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Toward a Standard for a "Utility-Drive" Cycle for Electric Vehicles: A Means to Reduce the Uncertainties for Vehicle-to-Grid Applications

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Abstract

Vehicle-to-Grid (V2G) applications, such as ancillary services to the grid, are generally recognized as having an important role in maximizing the total value of a vehicle. To help realize this potential, it is necessary to develop standard "drive cycles" for exposure of batteries to grid applications. Such drive cycles are, of course, important for stationary energy storage too. The following question is addressed in this paper: Can the characteristics of a typical regulation signal to be used for V2G applications be captured in a small number of test cycles for standardized testing of the performance batteries?

Extensive statistical, spectral, wavelet, and cluster analyses were performed on 4-second regulation signals from PJM over 175 days during March to August. The main conclusions are: (a) the diurnal and seasonal pattern of regulation requirements appears to be generally well-matched with the availability and charge/discharge requirements of vehicle batteries. When providing regulation services, higher overall charging is needed at night times. The regulation requirements are generally less during the day. High frequency regulation requirements are generally less during summer months. (b) Although the diversity in the signal was such that there was no clear indication of a specific profile, or a small number of them, recommendations have been developed for the selection of a "utility" drive-cycle for characterizing the regulation signals for such ancillary services.

Keywords: V2G, smart grid, standardization

1 Introduction and Motivation

Battery testing procedures are important for understanding battery performance, including degradation over the life of the battery. Quantitative characterization of battery performance requires standard battery testing procedures that reflect real-world applications of energy storage systems. Such drive cycles have been developed for vehicle propulsion [1].

In recent years, the research community has explored Vehicle-to-Grid (V2G) applications as a means to generate additional revenue for plug-in electric vehicle (PEV) owners that may offset some of the high purchasing cost of the nascent technology and to maximize the overall value of

PEVs. Despite the enthusiasm by the research community seeking to maximize the total value of a vehicle, the automotive manufacturing and transportation battery communities are reluctant to embrace V2G applications. This reluctance is based on a lack of knowledge about battery degradation associated with the exposure to grid applications.

This paper is the first of several steps to addresses this knowledge gap.

Pacific Northwest National Laboratory collaborating with PJM initiates an effort toward standardizing a set of duty cycles for battery performance testing procedures that will be representative of real V2G applications. The initial focus is on the characterization of grid services. We envision that this and follow-on work will provide the basis for standards-development discussions that cover the entire spectrum of conditions that a battery may be exposed to during V2G applications. This work is equally important for stationary energy storage systems because industry is demanding definitions and standardization of performance testing procedures that represent typical utility duty cycles.

2 Background

A high-value grid service is regulation and that is the focus of this work. Power system operators continuously balance generation and load. The load can be decomposed into base-load, load-following, and regulation components. The blue line in Figure 1 shows the sum of the base-load and load-following components [2]. The green line shows the actual load, and the difference between the green and the blue lines represents regulation as shown on an expanded scale by the red line.

Load following represents the general trend over a time scale on the order of 10 minutes, whereas regulation represents variations over a time scale on the order of 1 minute. Regulation requires online power sources under automatic generation control (AGC) that can provide rapid response to up and down requirements to correct for load fluctuations and unintended or unpredictable fluctuations in generator output. Electric batteries are excellent candidates as regulation providers because of their quick response and precise control. Both stationary batteries and batteries in plug-in electric vehicles (PEV) can provide regulation services.

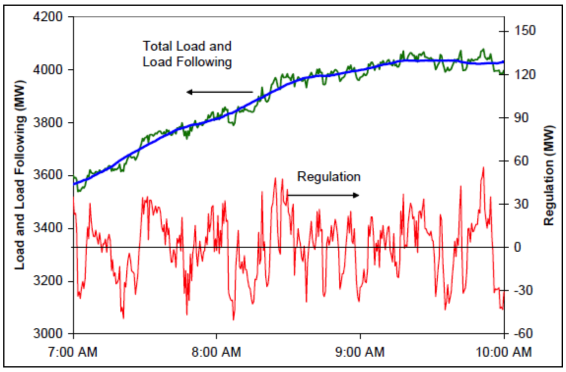

Figure 1: Load Profile at Different Scales

This paper discusses the results from a statistical analysis of one set of data from the PJM Interconnection. It explains the results from a statistical perspective and then projects the results into a battery context. In particular, the following question was addressed in this study: Can the regulation signal characteristics be captured in a small number of test cycles for standardized testing of the performance batteries when deployed to also provide regulation services to the grid?

3 Analysis of Regulation Signals

This study used publicly available data from the PJM[1]. They represent a portion of the frequency regulation signal that is sent out to grid assets (mainly generators who participate in the regulation services market) every 4 seconds. The portion that PJM made available is the frequency bias of entire regulation signal, which was used in this analysis. This portion of the frequency signal is particularly suited for V2G and stationary energy storage technologies because of the high dynamic content. The remaining portion of the frequency signal accounts for the difference between scheduled import and export of a balancing area of the grid.

The data used in this study span a period over 175 days during March to August of 2011. Figure 2 shows PJM regulation data for 4 randomly selected days.

[1] Available at http://www.pjm.com/markets-and-operations/ancillary-services/mkt-based-regulation.aspx#RegSignal09

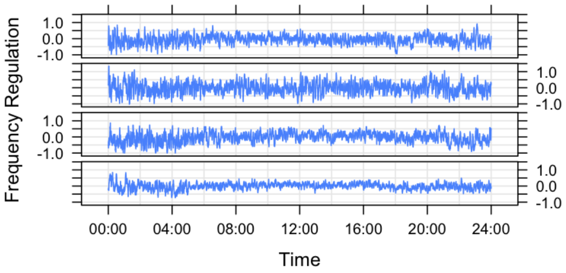

Figure 2: PJM regulation data for four arbitrarily selected days, one day in each of March, April, May and June. Data on the y-axis are normalized

3.1 Spectral results

An interesting property to study with signals such as regulation is the presence of cyclical or spectral behavior. One way to quantify this is the periodogram, which provides a measure of the relative strength of cycles of various frequencies [5].

Figure 3 shows a periodogram applied to the PJM regulation signal. The x-axis shows the frequency of the cycle, in cycles per second, while the y-axis is a measure of the strength of the signal at the given frequency. This figure reveals patterns in the regulation signal with distinct periodicities in the 1-hour, 30-minute, and 7.5-minute cycles. These periodicities are believed to reflect the specific PJM market design.

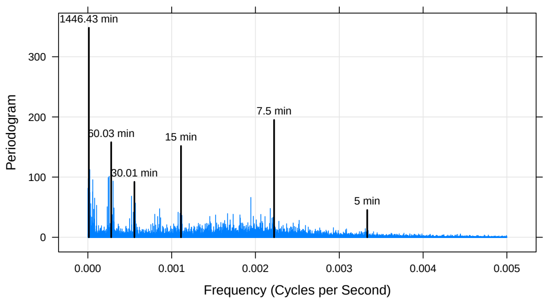

Figure 3: Spectral analysis of signals from PJM: frequency regulation component

3.2 Properties of regulation signal by time-of-day and month-of-year

An exploratory analysis of statistical quantities of the regulation signal by time-of-day and month-of-year revealed interesting properties that provide insight into regulation-following V2G applications. We investigated the statistical quantities of mean and amplitude.

3.2.1 Mean value of regulation

The means of 2-hour time blocks against time-of-day across month-of-year are shown in Figure 4. There is a propensity for the mean of the regulation signal to be slightly biased above zero during the middle of the day (06:01 to 18:00) and slightly biased below zero during the night (18:01 to 06:00). This finding has important implications to batteries in that, unless otherwise compensated, on average there would be a resulting net charge of a battery plugged in during the night and, conversely, a net discharge during the day. A net charge during the night for plug-in electric vehicles can be accommodated easily without any compensation, but a net discharge during the day will need to be compensated so the vehicle battery can be recharged for the next drive. In this study, we assumed that, within the state of charge range investigated, the battery can provide the needed power during regulation. A more detailed study can be done using protocols described in the *PHEV Battery Test Manual* [3] to estimate maximum power capability during charge and discharge of the battery.

3.2.2 Amplitude of regulation cycling

Figure 5 shows the amplitudes of 2-hour Blocks against Time-of-Day across Month-of-Year (differentiated by weekend and weekday). The amplitude swing (i.e., the minimum-maximum spread) of the cycles in the regulation signal has a propensity to be higher at night and lower during the day. In fact, we found that a significant relationship exists between the system load level and the amplitude of the regulation signal; that is, under low-load conditions, the amplitude of regulation grows exponentially compared regulation under high-load conditions. This means that, during the day, either fewer vehicle resources are necessary to meet the regulation requirements, or if the resource availability constant is kept constant during the 24-hour period (i.e., the same number of vehicles offering the same service for 24 hours), the individual contribution by each vehicle is less during the day than during the night. As a consequence, the amplitude for defining a performance test or drive-cycle could potentially be smaller during the day than at night.

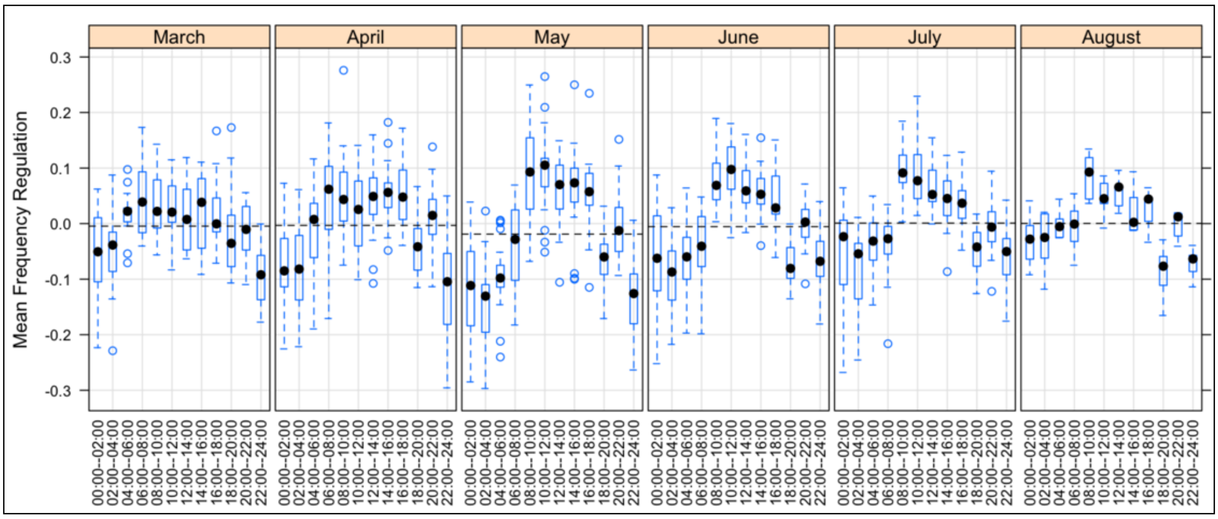

Figure 4: Means of 2-Hour Time Blocks against Time-of-Day across Month-of-Year

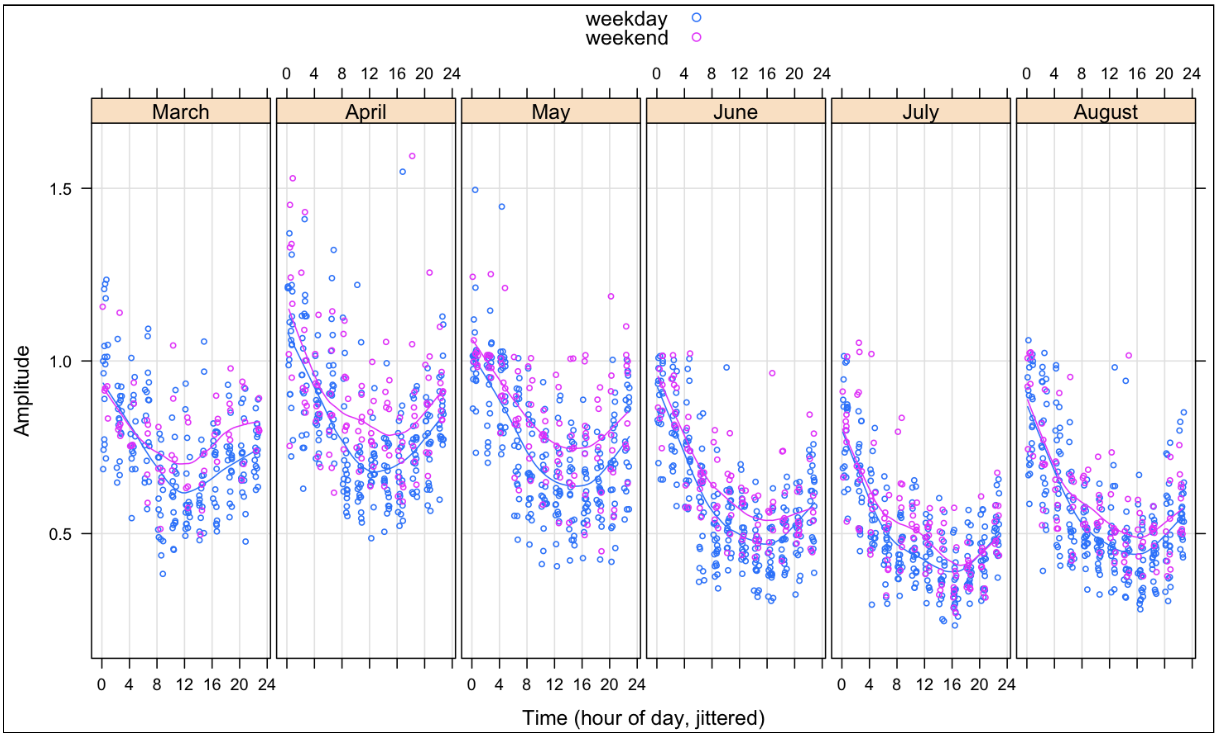

Figure 5: Amplitude of 2-Hour Blocks against Time-of-Day across Month-of-Year (differentiated by weekend and weekday)

3.2.3 Seasonal observations

The regulation signal shows important systematic dependence on the month of the year. Figure 6 shows boxplots of periodogram values, labeled as spectral density, vs. month of the year across each period. The amplitudes of low frequency components (top left) tend to go up from March to August, while the high frequency components (bottom right) tend to go down. Exploring the range of low-frequency (1-hour cycle) to high-frequency (7.5-minute cycle) signals across all seasons indicates that the lower frequency component in the regulation signal increases in significance during winter to summer months.

The mid-range frequency (30-minute cycle) remains constant over the months studied, while the higher-frequency components (7-minute cycle) slightly decrease their contribution to the overall signal from March through August. The periodogram units are proportional to energy (kWh), and we are only interested in relative differences. For the data presented, low-frequency cycles require more energy (kWh) capacity than do high-frequency cycles. Low-frequency cycles with higher energy requirements cause large cycles across the state-of-charge (SOC) scale for any given battery size. For transportation batteries, this would place a higher burden on the remaining life of the battery, as it may encounter deeper depths of discharge over any given period of time than would occur if the battery was exposed to higher frequency regulation signals. This also could affect thermal management of batteries at low SOCs as the internal resistance is higher at low SOCs. Hence, in addition to energy considerations, the ability of the batteries to provide the required power at low SOCs needs to be assured as part of the test profiles being developed.

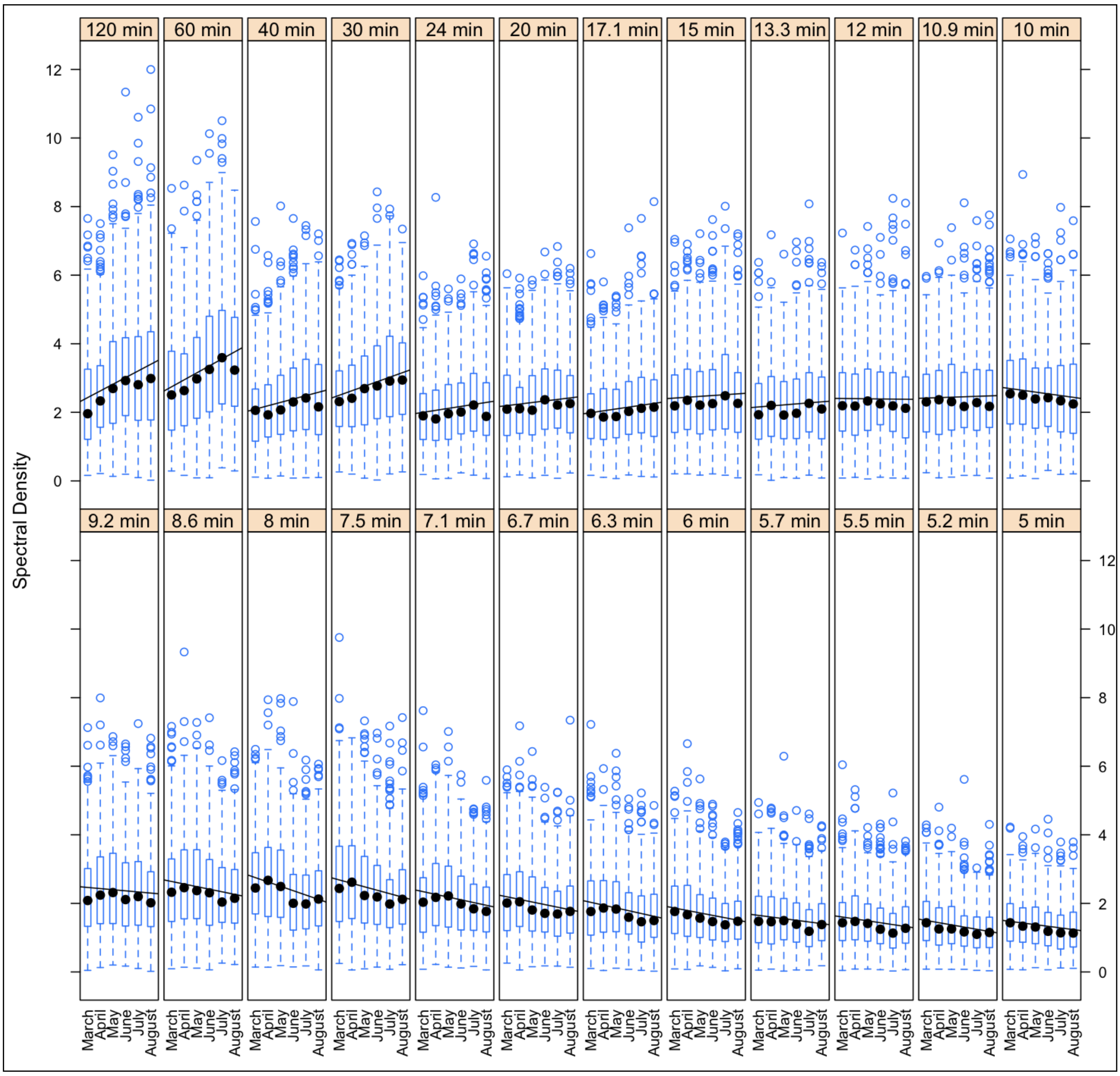

Figure 6. Boxplots of Periodogram Values vs. Month of Year across each Period

3.3 Clustering analysis of wavelet coefficients

Beyond understanding how statistical properties of the regulation signal vary over time, we applied unsupervised statistical learning techniques to the data in hope of finding similar patterns that appear repeatedly in the data. The hope is that a handful of battery drive cycle tests would emerge based on this analysis. We broke the data into 2-hour time blocks and treated each 2-hour period as one observation, so that we are searching for collections of 2-hour periods of time with similar frequency regulation signals.

To search for meaningful clusters, we applied several clustering studies. We relied mainly on the *k*-centroids clustering method [6], which takes a set of *d*-dimensional feature vectors and partitions them into *k* clusters such that the average distance from each feature vector to the centroid of the cluster is minimized.

In addition to the choice of clustering method, a very important consideration is the choice of feature vector. The goal of a good feature vector is to express all of the relevant information about an observation while having low dimensionality. The most trivial feature vector in our setting would be the actual time series data itself within each 2-hour block. Other representations we considered include the discrete wavelet representation of the series, the periodogram, and a condensed version of the periodogram.

The statistical clustering approach reflected the large diversity in regulation signal patterns, thus resulting in rather large numbers of clusters to characterize the entire data set [4].

Cluster analysis results using the discrete wavelet coefficients is shown in Figure 7. The lack of tight grouping around centroids suggests that the prospect of finding a small number of representative cycles solely derived from the clustering approach does not seem to be promising. Additional information based on an understanding of battery testing procedures must be used to inform the selection process. However, there are some interesting clusters that are worth discussion.

The overall directionality of the signal appears to be different for cluster 1 and cluster 7 in Figure 7, with the regulation going from negative to positive in cluster 1 and from positive to negative in cluster 7. From Figure 7, it is seen that cluster 1 events occur mostly at 20:00 from March 14 to April 18, with the cluster occurring from 12:00 to 16:00 from May 9 to August 1.

Cluster 10 shows a representative low-frequency duty cycle. This candidate would perform a larger 1-hour discharge-charge cycle superimposed by a higher-frequency cycling. The net energy charged and discharged for the 2-hour duration would be approximately zero. However, the depth of discharge for each half cycle is quite high; thus, the battery cycle life would be directly impacted. This would mean that the starting and ending SOC would be identical. This particular testing cycle candidate would lend itself to be repeated multiple times without any further charge corrections.

The other key point is that cluster 17 is power intensive, with the power oscillating with a period of 8 minutes, while cluster 1 has a dominant low-frequency behavior with a period of 60 minutes. By determining the actual power scale for these clusters, one can develop a boundary condition for energy- and power-related strains the PEV batteries will be subjected to during the course of a year. The energy related-strain would be the imposition of sequentially lower or higher SOC at the end of each hour for cluster 1 or cluster 7. The power-related strain would be the imposition of discharge pulses at a low SOC and charge pulses at a high SOC, especially at low ambient temperatures.

Despite the large diversity in regulation data, the analysis distinguished clusters of similar behavior based on dominant low-frequency cycles (30-minute to 1-hour cycles). Cycles in the same cluster have similar time-of-day properties, indicating similar patterns occur in many cases at the same time of the day.

The regulation signals revealed system behaviors of PJM’s market structure. The 1-hour cycle components of the regulation signal clearly reflect the hourly markets, thus causing a rearrangement of generators participating in the day-ahead hourly energy market. The regulation signal dependency on the frequency and timing of market clearings suggests that the results are strictly valid for the current PJM wholesale markets. As PJM’s market design changes, it is very likely that the key cyclical content also will change. With the general trend in the competitive wholesale market to clear in shorter and shorter time periods, there could be a propensity for regulation signals to increase the importance of the shorter cycles. Furthermore, integration of the increasing capacity of intermittent wind and solar resources will very likely introduce new dynamics to the regulation requirements caused by the varying output of the wind and solar installations. How the growing wind and solar capacity may influence the regulation signal is unclear. Weather phenomena and the diversity of the wind and solar insolation across a balancing area will impact the regulation signal. Furthermore, the change in the generation inertia by the growing wind and solar generation also may influence the dynamics of the power system and, in turn, impact the regulation signal.

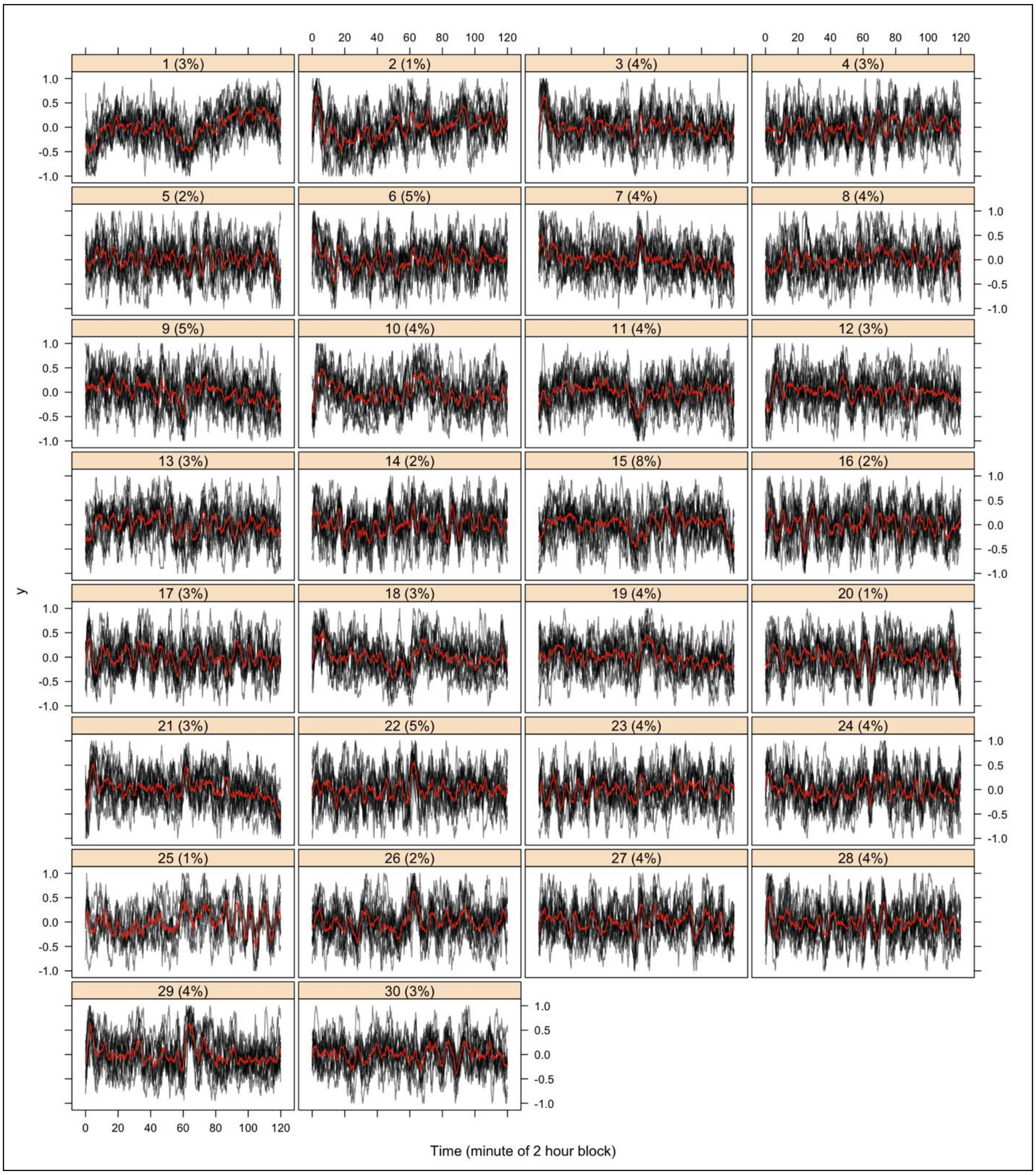

Figure 7: Clustering results for k-centroids clustering with k=30 and using DWT coefficients as the feature vector. Each individual regulation signal is plotted in black, with the cluster centroid in red. The percentage of observations contained in the cluster is given in the cluster label.

4 Recommendations for selection of V2G drive cycles

Despite the large diversity of lower- and higher-frequency characteristics across the time scale in the PJM data set, we do offer some recommendations for the selection of potential candidates for testing cycles that is informed by battery experts. As a result, the recommendations are based on both the findings of the cluster analysis and then further informed by an understanding of battery degradation mechanisms and battery performance testing. From 30 distinct clusters, a set of individual duty cycles from three particular clusters or a combination of them are recommended as potential candidates for future standards development:

1. A low frequency signal with a period of about 1 hour.

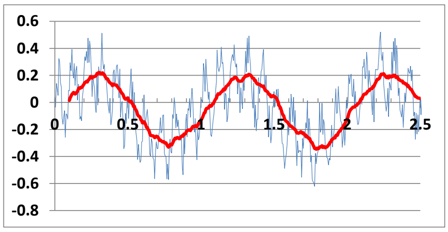

Figure 8: Stylized signal representing cluster with 1-hour period low frequency

2. High frequency signals oscillating symmetrically around zero.

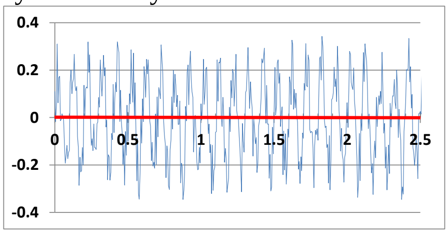

Figure 9: Stylized signal with high frequency

3. Charging and discharging curves with a superimposed upward and downward slope directionality and sign of the signal changing from positive to negative or vice versa.

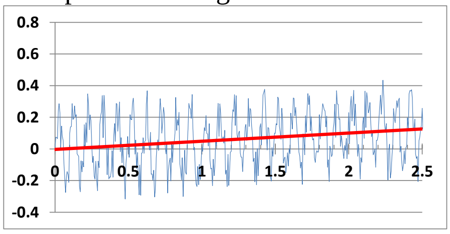

Figure 10: Stylized signal with upward trend

5 Next Steps toward standardizing V2G drive cycles

This analysis is the first of several steps toward standardizing V2G drive cycles or battery testing cycles. The next step is to perform a similar exploratory analysis with regulation data sets from other regions of the United States to explore potential regional differences that are reflective of different market designs, system responses, and system characteristics. After these regional studies, the results can be discussed from a national perspective to identify a set of characteristics that are sufficiently representative of the U.S. national grid or for a specific regions of the US grid.

An analysis for the entire United States needs to be completed and formulated into a set of test procedure proposals for consideration by an appropriate standards body likely the Institute of Electrical and Electronics Engineers.

6 Summary and Conclusions

Four-second regulation signals from PJM over 175 days during March to August were analyzed to address the following question:

Can the characteristics be captured in a small number of test cycles for standardized testing of the performance batteries when deployed to also provide regulation services to the grid?

Extensive statistical, spectral and wavelet and cluster analyses were performed to address these questions. The main conclusions are:

1. The diurnal and seasonal pattern of regulation requirements appears to be generally well-matched with the availability and charge/discharge requirements of vehicle batteries. When providing regulation services, higher overall charging is needed during the night. The regulation requirements are generally less during the day. High frequency regulation requirements are generally less during summer months.
2. The diversity in the signal was large such that there was no clear indication of a small number of distinctive "utility drive-cycles. Nevertheless, recommendations have been developed for a set of a "utility" drive-cycles that are informed by a deep understanding of battery stress tests. The recommendations are summarized as follows:
    i. A low frequency signal with a period of about 1 hour
    ii. High frequency signals oscillating symmetrically around zero

iii. charging discharging curves with an superimposed upward and downward slope directionality and sign of the signal changing from positive to negative or vice versa.

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