Impact of Background Devices on Modern Energy Disaggregation
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NILM (Non-intrusive Load Monitoring)[1], a computational technique that separates aggregate power data monitored from a single point source into constituent appliance loads, is employed provide feedback to occupants about how energy is used within their home, allowing them to make more informed choices regarding conserving power. One of the key challenges in NILM is performing accurate disaggregation in environments containing large numbers of independent devices, which include most real-world buildings. Considering the impracticality of complete energy breakdowns, load disaggregation often focuses instead on specific devices of interest, or so-called foreground devices, while leaving the large number of smaller and potentially unknown devices in the background. My summer research highlights the outsized impact of specific types of background activity and provides insights regarding the identification of significant devices in complex, noisy operating environments.

First, to investigate the impact of background devices on modern disaggregation algorithms in the NILMTK toolkit[2], I conducted an empirical study in which I disaggregated fixed appliance sets from real-world data while systematically varying the complexity of the background loads. Each of my experiments is configured as a particular set of foreground devices to disaggregate in the presence of zero or more background devices. I focused on four typical devices from the Dataport dataset: a refrigerator, a microwave, a dishwasher, and an electric vehicle as these devices are significant energy consumers. Figure 1 shows the averaged RMSE, MAE and F1 scores across all foreground devices for each test run.

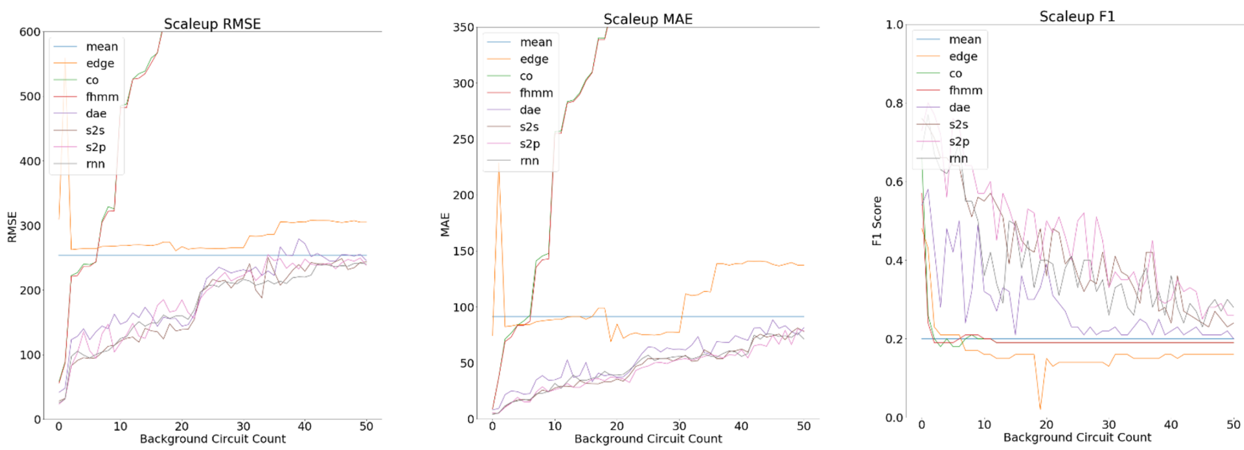

Figure 1: Average RMSE, MAE and F1 score for all foreground devices as background activity increases.

In the second stage, I employed the ranking algorithm to estimate the five most significant background devices. Since the ranking algorithm requires a choice of a disaggregation algorithm as well as a target metric, I considered 4 different configurations, which are summarized in Table 1, along with the resulting top 5 background devices for each configuration.

Name	Ranking Algorithm	Metric	Rounds	Top 5 Devices (ordered)
SP-M	Sequence-to-Point	MAE	5	1642-livingroom, 4373-car, 1222-heater, 3517-garage, 3996-waterheater
SP-M1	Sequence-to-Point	MAE	1	1642-livingroom, 4373-car, 1642-venthood, 1222-kitchen, 2335-disposal
SP-F	Sequence-to-Point	F1 Score	5	4373-car, 2096-lights, 27-airconditioner, 3517-garage, 1222-heater
ED-F	Edge Detection	F1 Score	5	1642-furnace, 1222-heater, 3996-wellpump1, 2096-waterheater, 3039-waterheater

Table 1: Ranking configurations and corresponding top five devices.

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References: [1] G.W. Hart. 1992. Nonintrusive Appliance Load Monitoring. *Proc. IEEE 80*, 12 (Dec. 1992), 1870-1891. https://doi.org/10.1109/5.192069; [2] Nipun Batra, Jack Kelly, Oliver Parson, Haimonti Dutta, William Knottenbelt, Alex Rogers, Amarjeet Singh, and Mani Srivastava. 2014. NILMTK: An Open Source Toolkit for Non-Intrusive Load Monitoring. In *Proceedings of the 5th International Conference on Future Energy Systems* (Cambridge, United Kingdom) (e-Energy'14). Association for Computing Machinery, New York, NY, USA, 265–276. https://doi.org/10.1145/2602044.260205.