

# Does disaggregated electricity feedback reduce domestic electricity consumption? A systematic review of the literature

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**Abstract**—We examine twelve studies on the efficacy of disaggregated energy feedback. The average electricity reduction across these studies is 4.5%. However, 4.5% may be a positively-biased estimate of the savings achievable across the entire population because all twelve studies are likely to be prone to ‘opt-in’ bias hence none test the effect of disaggregated feedback on the *general population*. Disaggregation may not be *required* to achieve these savings: Aggregate feedback alone drives 3% reductions; and the four studies which directly compared aggregate feedback against disaggregated feedback found that *aggregate* feedback is *at least as effective* as disaggregated feedback, possibly because web apps are viewed less often than in-home-displays (in the short-term, at least) and because some users do not trust fine-grained disaggregation (although this may be an issue with the specific user interface studied). Disaggregated electricity feedback may help a motivated sub-group of the population, which we call ‘energy enthusiasts’, to save more energy but fine-grained disaggregation may not be necessary to achieve these energy savings. Disaggregation has many uses beyond those discussed in this paper but, on the specific question of promoting energy reduction in the general population, there is no robust evidence that current forms of disaggregated energy feedback are more effective than aggregate energy feedback. The effectiveness of disaggregated feedback may increase if the general population become more energy-conscious (e.g. if energy prices rise or concern about climate change deepens); or if users’ trust in fine-grained disaggregation improves; or if innovative new approaches or alternative disaggregation strategies (e.g. disaggregating by *behaviour* rather than by *appliance*) out-perform existing feedback. This paper also discusses opportunities for new research into the effectiveness of disaggregated feedback.

## I. INTRODUCTION

Electricity disaggregation estimates the energy consumption of individual appliances (or load types or behaviours) using data from a single meter. One use-case is to estimate an itemised electricity bill from a single smart meter measuring the whole building’s electricity demand.

Research into electricity disaggregation algorithms began over thirty years ago [1], [2]. Today, there is a lot of excitement about energy disaggregation. Since 2010 there has been a dramatic increase in the number of papers published on energy disaggregation algorithms and since 2013 there have been over 100 papers published each year [3]. Disaggregation is big business: In November 2015 disaggregation provider *Bidgely* raised \$16.6 million USD [4]. There are now at least 30 companies who offer disaggregation products and services [5], [6].

This paper discusses four main questions: 1) Can disaggregated energy data help an already-motivated sub-group of the general population (‘energy enthusiasts’) to save energy? 2) How much energy would the *general population* save if given disaggregated data? 3) Is *fine-grained* disaggregation required? 4) For the general population, does disaggregated energy feedback enable greater savings than *aggregate* data?

## A. An introduction to systematic reviews

This paper is, to the best of our knowledge, the first systematic review on the effectiveness of domestic, disaggregated electricity feedback.

Systematic reviews are common in fields such as medicine and the social sciences. Systematic reviews aim to find results which are robust across *multiple* studies as well as opportunities for future research. The process starts with a search, using predefined criteria, for existing papers. Results and possible biases are extracted from each paper, collated and combined. See Garg et al. [7] for a discussion of systematic reviews.

There is a distinction between *narrative* reviews and *systematic* reviews. Most review articles are narrative reviews. These are written by domain experts and contain a discussion of existing papers. Narrative reviews are often very valuable. But they are rarely explicit about how papers were selected and rarely attempt a quantitative synthesis of the results.

Systematic reviews aim to cover *all* papers which match defined criteria relevant to a specific research question. Systematic reviews are explicit about how papers were selected and present a quantitative summary of each paper and a quantitative synthesis of the results. Systematic reviews may contain a ‘meta-analysis’ where results from each study are combined into a single statistical analysis which provides greater statistical power than any individual study can deliver.

Systematic reviews are not perfect, of course. Bias can still creep in via the selection process; and different statistical analyses may present different results.

Why bother with systematic reviews? *Replication* is an essential to the scientific process. Peer review is necessary *but not sufficient* to ensure that individual studies present an accurate estimate of the ‘true’ state of the world. Reviewers rarely, if ever, attempt to replicate results; possibly because there is insufficient reward to motivate reviewers to spend time on replication. Instead it is left to the community to attempt to replicate results. Recent large-scale replication projects suggest that replicable results may be the *exception* rather than the rule. An attempt to replicate results from 98 psychology papers could only replicate 39% of the results [8], [9]. A similar study in cancer biology found that only 6 of the results in 53 high-profile papers could be replicated [8], [10]. Hence it is advisable to exercise appropriate scientific scepticism when reading any single study; and it is beneficial to collect all papers on a specific question to identify results which are robust across studies.

## B. Methodology

Broadly, this paper discusses whether deployment of disaggregation across the entire population is likely to reduce energy consumption. We assume that disaggregated data for a population-wide deployment would be delivered via websites, smart-phone applications or paper bills.

We found twelve groups of studies on the question of whether disaggregated energy data helps users to reduce their energy demand. These studies are summarised in Table I.

We aimed to do an exhaustive search of the literature although it is not possible to rule out the possibility that we missed studies. We used three search engines: Google Scholar, the ACM Digital Library and IEEE Xplore. The search terms we used were ‘disaggregated [energy|electricity] feedback’ and ‘N[I|A|IA]LM feedback’. These searches produced a huge number of results, many of which were not relevant to our research question. We manually selected papers which test the effectiveness of disaggregated electricity feedback. We accepted experiments conducted either in a laboratory environment or in a field test. We also searched the bibliography sections of papers to find more papers. For example, a review article by Ehrhardt-Mertinez et al. [11] contained references to five relevant studies on disaggregated energy feedback.

## II. CAN DISAGGREGATED ELECTRICITY FEEDBACK ENABLE ‘ENERGY ENTHUSIASTS’ TO SAVE ENERGY?

The mean reduction in electricity consumption across the twelve studies (weighted by the number of participants in each study) is 4.5%. However, as we will discuss below, this figure is likely to be positively-biased and has a substantial (although unquantifiable) amount of uncertainty associated with it.

Aggregating the results by taking the *mean* of the energy savings across the twelve studies is a crude approach. It would have been preferable to do a full meta-analysis where biases are identified and compensated for [7]. Davies et al. [12] did such a meta-analysis for studies on *aggregate* energy feedback. But the studies on disaggregated feedback appear to us to be too varied and, perhaps most fundamentally, six of the twelve studies only provided a point estimate of the effect size. At the very least, a meta-analysis requires that each study provides a point estimate *and* a measure of the *spread* of the results.

We must also be explicit about the likely biases in each study. Please note that this is *not* an attack on the papers in question! We appreciate that it is not possible to conduct a ‘perfect’ study. The real world is messy and researchers cannot control for everything! Being explicit about the biases allows us to assess how much trust we should put into the assertion that disaggregated energy feedback reduces consumption by 4.5%.

There are several sources of positive bias present in the papers. All twelve studies are prone to ‘opt-in’ bias, where subjects self-selected to some extent and so are likely to be more interested in energy than the general population.

Eight studies did not control for the Hawthorne effect. This strange effect is where participants reduce their energy consumption simply because they know they are in an energy study. For example, Schwartz et al. [13] conducted a controlled study on 6,350 participants, split equally between control and treatment groups. Subjects in the treatment group received a weekly postcard saying: ‘*You have been selected to be part of a one-month study of how much electricity you use in your home... No action is needed on your part. We will send you a weekly reminder postcard about the study...*’ Participants who received these postcards reduced their consumption by 2.7%. Hence studies on disaggregated energy feedback which do not control for the Hawthorne effect are likely to over-estimate energy savings attributable to the disaggregated energy feedback.

Six studies used feedback displays which were probably more attention-grabbing than the feedback mediums that would be used in a population-wide roll-out of disaggregated energy feedback. Some studies gave home-visits to some participants to enable additional reductions (e.g. [14]–[16]). All but two studies were too short to observe whether energy reductions persist long-term. Perhaps some authors experimented with multiple statistical techniques until one delivered a significant result. And, finally, eight studies used sub-metered data, hence avoiding any mistrust of disaggregated estimates [17].

As well as being explicit about biases in each study, we must acknowledge that the *literature* as a whole may be prone to publication bias. How many *negative* results exist unpublished? Perhaps academics fear that reviewers would reject a null result? Might companies fear that customers or shareholders would be driven away? A study on publication bias in the social sciences found that positive results are 60% more likely to be written up than null results and 40% more likely to be published [18]. They propose that science would benefit from mechanisms to reduce the effect of publication bias, such as pre-registering experiments.

Despite these sources of bias, there is evidence that energy disaggregation *can* enable energy savings for ‘energy enthusiasts’. Two large studies illustrate this assertion:

One group of studies analysed the disaggregation service provided by Home Energy Analytics (HEA) [15], [16], [19]–[21]. All participants *opted into* HEA’s system and hence could loosely be considered ‘energy enthusiasts’. In total the HEA papers examine 1,623 users. 1,239 used the system for up to 44 months; the rest used the system for one year. The average reduction in electricity consumption across all 1,623 ‘energy enthusiasts’ was 6.1%. The top-quartile (310 ‘super-enthusiasts’) reduced their electricity consumption by 14.5%. But note that none of the HEA studies had a control group.

Another large study was performed in 2014 over three months on 1,685 PG&E users [17], [22]. Half received an in-home-display (IHD) and half received access to Bidgely’s website (which includes disaggregation). No statistically significant reduction in consumption was found across all 1,685 users, despite positive biases (e.g. users could *choose* between the IHD or Bidgely). However, a sub-group of users on a time-of-use (TOU) tariff (‘energy enthusiasts’) saved 7.7%. The TOU group consisted of 142 IHD users and 136 Bidgely users.

## III. HOW MUCH ENERGY WOULD THE *WHOLE* POPULATION SAVE IF GIVEN DISAGGREGATED DATA?

All twelve studies suffer from opt-in bias to some extent. Seven studies have a *high* risk of opt-in bias because participants sought out the intervention. As such, the study participants are unlikely to be representative of the general population. No ‘perfect’ correction for opt-in bias exists.

What will the *average* energy saving be across the population if, say, the majority of the population completely ignores disaggregated energy feedback but a small sub-population of ‘energy enthusiasts’ save 4.5%?

How can we estimate the proportion of ‘energy enthusiasts’ in the population? Three studies reported the number of people *approached* to participate versus the number who *agreed* to participate [16], [25], [37]. This ‘opt-in rate’ is a crude estimate on the *lower bound* of the proportion of the population who are ‘energy enthusiasts’ (because, in order to agree to participate in

Table I  
STUDIES ON THE EFFECTIVENESS OF DISAGGREGATED ENERGY FEEDBACK.

Study	Feedback presentation	Num. houses in disag. group	Num. houses in study	Num. disaggregation categories	Duration (months of disag)	Reduction in electricity use <sup>U</sup> (%)	Reduction is for whole house?	Sample period of meter	Feedback delay	Timing: Historic or Concurrent?	Time frames for historic <sup>T</sup>	Recommendations given? <sup>R</sup>	Control group?	Controlled for Hawthorne?	Volunteer bias? <sup>V</sup>	Controlled for weather?
“RECS” [23]	dedicated computer	25	100	~ 8	2	12.9	✓	0.6 sec	0	H&C	HDM	✗	✓	✓	L	✓
McCalley & Midden 2002 [24]	Virt. wash. machine	25	100	1	-	0.0	✗	-	0	H&C	-	G	✓	✓	L	-
Wood & Newborough ’03 [25]; Mansouri & Newborough ’99 [26]	LCD by cooker	10	44	1	≥ 2	12.2	✗	15 sec	0	C	-	✗	✓	✓	L	✓
“ECOIS-I” [27], [28]	Dedicated laptop	8	8	16	2	9	✓	30 min	next day	H	D, 10D	P	✗	✗	H#	✓
“ECOIS-II” [28]–[30]	Dedicated laptop	10	19	16	3	18	✓	30 min	next day	H	D, 10D	P	✓	✓	H#	✓
“EnergyLife” trial 1 [31]–[33]	iPhone	13	13	7	3	5	✓	?	1-2 min	H&C	D	P	✗#	✗#	H#	✗#
“EnergyLife” trial 2 [34]	iPhone	4	4	7	4	38	✗	?	1-2 min	H&C	D	P	✗	✗#	H#	✗#
Home Energy Analytics [15], [16], [20], [21]	Web & email & home visits	1623	1623	5	≤ 44	6.1	✓	hourly	0	H	Y	P	✗	✗	L	✓
Bigdely 2013 [35], [36]	Web, mobile, email	163	328	≥ 3?	-	6	✓	30 sec & 1 hr	0	H&C	DBY	P	✓	✗	H	✓
PG&E Pilot 2014 [17], [22]	Web, mobile, email	844	1685	≥ 3?	3	2.1	✓	30 sec	0	H&C	DBY	P	✓	✗	H	✓
Schwartz et al. 2014 [14]	Web, mob, TV	6	6	~ 10	18	7.8	✓	?	0?	H&C	?	?	✗	✗	H	✗
Sokoloski 2015 [37]	Web, mob, email	12	70	≥ 3?	0.75	3	✓	30 sec	0	H&C	DBY	P	✓	✗	L	✓

A dash ‘-’ in a cell means ‘not applicable (NA)’ and ‘?’ means ‘not specified in paper’.

<sup>U</sup> Absolute reductions minus reductions for the no-contact control (or the most similar group to a no-contact control available).

<sup>R</sup> Recommendations can be ‘P’ for ‘personalised’ or ‘G’ for ‘general’ or ‘✗’ for none given.

<sup>V</sup> Volunteer bias can be ‘H’ for ‘high’ (subjects sought out the intervention) or ‘L’ for ‘low’ (subjects were approached by the experimenters but only a fraction agreed to participate).

<sup>T</sup> H=hourly, D=daily, M=monthly, Y=yearly, B=current billing cycle.

# Paper is silent on this question. Assume the worst.

an energy study, people probably need to be energy enthusiasts *and* also have time to participate in the study *and* be willing to let experimenters into their homes etc.). The average opt-in rate is 16%. This is consistent with [38] who estimate that 20% of the population are ‘[energy] monitor enthusiasts’. If 16% of the population reduced their energy consumption by 4.5% then the mean reduction would be 0.7%.

This may seem rather pessimistic. We assumed that 84% of the population (the ‘disinterested’) would save *no* energy. Perhaps this is a little unrealistic: We might hope that some proportion of the ‘disinterested’ group would save a little energy. Furthermore, we used a crude method to determine a lower bound on the proportion of ‘energy enthusiasts’ in the population. But remember that we have multiple reasons for believing that a 4.5% saving across the ‘energy enthusiast’ population is an *over-estimate*. We assume that these negative

and positive biases cancel out, although we cannot be sure.

Also note that we simply have *no* good evidence for how the *general population* would react to disaggregated energy data. However, related studies have found that effect sizes reported on opt-in groups are often substantially diminished when studied on the general population [12].

Can we compare these figures to other research? A study involving 2,000 Swedish households found that participants who visited a website which provided user-friendly analysis of their aggregated electricity consumption reduced their electricity consumption by 15% on average [39]. The savings sustained for the duration of the four-year study. But only 32% of those with access to the website visited the website. Households who did not visit the website did not reduce their energy consumption. Hence the average energy reduction across all households with access to the website was  $32\% \times 15\% \approx 5\%$ .

#### IV. IS ‘FINE-GRAINED’ DISAGGREGATION NECESSARY?

Much research into disaggregation aims to deliver ‘fine-grained’ estimated power demand for each appliance at relatively high temporal resolution (e.g. 0.1 Hz). Fine-grained disaggregation is complex to engineer and often computationally expensive to run. Is it worth the effort? Home Energy Analytics (HEA) do ‘coarse-grained’ disaggregation: they disaggregate energy usage into five broad categories at *monthly* temporal resolution. Despite the coarse granularity of the feedback, HEA achieved significant average reductions in electricity usage of 6.1% [15], [16], [19]–[21]. HEA’s results tell us that fine-grained feedback is certainly not *required*. Fine-grained feedback enables many use-cases not discussed here but, on the question of the efficacy of feedback to drive energy reductions, we simply do not know if fine-grained feedback is more effective because no studies compared fine-grained against coarse-grained feedback. Fine-grained feedback might be *less* effective because some users do not trust it [17].

#### V. DOES AGGREGATE OR DISAGGREGATED FEEDBACK ENABLE GREATER SAVINGS FOR THE WHOLE POPULATION?

Four studies directly compared aggregate feedback against disaggregated feedback. Three of these studies found aggregate feedback to be *more* effective than disaggregated feedback [17], [37], [40]. The fourth study found disaggregated feedback and aggregate feedback to be equally effective [24]. Are there any explanations for this counter-intuitive result?

Two of the four studies [24], [40] were synthetic computer simulations and so may not generalise.

The other two studies were well controlled field studies [17], [37]. In both field studies, aggregate feedback was displayed on an always-on IHD whilst disaggregated data was displayed on Bidgely’s website (which has since been redesigned [22]). Participants in the disaggregation groups did not have an IHD. Sokoloski [37] found that, on average, participants in the IHD condition viewed the IHD eight times per day whilst participants in the disaggregation condition viewed the website only once per day. Churchwell et al. [17] found a similar pattern and also reported that some participants did not trust the fine-grained disaggregated data. Perhaps aggregate data is not *intrinsically* more effective than disaggregated data; instead, perhaps *IHDs* are more effective than *websites* or mobile apps.

Perhaps *dedicated* displays for disaggregated data may help enhance efficacy, although this adds costs. Or, as Sokoloski [37] suggests, efficacy may be increased by *combining* disaggregated feedback presented on a website with aggregate feedback presented on an IHD.

Furthermore, a meta-analysis of the efficacy of *aggregate* energy feedback suggests it alone achieves 3% energy savings [12]. This analysis adjusted for several (but not all) biases.

#### VI. SUGGESTIONS FOR FUTURE RESEARCH

There are several gaps in the existing literature. Below is a list of potential experiments (more ideas are listed in [6]).

No existing field studies compared aggregate feedback against disaggregated feedback *on the same type of display*. The studies which *did* compare aggregate feedback against disaggregated feedback used an IHD for aggregate feedback and a website for disaggregated feedback and found that the aggregate feedback was more effective at reducing energy demand. But we cannot rule out that this result is simply because users

viewed the IHD more frequently than they viewed the website. Hence it would be valuable to run an experiment where both the ‘aggregate’ and ‘disaggregated’ groups received feedback on the same device (e.g. an IHD with a dot-matrix display to display disaggregated feedback).

A related study would explore the effectiveness of aggregate feedback presented on an IHD *combined with* access to disaggregated data on a website; compared to just the IHD. The IHD might pique users’ interest and motivate them to explore their disaggregated energy usage on a website or smart phone.

Another study would compare fine-grained disaggregated feedback against coarse-grained disaggregated feedback.

Below is a list of suggestions for how to make future papers on feedback as useful as possible: If possible, conduct a *randomised controlled trial*. Publish as much information as possible. How were subjects recruited? Were subjects selected from the *general population*? Did any subjects withdraw during the study period? Was there a control group? Did the study control for the Hawthorne effect and weather? What sources of bias may influence the result? How exactly was feedback presented; and how rapidly did the information update? How often did participants view the display? Was disaggregated data available from the very beginning of the experiment or did the disaggregation platform take time to adapt to each home? Publish the results of *all* the valid statistical analyses performed; not just the ‘best’ result. Crucially, please publish some measure of the *spread* of the result (e.g. the standard deviation). Ideally, publish online, full, anonymised results so researchers can collate your results into a meta-analysis.

#### VII. CONCLUSIONS

Disaggregation has *many* use-cases beyond feedback. This paper specifically considers a single use-case of disaggregation: Reducing energy consumption via feedback. Averaged across the population, there is evidence that disaggregated feedback *may* help to reduce electricity consumption by ~0.7-4.5%. But disaggregation might not be *necessary* to achieve this saving because aggregate feedback may be equally effective. Amongst ‘energy enthusiasts’, disaggregated feedback might save more energy but fine-grained disaggregation may not be necessary.

We must emphasise that all we can do is report the current state of the research. We *cannot* rule out the possibility that disaggregated feedback is, in fact, more effective than aggregate feedback. Neither can we rule out that fine-grained feedback is more effective than coarse-grained. All we can say is that current evidence contradicts the first hypothesis and that there is no evidence available to address the second hypothesis.

Importantly, note that the existing evidence-base is heterogeneous and has many gaps. Perhaps a large, well controlled, long-duration, randomised, international study will find that disaggregated feedback is more effective than aggregate.

Perhaps users will become more interested in disaggregated data if energy prices increase or if concern about climate change deepens. Or perhaps users in fuel poverty will be more likely to act on disaggregated feedback in order to save money. Or perhaps users will trust disaggregation estimates more if accuracy improves or if designers find ways to communicate uncertain disaggregation estimates. Or perhaps real-time feedback or better recommendations will improve performance. Or perhaps disaggregating by behaviour rather than by appliance will make disaggregated feedback more effective.

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