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High-Resolution Residential Feeder Load Characterization and Variability Modelling

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***Abstract* — Data from of a highly instrumented residential feeder in Ota City, Japan was used to determine 1 second load variability for the aggregation of 50, 100, 250, and 500 homes. The load variability is categorized by binning the data into seasons, weekdays vs. weekends, and time of day to create artificial sub-15-minute variability estimates for modeling dynamic load profiles. An autoregressive, AR(1) function along with a high pass filter was used to simulate the high resolution variability. The simulated data were validated against the original 1-second measured data.**

***Index Terms* — advanced inverter functionality, advanced grid functions, smart grid, voltage support, frequency support, photovoltaic systems, PV reliability.**

I. Introduction

PV output variability on distribution circuits may lead to excessive voltage swings and increased tap changes on voltage regulation devices. PV variability is often considered as a major driver in voltage challenges in the sub-minute time frame, but there has been limited analysis of the impact of load variability for the same resolution. Most utilities collect load data at intervals of 10-minutes or greater, so it is often not possible to directly compare load variability to 1-minute or 1-second PV variability.

There have been a number of investigations into the effects of PV variability on distribution circuit voltage [1]. Due to load data resolution limitations and the difficulty in estimating feasible load variability, many time-series power flow simulations are performed using linearly interpolated load data. Measured sub-15 minute residential load variability was investigated in this analysis.

This project was separated into two goals:

1. Quantify the load variability between 15-minute residential feeder measurements using high temporal resolution data collected at Ota City, Japan. Analyze the load variability for differences due to the number of homes, time of day, days of the week, and different seasons.
2. Create a method of artificially generating similar variability between 15-minute measurements that could be generally applied to distribution modeling. Validate the results using the Ota City measured data.

Ideally the method should be validated or updated with 1-second load data from the region of interest when conducting site specific studies.

II. Characterization Of Load Variability

Data from a highly-instrumented testbed of 553 homes with PV installations in Ota City, Japan were used, shown in Fig. 1. Load and PV data were collected at each home. There were also weather stations that collected plane of array irradiance, wind speed/direction, and temperature.

Fig. 1. Layout of homes with PV (black dots) in the neighborhood and a photograph of Pal Town in Ota City. [2]

The process used to determine the standard deviation in the variability between 1-second data and 15-minute data is shown in Fig. 2.

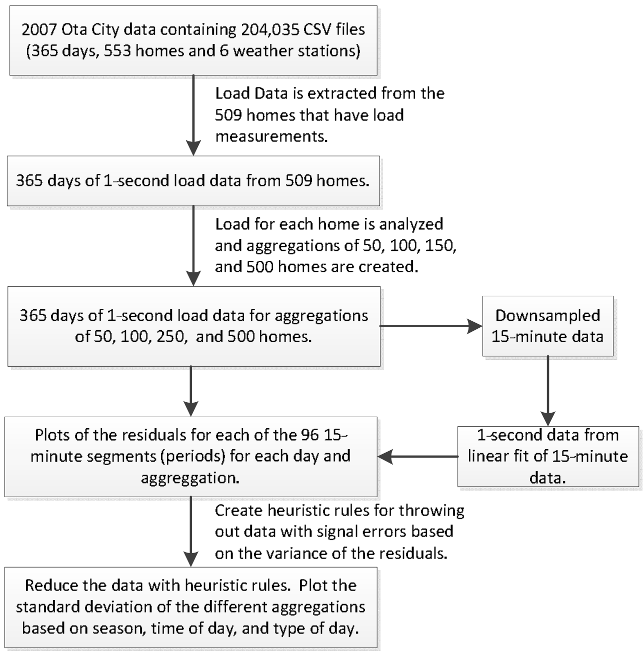

Fig. 2. Process used to determine the sub-15-minute standard deviation of load variability for different numbers of homes, times of day, days of the week (weekday/weekend), and seasons.

A. Load Data Aggregates and Scrubbing

Load data were collected on 509 homes at Ota City. This information was analyzed for each of the homes for the 365 days of 2007. Fig. 3 shows all consumed power data for 500 homes on 1 Jan, 2007. Each box has a trace of consumed power for five different homes.

The data from Ota City were aggregated for different numbers of homes to determine the change in sub-15-minute variability between aggregates. A plot showing a year of data with each box representing the load for one day of the year with the month indicated on the right for 100 homes is shown in Fig. 4.

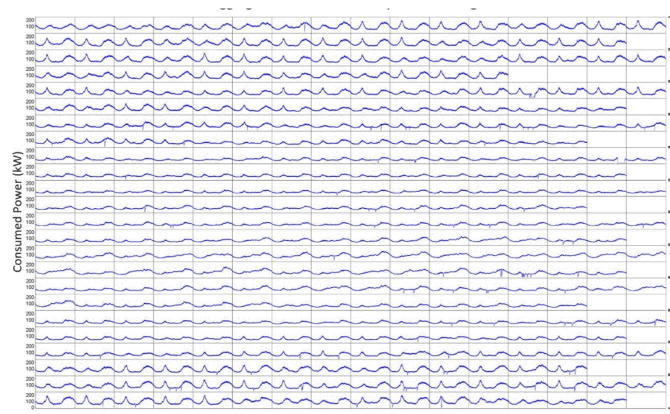

Fig. 4. Plots of the 100 home aggregate for 2007. Some of the sensor errors can be seen, such as in the last day in Nov.

By looking through the 365 days of data for the 50, 100, 250, and 500 aggregates, heuristic rules were created to remove segments with clear sensor errors. For each aggregate, the segment data were removed if the variance of the 15-minute residual was greater than or less than 4 standard deviations away from the mean value of all similar 15 minute values in the same month.

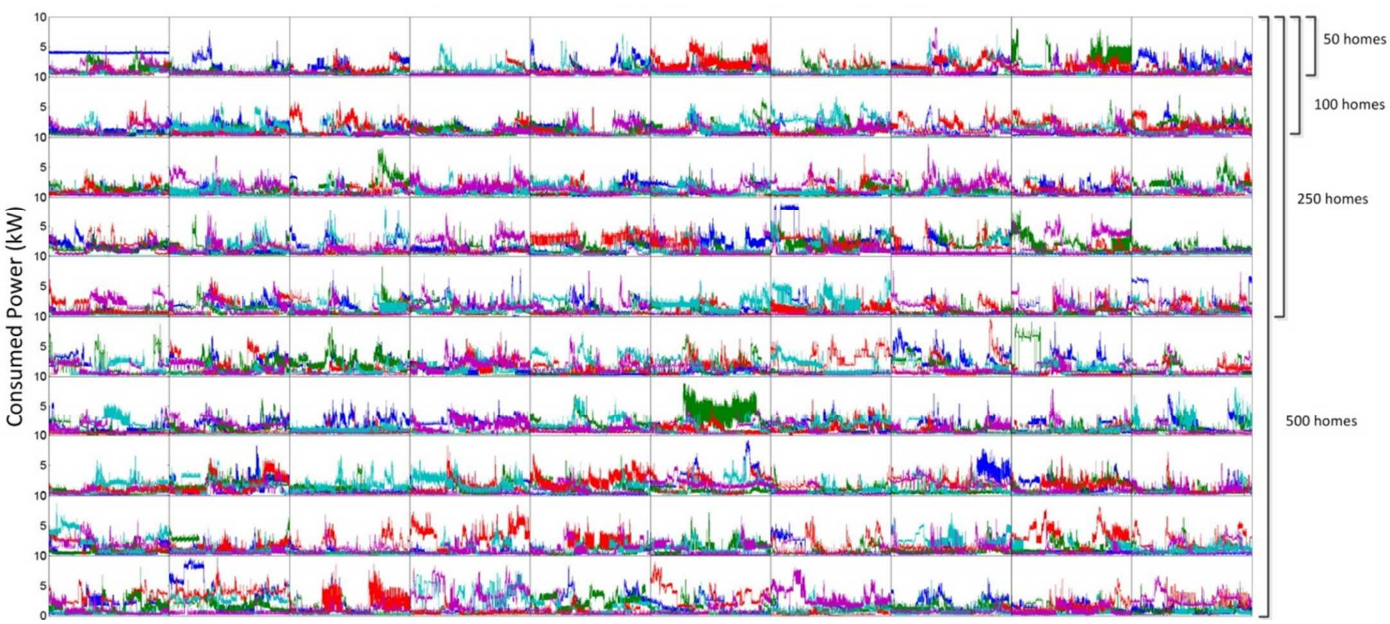

Fig. 3. Load data from 500 Ota City homes on 1 Jan, 2007.

Similarly, a threshold of 4 standard deviations was put on the 15 minute mean values. If a 15 minute mean value fell further than 4 standard deviations away from the mean over the season in which it falls, the segment of data would also be removed.

Although an identical threshold could have been picked for the standard deviation, σ, as opposed to the variance, σ^2, the variance was used to better guarantee that large sensor errors would be removed from the data set.

A day in April without measurement problems is shown in Fig. 5, whereas a day in May with sensor errors or dropouts is shown in Fig. 6.

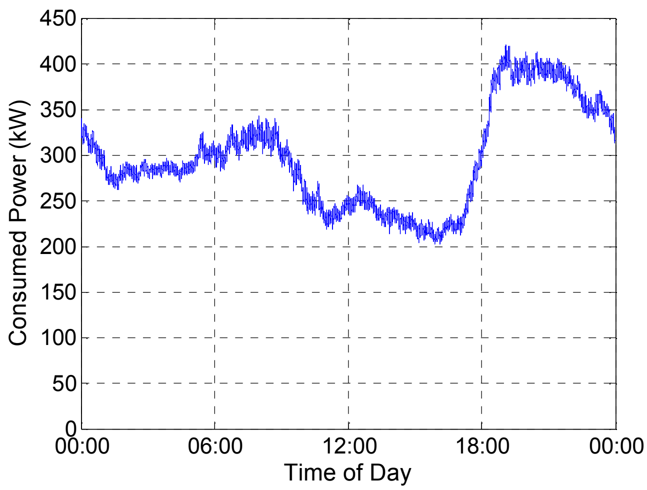

Fig. 5. Plot of 500 home aggregate for April 14, 2007 without measurement problems

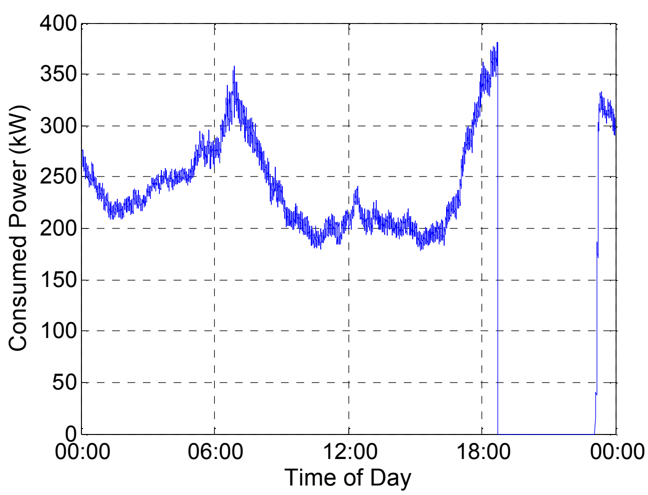

Fig. 6. Plot of 500 home aggregate for May 15, 2007 with measurement problems

III. Simulating sub-15-minute load variability

The difference in the 15-minute linearly interpolated load data and the 1-second load data was calculated for each day and each aggregate. The remaining residual is the noise signature that must be recreated to estimate the variability of the load data. The 15-minute data were connected with a spline curve between the data points. This was selected over a linear or other fit because it would provide a better match to the data and reduce the variance of the noise. The spline curve helped recreate similar ramp rates to the measured data at higher time intervals such as 5 or 15 minutes.

The target noise was the difference in the 1-second consumption data, *Cons(t)* and 15-minute spline interpolation of the consumption data, *Spline(t)*, and could be defined by a function *N(t)*, such that,

$$N(t) = Cons(t) - Spline(t). \tag{1}$$

The noise data were then differenced, i.e. D(t) = N(t+1) – N(t). The standard deviations (b) and mean values (u) for each 15 minute period of data were calculated for the Ota City difference data, D(t). The sample data was created by running the AR(1) model using Laplace(u,b) and AR parameters estimated by the Yule-Walker method. The Laplacian random noise used the calculated standard deviations (b) and mean values (u) for the given 15 minute window being sampled. Then the cumulative sum was run through a high pass filter and added to the spline curve to create the simulated sub-15 minute load variability. Fig. 7 shows the result of the simulation plotted along with the measured data. The inset shows the high frequency similarities between the simulated and the measured data.

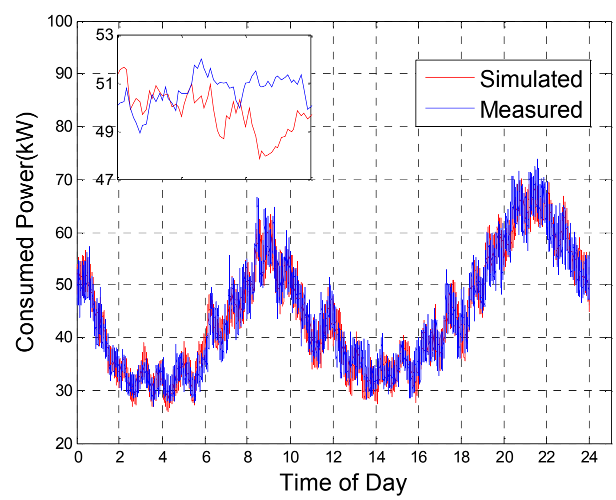

Fig. 7. Plot of 100 home aggregate for January 1, 2007 with simulated and measured consumed power, inset is one minute of data in the 8:00 hour.

IV. Results and Validation

It is necessary to compare the simulated consumed power and the measured consumed power in a way other than the standard mean bias error and mean absolute error. If evaluated based on the methods mentioned, the linear interpolation or a spline curve through the 15 minute points would give better results than our simulation.

The goal for this study was matching the ramp rates over different lengths of time. A variety of ramp rate lengths were investigated, including 1 second, 15 seconds, 1 minute, 5 minutes, 10 minutes, and 15 minutes. To do this, distributions of each of the ramp rates in question were created. For example, the first value in the distribution for the 15 second ramp rates would be the difference between the consumed power at 16 seconds and 1 second, the second would be the difference between consumed power at 17 seconds and 2 seconds and so on until the end of the data set. Fig. 8 shows the CDF plots of the ramp rate distributions for the measured and simulated consumed power. The plot includes 100 homes over the entire 2007 year.

V. Conclusion

Analyses indicate that load variability can be categorized by season, day of the week, and time of day for different aggregates of homes. Validation shows success in the ability to produce simulated load variability for 2007 Ota City data with similar characteristics. It was important to capture the high frequency along with the low frequency movements in the simulation. This was made possible by using the high pass filter along with the spline curve through the known 15 minute points.

Future goals include obtaining high resolution data sets from the U.S. for comparison. There is also interest in looking at the effects of having commercial and industrial components in addition to residential. Time series simulation comparisons will be used to assess the impact of inserting artificial load variability on voltage regulation equipment operations.

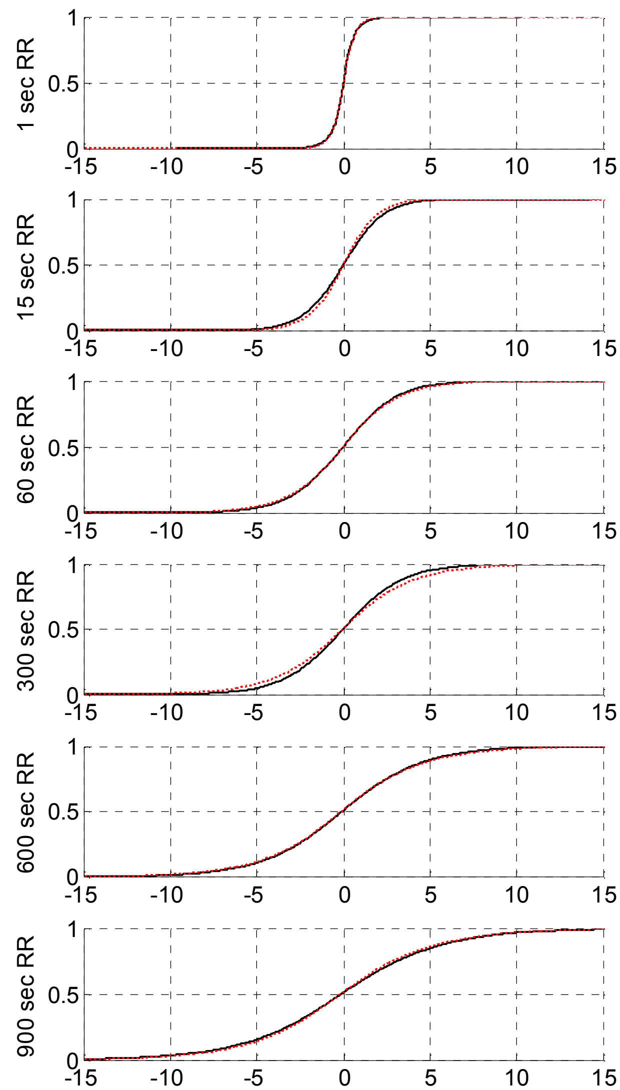

Fig. 8. CDF plots for various ramp rates comparing simulated and measured data from 2007 Ota City data for 100 home aggregate.

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