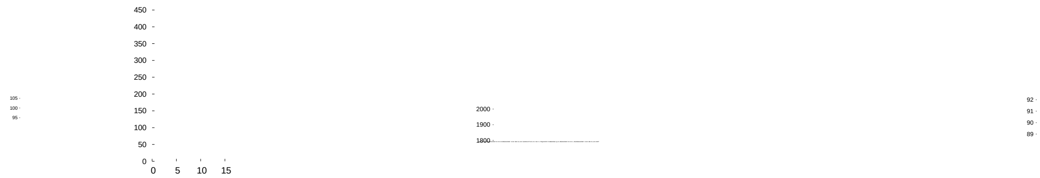
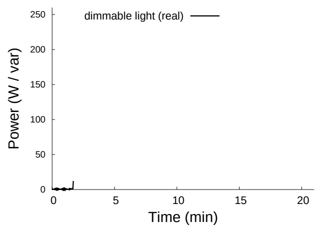
25% in our experiments). Finally, we use our models as queries to a variable-length subsequence matching algorithm to detect the presence of specific loads in smart meter data.

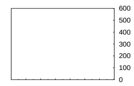
II. E

(a) Light bulb (b) Toaster (c) Coffee maker (d) Sandwich press (e) Pod Coffee

Fig. 2. Example resistive loads, demonstrating “step” behavior with a possible initial surge and slow decay to a stable power level.



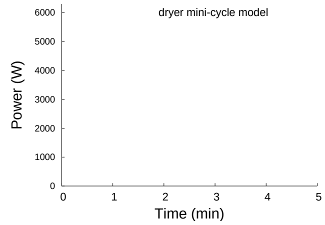




(a) Dimmable light (0% to 100%) (b) Refrigerator (c) Duct Heater (d) Dishwasher 1

Fig. 6. Reactive power demonstrates the same types of patterns as real power and can help in identifying different types of electrical loads.

only non-resistive loads generate reactive power. At a high level, reactive power is the result of the instantaneous power (the product of current and voltage) occasionally becoming negative within each AC cycle, due to out-of-phase current and voltage. This state cau76.cau76.[(oming)]TJ 0 -11.955 giger2956 Td [296t*956 Reactiv


dryer mini-cycle model
Power (W)
6000
5000
4000
3000
2000
1000
0
0
1
2
3
4
5
Time (min)

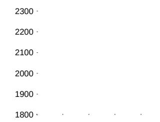

2300
2200
2100
2000
1900
1800

Fig. 10. A single complete cycle of a washing machinenannotated with the model types for the operation of simpler internal loads.

challenges. Since the time-series data for a load captures the power usage for all components that are concurrently

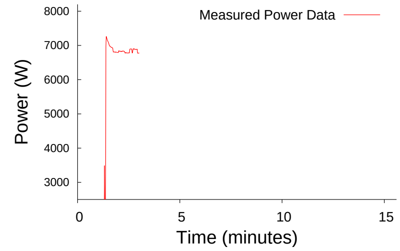
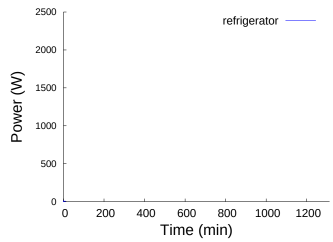

Measured Power Data
Power (W)
Time (minutes)
8000
7000
6000
5000
4000
3000
0
5
10
15

Fig. 13. A few highly variable (non-linear) loads are responsible for the vast majority of power variations in a home's per-second smart meter data.

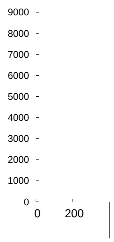
Fig. 14. The stable maximum power enables a filter that removes power variations in smart meter data, making it easier to detect on-off transitions.

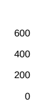
data (a) and the disaggregated refrigerator and model-derived



(a) Aggregate trace (b) Refrigerator Euclidean distances (c) Zoomed-in

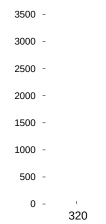
Fig. 16. Refrigerator matches using Euclidean distances





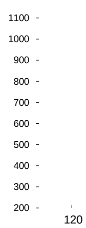
(a) Aggregate trace (b) Washing Machine Euclidean distances (c) Zoomed-in

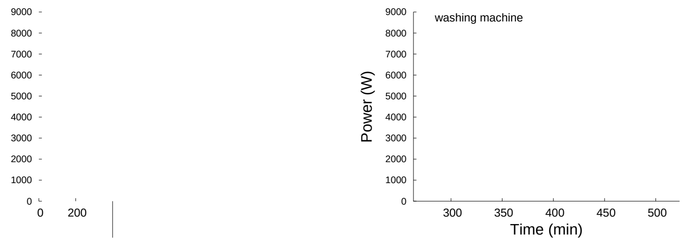
Fig. 17. Washing Machine matches using Euclidean distances where the model used is one entire cycle of the washing machine turning on



(a) Aggregate trace (b) Dishwasher Euclidean distances (c) Zoomed-in

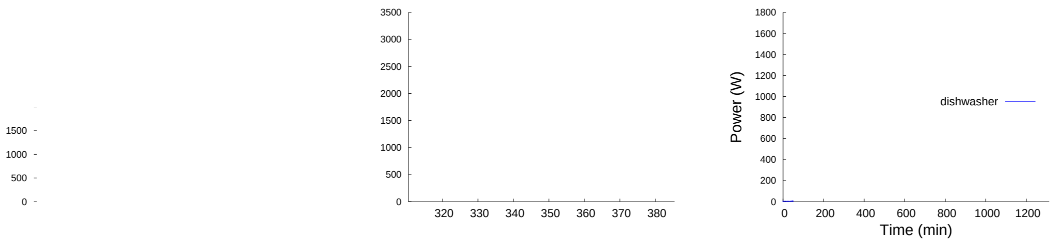
Fig. 18. Dishwasher matches using Euclidean distances





(a) Aggregate trace (b) Zoomed-in aggregate (c) Washing Machine matches

Fig. 20. Washing Machine matches using augmented Euclidean matching where the model used to match is the on-off decay cyclic part at the end



(a) Aggregate trace (b) Zoomed-in aggregate (c) Dishwasher matches

Fig. 21. Dishwasher matches using augmented Euclidean matching

of the third device cycle are not matched, as the match is obscured by another large device operating during this period, which we can see around t = 480 min in Figure 20(a).

Finally, we tried the augmented Euclidean matching on the dishwasher cycle as shown in Figure 21, but here, no real matches were located at all – the technique simply 'matches' the entire trace, which provides no useful information. This behavior is likely due to the fact that the dishwasher exhibits fairly simple stepping behavior between static states as shown in Figure 5(c) – as a result, it can be morphed in the time and amplitude domains to match the entire aggregate trace. Despite this, augmented Euclidean matching tends to be more conservative in matching than straight Euclidean distance, which tends to result in more false positives.

Both strategies demonstrate that matching within aggregate traces is a difficult problem given the noisiness and complexity of typical aggregate traces. Despite this, we believe that our models can be useful across a variety of matching techniques, as demonstrated in the examples above.

Result: *Our models are useful in detecting the presence of specific loads in smart meter data by matching them against a home's aggregate time-series power data.*

V. Related Work

In this paper, we focus explicitly on modeling the power usage of common electrical loads. While recent work targets modeling for specific appliances, e.g., a particular brand of refrigerator [31], it does not generalize to a broad range of devices. Much of the prior research on modeling power usage for individual loads has been done in the context of Non-Intrusive Load Monitoring (NILM). While we expect our models to be broadly useful for data analysis, including, but not limited to, NILM, we survey related work in NILM below.

NILM techniques differ significantly basIm55 Do(hasi63 -(prog582rticu9(b-(wer)]TJ -9.963 -11.955 TiarietM)-373(of)-435(tof)-curr(redi