Direct, Instantanious Identification of Home Appliances

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Abstract*—*This paper discusses a combination of low cost hardware and software solution to direct, instantaneous non-intrusive load monitoring (NILM) and energy desegregation of individual home appliances as the first step in enabling better demand side energy management and power brokering; matching power companies imperative needs of reduced peak demand and flattened load profile with user's expectations of lower costs and higher service level; with an emphasis on methods and equipment needed for load monitoring, including identification of individual loads by non-intrusive methods.

Keywords*—*peak demand; load monitoring; load identification; non-intrusive; load profile; energy disaggregation.

I. INTRODUCTION

Peak demand requires a disproportionate share of generation and network investment and drives up the cost of electricity [1] and capital expenditure to accommodate peak load growth in Australia accounts for nearly half of total network investment and slightly more than half of all transmission spending [2]. This equates to over AU$ 1 000 per customer over the lifetime of the latest 5 year electricity price determinations.

The increasing cost of peak energy has been a major contributor to the overall increase in electricity prices, with retail electricity prices increasing by around 50 per cent in real terms from June 2007 to June 2012 [2].

Fig. 1 shows Australian household electricity prices divided by the CPI average, showing how much household electricity prices have increased above inflation.

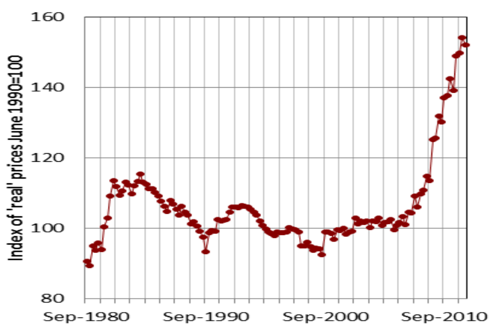

Fig. 1. Real Australian household electricity prices [2].

Peak demand is a growing problem for electricity supply systems world-wide as electricity network infrastructure is designed to cope with the peak demand and the cost is simply passed on to consumers [3]. However, as these critical peaks are of relatively brief duration, the full capacity of the electricity system is under-utilized for most of the time [3].

II. MANAGING PEAK DEMAND

The New Zealand government is interested in exploring the potential for improving energy efficiency through smart technology. But the successful deployment of appliance demand response is contingent on the implementation and adoption of other elements of the smart grid, including advanced metering devices and appropriate tariff structures [2].

III. INTELLIGENT MONITORING AT HOME

Our past research into the identifying disturbing loads [4] and our subsequent research into non-intrusive load monitoring (NILM) and identification [5] indicated that new methods and equipment were needed for load monitoring, including measurement and identification of individual loads by non-intrusive methods.

There was an expectation that 'smart' domestic meters would have the intrinsic ability to acquire the power usage status of devices in a residence. Smart meters were expected to support time-of-use metering and two way communication between households and electricity supplier for demand side flexibility [7]. However most of the advanced meters were installed without 'smart' capability. The two main reasons for the installation of advanced meters without the smart home area network (HAN) facility are firstly the HAN chips were based on open access XBee technology and secondly the non-availability of 'smart plugs'. Proliferation of intelligent consumer DR-enabled devices at residences that can be connected directly to the Smart meter will not happen immediately; neither will the existing residences be rewired to implement smart meter functionalities over a short period of time [6].

IV. HARDWARE DEVELOPMENT

The promise that so called smart meters brought was never realized as (in NZ at least) smart meters just aren't so smart, so in order to get to the expected smarter, energy wise future we desire, a range of smarter demand side technology is needed.

This section outlines research into the development of the hardware needed for NILM; to measure, monitor log and analyze end user load data to identify each individual load. This work lays down the foundation for a new smarter energy wise future.

For many domestic loads the power we need to measure is in the order of Watts and fractions of Watts, especially when the loads are in standby mode where we need to resolve the power into the mWatt range, implying that we are measuring current down into the µAmp range. This is required to provide accurate readings to the software with the required resolution.

Most small loads (and many large loads when in standby) draw very little energy from the grid, and much of this energy is in the harmonics and not in the fundamental.

In order to achieve our objective of load identification through harmonic analysis, the hardware needs to resolve currents as low as 50µAmps at frequencies as high as 4 kHz with as close to zero phase difference between current and voltage signals as possible.

We went through several iterations of the first stage of the hardware, the sensors and the Signal Conditioning Unit (SCU), and found that the traditional, low-cost, 'off the shelf' current and voltage sensors, while perfectly acceptable when measuring most equipment under normal load conditions, are incapable of accurately sampling the true instantaneous voltage (v_i) and current (i_i) under the ultra-low signal level conditions found when measuring small loads and even big loads when in standby mode. More expensive devices are available such as those used by Gupta et al. [9] may be equivalent, however they detract from our goal of a low cost domestic solution. The relatively high power drawn by traditional sensors also means that they add to the background "noise" and so hide the signal, as the noise level can become higher than the signal we need to measure.

After experimentation, we chose to develop our own matched pair of voltage and current sensors and a new "Zero" approach for the SCU which calculates the standby current drawn by the unit under test by determining what current is needed to cancel out the current coming from the sensors and using this to accurately represent the actual voltage and current, while drawing zero current from the circuit under test.

The first stage of the hardware, the sensors and the SCU, delivers two analog signal streams; one representing the instantaneous voltage (V_i); the other representing the instantaneous current (I_i). The next stage, the Analog to Digital Converter (ADC), is still under development, so a dual channel external sound card is currently being used as the ADC temporarily, so as not to hold up the software development. See Fig. 2.

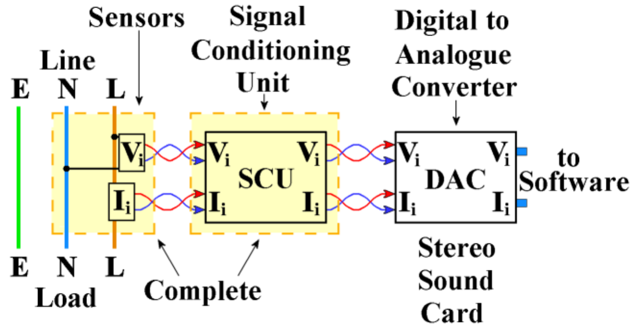

Fig. 2. Status of Hardware Development.

The task of developing the Analog to Digital Converter (ADC) is not easy as we are working at the limits of the capabilities of some of the best ADCs available, while still providing a low cost solution. However, it is expected that this work will be satisfactorily completed by the end of 2014.

Although, still under active development, the current hardware is working as expected while meeting our goal of a low cost solution. The first prototype cost approximately NZ$ 100. This could conceivably be cut much further with further development. TABLE I. lists overall costs for the first prototype.

TABLE I. ESTIMATED HARDWARE COSTS

Item	Cost
SCU	NZ$ 30
ADC (Sound Card)	NZ$ 50
Housing and Connectors	NZ$ 20

V. SOFTWARE DEVELOPMENT

A. Goals

This stage of the research creates a low-cost hardware and software solution. Here we discuss the software framework constructed with the main goals being to;

- discover the sample specifications to achieve the confidence and accuracy needed for energy disaggregation.
- show that the harmonic signal analysis algorithm we have devised will be able to identify multiple loads simultaneously.

B. Approach

The framework for the monitoring tool has been built with the intention of further development into a commercially viable product. To allow for flexibility in experimentation and easy adaption of the process, the framework comprises loosely connected modules, each performing part of the process. Modules can be added, removed and rearranged without needing to rebuild or restart the application. Each module may also be developed to run in parallel with any linked modules, allowing for scalability and faster processing times, see Fig. 3.

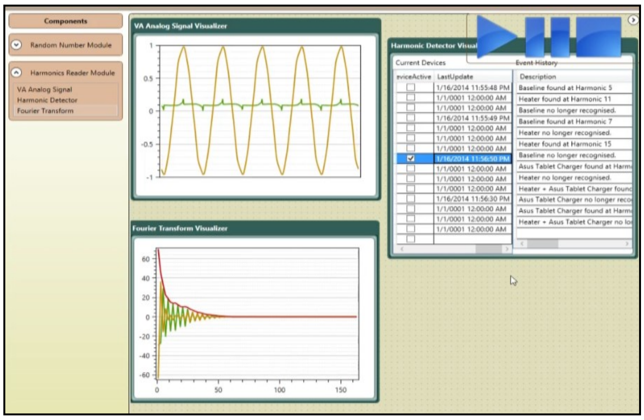

Fig. 3. Framework Running Harmonic Signature Analysis.

The framework accommodates multi-threading and module outputs are streams made available as inputs to other modules, making the framework well suited for real time monitoring. Historic analysis is also possible with no modifications. The framework uses the analysis algorithm shown in Fig. 4 to perform the monitoring of loads.

The following modules have been built:

a) Signal processing – The first phase is receiving the input data from several sources, either in real time from the Hardware or as 'historic data' using file formats such as the Reference Energy Disaggregation Dataset (REDD) format [8].

b) Pre-processing – Errors created by the hardware need to be eliminated and a Fourier Transform is performed.

c) Load Identification – The load identification phase consists of multiple connected where the identification algorithm is applied and the confidence of an event occurring returned. Nodes are executed in sequence until a confidence threshold has been achieved. The event is then displayed with its confidence level.

d) Visualization is required to gain understanding of how the system is function and perform any testing and debugging. These visualizations will only be required for research and for design purposes in the final product. Fig. 3 illustrates some of these visualisations.

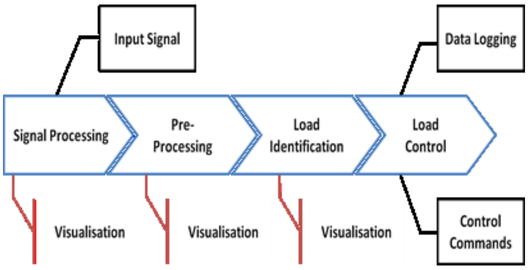

Fig. 4. Analysis algorithm.

e) Data logging - to displays household energy status. A number of other modules will be built, such as interfaces to advanced metering infrastructure and Demand Response Enabled Devices (DRED's), and storage mediums such as internal databases and clouds.

C. Current Status

The framework has been completed but will require more polish before it is released; ideally with instructions for anyone to build their own modules and perform further experiments.

Using the framework, we developed a series of modules that can be linked together to process the instantaneous voltage and current information provided in a digital form by the hardware.

The first step is to receive the input data through a signal processing module. In each version the data is a block of 6652 bytes. Each sample is 4 bytes divided into a current value and voltage value of 2 bytes (16 bits) each.

The samples are converted into a format suitable for processing. The voltage and current values are time-stamped and sent through as two separate streams which are linked to inputs on the next module for further processing. There is also another module that reads current and voltage values from a Comma Separated Value (CSV) file for testing. The current signal is then passed into a Fourier Transform and then onto the load identification module.

Load identification is the most important part of the algorithm. This is planned to utilise a number of different algorithms in combination, however, the current version only uses harmonic signature analysis. Load identification is performed by matching the transformed signal to harmonic values in a signature database. These signatures are formed by recording the FFT value for the fundamental frequency and the value of each odd harmonic up until the point that the value is less than a specified threshold.

Matching begins with the fundamental frequency and calculates an adjusted distance value to the most likely devices. That is the one that is the closest match with both the real and imaginary parts of the harmonic.

The result of this calculation is added to a confidence counter and a check is performed to see if this value is above the set threshold. Comparison continues until either the confidence threshold is reached or the 21st harmonic is reached.

Finally, the device is marked as active and a timestamp attached if the confidence threshold is reached. If the 21st harmonic has been found and the confidence ratio is not reached, then no devices are recognised. If a particular device is not recognised with a pre-assigned timeout period, the device is marked as inactive again.

This approach allows all the processing to be viewed in real time. The signal processing displays the raw input from the hardware. The pre-processing library displays a subset of the Fourier series from the processed signal. This subset is the value of the fundamental frequency and every odd harmonic up to the sample rate.

Currently, data logging is optional and is performed by writing the various streams out to a Comma Separated Value

(CSV) file which can be analysed in excel. This will be expanded to be record values to a variety of formats.

VI. Related Work

The field of NILM research has expanded quickly in recent years and the work we are doing builds on that of many others in this field.

For instance, Gupta et al. [9] provides much insight to a variety of monitoring techniques. Our work could be classified as Infrastructure-Mediated Sensing similarly to that presented. Our work is focussed on low cost current measurement, minimal detection speed (~1sec.) and steady state signals rather than transients. This has the disadvantage of requiring the sensors to be in series with household load. For example, at the meter or circuit breaker instead of at a single plug point. The advantage it shares with approaches such as that taken by Parson [10] in his thesis are that detection may occur with minimal training or none at all depending on signatures used. The steady state features extracted via harmonic analysis of the current signal is closely following the approach of Chiang et al described in Load Disaggregation Using Harmonic Analysis and Regularized Optimization [11].

VII. Results

The approach we have taken has allowed for easy experimentation and the ability to adjust the algorithm to achieve more accurate results faster.

To prove that our technique could be used to disaggregate multiple loads of similar type and different types, we used a wide range of loads such as heaters, lamps, small appliances and external power supplies.

Initially the input signal from the first iterations of the hardware was not stable enough to accurately differentiate between multiple loads although each load could easily be correctly identified on its own. After introducing the new "Zero" concept hardware which provided a stable signal; and making adjustments to the pre-processing module to remove dc offsets and other noise created by the sound card ADC, this was greatly improved.

TABLE II. Accuracy of Initial Tests

	Average Timing			**Events**		
Load	**Actual On Time**	**Estimated On Time**	**Accuracy**	**Act.**	**Est.**	**Err.**
1kW Heater	116	228	50.65%	6	10	4
75W Light	128	141	89.28%	2	6	4
Charger	126	85	66.55%	4	8	4
Total	370	454	81.50%	12	24	12

These results indicated that further improvements are required if we are to meet our desired goals. Therefore we will continue our efforts to make these improvements.

We have undertaken a number of tests to ascertain the accuracy of the current setup. These results are described in TABLE II. The timings are averaged over 5 minute blocks with the number of actual, estimated and erroneous events included.

VIII. Conclusion

In conclusion, the New Zealand government is interested in exploring the potential for improving energy efficiency through smart technology. Accurately identifying and monitoring loads individually in a more considered way using direct and instantaneous NILM and energy desegregation of individual home appliances is the first step towards better understanding demand side energy usage.

Previous research showed new methods and equipment were needed to more accurately identify loads. Several iterations of hardware and accompanying software have been developed. However, existing results indicate further improvements are required to both the hardware and software.

This development is expected to eventually lead to satisfying the imperative need of reduced peak demand and flattened load profile and the end user's expectations of lower costs and higher service levels.

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