neuron weights, terminating the setup phase.

Interface with the user is provided by a graphical user interface (GUI) implemented with Processing [6]. The GUI intervenes at two stages in the process, for handling the acquisition of appliances’ signatures and for visualising the disaggregation output. RECAP processes for profiling appliances, training the neural network and monitoring appliances loads are implemented in Java, and packaged in Processing libraries for integration in the GUI. As per Processing programming model, the RECAP libraries are imported, thereby making the interface between the GUI and RECAP processing via API calls to libraries functions. This software architecture has been chosen to disentangle these two large pieces of code for reuse.
and easy debugging. Figure 2 shows two GUI snapshots, taken during the profiling and monitoring stages.

The presented ALM system has achieved an average 87% recognition accuracy in deployment [4]. During the demo, users will be able to profile and operate the provided appliances, guided by the graphical user interface, demonstrating that minimal human supervision is required. Figure 3 shows the demo, comprising the power strip, the electricity monitor, the two PC-class units, and the set of appliances that are monitored.

### IV. Conclusions

This work demonstrates the feasibility of real-time appliance load monitoring. As a powerful tool to disaggregate power loads, it provides valuable information for enabling energy efficient solutions, ranging from recommendations systems and electricity billing decomposition, to accurate electricity profiling of residential and commercial buildings.

Deployment of the presented system is ongoing in a commercial building, obtaining electricity data from a 3-phase electricity monitor to profile HVAC and heating systems.

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