Home area network accountability with varying consumption devices in smart grid
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ABSTRACT
Among the principals for securing smart grid infrastructure, accountability is one with lesser addressed concepts in smart grid literature. Even further, studies in the home area network are lacking in enforcement of accountable mechanisms as assigning responsibilities for devices’ actions are generally made the responsibility of the utility. This paper addresses accountability of devices in the home area network by providing a witness-based method for more accurate monitoring and estimation of the energy usage for devices whose power consumption varies while these devices are powered on. Algorithm analysis and simulation results show that the method is effective, and the method is well within the acceptable rate of error based on today’s standards of estimation without need of previous knowledge of device profiles. Copyright © 2015 John Wiley & Sons, Ltd.

KEYWORDS
accountability; smart grid; security; varying consumption

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1. INTRODUCTION
With the current state of technological advancement, the demand for energy has begun to outpace the growth of efficient production capability [1]. Inaccuracy in estimation that causes misleading energy readings and malicious devices are a few of the problems that are to blame. This of course requires the energy sector to create a more efficient demand–response cycle. Solutions of many of these energy inefficiencies are addressed in the smart grid convention. The smart grid can be described as the current power delivery system with integrated bidirectional communication and real-time analysis on energy generation, transmission, and distribution data in order to create predictive and necessary recommendations for consumers [2,69,78,82]. The National Institute of Technology and Standards defines six key areas that make up the grid below [3]: bulk generation domain, transmission domain, distribution domain, operation domain, service provider domain, and consumer domain. These areas are expressed as domains that house several major components in the energy arena. Each domain has a unique distributed computing environment, sub-domains, and equipment to suit its mission-specific needs. It is also important to note that the domains of the grid are interconnected with adjacent domains with which they provide coordinated functionality.

To utilize the maximum efficiency in a smart grid, the power utility must employ a customized energy demand management scheme that will allow for balancing of demand and supply in a manner that reduces costs for the consumer and producer [4,5]. For example, power usage can be scheduled to avoid peak load times that incur higher costs for both the utility and the consumer. This is one of the basic requirements for a smart grid and one of the concepts that make smart grid novel.

An unsolved and scarcely addressed problem in this arena lies in not only the general concept of estimating power usage, but estimating power intricately in the home area network (HAN) and establishing accountability in this domain. Accountable environments in smart grid have been researched in [6–8,72] while making some assumptions such as activity patterns of varying consumption devices, generation, and storage devices, which may or may not lead to sufficiently accurate estimations in the HAN.

This paper will detail a method for more intricately estimating and monitoring usage of varying consumption devices in order to create a more fully accountable and accurate environment in the HAN. The “witness” concept is used to provide a solution to the assurance problem.
between normally trusting devices and the smart meter. Each device will be assigned \( w > 2 \) witnesses based on the network size and policy that will allow for multiple usage reports on a single device to ensure this device is accountable for its actions. Aside from the overall method, contributions include:

- a proposed method, called varying consumer (VC) algorithm, which establishes the energy-related category so that each specific device will belong to and continuously converge on a range most suitable for estimating energy usage;
- usage state infrastructure, which provides a baseline for further establishment of energy categorizing and thresholding and allows for more accurate recognition of a device’s expected usage while in a certain “mode”;
- and a threshold selection method, which utilizes recurrence quantification analysis to identify and converge on common usage amounts within a usage state.

The rest of the paper is organized as follows. Section 2 provides some background. Section 3 describes the problem statement. Section 4 details the proposed method, which includes several mechanisms. Section 5 presents the evaluation. Finally, the paper is concluded in Section 6.

2. BACKGROUND

The smart grid is an increasingly expanding network of networks and system of systems. It is integral to have simple knowledge of the grid to understand how the consumption of energy and its accurate estimation in the HAN have a great effect in every domain.

Advanced metering infrastructure plays a large role in the consumer domain with two-way communications from the consumers to the system operators [9,69]. From the data, the consumer can receive pricing information and schedule/modify their power usage according to their preference or some peak rate avoidance scheme.

Sensing and measurement are constantly occurring and reported in the smart grid. Once the data are analyzed, tendencies can be created and major and catastrophic events can be predicted and avoided based on past measurements. This type of wide situational awareness plays a large role in demand response. When catastrophic events are avoided, price spikes will decrease. The same action and consequence are often replicated in the HAN. If energy usage can be more accurately predicted and identified, peak prices will not be as high or occur as often.

Achieving accountability in the HAN has rarely been studied in the past. Related areas such as disaggregation and load monitoring [10–12] are useful but normally estimate device usage based on the aggregate amount from the residence as a whole and the normal consumption of a device. This type of estimation is more useful when identifying consumer behavior patterns and device malfunctions instead of a more fine-grained approach of estimating and assuring that each device is accountable.

2.1. Accountability

Security has been one of the key areas of research in the smart grid landscape, which will not soon be changed [73–75]. This is and has been the case as new technology is introduced, so follows new vulnerabilities. Accountability serves as a complement to the core principals of information security and the component that allows authorized individuals more robust tracking and auditing history as well as establishing trust and confidence within the HAN between devices [13,14,70]. Currently, accountability in the distribution end of the grid only extends to a single residence, which aggregates the appropriate data of all of the devices located therein. This is sufficient for the currently required duties of billing the consumer based on total use of all appliances to be fulfilled, but in order for demand response to be optimized on both sides of the equation, a more fine-grained approach must be utilized.

There are several requirements that can contribute to an effective accountable environment or mechanism. These include [15] decentralization of accountability mechanisms, scalability, minimal impact, data collection, and identity management. Inclusion of these elements in the accountable scheme can be very profitable and will help to cover the accountability requirements.

Lightweight functions are imperative in the smart grid as the devices utilized throughout are normally resource constrained or given computational and networking resources that are not sufficient enough to handle heavy encryption and simultaneously satisfy the real-time demands of the grid. This also applies to any subset of software functionality included in the grid including accountability measures.

Sufficient and appropriate data must be extracted and archived for review and evaluation. It is imperative to discern the most effective location and type of data to archive and evaluate in each environment. Some devices may require a specific set of data to be analyzed, while others may require a set of data that includes a few of the parameters explicitly required by one, and a few not needed to satisfy the requirements of another. Although in most environments, these parameters will be uniform.

Inter-domain identification is also necessary. We assume that devices in the same domain will maintain uniform identification mechanisms that will allow them to distinctly refer to and differentiate between devices on the network. For smart grid applications, the main objective of accountability currently is to maintain record of and assure that a device acts as it says and/or is expected to. In other words, a device should truthfully report its power usage and other parameters required at a pre-specified time interval and/or when requested.

Maintaining the previously listed requirements for achieving accountability in a smart grid environment is a huge upgrade to still widely implemented automatic meter
reading methods in which the sum of the power over a certain period is collected from aggregate data of all devices at the consumer's residence. Even in the case of advanced metering infrastructure, there is still much room for error, and we cannot always expect for the record that the utility manages and what is recorded at the consumer’s end to be identical. Malicious action, malfunction, miscalculation in estimation, or calibration may be the cause of such differences. Making the HAN accountable on a more fine-grained level can help alleviate problems such as these and provide us with a means of locating a compromised device that can immediately be disabled or serviced instead of canceling service to the residence indefinitely.

2.2. Energy consumption in the home area network

Energy sustains life for many people, and rightfully so, domestic usage is behind a large portion of most grids’ electric power consumption. Many devices and methods are being put into place, which will give consumers the option of employing more energy efficient options in their homes. Energy efficiency means that there is a reduction in energy used for a given service or level of activity because of some technological change of an existing infrastructure [16,17,79]. This is of particular interest as the majority of consumers prefer to purchase lower end devices, which although cheaper, also generally provide less energy efficiency of energy use [18].

Many factors are combined to determine household consumption rates. These are highly affected by environment conditions and consumer personal preference. This energy consumption is transient and varies dramatically at specific times. These factors play a large part in the determination of the peak rate times, which are determined by the utility based on large overall usage by its consumer base. Peak rates are normally achieved during specific times of day when many consumers use considerable amounts of power. Although many devices in the home use small amounts of energy, when large amounts are powered on simultaneously, peak times and rates can be heavily influenced by this factor.

3. PROBLEM DEFINITION

In the currently implemented power grid, the only accountability required in the distribution domain is the periodic reading of the power meter, which records aggregate energy usage at each user location. The frequency of readings is dependent on the utility and is generally limited to a few times per month. Inside the HAN, security measures can be put in place to introduce some level of networking accountability through a specific entity such as the intrusion detection system [76,77] or the energy service interface, but in an environment such as the HAN where the number of devices will greatly increase over time, it is a good practice to make the accountability mechanism distributed. This is also important as the resources that many devices maintain are constrained in the HAN, and additional computationally expensive software is difficult to run while maintaining its primary responsibilities.

Disaggregation techniques are wide ranging and have been well researched. The three major techniques include [19] survey, single point sensing, and distributed direct sensing. These techniques alone are simply not sufficient as more smart devices are being added to homes that are programmable. This means that the threat of malicious and/or malfunctioning devices is greater than ever and still increasing and brings about the need for a more fine-grained model for accountability in the HAN.

In addition to creating an environment where the devices are accountable for their energy usage, the devices should also be made accountable for all of their actions with a scheme implemented in a distributed fashion. If a device takes an action that causes an unexpected amount of energy use, that action and the energy should be verified and the device accountable for it.

HAN devices’ energy consumptions patterns are not necessarily static in the sense that although operation may be scheduled, they may use varying amounts of energy at any given time. These devices may also have a non-constant power capacity factor at any given time while it is active. Some examples of these types of devices include water heaters, boilers, even coffee makers. It is of great importance to implement a mechanism that can correctly assure accountability in environments utilizing such devices as well as detect any events that can be problematic. Once the events have been discovered in a timely manner, it should be categorized so that the appropriate actions can be taken to resolve the issue.

We may consider a modern house with full smart grid capabilities and numerous smart devices in the home. Current technology requires the inclusion of some legacy devices, which are also included in the home and can not necessarily communicate using required protocols to maintain accountability in the scheme which will be proposed later. The home will have at least one smart meter which will measure the usage and serve as the “trusted” entity and will normally communicate with the utility and other authorities outside of the home premises along with the energy service interface which the consumer will utilize.

Note that a much shorter and preliminary work of this paper was presented in the conference [71].

3.1. Architecture

The HAN will serve as the basic communication infrastructure for management of energy in a smart grid. Normally, it is composed of a smart meter, many smart and connected devices, and alternate private energy sources and devices that are involved with storing energy. There is a general understanding that there are two basic architectures for the HAN and its interconnection to the smart grid [20]. Figures 1 and 2 show two kinds of smart grid
HAN architecture. Figure 1 allows for the utility to have direct control of the HAN devices for those who have, for instance, opted into policy that allows the utility to modify device operation at specific times to minimize peak times and rates. Figure 2 splits the device operation adjustment responsibility between the consumer and the utility, or per the consumer’s desire, solely on the consumer.

Here, the smart meter, in either approach, is responsible for collecting consumption and generation of the aggregate of these devices in real time over one of the many popular wireless technologies. The devices can be divided into three categories. These include smart devices, connected devices, and legacy devices. In the context here, smart devices are fully qualified devices that maintain software and hardware capabilities to communicate over the protocols implemented on the network that it is connected to. These devices can also participate on the required schemes and algorithms being used therein. Smart devices also have the ability to modify their operation to better achieve objectives that benefit the network or operator of the device.

Connected devices are many times mistakenly categorized as smart devices but lack the capabilities to modify their operation to positively achieve certain goals. While maintaining the hardware and software capabilities to communicate over the network, these devices only have the ability to report and/or observe their surroundings.

Legacy devices may lack networking completely or simply may not be able to utilize certain protocols and,
while still smart or connected, are rendered useless in the context of the HAN and its communication. Devices can also be categorized as schedulable and non-schedulable. This means that for scheduled devices, we will likely have more insight into the specific times in which the target device will be using power.

3.2. Varying energy consumption in the home area network

There are hundreds of millions of devices that have flexibility or varying consumption in the HAN. Much of this flexibility can be attributed to the time flexibility of the device usage because of management, or the upper and lower bounds of flexible energy usage amounts. In addition to this inherent variability that may or may not be induced by user interaction, many devices also host a range of energy consumption settings and the actual amount of energy consumption depends on the setting at that time. The paper [21] describes the aggregation and disaggregation of these flexible devices and their flexible timing constraints. Although the aim of our paper is accountability and accuracy in the HAN, aggregation and disaggregation is out of the scope and of small benefit in this discussion.

Energy consumption is considered to generally be constant in most devices when estimating power consumption. This means that there will normally be some overuse or/and underuse. Therefore, for many reasons, including the previous, the measurement and estimation techniques are threshold based. Scheduling helps to manage and estimate energy use to a certain extent, but the details of a varying consumer are normally partially defined by the habits of the user and cannot be sufficiently estimated unless sample testing and forecasting is in place along with high level control of the VC devices introduced later.

3.3. Problem statement

Accountability in the HAN is at best the minimal in that only readings of aggregate consumption are estimated daily. Disaggregation techniques cannot provide the fine-grained accountability required for the smart grid. The objective here is to verify and report device’s actions inside of the HAN. A unique problem provided in the HAN is the accountability in energy usage of devices that have a varying power capacity factor and requirements.

Our goal is to provide an accountable environment in the HAN so that devices will be held accountable, while the devices’ power consumptions are not constant, but varying over time. Therefore, we will propose a solution, that is, a mechanism to achieve accountability for devices with varying power consumptions over time.

We will also conduct some evaluations of the proposed method in terms of observing the amount of work required by the proposed method in comparison with a typical method and device usage accuracy and estimation efficiency utilized as a metric.

4. ACCOUNTABLE METHOD

The proposed method utilizes group witnessing such as that which is proposed in [6]. This discussion will detail the status reporting and inspection mechanism that is required to create an accountable environment in the HAN. The premise of the protocol is that devices called witnesses are used to monitor other devices in order to verify their actions. When multiple witnesses are utilized to monitor a single target, the target device will be held accountable by multiple entities as opposed to a single device that authorities would be solely forced to trust with the reporting of its target’s actions.

We assume that the smart meter is the only trusted entity in the network and may also be considered as the device that aggregates all records of inspection required for witnessed accountability of each device. In the case of multiple smart meters, each of the meters must be accountable to each other and decide on a lead meter that will take on the inspection evaluation role. We assume that each device is fitted with a sampling unit that has the ability to sample the amount of energy the fitted device is using at any time. It is also assumed that the operational time for each device is easily observed by each required witness device through the use of a non-intrusive load monitoring (NILM) technique or communication with the sampling unit. Finally, every device maintains witness and target attributes that are filled by other devices in the network.

The target-witness structure gains its validity and accuracy partially through a single device \( w_1 \), which serves as a witness to its target device \( t \). \( w_1 \) utilizes readings from the sampling unit that is monitoring \( t \), and together with two other witnesses \( (w_2, w_3) \) of which the latter two use NILM algorithms to estimate the usage of \( t \), create an accountable witness target structure for each device in the network.

Once the reports are gathered, the inspector must discover and report inconsistencies in the witness reports given by devices in the network that will be monitoring and reporting the actions of their target devices including energy consumption. A single pass through the set of inspectors \( I \) can determine the state of the network and each device therein to evaluate the network with a single inspector it takes at least \( n \) tests to evaluate a network with \( n \) operational devices in a one by one testing scheme. In order to reduce the number of work required for a full inspection, two options are possible: reduce the number of witnesses per device and utilize a better method.

To identify any device as a VC, the consumption patterns must be identified. Some details may also be inferred from the devices rated power usage even though this amount will likely not be constantly consumed during the duration of the device active phases. A probability distribution of the device’s energy consumption will be built to estimate the usage. To complete this, each device will communicate with each of its witnesses, which entails the minimum and maximum power consumptions. With this and some additional information, we can construct the probability distribution table (PDT) explained in the following subsection.
4.1. Probability distribution table

The proposed method utilizes a PDT to help create a higher level of accountability. The PDT allows for some levels of forecasting based on previously observed energy usage. The initial communication between two devices that are establishing a witness–target relationship will contain several pieces of information, which are integral for the witness devices to perform their duties in the accountable scheme. These include minimum and maximum power ratings of the potential target device. These values will be used for the potential witness device to define which usage group the target device will be in and in turn, to estimate the energy usage of the device at certain times more accurately.

Once initial information is acquired, in order to obtain the probability distribution of the target device, the “on” status probability must first be determined. In the initial phases of interaction after the contract between the witness and target, the active usage patterns including the patterns of device activation are observed. From this information, the table of usage probability is created. Upon multiple observations of the target device, its habits over specific time lengths can be determined. The continuation of these observations will allow for corrections and a more complete analysis of the device’s actions. Table I shows an example PDT that is specific to the day and time of the week.

Management of data in the PDT and the access thereof will be monitored and controlled by a policy. This policy will ensure that the accountability is not solely ensured by sampling capability, but in more of a non-intrusive manner.

There is normally a fairly high amount of uncertainty in dealing with usage forecasting and therefore a model for each period of a half hour is established. Similar procedures can be found in the following works [22-25, 80, 81]. In each half-hour interval, we establish the logarithmic or raw demand model as

\[
\log(y_{t,p}) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + a_p(y_{t,p}) + n_t \quad (1)
\]

where \(y_{t,p}\) is the demand and \(p\) is the one half-hour measurement period; \(h_p(t)\) is the calendar effects including seasonal patterns and holidays; \(f_p(w_{1,t}, w_{2,t})\) represents temperature effects with \(w\) representing the past temperature at the location; \(a_p(y_{t,p})\) represents recent past energy usage observations; \(n_t\) denotes error at a specific time \(t\).

With this equation, we can calculate values for the PDT at various times for devices that we have some energy usage data for. The PDT with these values will be used in the proposed method for furthering the accountability of the devices in the HAN. The values calculated here can be used as a measure to compare actual usage or usage estimated by some NILM method to in an attempt to establish a devices status.

In order to lessen what would be difficult computational requirements in the face of calculating much historical forecasting and environment data, a more streamlined bootstrap process is designed similar to [26]: retrieve and utilize forecasting data and model, calculate load forecasts using temperature and calendar forecasts, block bootstrapping for the forecasting residuals, and update model through observations and historical data.

Many devices in the home will be able to even further streamline this process as many of the effects due to calendar and temperature variability will be negligible. After sufficient observation and/or categorization, the model can be reduced further. This will also make concessions for the devices that are resource constrained.

4.2. Device power sampling

Power sampling plays a large role in the proposed method. Each of the devices in the home is assumed to be fitted with a sampling device for frequent sampling of the devices’ energy usage. This section details some background of power sampling for appliances similar to the ones found in the HAN.

For a high level of accuracy, it is mostly agreed that monitoring devices must examine many features of the electric signals including the microscopic and macroscopic attributes. Microscopic here means harmonics and signal waveforms, while macroscopic means power state changes [26]. According to the Nyquist sampling theorem, it is necessary to sample at more than two times the frequency of the signal in order to capture the highest harmonic [27]. This detail is important as the real-time demands of the smart grid require for the data to be processed and forwarded very quickly. With sampling rates above 2.0 kHz, it may be generally difficult to overcome some of the inherent transmission and storage requirements for generally lower end data in the HAN. It is more realistic to envision mechanisms that record voltage around 1 Hz. Devices with this type of capability are normally more inexpensive and sufficient where the period is either 1/60 or 1/50 s [26].

Two feasible methods for sampling are described here. Considering the current state of technology and the direction in which it is headed, we can assume that most homes do not currently have advanced current flow detection mechanisms built into the internal circuitry of the A/C port that can acquire the voltage and current signals. With this understanding, we can add these types of mechanisms to our definition.
of a “smart home.” This will provide the witness devices access to sample readings of their target’s current usage.

The second method relies on appliances and other devices with advanced hardware and sampling units fitted onto them. This will also provide the witness devices the ability to sample their target’s usage. With sampling units fitted onto devices, or incorporated into the home wiring, the computational complexities and requirements can be offloaded from a central point. This will prevent from possible computational bottlenecks. These external devices can be the sampling units, or the devices that they reside on. Another method of maintaining efficiency is to only relay and store specific information about the devices load and events. Load changes and other events are not necessary to successfully verify the load reported by a device, and therefore, there is no need to store or communicate all information.

4.3. Varying consumer algorithm

During the initial phases of activation, witness devices observe the VC and build a table according to its tendencies over a specific time length. Observations of target device’s state and energy usage are recorded over a period of time. These measurements can be scheduled or initiated when certain conditions are met, that is, high resource availability, and the status of the device being turned on. Once observed, this data may be used to challenge the accountability of the device. With the values in the PDT generated, one can assume and estimate the power usage at a certain time or phase of operation for a specific device. This makes testing for accuracy less error prone, as without knowledge of how much energy a device uses at a specific time, it is nearly impossible to create a threshold delta in which the device will be within at any stage of normal operation. The sampling and table construction are continued until the table is filled, and then passes are periodically made to verify and update the data to account for device behavioral changes (which are normally caused by the user).

We can assign each device $i$ in the network to a specific grade of rated power usage. Each of these devices possesses a certain number of attributes $attr$ defined by the environment as \{attr$_{r1}$, attr$_{r2}$, attr$_{r3}$, ..., attr$_{rn}$\}. Once the attributes of the device are combined, we find the rated power usage grade of that specific device, $G_p \in \rho$, where $\rho$ denotes the number of grades in the HAN. Calculating the grade of the device can be completed using Equation (2):

$$n' = \sum_{k=0}^{n} w_{ik} \text{attr}_{ri,k}$$

(2)

where $w_{ik}$ denotes the weight of the attribute represented in the summation while $n'$ will be assigned to one of the power usage grades by the following:

$$if(G_{\min} < n' < G_{\max}) \cdot n' \in \rho$$

(3)

$G_{\min}$ and $G_{\max}$ denote the lower and upper limits of the specific usage grade $G_p$, respectively. The value of $n'$ depends heavily on the environment and the attributes considered with the device. With the usage grade of a specific device known, the range of its power consumption can more effectively be estimated. The VC algorithm that helps to generalize a device’s consumption range is defined in Table II.

4.4. Multiple status reporting

Any status report made by a witness device, whether requested or scheduled, will contain the target device’s usage state. Instead of defining this with only two values (on/off), we have at least four states for the target report. With these various reporting states, we can more closely estimate the power usage of the current device without sampling it. This is necessary for the witnesses of some target that do not have access to the sampling unit on the target device. How these states are defined is based on the reported consumption capability amounts of the target device. While the power usage grade is known, we can more precisely estimate the device’s energy usage at a specific time by having multiple states (levels) within that devices usage grade that are relative to the device.

As $G_p$ has an explicit minimum and maximum, we can further divide the state into four power ranges. The power consumption can be even more accurately estimated as future power sampling observes energy usage and consistently finds a more specific reading within a state that is constantly sensed. With this information, the witness can assume that the target device uses a specific amount of power (which has been consistently observed), while the target device reports the recently reported state.

Figure 3 shows the upper and lower bounds of a target device’s consumption range. This range is further divided into several smaller ranges with sub-thresholds (STs) at the lower and upper bound of each. The four ranges will initially be equal in width with the ST values are chosen as

<table>
<thead>
<tr>
<th>Table II. Varying consumer algorithm.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Function Group (witness_devs, target_dev)</td>
</tr>
<tr>
<td>2. //target_dev reports max possible power usage</td>
</tr>
<tr>
<td>3. discover_VC_tendencies(target_dev) // samples usage, or infer from target’s broadcasted energy capabilities</td>
</tr>
<tr>
<td>4. REPEAT UNTIL usage_group(target_dev) // $G_p$ is discovered</td>
</tr>
<tr>
<td>5. IF $G_p$ is correct $G_p \in \text{GROUP}(i)$</td>
</tr>
<tr>
<td>7. usage_group(target_dev) = $\text{GROUP}(i)$</td>
</tr>
<tr>
<td>10. Verify usage_group(target_dev) with sampled power usage</td>
</tr>
<tr>
<td>11. Build PDT with usage and time data</td>
</tr>
<tr>
<td>12. REPEAT discover_VC_tendencies(target_dev)</td>
</tr>
<tr>
<td>13. IF sampling data and PDT are differing above $\Delta$, mark target_dev “suspect” or “faulty”</td>
</tr>
<tr>
<td>14. ELSE update or confirm PDT based on newly acquired data</td>
</tr>
<tr>
<td>15. RETURN PDT</td>
</tr>
<tr>
<td>16. END REPEAT</td>
</tr>
</tbody>
</table>
\[ ST = \begin{cases} \hat{\lambda}_2 + D \\ \hat{\lambda}_2 + 2D \\ \hat{\lambda}_2 + 3D \\ \hat{\lambda}_2 + 4D \end{cases} \]  

(4)

where \( m \) and \( n \) are local decision variables which are defined by the current usage observed by the witness device. If the observed values fall within or outside of \( \lambda_1 \) and \( \lambda_2 \), it generates values as described in Equation (7) and Equation (8).

The decision model can be created as shown in Figure 4 utilizing the Equations (7) and (8):

The decision model combines \( m \) and \( n \) with the addition operator “+” and outputs the usage state of the device for the witnessing device that is observing the targeting device that is using the energy.

### 4.5. Estimating power usage

In order to calculate the power usage of any device or to closely estimate it, the operational capacity \( P_i \) and the state of the device must be known [1]. In the case of VC devices, the energy usage is not necessarily known at any time. This means that outside of random/scheduled sampling of the target device’s power usage, there is no definite way of knowing exactly how much power that a single device is using outside of inferring through deduction if the usages of the other devices in the HAN are available. There is also the threat that the device malfunctions or is behaving with malicious intent. Here lies our problem, and our solution lies within the estimation and accountability measures.

With the knowledge of the power usage grade \( G_p \) and the status communicated from the target device, we can more accurately estimate the power usage at time \( t \) for any device \( d \) with one of the witness devices \( w_d \) in question having the ability to sample the target device’s power consumption through the sampling unit attached to its target, which is carried out regularly. We understand that we can derive the power usage \( P_d \) of a particular device \( d \) as displayed in Equation (10):

\[ P_d = \int_{ta}^{tb} p(t)R_{d(t)} \]  

(10)

where \( p(t) \) is the expected power consumption at time \( t \) and \( R \) is the running state that the device is in at time \( t \). Understanding the rated power usage amount is not sufficient for the VC device, as the amount of power that this device uses is not necessarily constant. Therefore, in the previous discussion, we introduced the premise of a power usage

\[ y = (m + n) \]  

(9)

Figure 3. Usage states.

Figure 4. Usage state flow.
status for a specific device, in this case device \( d \), \( ST_d \), which is partially determined by the power usage group \( G_p \). These values are used to more accurately estimate the power usage at a specific time. It is understood that if \( d \in G_p \) then at any time \( p_d < \max(G_p) \). In other words, the power usage for device \( d \) will never be greater than the upper bound on the range or the group that it resides among. If this anomaly data does occur, the device that reports this reading will be considered suspect or faulty and marked for further evaluation.

4.6. Varying consumption device reporting

With the usage grade and the device power level status known, we can effectively construct a table for quick reference or calculate the estimated amount on board the witness device at the necessary time. The scheme for building accountability into varying consumption devices is presented in the following steps.

- The potential VC device is connected to the network. Recommended scheduling is verified as well as device attributes.
- The potential VC device informs proper authorities (e.g., witnesses, smart meter) of the minimum and maximum power usage/requirement. This value will be used to assign the VC into a usage grade \( G_p \).
- The VC device informs proper authorities of its initial usage state (level 0–4) while witness \( w_j \) samples the VC device’s power consumption. Witnessing devices calculate the expected power usage (from the usage grade and the status report) and create a status report. If the reported usage states differ between witnesses, label the device faulty.
- Witness devices build PDT while continuing scheduled sampling of the target’s (VC device) power consumption. This information is used to update the PDT as well as challenge the target’s accountability.

At any time that a device’s reported status or time constraints are found to be incorrect or suspect, that device is labeled as suspect or faulty.

4.7. Legacy devices

Although legacy devices participate in the accountability protocol, they most likely will not have the software and hardware components to communicate over a network with the required protocols. The proposed algorithm allows us to estimate their power usage more accurately. With this more accurate approximation, we can patrol even legacy devices with static energy consumption and derive whether or not the device is behaving correctly. The difficulty here is that the legacy device cannot serve as a witness. As the proposed method allows for efficiency in such a way that all devices are not required to serve as witnesses, legacy devices will exclusively serve as targets and be evaluated in the same way that non-legacy devices are.

4.8. Threshold detection

Determining faulty devices can be accomplished by comparing the current usage with the expected or reported usage at a singularly specific time. If these two numbers do not maintain proximity within a certain delta, the target device will be labeled according to the event management policy. This delta will be the threshold with which detection and comparison will either earn the device in question a faulty or clean labeling.

The comparison of the energy usage and the threshold is trivial; however, the process of establishing an acceptable threshold is most important and normally device attribute dependent. As stated earlier, many VC devices have modes of operation, and this means that the energy usage amounts for each of those modes will likely be very much similar whenever the device is operating in that specific mode. In the case that this usage amount is not within its specific threshold level, witness devices can more accurately estimate the usage when the device is operating in an expected mode. VC devices that do not have defined operation modes generally operate on a sliding scale, which is influenced by external conditions or an interval-based time schedule. A water heater, for example, maintains and heats the temperature of water and uses energy according to the temperature of the water, which is in turn influenced by external temperatures among other variables. Determining the amount of energy these types of devices will use is very difficult as current policy attempts to estimate based on forecasted conditions and other events. Operation in this capacity is more likely to produce energy usage that is close to the thresholds, and in some instances, will produce conditions that will likely be further away from acceptable than desired.

4.8.1. Threshold analysis

A recurrence quantification analysis (RQA) can be used to generalize the usage of a generic device, and from this, we can establish the necessary thresholds based on its habits. With use of the analysis, densities of recurring energy usage amounts can be identified and used to establish quality thresholds. Recurrence analyses in the past have been used to locate recurring patterns and structural changes in dynamical systems [28], and with data from one of the VC devices based on a univariate time series, which is of some n-dimensional model, the systems behavior detailed in the time-delay statistics can be constructed into phase space vectors and then to a topologically equivalent multidimensional plot [29]. This recurrence plot (RP) is simply a visualization of the recurrence matrix \( R \) in which we can define each of the entries in this matrix, \( R_{j,k} \), at row \( j \) and column \( k \) using the subsequent equations [30]:

\[
R_{j,k} = H(\lambda - d_{j,k})
\]

where

\[
d_{j,k} = |\bar{V}_j - \bar{V}_k|
\]

where \( H \) is the Heaviside step function that is assigned a value relative to zero as denoted in Equation (13):
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E. McCary and Y. Xiao

4.8.2. Threshold selection

Throughout the history of fixed threshold selection methods, many types have been included using graphical and diagnostic approaches in order to assess a model for threshold choice beforehand. Several of these include stability plots, mean life residual plots, and general distribution plots, to name a few [31–36]. In certain cases, graphical approaches can be difficult to interpret, and uncertainty of the threshold is not well accounted for [37]. Although many studies maintain such hindrances, some informal remedies have been proposed in the form of resampling-based approaches [38–40].

There have been several general guidelines suggested for the selection of a desirable threshold [41]. These values should be represented within a small percentage of the phase space diameter. In terms of device energy usage, the phase space diameter can be defined as $Gp$ or the entire possible energy usage range. Also, threshold uncertainty should be incorporated into the analysis as well as removing the necessity of subjective selection of parameters of the threshold. In order to ensure effective threshold selection, the method proposed in this work incorporates some components of a Bayesian mixture model, which helps to find values based on a certain criteria from some overall set of values. RQA will also be utilized in the refining of the thresholds to create a more accurate environment.

The phase space of a VC device encompasses all usage states possible for the device, or in other words, the complete consumption range. The consumption range properties can be characterized based on a partitioning $\{S_1...S_n\}$ of the device’s phase space into $n$ disjoint sets [42]. As explained earlier, each one of these sets represents a usage state.

There must be at least two stages of the threshold defining method. The first will provide for defining threshold for devices where there is minimal or no usage correlation data, while the second will provide devices that have sufficient usage data available for analysis. For the first, the initial phase space partitioning is described in Subsection 4.4 by equally distributing the consumption range of the device among the usage states. The upper and lower thresholds will be initially among the more extreme percentages of the usage states amounts in the case of devices with insufficient observable data.

Upon further observation while the device is active, the RQA can be used to reveal the bounded areas of the highest concentrations of usage amounts. With such an analysis, the thresholds can be placed at values that are most effective in categorizing the usage states efficiently by ensuring that the thresholds are placed in areas of little to no recurrence density through normal operations.

The papers in [43,44] demonstrate a method to generalize the extreme values given usage observations, $X_1, X_2, X_3, ..., X_n$. This can be done through utilizing a distribution function $F(x)$, under conditions $F(X \leq \lambda)$ can approximate these values by a general Pareto distribution (GPD) with a density function defined in Equation (15) [33,45]:

$$H(x; \sigma, k) = 1 - \left(1 - \frac{kx}{\sigma}\right)^{1/k}$$

while,

$$\begin{cases} 0 < x \leq \sigma, k \leq 0 \\ 0 < x \leq \sigma/k, k > 0 \end{cases}$$

where $k$ is the shape, $\sigma$ is the scale, and $x$ is a random variable with a standard exponential distribution. With estimates from the initial graphically established threshold, the general Pareto distribution has an interpretation as a limiting distribution in such a way that we can use this to generalize extreme values within the current usage state based on the observations. This will allow us to modify the threshold in such a way that the majority of points in the RP occur well within the usage state in question. This will increase efficiency and maintain the threshold and the usage state in its entirety at the optimum placement.

4.8.3. Pitfalls and limitations

Any method of detection or estimation has some type of performance limitation. These types of drawbacks can easily result in the producing of false positives and/or false negatives. Consideration of analytical variability can help to resolve conflicts arising from inaccuracy of estimation or measurement [46]. Instilling a system where multiple entities concurrently verify the accountability of each other.
may also help to pre-empt inaccurate measurements that may lead to malicious or damaging activity, which is the objective of this study.

Many household appliances and devices are composed of sophisticated circuitry and many components and circuits. This creates possibilities for electrical interference of many types, which can lead to inaccuracies in measurements or the improper calculation of a device’s usage. Often, these inaccuracies are caused by some defect or failure, while in other situations, devices constantly produce interference as a byproduct of their operation [47]. It is well to note that manufacturers are generally required to follow standards provided to them by various entities when designing and manufacturing their products in order to avoid excessive electrical interference [48]. Even with these considerations, there are still certain families of devices typically used in the home that are not under the jurisdiction of these regulations and can interfere with other devices if certain precautions are not taken.

Under normal conditions, when a device acts as a source of interference to another, the device itself is susceptible to interference of the same type. The most frequent offenders in the home tend to be lighting fixtures and halogen light bulbs, also, touch and air conditioner controls. The framework used in the distribution and transmission line systems are also causes for heavy interference over areas as large as the typical neighborhood [49]. Figure 5 displays the flow of the threshold management process.

5. EVALUATION

This section will analyze the proposed method detailed in the earlier sections. It must be understood that the purpose of this effort is to contribute to and enhance accountability in smart grid networks. Most publications in today’s smart grid HAN energy academic area focus on optimizing load scheduling in the consumer domain. Establishing accountability is also an extremely important feature that the grid must enhance, which the proposed algorithm helps to accomplish. This accountability is furthered on a per-device basis, which differs from other studies in accountability that focus on multi-user households [50], and understanding users and how to motivate savings [51]. The simulation programs were conducted based on discrete event simulation using C++ language.

5.1. False positives/negatives

We can model the probability of the behavior of devices using two parameters: probability of detection, \( p_d \) and the ratio of false alarms \( \left( p_{fa} \right) \). \( p_d \) represents the probability that a witness device has sufficient information about its target device to evaluate and generate a sufficient and effective status report. This report labels the target device faulty, suspect, or clean. In either case, there is a probability that this event result can be false. False or incorrect labeling of a device can be categorized into two types: false positive or result in a device falsely being labeled as “faulty” or “suspect”. Because each device in the network participates in the inspection and has the authority to implicate other devices to malicious intent in the network, namely its targets, each device is always untrusted by default. Therefore, we can observe false positives as the case that a clean device falsely labels a clean target device as faulty and a clean device falsely labels a clean target device as suspect.

On the other end of the spectrum, false negatives or \( p_{fn} \) can be defined as a witness device incorrectly labeling its target device as clean in the instance that it is actually suspect or faulty as the case that a clean device falsely labels a faulty target device as clean.

There may be several reasons for which a false alarm may occur. Device \( d \) provides some indication of its target \( t \)’s status after some information either gathered from the sampling unit or from estimation with some NILM mechanisms. There is a possibility that device \( d \) may become compromised and is intentionally committing malicious acts such as providing false reports of device \( t \) on the network. The method assumes that not all witnesses of a single device are compromised at the same time, and therefore during regular operation, device \( d \) observes its target device \( t \) and evaluates the details of its energy usage. With this information reported, a status indication for \( t \) is developed and communicated to the management unit, which will normally be the smart meter, and the appropriate actions will be taken to have the device properly serviced based on its condition.

In the instance that \( d \) is compromised, it may report false information, which forces an issuance of a “faulty” status to \( t \). Similar to [52,53], all information that is observed from and originates at \( d \) is unforgeable. Only in
the case of dropped messages or lack of measurements can
the false positives of this type be generated and commu-
cicated as long as there is at least a single correct witness.
Any other false positives may be due to malicious action
or faulty estimation/reading.

While assuming that the number of witnesses per device
is fixed, we can display several important properties. Evalu-
esting a correct device and producing a correct report can be
accomplished with a probability of \( p_d \). \( p_d \) is dependent on
the sampling unit or the NILM mechanism used to gather
data about device \( t \)'s energy usage. The probability of false
reports and the events creating these are used to come to a fi-
nal ruling on device \( t \) and assign a status for further action.

We must review the load disaggregation algorithms,
which may be utilized in the estimation of the energy usage
of the devices in the HAN. Current literature generally uses
recognition accuracy as the main metric for measuring the
effectiveness of NILM research. Although much of the
work here provides accuracy metrics, it is difficult to draw
meaningful comparisons and conclusion from the metrics
provided by differing algorithms. The paper [54] suggests
three accuracy measures for performance evaluation:
detection accuracy, disaggregation accuracy, and overall
accuracy. Taking this into consideration, Table III displays
several popular types of disaggregation techniques and
their typical overall accuracy rates.

We can describe the accuracy rates as the acceptable
and common percentages experienced when utilizing these
methods.

Upon observing Figure 6, we can understand how the
false alarm rate is affected by NILM accuracy.

As shown in Figure 6, the number of false alarms is
affected greatly by the NILM accuracy at a linear rate.
With 20 devices in the simulation and 200 comparisons
of energy use per device, we have a false alarm rate of
0.19 when using a disaggregation algorithm that has
85% overall accuracy, and when using an algorithm with
95% accuracy, we have a false alarm rate of 0.12. These
percentages are observed in the initial usage states with
no training time required. After proper usage state train-
ing, the usage states will be more closely fitted to the
typical amounts of energy used in its state, which will
create a situation where fewer false alarms are signaled
during the method’s operation.

The accuracy is heavily dependent on the original
source estimation (NILM) of energy usage as the proposed
method looks to assure accountability in the energy usage
of these devices. The false alarms are detected whenever
one of the usage amounts produced by a target device
has two reports that do not match each other. The sampling
unit on each device must maintain a high detection accu-
racy to justify the initial error of the NILM. These efforts
together can provide a significantly acceptable accuracy
for usage accountability.

5.2. Energy usage

The following will discuss the performance of the pro-
posed method. In the considered smart grid HAN, the
simulation will encompass the devices connected in the
network, which is also interconnected digitally and electri-
cally with the smart grid. We assume that each device in
the HAN is complete with an energy sampling unit in order
to verify attributes and actions of peer devices in the
network. This is a responsibility of each device that, in
working together, will work to create a trusted and
accountable environment. There are \( n = 40 \) devices in each
home, and a single home represented in each simulation.
Attributes of each of the devices are all extracted from
the Appliance Consumption Signature Database (ACS-
F1) database for appliance consumption signatures [54].
The ACS-F1 appliance signature database contains device
consumption signatures that were acquired by plug-based

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Features</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM [56–58]</td>
<td>SS and Tr</td>
<td>75–98</td>
</tr>
<tr>
<td>Bayes [58,59]</td>
<td>SS</td>
<td>80–99</td>
</tr>
<tr>
<td>HMM [60–62]</td>
<td>SS</td>
<td>75–95</td>
</tr>
<tr>
<td>Neural Networks [57,61,62]</td>
<td>SS and Tr</td>
<td>80–97</td>
</tr>
<tr>
<td>KNN [63–65]</td>
<td>SS and Tr</td>
<td>70–90</td>
</tr>
<tr>
<td>Optimization [66–68]</td>
<td>SS</td>
<td>60–97</td>
</tr>
</tbody>
</table>

SS, Steady State; Tr, Transient.

Figure 6. False alarms as affected by non-intrusive load monitoring (NILM) accuracy.
sensors. Acquisition was performed with a device in the database undergoing two acquisition sessions of an hour in which specific details about the device's consumption were recorded. For simplicity, the data utilized spans a single hour of the 2-hour acquisition phase which is carried out on each device.

We assume that witness devices are able to discover the operational time of each device, as well as its power requirement information. This functionality can be programmed into the specific device so that this information is broadcasted upon connection. Also, assumptions can be made of legacy devices and verified with the sampling unit and/or NILM technique. Flexibility in operational time should be available, but as discussed earlier, load management and estimation of future energy usage are not of concern in the assurance of HAN accountability.

Figure 7 shows the results of energy usage in the HAN comprised of VC devices that use a presumably non-static amount of energy in kW-h format. Presented here is the total energy usage of each device throughout the 20 simulations. The measurements are carried out under the same per device load signatures that are found in the ACS-F1 database, and the energy data is represented for 1 h of each device’s acquisition period. The amount of energy usage difference here is fairly significant when evaluating a single hour of device powered on activity. The regular usage in Figure 7 is defined as the maximum amount that the device would use at any time, but for the simulation, in order to stay in the bounds of the ASC-F1 database, we utilize the maximum amount recorded in the device record. The VC usage in Figure 7 is the total amount that the VC device’s used over the acquisition period. The most important observation from Figure 7 is the disparity between the VC and regular usage for each device. This shows that any estimation using a device’s maximum consumption over its active time would be significantly over the actual usage amount. Generally, utilities use methods that can more accurately estimate usage than the disparity displayed on Figure 7, but this is giving us an extreme baseline for measurements and evaluation.

Figure 8 gives us insight into the increased usage estimation created through usage state utilization for the VC devices.

For simplicity, each of the devices is limited to only three usage states. In the typical HAN, this could affect the accuracy for devices that use a much broader range of energy during their operation. Devices such as heating ventilation and air conditioning, which maintains a very wide
possible consumption range, would likely need several more usage states to make estimation as efficient as possible. Figure 8 details how, on average, much power the devices used in the simulation in each of the three usage states. We can see that once again there is a disparity between the lower and higher usage amounts. Generally, according to Figures 7 and 8, we see that these types of appliances’ usage have been most often near the upper or lower ends of their consumption ranges. With this type of usage, assumptions along with usage states can very easily be implemented to understand energy usage of a device for accountability purposes without implementing a full NILM mechanism. Even in instances where the usage range is very small (simulations 2–4, 9–12), the majority of the usage remains near the extreme upper or lower usage amounts. Therefore, the usage state has a more accurate labeling on the amount of energy used whenever usage is in its range.

In the instance that a device has a small usage range such as the iphone 4 in Figures 9 and 10, we can see that among the rises and falls of usage amounts, the most time is spent at either end of the highest or lowest usage state. Also, the amounts of energy usage are fairly constant, which provides a level of confidence in efficient procedure of the usage state estimation algorithm.

The VC method evaluates the power usage of a device with a threshold-based algorithm and categorizes the amount in one of several categories. For simplicity, the usage states are broken down into three (high, medium, and low). The basic method does not take usage states into account. Although any checks and balances of systems are also threshold based, they do not take into account VC devices, and therefore a larger deviation from what is estimated may occur. This can lead to an increase in the number of false positives or negatives. We can also see from Figure 10 that the distance can be fairly dramatic relative to the usage space between the high and low states. This usage amount difference must be accounted for even if the devices are in those phases for a short time. This will make estimation more effective.

It is also necessary to understand and analyze the time that the devices are operating in these states as its importance cannot be understated. Figure 11 gives us insights into these measurements.

As shown in Figure 11, much time is spent outside of the middle power usage states with the VC devices. In instances where more middle usage state time is observed, this happens in instances when devices make many state transitions, or when the device has a small consumption range. The thresholding method will modify the usage

![Figure 9. Initial usage states for iphone 4 over an hour of usage.](image)

![Figure 10. Usage states for iphone 4 after an hour of usage.](image)

![Figure 11. Usage state time for varying consumer devices.](image)
We present the accountability goals: apply speci-fic state or not. Through the simulations, the average difference in the accuracy that is created by understanding the usage states accordingly in order to avoid increasing false positives. With this taken into consideration, we see that the variation in energy usage, which normally makes estimation without lengthy training very difficult, is accomplished with adequate accuracy.

5.3. Varying consumption performance

This VC accountability method requires a certain amount of parameters to be set prior to its execution. The usage state details pertaining to the separation of state space is required. Increasing the number of usage states will not degrade the performance of the algorithms but instead will allow witness devices to more accurately determine the current usage of its target device. Also, the details of the power capacity of each device will need to be known. In the process of estimation of the energy usage of a target device, the witness device does not always sample the target’s usage: the PDT and/or knowledge of the current usage state will in most instances suffice for estimation purposes. Another important detail is understanding that devices with differing operational modes or phases normally use similar amounts of energy while residing in a specific state. With some knowledge of the usage states, we can sufficiently know the estimate on how much energy is being used. Table IV displays the variances in recurring usage state values and their actual values which were recorded during the simulation.

As shown in Table IV, there is definitely a discernable difference in the accuracy that is created by understanding the usage in a specific usage state as opposed accepting the maximum usage amount for each device whenever in an “on” state or not. Through the simulations, the average difference in measurements is 21.90%. It is important to state here that the method proposed is not to rely on the sampling units for measurements, but to ensure accountability through multiple witnessing; with this, most of the estimation can be done through simply having knowledge of usage states and accessing the PDT for prior usage information.

In modern estimation and load monitoring, nearly 90% accuracy is acceptable, especially in non-intrusive load monitoring scenarios [52,53].

5.4. Message overhead

In order to analyze the message overhead of the accountable method, we adopt the analysis method used in [6,55]. d represents any device on the network, while w represents some witness on the network. The assumptions apply specifically to any device w that has a witness–target relationship with device d. M represents the smart meter. We present the accountability goals:

G1: M can prove (d is faulty or correct for all D)
G2: w can prove (d is faulty or correct)

We assume that public key infrastructure (PKI) is being implemented on the network in the communications taking place in the fashion described below. Only signed messages are considered after target–witness establishment.

Message 1: w receives (\(t_w, [G_{\text{max}}] unsigned with K_w^{-1}\))
Message 2: M receives (\(t_w, [G_{\text{max}}] unsigned with K_w^{-1}\))
Message 3: M receives (\(t_w, [\text{Ace}_{Gd}] unsigned with K_w^{-1}\))

Assumptions required for accurate analysis of the communication flow are:

A1: All d can prove M is trusted (by default and PKI implementation)
A2: w receives (\(t_w, [\text{Ace}_w]\) signed with K_w^{-1}); therefore, w can prove d is trusted because of the PKI implementation.
Message 1: When w receives message A1, integrity and non-repudiation can be verified based on the unique signature. With w serving as device d’s witness, it can calculate d’s power usage at any time t either by querying d’s usage monitor or by utilizing the NILM scheme. This satisfies G1.
Message 2: M receives message 2 at the same time as w receives message 1 and can also prove that device d is trusted. Message 3: M receives message 3 and, by comparison of the accusations from all device d’s witnesses, can come to a conclusion about device d. This satisfies G2.

Figure 12 shows the network overhead experienced in the method process. The results are gained after a series of 200 simulations of the witness–target status relationship handshake process for each device and a single inspection.
procedure. The growth rate is almost linear while the curve is produced because of the variable amount of extra witness request response messages that are sent to devices requesting witnesses upon initial connection to the network (or upon losing a witness because of inactivity/departure).

6. CONCLUSIONS

The state of smart grid capabilities will continue to evolve as time passes. This means that technology and all other necessary components will continuously advance. Without accountability in the HAN, many deficiencies in security and accuracy can be exacerbated. This paper highlights the modern state of accountability in the HAN and typical home energy usage. The proposed VC energy usage accountability algorithm was given as a solution to more effectively provide accountability and enhance accuracy in the HAN energy calculation schemes. Simulations of the method show the ability to efficiently monitor and identify malicious devices using unexpected amounts of energy. The simulations also demonstrate a marked improvement over estimation with trivial amounts of knowledge of a device’s energy usage during operation. The accuracy and overhead required are both well within the typical bounds of current estimation methods.

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REFERENCES

42. Donner R, Zou Y, Donges J, Marwan N, Kurths J. Recurrence networks—a novel paradigm for nonlinear
71. McCary E, Xiao Y, "Smart grid HAN accountability with varying consumption devices,” Proceedings of
The 2014 International Conference on Security and Management (SAM’14).


