HIGH-RESOLUTION RESIDENTIAL ELECTRICITY USE DATA FOR IMPROVED REALISM IN BUILDING ENERGY SIMULATIONS

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ABSTRACT

Observing and measuring transient energy events may help to improve building energy performance. This paper presents a method of using one-second resolution residential electricity data to create highly granular simulation inputs to improve the realism of energy models. We developed a method for collecting one-second electricity data. One-second electricity data from a 5-person residential building was collected using commercially available hardware for several usage intervals. A web-based MySQL database platform was implemented to store incoming data. A simple model was constructed to compare results when evaluating one-second, one-minute, and one-hour input data. Initial results show important differences in energy demand that have implications for electrical system sizing and energy costs. We believe that a number of existing models would benefit from using highly granular electricity data to realize more accurate simulations.

INTRODUCTION

Electricity is widely viewed as one of the highest quality forms of energy. Reliable access to electricity is viewed as a key factor in facilitating the development of human society and modern economies (Momoh, 2009). In many regions of the globe, electricity is a major source of both economic and environmental cost. This is particularly true in areas where fossil-fuel based generation is the predominant form of electricity production.

Electricity consumption has shown important increases over time, and like other forms of energy-consumption, shows relationships to levels of economic activity and population size (Narayan, Smyth, and Prasad, 2007). Figure 1 shows a roughly four-fold increase in electricity production since 1971.

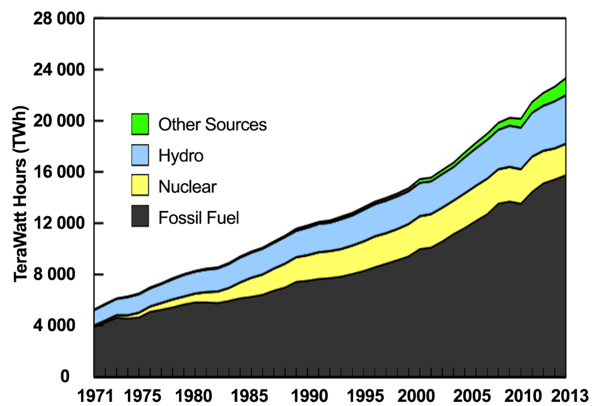

Figure 1. World Electricity Production from 1971 – 2013 in Terawatt hours. (IEA 2015)

Efforts to improve the measurement of electricity usage for the average consumer have been limited until only recently. The increasing availability of low-cost electronic, computing, and communications devices has lead to a number of low-cost electricity monitoring technologies that are suitable for research purposes and also broader implementation as tools to manage electricity use in residential and commercial infrastructure. These tools can help supplement planning of electricity demand and distribution (McQueen, Hyland, and Watson, 2004:2015)

This paper presents measured electricity data, gathered using a variety of electricity monitoring technologies, for a 5-person residential structure located in Eastern Canada. The collected data, and the nature of the electricity monitoring tools themselves, suggest that existing electricity use models may not adequately capture short-term electricity use events, such as transient spikes in power demand. Recognizing these events may prove to be a useful improvement in energy modeling software.

METHODOLOGY

This study employed five (5) commercially available electricity monitoring systems. Each system was tested and calibrated, initially under laboratory conditions, then followed by in-situ testing within a residential dwelling. Table 1 presents an overview of the technologies evaluated.

Testing Protocols
Prior to installation, devices were tested and verified in a lab setting. Hardware was setup on a customized lab bench consisting of switch-operated electrical outlets. A range of loads were measured, from low-draw devices such as LED lamps (9W) to larger loads such as electric heating elements (1500W). Device current and voltage was manually evaluated using a Fluke 376 clamp multimeter, and monitoring system cross-verification was conducted by measuring dynamic appliance loads with several electricity monitoring devices simultaneously.

Deployment
A typical deployment of these systems involves the installation of precision electricity sensors, Current Transformers (CTs), on the 'mains' electricity circuits of a structure, at the interface with the electricity grid. In this case, CTs were installed within the electricity panel of the structure by a qualified technician, according to each manufacturer's specifications.

Deployment also involves connecting the monitoring devices directly to the Internet via Wi-Fi or Ethernet in the consumer's home and programming the device to upload data to their respective manufacturers' database systems in the cloud.

Data Storage
Because of the large data storage requirements for 1-second data, manufacturers of electricity monitoring devices do not often harvest or store data on their web servers at a 1-second resolution. Our method for acquiring and storing 1-second data involved 'scrubbing' data from manufacturers online databases using custom program scripts.

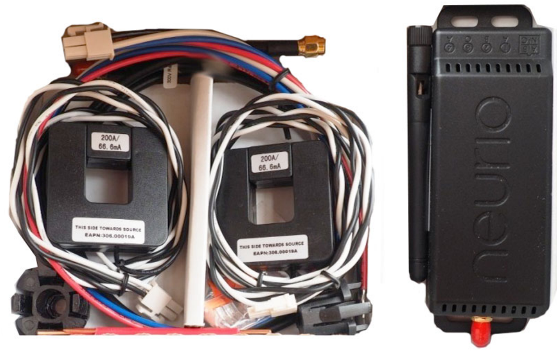

Figure 2. Current transducers (CTs), and a Wi-Fi microprocessor-based electricity monitor.

To assist in data collection, the following steps were required:

a) We constructed a MySQL database to store the data. The database provides a central storage location for our data and also provides the capacity for trending and analysis.

b) Several device manufacturers provide an application programming interface (API) by which data from their database can be polled. Python scripts were written to execute data file downloads from the manufacturer's cloud storage to our research servers. The scripts have been set to automatically run on a daily basis using a task scheduling software utility.

c) Once downloaded to the research servers, the data is processed and uploaded to the previously described MySQL database.

Collected data was prepared for analysis by synchronizing and converting time-stamps to similar format. Data analysis was conducted using a variety of tools including IBM Watson Analytics, MySQL Viewer, and Microsoft Excel. Simple data-models were constructed in Excel to evaluate effects of time-averaging and sampling methods used to 'roll-up' highly granular data into larger time increments.

Table 1. Electricity Monitoring Devices Tested.

	Device	Manufacturer	Manufacturer URL:
1	**Efergy Elite Classic**	Efergy	http://efergy.com/
2	**Open Energy Monitor**	Megni / OpenEnergyMonitor	http://openenergymonitor.org/emon/
3	**Egauge**	eGauge Systems LLC	https://www.egauge.net/
4	**Blueline Powercost Monitor**	Blue Line Innovations Inc.	http://www.bluelineinnovations.com/
5	**Neurio**	Energy Aware Technology	http://neur.io/

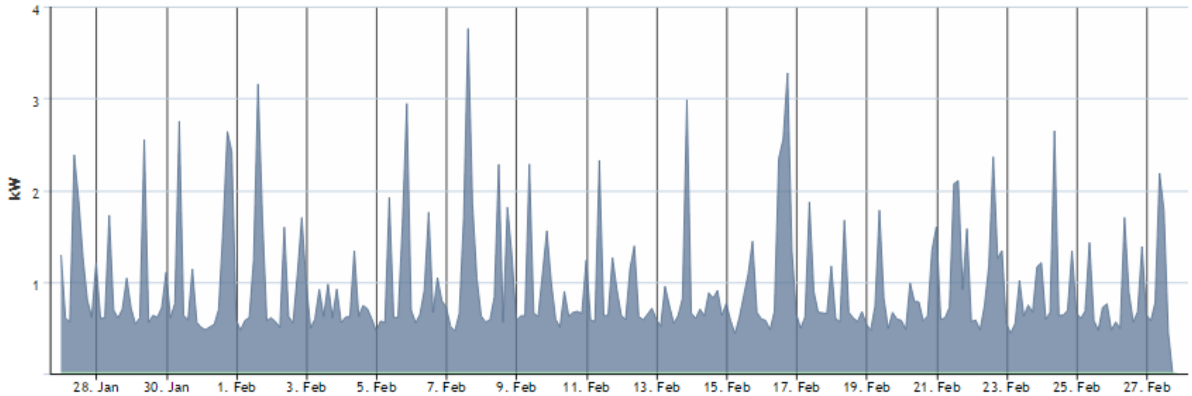

Figure 3. A 30-day record of residential electricity demand reveals the stochastic nature of electricity use.

RESULTS

The data collection systems employed in this study provided a large volume of empirical data for analysis. We believe these observations may provide useful for other researchers engaged in building simulations and modeling. Models, and the simulations they permit, are highly influenced by the quality of underlying data used to generate theoretical understandings of system behavior. Changes in technology make it increasingly feasible to collect high-resolution electricity use data, and this leads to a number of useful insights.

Appliance Description Variability

The nameplate electricity ratings of most appliances correspond only roughly to their actual power consumption. Table 2 shows stated versus measured power demand for several large loads at the test residence. Operating environment and other factors create variations in power demand, and relatively simple simulations may not account for this, and instead rely on nameplate values. Test observations suggest that there are significant deviations from typical nameplate values, with power demands varying considerably over the operating period of a device or appliance.

When individual appliances are tested, the in-rush current of induction devices such as motors or compressors is easily observed as sharp peaks upon device start-up. Figure 4 shows a 150 W spike associated with a portable dehumidifier. The majority of large loads in many homes are resistive in nature, such as heating loads, however short-duration spikes can play a significant role in influencing overall system demand profiles. This can be an important factor when sizing certain elements of electrical systems.

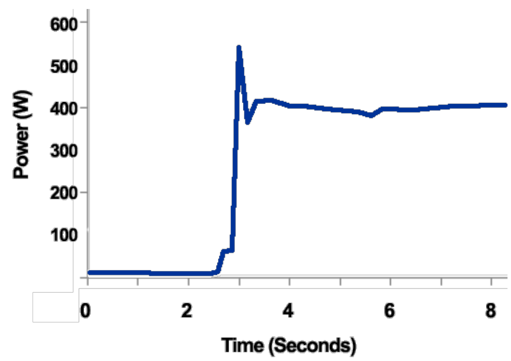

Figure 4. Appliance start-up demand 'spike'

Thermostatically controlled devices, such as electric range elements demonstrate a pulsing demand. Figure 5 shows the 1600 W short duration pulses exhibited every 40 s by an element on the mid-setting. Because various peaks and pulses are additive across all the electricity consuming devices within a residence, during certain brief intervals, electricity demand can spike considerably beyond what would be anticipated through the simple summation of the nameplate capacity of the various devices.

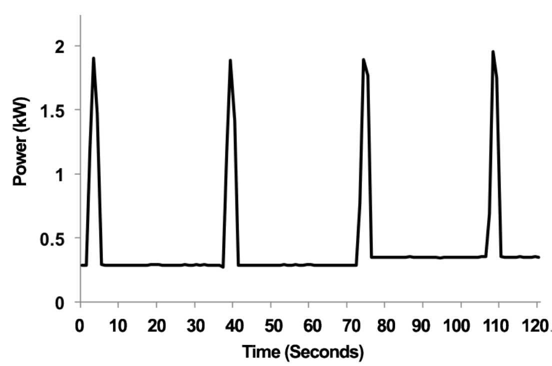

Figure 5. Pulse-modulated electricity demand

Table 2. Nameplate power versus measured power demand in watts (W).

Device name	Voltage	Amperage	Power (W)	Observed (W)
Dehumidifier	115	6.5	710	500
Microwave	120	12.5	1500	2000
Fridge	120	6	720	280
Oven	240	17	4090	3800
Toaster	120	6.5	780	1100
Kettle	120	12.5	1500	1385
Water Heater (Oil)	115	5.8	667	600
Washer	120	10	1200	625
Dryer	240	24	5600	6000
Furnace blower	115	2.35	270	300
Furnace burner	115	5.70	656	600

Aggregation and Disaggregation of Electrical Loads

Figures 7 and 8 present a 24-hour snapshot of electricity consumption for the same residential dwelling, measured at differing 1 s and 1 minute time resolutions. Electricity demand at a residential level, and ultimately demand at the grid level represent the cumulative effect of multiple simultaneous loads in operation. The timing of individual usage events is subject to user-behavior and environmental factors such as temperature. This results in the well-documented phenomenon of demand peaking at times of coincident usage of multiple loads across the system.

Electricity monitoring systems provide an opportunity to evaluate both aggregated and individual device loads depending on how the tools are employed. In the case of this study, devices were used as both a tool for characterization of individual loads, and a means of recording extended periods of user operation and system behavior. Electricity monitoring device manufacturers are currently piloting methods to disaggregate individual appliances from complex load profile data using machine learning and other analytical techniques. This type of activity is in the early stages of development and requires system users to initially train the electricity monitoring device. Due to the complexity of the data and the high variability of user behavior, the models and algorithms underlying this approach require considerable effort. Figure 6 shows an example of appliance monitoring offered using this approach.

High resolution energy data offers not only the ability to manage energy, but to provide a wide variety of monitoring and evaluation services. The trend towards this type of activity suggests that the building modeling and simulation community begin to adopt finer timescale data, despite the challenges it poses in data collection, storage, and processing.

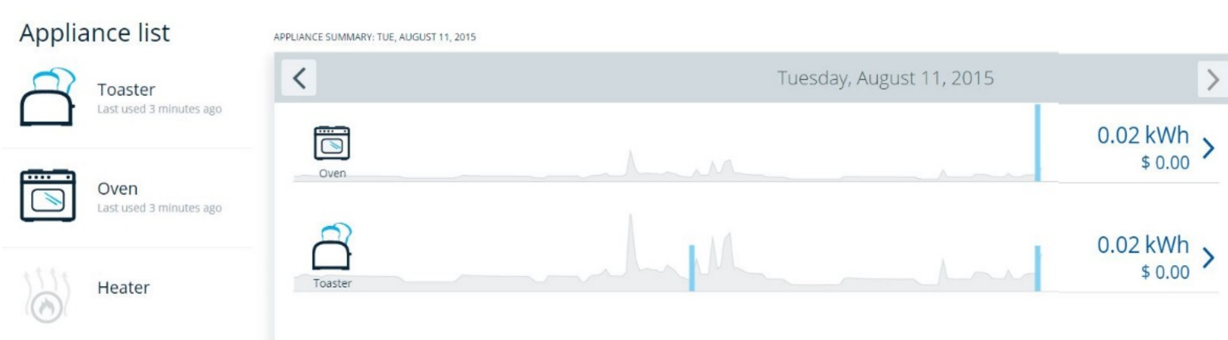

Figure 6. Software-based disaggregation of individual appliances derived from a residential load-profile.

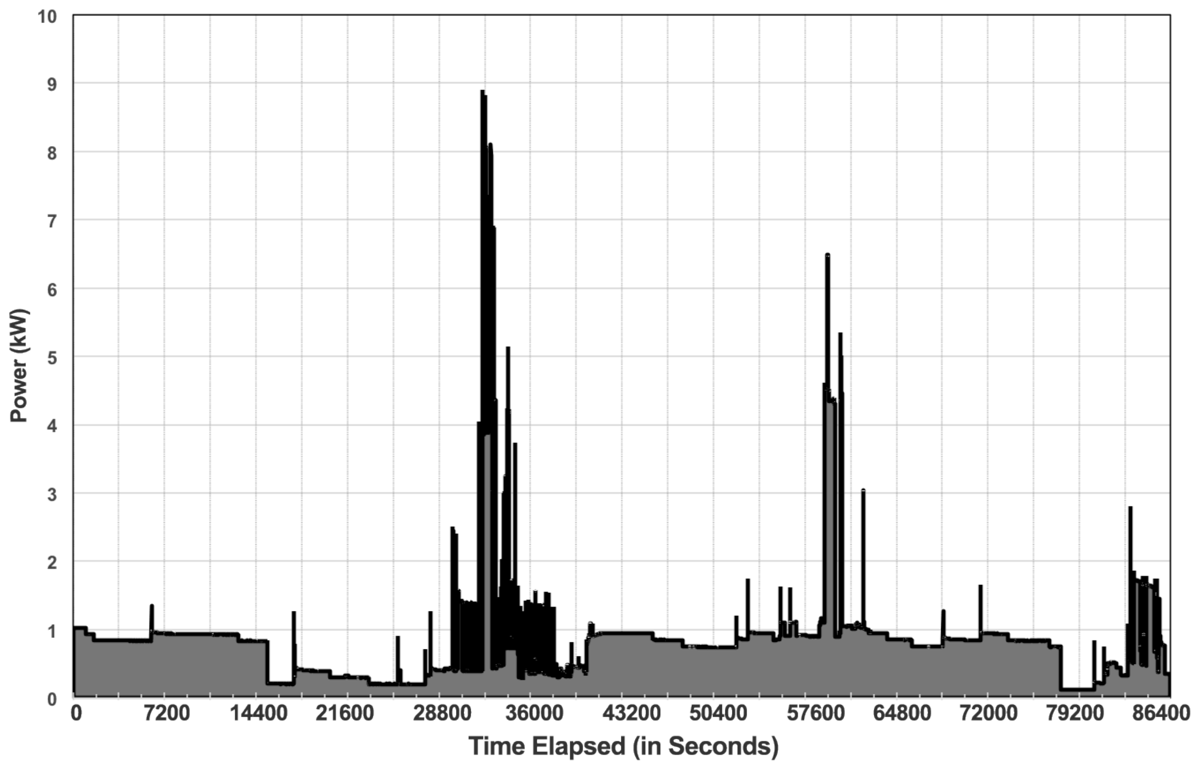

Figure 7. 24-hours of 1-second electricity load data from a residential dwelling, measured August 1, 2015.

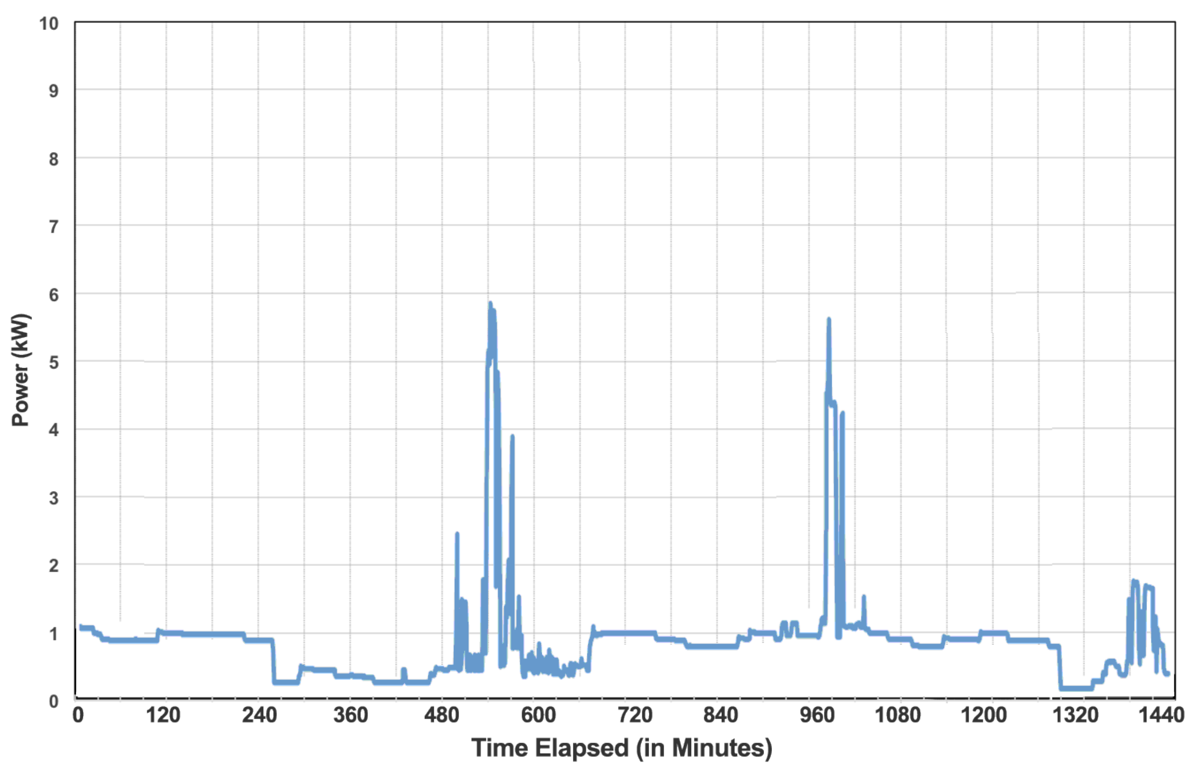

Figure 8. 24-hours of 1-minute electricity load data from a residential dwelling, measured August 1, 2015.

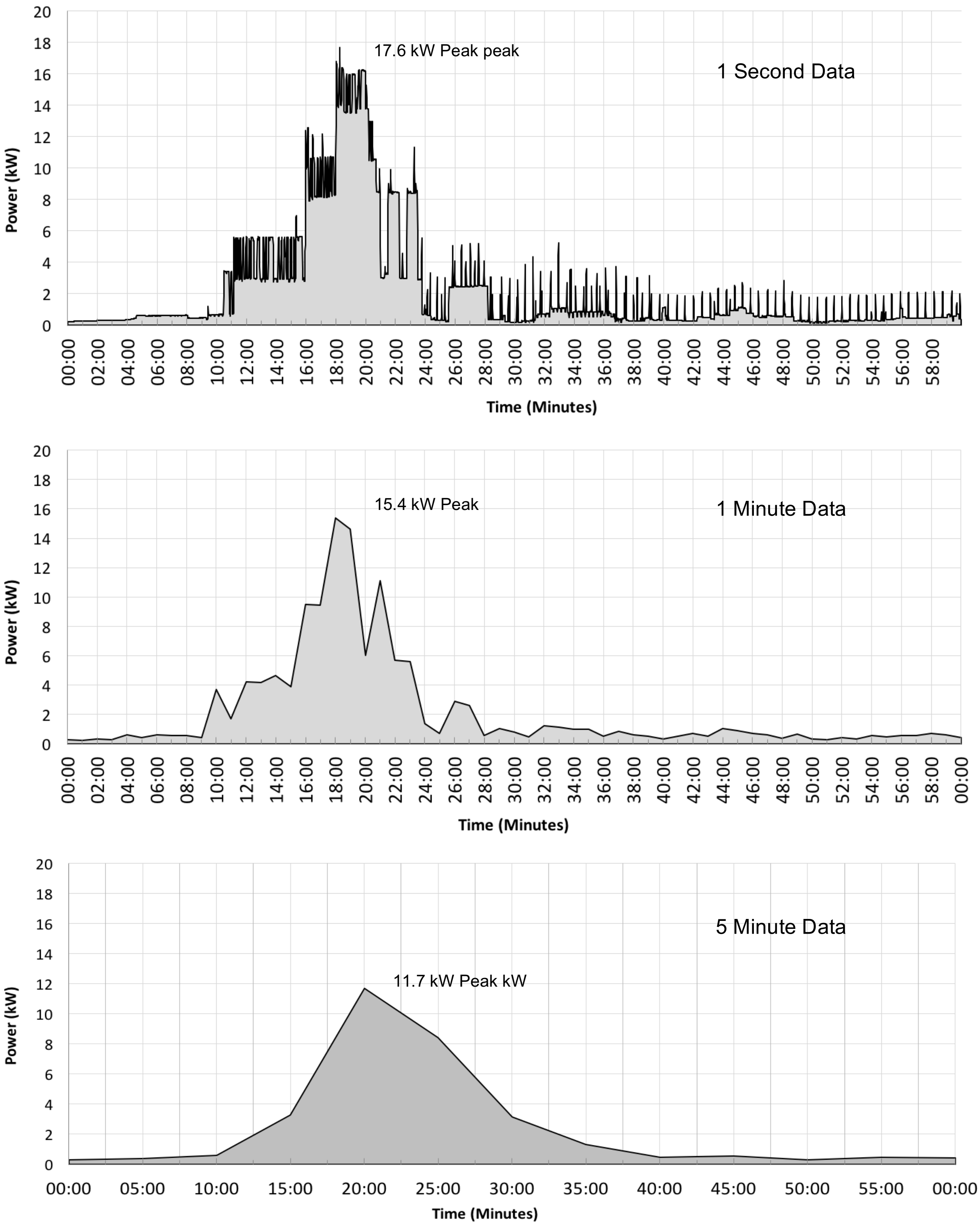

Figure 9. 60 minutes of electricity load data from a residential dwelling, representing supper-hour on-peak activity measured March 10, 2016, showing 1 s, 1 min, and 5 min data capture.

Peak Power Discrepancies

One second and one minute data capture rates did not result in identical power measurements. Figure 7 shows a 24-hour measurement profile, recorded at 1 s intervals, with a peak power demand of 8.903 kW measured after 3.22 x 10^3 seconds. The corresponding peak-values observed using 1-minute measurement (seen in Figure 8) was 5.817 kW, observed at 542 minutes. In this case, the difference in peak power observed is 3.086 kW, and represents a 34.6% larger value when using per/second observations. Figure 9 shows a 60 minute high-electricity use period at three time resolutions, with diminishing observed peak kW.

This effect was consistent across the collected data. An explanation for the higher peak-power effect is related to the measurement algorithms employed in the electricity monitoring devices, and the fact that they employ forms of measurement sampling or measurement averaging. The higher values observed are transient in nature, but can represent an important consideration for the sizing of residential building electrical-systems, notably where systems incorporate any form of electricity conditioning equipment such as power-inverters associated with renewable energy and energy storage installations.

DISCUSSION

At the present time, energy modeling tools are focused primarily on aggregate energy use over long periods of time, rather than detailed observation of electricity demand. The success of solar photovoltaic technology and emergence of lower cost energy storage is driving a transition towards greater electrification. As electricity becomes a more dominant form of energy use, it will become increasingly valuable to use higher resolution modeling and simulation tools. The aim of this paper is to suggest that empirical datasets to support the development of these tools is readily available.

A number of models incorporate functions that involve electricity data, some notable tools include:

HOMER – microgrid modeling software

RETScreen – clean energy management software, for evaluation of technical/financial viability of projects

HOT2000 – energy simulation and design tool for low-rise residential buildings

Equest / CAN-QUEST – energy modeling and design software for high performance commercial-institutional buildings

TRNSYS -Transient Energy System Simulation Tool.

A variety of other tools exist or are under development, and share the common thread of energy performance analytics. They are all used as a design aide, generating energy performance metrics to guide decision-making. Electrical energy usage reported by these models is generally the result of either a) user input, or b) estimated values. Of the various programs that we examined, TRNSYS was the only example that can readily accept usage profiles on a granularity of 1-second. This data time-scale is currently prohibitive in its storage size and management, with a single day comprised of 14,400 data points, however we anticipate these challenges will soon diminish.

CONCLUSIONS

Electricity monitoring technology is becoming a widely-available consumer product. The resulting information will provide value to both consumers, and others who may be able to offer value-added services to improve efficient operation and design. The modeling and simulation tools currently employed for planning net-zero, off-grid, and micro-grid projects may not be taking full advantage of relatively low-cost, high-resolution data now available. The nature of electricity use, from a variability and peak kW perspective, looks considerably different when viewed at high time resolutions. Recent trends in distributed generation, load-shifting, and electricity storage suggest there may be value in further investigation of how transient electrical events impact design and operation of advanced buildings. Electricity is arguably the highest quality form of energy, and electricity monitoring is an important tool in overall energy management that provides considerable insight into the energy behavior of homes and buildings. Monitoring technology is constantly evolving, bringing higher quality and increasing quantities of real-world data to support modeling and simulation.

On its own, electricity monitoring data provides useful insights for managing energy. When incorporated with modeling and simulation tools, this information plays a vital role in helping communities manage their energy future.

ACKNOWLEDGEMENTS

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