Abstract—In this paper, we investigate the performance of wireless technology for monitoring and controlling the electrical load of a residential neighborhood. An event-based power metering scheme is assumed where transmissions are sent only when a change occurs in household consumption. Analysis of high-resolution, empirical data suggests that consumption transitions can be modeled as a Poisson process in the time-domain. A peer-to-peer 802.11 wireless network was simulated to determine latency between houses and a local sub-station. Probability distributions for monitoring and control traffic show that packet latency is exponential distributed and neighborhoods larger than 400 homes may not be able to respond within a fraction of the 60 Hz cycle.

Index Terms—Demand participation, residential load modeling, Poisson processes, smart grid, wireless networks.

I. INTRODUCTION

In order to maximize the performance of existing power systems, there has been an increasing amount of interest into utilizing advanced communications networks as part of the future smart electric grids. These grids will allow system components, including residential loads, to be capable of participating in the energy management process in near real-time.

The residential sector is responsible for, on average, about 30% of electric energy consumption in all consumer sectors [1]. Residential customers will be expected to play a bigger role in energy management and conservation in various ways, such as shifting their consumption in response to market price, providing ancillary services (e.g., automatic demand control) with storage from plug-in hybrid electric vehicles, or pooling the excess/stored electrical energy from in-house energy production with neighbours or other consumers on the grid.

This paper will specifically focus on evaluating the effectiveness of wireless technology for monitoring and controlling the load of a residential neighborhood. It is assumed that communication exists between houses and a sub-station using a peer-to-peer wireless network based on conventional, low cost 802.11 WiFi technology.

An important contribution of this paper will be to present a new high-resolution household power consumption model that will be used to predict traffic on the network. To avoid unnecessary transmissions when monitoring power consumption, it is assumed that a household power meter will transmit information only when it detects a change in power consumption. This takes advantage of the discrete nature of residential load power consumption [2]. To predict network traffic, a new per-second power consumption model is presented with much finer time resolution than existing models [3]. For controlling the residential load, it is assumed that the residential consumers will be participating in a demand participation program where a certain fraction of their load is available to be cut when needed. For example, when a fault occurs on the grid, the operator can reduce the load in the neighborhood as part of a protection relaying scheme. Another example is the situation in which the distributed storage capacity in the neighborhood is employed in mitigating the intermittency of variable generators (e.g., wind-powered generators). Thus, it is desirable that each household will receive a load reduction command from the sub-station in a fraction of a cycle. Another contribution of this letter will be to use a full wireless network simulation to determine the latency or delay of the wireless network for the load monitoring and control applications described above.

The rest of the paper is organized as follows. In Section II, a review of residential load modeling techniques is provided and the load model employed in this study is described. In section III, the details of the simulated wireless network are presented. Finally, concluding remarks are provided in Section IV.

II. RESIDENTIAL LOAD MODELS

A. Literature Review

There has been a considerable amount of effort to model the energy consumption in residential sector in the literature; a review of some of the existing residential load models can be found in [4]. It has been identified that factors such as family size, occupant behavior and change of technology alter the end-use residential demand profile. It is also shown that top-down and the bottom-up approaches form the basis of those modeling methods. A top-down model considers the residential sector as a whole and uses historical data and econometric variables to estimate the energy consumption. Generally, top-down models focus on modeling energy consumption on a daily to annual basis which is not within the time resolution of our interest. On the other hand, bottom-up models aggregate individual energy consumption and can be used to generate realistic outputs with much finer time resolution. Therefore, the bottom-up models are better suited for the applications studied in this paper and are briefly reviewed in this section.
In [5], a model is proposed to study the electricity usage pattern and the maximum demand requirement within the residential area in Italy. The model is developed to match the actual power consumption data collected with a 15 minutes sampling resolution. In spite of its highly accurate outputs, the major drawback of the model is that it requires fine detail information such as life-style factors of the occupants in different families. This type of information is not usually readily available.

In [6], a simplified version of the model of [5] is proposed with a 1 hour resolution. The model was developed to evaluate the potential of appliance level demand-side management. The model introduces stochastic process for the random nature of energy consumption in each family. However, the aggressive assumption in the stochastic process oversimplified the true nature of consumption. It is observed that finding the proper balance between the detail of input information and output accuracy is one of the main objectives when developing residential load models.

Higher resolution models for analyzing residential electric energy consumption have also been reported over the recent years [7]–[9]. Such models use public available survey data (e.g., Time Use Survey) to create the relationship between occupant activity profiles and appliance usage to come up with the energy use in a single house and then aggregated within a concern area. In [7], a 5-min resolution model is proposed to examine system performance, efficiency and emission reduction potential of residential cogeneration technologies. In, [8], a 1-min resolution model is proposed to study on-site distributed generation. Similarly, [9] proposed a 1-min resolution model with different stochastic approach to study the local distribution networks.

B. Measurements and the Employed Load Model

In our paper, we focus on very high resolution data, i.e., 1 second resolution. To properly model the source traffic, we examined the time-dependent characteristics of household appliance events (an appliance being turned on or off) for a typical domestic load. Using a commercially available home energy monitoring device, consumption data was obtained from a family household with 5 occupants in Calgary, Canada. Daily power consumption was measured with 1 second granularity for the duration of 19 consecutive days in February 2009.

In our analysis, we found it useful to identify periods of high occupant activity within the household. The capacity limit of an event-driven monitoring communications network would be reached during “peak hours” when inhabitants are most likely to be engaged in several activities that require simultaneous use of lighting and multiple appliances. We defined an occupancy flag to indicate periods of high activity when 12 or more positive transitions occurred in a single hour. An example plot of a daily profile with event times and occupancy flag is shown in Fig. 1.

To create a suitable traffic model, we examined the probability distribution of the time interval between power transitions caused by appliance events. The intervals between consecutive transitions, either positive or negative, were measured for periods of high occupant activity and placed in a normalized histogram to form the probability density function (pdf). Comparison of this measured pdf with the familiar exponential pdf revealed a close correlation when the exponential rate was set to \( \lambda_a = \frac{1}{22 \text{secs}} \). This result provided an indication that appliance activation and deactivation events could be modeled as a Poisson process with the inter-event pdf given by

\[
f(t) = \lambda_a e^{-\lambda_a t}
\]

where \( t \) is the random time interval between appliance events. Note that, compared to the models available in the literature, our model describes the transitions in power consumption, rather than the actual power consumption itself.

III. WIRELESS NETWORK

The networking scenario modeling in this paper is one where the power utility has deployed its own communications infrastructure to maintain connectivity with households. While many network architectures can be chosen for this scenario, this paper considers one where residences are connected using a peer-to-peer wireless network that utilizes conventional 802.11b WiFi technology. The advantage of this architecture is that it is very low cost and requires no infrastructure beyond an additional wireless interface for the power meter in each home. While much higher rate variants of 802.11 do exist, the additional throughput and expense is not warranted for this application. Using well established technology also helps to ensure the reliability of the communications hardware.

It is assumed that one 802.11b device is installed in each home. Each device communicates with the devices in neighbouring houses in a peer-to-peer fashion such that a mesh network is formed that connects the entire neighbourhood to a substation. A square neighborhood is assumed with houses separated by 50 m in the x-direction and 20 m in the y-direction. A sub-station located in the lower left-hand corner of the neighborhood is the destination for all monitoring packets and the source for all load control commands.
In load monitoring mode, it is assumed that a household power meter will transmit information only when it detects a change in power consumption. While this is a departure from sampling power levels at regular intervals, this scheme is selected to avoid unnecessary traffic over the wireless network. Due to the discrete nature of residential power consumption [2], it is not expected that this sampling approach will introduce any significant error in the power profiles.

For controlling the residential loads, it is desirable that each household receives a load control command from the sub-station within a very short period of time, preferably a fraction of a cycle. A short delay in such communication is important in efficient demand-side participation programs in the context of smart grids. Assuming that the residential consumers will be participating in demand participation programs, a certain fraction of their load is available to be controlled when needed. For example, when a fault occurs on the grid, the operator can reduce the load in the neighborhood as part of a protection relaying scheme. Another example is the situation in which the distributed storage capacity in the neighborhood is employed in mitigating the intermittency of intermittent generators (e.g., wind-powered generators).

For load monitoring, a geographic routing algorithm is assumed for the mesh network where the WiFi devices utilize knowledge of their position when determining how to route packets through the network. A simple greedy forwarding scheme is assumed where each WiFi device forwards all packets to the neighbour that is geographically closest to the sub-station [10]. Each house generates monitoring information at random times according to the exponential distribution described in Section II.

It is assumed that load control messages are to be delivered to every home in the neighbourhood. Rather than addressing and routing individual control messages to each home, a broadcast routing algorithm is assumed where each house relays the control command to its neighbours until it has been received at least once by all households. Sequence numbers are utilized to ensure each house does not forward the same packet more than once. This prevents flooding of the network by control messages. Sub-station control commands are generated and spaced in time such that consecutive control commands do not interfere.

The performance of this network is simulated using the ns2 simulator which includes a full implementation of the 802.11 protocol stack. WiFi transmit power is 1 W. The number of neighbouring WiFi devices in range of each house are determined by this transmit power level, the wireless receiver sensitivity and the attenuation of the radio channel. Channel attenuation increases with distance and is calculated using the standard path loss model with an exponent of 3 [11].

Due to collisions, packets will periodicaly be lost as they traverse the network. The network protocol will automatically detect these lost packets and retransmit them in order to ensure the data is delivered. However, these retransmissions add to the amount of time required for the information to reach its ultimate destination. Due to the random nature of traffic on the network, packet collisions, retransmissions and the ultimate latency of each packet to reach its destination will also be random. It is important to characterize this latency since it will determine whether the network is capable of meeting the demand-side management delay requirements.

The latency a monitoring or control packet traveling through the network can be represented by a random variable with a particular pdf. The latency pdf’s for the monitoring and control traffic in a 400 home network is shown in Fig. 2. The peaks in the pdf’s are located at the delay values required by a packet to traverse a fixed number of relay nodes in the mesh. Packet collisions then add an extra amount of random delay that cause deviation from these fixed delays and results in a slightly smoother pdf.

Figure 2 also shows an exponential approximation of the latency distributions offset so that the start of the distribution lines up with the minimum latency value. If the random variable $X$ represents the simulated latency values, then the exponential pdf is given by $g(x) = \lambda \exp[-\lambda(x - \min(X))]$ where $\lambda = 1/[E\{X\} - \min(X)]$, $E\{X\}$ is the mean of $X$ and $\min(X)$ is the minimum value of $X$. While the exponential approximation is clearly very loose in Fig. 2, it is still a useful tool since it allows a power system operator to generate random latency values in a demand-side control simulation to first order accuracy without resorting to a full network simulation.

Due to the relay nature of a mesh network, latency increases with increasing network size. Therefore, it is important to determine how large a neighbourhood can still be in order to still meet the demand-side control latency requirements. As a result, simulations are conducted for neighborhood sizes of 100, 400, 900, 1600 and 2500 homes. The values of $E\{X\}$ for these neighborhoods are 2.43 ms, 4.66 ms, 7.42 ms, 10.67 ms, and 15.67 ms for the monitoring commands, respectively, and 2.10 ms, 6.60 ms, 10.37 ms, 12.52 ms and 13.89 ms for the control commands, respectively. The value of $\min(X)$ is 1.43 ms for the monitoring traffic and 1.08 ms for control traffic for all neighborhood sizes.
IV. CONCLUSION

This paper shows that the time between transitions in household power consumption can be modeled as a Poisson process at per-second resolution. This paper also shows that the latency of a mesh network based on existing WiFi technology makes it useful for smart grid monitoring and control applications in residential load level. However, beyond a neighborhood size of approximately 400 homes, the network may no longer be able to respond within the fraction of a 60 Hz cycle.

REFERENCES


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