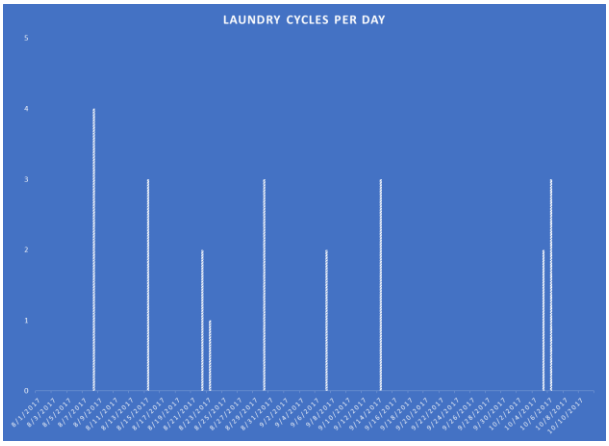
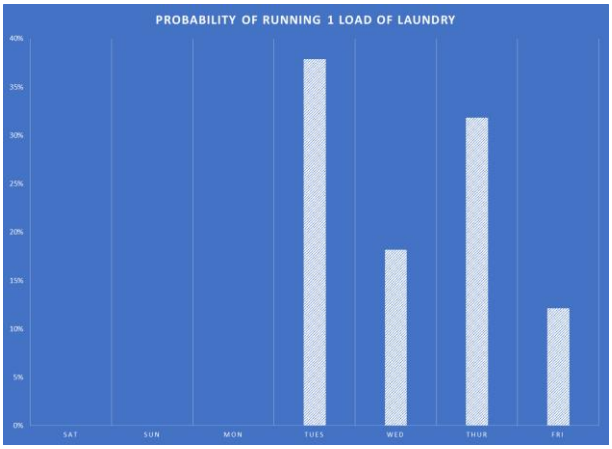
Making existing appliances Smart Appliances

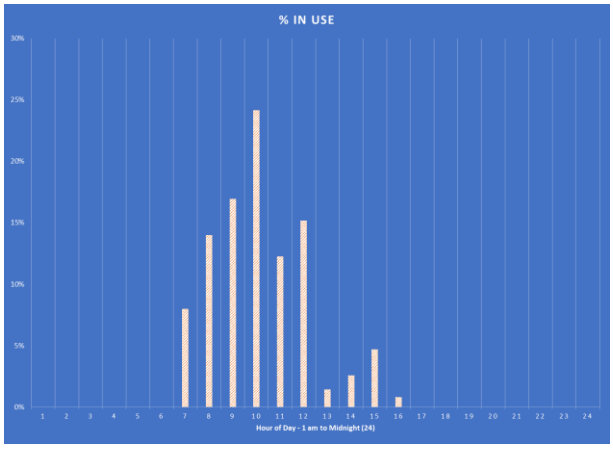
Why it matters: Appliance use in a home provides a direct indicator of healthy living patterns. Refrigerator and stove or oven correlation indicates food preparation and eating patterns. Cleanliness is indicated by hot water usage, or dishwasher and laundry machine use. Increases in TV usage may indicate depression or social isolation. Night time appliance use may indicate day night confusion.

Background: The Birkeland Current system utilizes high temporal, spatial, and energy use change detection to autonomously identify and quantify appliance use by individual in a home or health care environment. The examples shown below are based on a series of 2017 in home pilot projects. These examples include a rural independent aging retired couple, a suburban working middle aged couple, and a single disabled senior adult in an urban apartment. Use of the Birkeland Current power strips and battery-operated current/temperature/light sensors provides direct insight into appliance usage and can be used to enable various analytics or notifications as well as direct controls when required. Household appliance examples available include; refrigerators, washers and dryers, dishwashers, ovens and stoves, toasters, blenders, coffee makers, hot water heaters, TV's, computers and peripherals. Most of these devices become 'smart' by simply plugging them into an open socket on the Birkeland Current 120-volt smart power strip. If required, power limiting, time limiting, behavior based, or remote controls can be implemented using the Birkeland Current devices for enhanced safety or special circumstances.



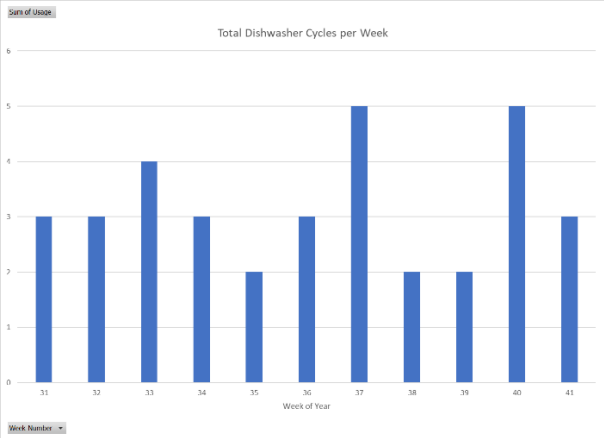
Washing Machine Example: In this example of a retired aging couple in Tennessee, the baseline data shows an average 43-minute energy use cycle for their washing machine. A general device data query provides the number of minutes per day that a device is used in up to 4 automatically detectable or assignable power states. On average, this couple runs 3 loads of laundry per week, typically on a single 'laundry day' morning which is never on the weekend or Monday as seen from the second plot. In this 2.5-month assessment the home had one week where they did no laundry, but twice as many loads the following week. The third plot uses a time of day query to show probability of the washing machine being in use for a given hour of the day. This type of data allows normal usage behavior to be identified and conversely allows abnormal behavior to be identified. (i.e. a laundry run at 11pm for this household may be a factor in determining if an illness or event is occurring or had occurred. For a different household that may be normal behavior.)

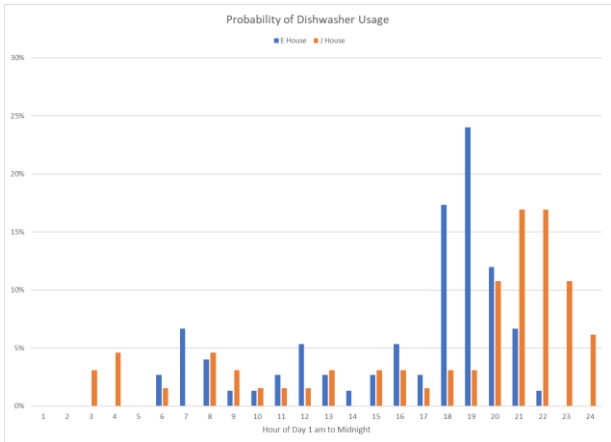




Significant additional data is available from the energy usage of the washing machine and hot water heater. For example, careful analytics of the washing machine total cycle time and peak wattage used during the wash cycle allows for determining the size of the load (i.e. longer spin time and higher torques (watts) for larger loads.) Correlation of hot water inlet pipe temperature (direct) or hot water heater outlet (indirect) allows for determination of hot water versus warm water versus cold water washes. Water usage starts prior to energy usage on devices such as washing machines and dishwashers that have an initial 'fill' cycle. The time lag between hot water start and machine start is also used to determine size of load and temperature settings. Machine mode behavior and characterization can be 'learned' by the system to automatically detect operational modes for a given device. Additional information on "who" did the laundry is automatically available with the active tag system.

Dishwasher Usage Example: In this case, the same queries are used however the data is provided by a clamp on current sensor on the dishwasher. In this case the number of cycles per week (by week number) is shown. More telling for the E-House example is the hour of day utilization which shows a small peak at breakfast (7 am), lunch (noon), and late afternoon (4pm). However, the preponderance of operation occurs after the evening meal (6 pm – 8 pm). For comparison the same data from a second house is shown by hour of day. In the E-House example the couple is retired and at home most of the day. In the J-House example the couple is still working and the dishwasher usage is even later in the evenings (8pm-midnight). Details on day of week usage, and mode of operation are also available. Details on "who" did the dishes is automatically available with the active tag system.





Example Refrigerator Usage:

The charts below utilize a query developed to provide metrics on a defined step in energy usage. In this case it is the light in the refrigerator coming on when the door is opened. The change in energy usage is determined from the baseline data through an automated routine. This is a slightly different analytics example from a state change shown above as this case takes into account the potential for the light to come on from any normal state (i.e. compressor on or off). In addition, for a refrigerator we speed up the sample time to an approximately 3 second interval (from the nominal 10 sec) to insure even short door openings are captured. (These types of changes are done at installation or remotely after the initial 2 week baseline/commissioning period.) The data presented shows total number of openings per day in one of the pilot homes. In addition, the profile of door openings per hour of the day are shown, clearly indicating 3 distinct peaks around breakfast, lunch, and dinner time periods. Additional inference can be made such as: the breakfast and dinner time periods are spread out compared to the sharper 'routine' of lunch at noon; little or no after dinner snacking occurs (after 8 pm) with the exception of a small bump in a 'midnight snacks' or possibly a leftover that didn't get put up. Note that this type of data is also a factor in the overall household wake/sleep cycle and provides a definitive data point on when the occupants start their day. Data from the RTLS part of the system determines "who" is in the kitchen when the door is open. All of this is highly summarized and detailed information is available down to the second. Additional queries can show how long the door is open each time, when large new food installs are made (i.e. grocery runs from combined door open time and compressor cycle duration), refrigerator versus freezer usage (two different light values), etc. Finally, text or email notifications can be sent if the door is left open or if the compressor appears about to fail or has failed. All data is achieved from simply plugging the refrigerator into the power strip.