

Closure Rules for Energy Load Disaggregation

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SUMMARY

We describe our recent findings related to improving the accuracy of event based Non-Intrusive Appliance Load Monitoring. The results are based on experimentation in residential and industrial settings. We describe the use of closure rules to resolve the state of an appliance when the total circuit power has returned to a previously resolved steady state.

Keywords

NIALM, state models, transitions, load disaggregation.

ABSTRACT

NIALM is a technique to provide *disaggregated* feedback by monitoring electrical current flow into the house at the circuit breaker box. A computer algorithm to separate individual loads was first developed by Hart (1992) and Leeb (1995).

NIALM methods have improved with published innovations from EPRI (1997), Pihala (1998), Drenker and Kader (1999), Marceau and Zmeureanu (2000), Baranski and Voss (2004), Lee et al. (2005), Berges et al. (2008), Liang et al (2010a and b), Chang and Lin (2010), and others. These approaches largely focus on using the metrics associated with the transition period when an appliance turns on or off and have accuracies of 80% to 95%. Due to the lucrative potential of products developed with NIALM technologies, many recent and relevant innovations remain trade secrets or are hidden until a patent publishes. Few details are available about the performance and accuracy of products developed by Belkin, GE, IBM, Intel, and others. A literature survey and technology assessment by Ziefman and Roth (2011) showed that this was an accelerating field of development with increasing numbers of US patents granted from 0.3 per year beginning in 1989 to ~4 per year in 2010. The 2011 study summarized several of the published methods in terms of specific shortcomings (i.e. *Variable Loads*, *Multistate Loads*, *Same Load Appliances*, and *Always On Loads*).

Load IQ's patent pending approach addresses each of the shortcomings identified by Ziefman and Roth with the exception of Always On Loads that never turn on or off and are inherently tracked as a single inseparable load. Through repeated examination of archived datasets from Load IQ's testing in residences, it became clear that it was necessary to separate the on transition signatures from the off transition signatures. This realization created a problem in that a new approach was needed to link those two unrelated transition signatures to a single appliance. A major breakthrough in the accuracy of the NIALM algorithm came with the implementation of *closure rules* that exploit the simple fact that the baseline power signature of a circuit should be the same before and after an appliance is used when no other appliance changes state.

The steady state before the on event is the same as the steady state after the off event, thus a closure rule can be generated to link these two transitions to the one appliance. Using this rule, our algorithm is able to link together transition signatures from appliances that turn on and off with different amounts of power

(i.e. refrigerators, fluorescent lights, HVAC fans, etc). In most cases, an appliance's on transition will not immediately be followed by the corresponding off transition. Whenever a steady state is observed to repeat a closure rule is created that implies all appliances actuated in the interim have returned to their original state. As closure rules are accumulated, the more complex rules can be simplified by eliminating the shorter and simpler rules within them. For example, a light may be on for two hours and the oven may run while the light is on. The power cycles of the oven may be removed from the light's closure rule leaving the matching on and off transitions of the light.

Based on these principals, our approach can efficiently process a week's duration of data and extract closure rules that range in length from the trivial (rule of length one), to simple switching of a two state load (rule of length two), to matching combined transitions of two loads that turn on at the same time (rule of length three), and interleaved two appliance actuation (rule of length four). More complex rules involving interleaved switching of three or more appliances can also be detected and solved using transition linkages extracted from shorter rules (Figure 2). Using this approach, Load IQ addresses Ziefman and Roth's first shortcoming *Variable Loads* that have on and off transitions that are not simply the inverse of one another.

Multistate Loads (i.e. load such as front loading washer, plasma TV, or Variable Speed Drives (VSDs) by identifying matched loads that only occur when a baseline load is present (e.g Figure 2).

The closure rule approach reduces these complex loads to a finite set that only occur when the baseline load is present. This feature enables the algorithm to automatically find Multistate Loads without user intervention.

Same Load Appliances refer to indistinguishable loads that have identical transitions. Prior to the use of closure rules, NIALM techniques could not distinguish if two identical sequential transitions represented two identical appliances changing state or that the algorithm had not detected one of the inverse transitions. Application of closure rules enable multiple instances of indistinguishable loads to exist concurrently. Although the multiple appliances are indistinguishable, this information can be used to detect if one of the group begins to malfunction and consumes power in a different way from the other members of the group.

Load IQ applied these concepts in an industrial test facility in Nuremberg Germany in October 2011. Use of these principals isolated the three largest loads above a predefined clustering threshold with ~97% accuracy over two days of operation and dozens of power actuations (Table 1). In this example, the robots were not accurately resolved due to the fact that they completed their tasks in only 3 seconds which was roughly equivalent to the minimum defined steady state duration. Parametric modifications may be implemented to isolate the power used by short duration loads.

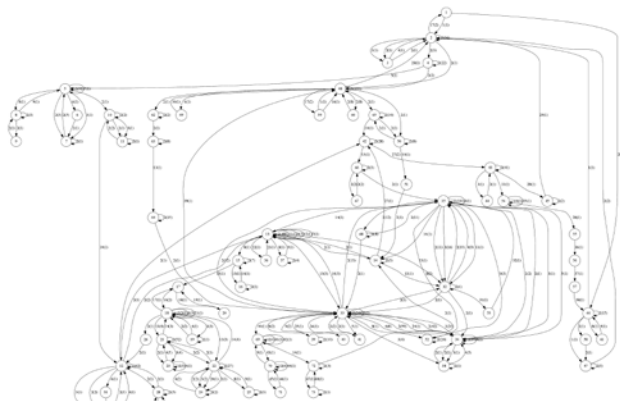


Figure 1. Example of more complex closure map from real measurements. Circles represent steady states and arrows represent transitions.

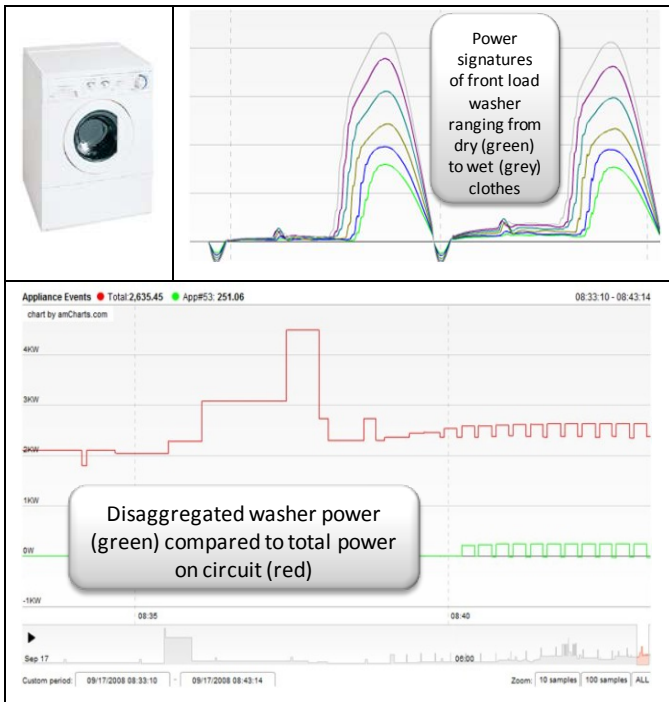


Figure 2. Grouping variable-load appliances that have different signatures based on load or mode of operation.

The closure method uses the combined information in the transitions and the steady states to improve the overall accuracy of the NIALM approach over the conventional transition matching method.

ACKNOWLEDGEMENTS

We would like to recognize the generous support of our sponsors, Siemens AG and the National Science Foundation (SBIR Grants 0912914 and 1058605).

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Table 1. Comparison of energy used by four highest power loads on Phase 3 at the Smart Automation Test Factory. PAC represents independently measured energy consumption compared with Load IQ measurements.

Load	Station	PAC (Wh)	Load IQ (Wh)	Percent Difference	Detected Events
Compressor	NKP	96	99	3%	100%
Conveyor	NTS	678	689	2%	100%
NTS Standby	NTS	853	878	3%	100%
Robot	NLK	5	1.3	-75%	50%

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