Extraction of Energy Information From Analog Meters Using Image Processing

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***Abstract*—There has been an ongoing effort to increase the number of advanced metering infrastructure (AMI) devices to improve system observability. When deployed across distribution secondary networks, AMI provides building-level load and consumption information, which can be used to improve grid management strategies. A barrier to implementation is the significant upgrade costs associated with retrofitting existing meters with network-capable sensing. One economic way is to use image processing methods to extract usage information from images of the existing meters. This paper presents a solution that uses online data exchange of power consumption information to a cloud server without modifying the existing electromechanical analog meters. In this framework, a systematic approach to extract energy data from images is applied to replace the manual reading process. A case study is presented where the digital imaging approach is compared to the averages determined by visual readings over a one-month period.**

***Index Terms*—Advanced metering infrastructure (AMI), electromechanical analog meters, image data extraction, time-activity curves.**

I. Introduction

AVERAGE coverage of advanced metering infrastructure (AMI) in U.S. power utilities has risen to 30.2% as of 2013 [1]–[4]. Increasing the number of metering points improves load observability. A higher rate of AMI deployment occurred between 2010 and 2011 due to the recovery act smart grid investment grant program [4] in addition to increased utility investments. However, there is not sufficient data to determine the level of smart meter penetration beyond 2013. The Internet Protocol (IP)-based electricity meter is the typical device used to collect real-time consumption data in secondary distribution systems [5]. Real-time data acquisition is one of the primary tasks, where usage information is periodically polled and transmitted to a central database using an IP-based communication network [6], [7]. As the first major milestone and the fundamental structure of the overall smart grid, an AMI is a system that measures, collects, and analyzes data about energy usage and power quality from the terminal smart meters, and achieves valid data exchange between the distribution dispatching center and the customer billing network [8], [9]. Due to information exchange between metering devices and the power distribution station, data observation and management of IP-based AMI play important roles in modernizing the distribution grid [10].

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Prevalent computing on mobile devices has revolutionized consumer electronic products and provided diverse applications in social networking. These devices are often embedded with powerful processors that can be utilized to perform relatively demanding tasks [11], [12]. The rapid pace of mobile device technology development results in a large secondary market of inexpensive devices with computing and imaging capability suitable for capturing and transmitting power consumption information from existing analog meters.

With accurate and timely information, the monitoring element has the capacity to estimate power quality [13], [14] and the state of the distribution system while the management console is able to realize troubleshooting and electricity control strategies [15], [16]. Distribution substations can guarantee high-efficiency electric energy and control the power transmission capacity according to the real-time load feedback facilitating energy conservation [17]. The contribution of this paper is to establish a framework to perform real-time energy information extraction from images of the existing electromechanical analog meters. The proposed framework provides an efficient method to increase the number of distribution network metering points. This additional data could be used to improve the accuracy of power-flow solutions used in advanced distribution management systems. The remainder of this paper is organized as follows. Section II provides an overview and comparison of different metering technologies. Section III describes the metering infrastructure of a campus distribution system to motivate this solution and as background for the case study considered later. Section IV details the algorithm of image data extraction. Section V provides case study results with the conclusion provided in Section VI.

II. System Metering Infrastructure

Table I shows a comparison between: 1) conventional electromechanical meters; 2) IP-based smart meters; and 3) the mobile device-based image extraction (IE) approach for the

TABLE I
COMPARISON OF UTILITY COSTS BETWEEN ELECTROMECHANICAL METERS, IP-BASED "SMART" METERS, AND THE IE APPROACH

	Electromechanical Meters	IP-based "Smart" Meters	Image Extraction Approach
Cost	Between $30 and $40 plus labor cost [18].	The estimated cost of a new meter is approximately $80 [19]. Price largely ranges between $200 and $800 per circuit plus installation, management, and operating costs [19], [20].	Between $100 and $150 to consumers. Zero cost on labor as it is being installed by the consumer. Zero cost on the IT services as it utilizes existing Wi-Fi network.
Frequency of Data Collection	Once or twice every month, manually by crew team at site [21].	The interval can range between 10 to 30 minutes, depending on the utility's preference. Data is sent to customer billing centers and being archived [22], [23].	The interval can be set between 5 to 30 minutes, depending on the utility. Data is sent to customer billing centers and archived.
Physical/Electronic Security	Physical perimeters are the setback due to energy thieves and malicious customers [24].	Prone to cybertampering. Malicious customers may alter the value of the energy consumption [19], [25].	May be prone to cybertampering. Utility would use security verification to accept or reject the acquired photos based on location and user account [26].
System Components	Electromechanical meters.	Smart meters, control panel, modem, and cables.	Timer camera device, device stand, wall charger.
Deployment Effort	De-energize the circuit and install the meter. Manhours would cost.	De-energize the circuit and install the meter. The technology may be obsolete and could be replaced with newer sensors [20], [22].	Does not require to de-energizing the circuit for installation. It is at consumer discretion whether they would participate in this program. Approval would be subject to security verification.
Data Flow	No data flow.	Open two-way communication, possibly with control variables [4].	One-way communication. Only kWh and kW information being sent.
Network Connections	Not required.	Wireless or wired connection [25].	Wireless connection.
Data Reliability	Not applicable.	Depend on home area network (HAN)/neighborhood area network (NAN) [27].	Depend on Internet availability at home by consumers.
Home Energy Management	Not available.	Metering and control modes [4].	Only metering mode.
Real-Time Pricing Mode	Fixed price.	Dynamic price [4].	Fixed price.

task of extracting kW and kWh information. The major differences between the methods are the frequency of obtaining the consumption data, equipment, and installation costs, as well as data reliability and privacy. The IE approach not only has low deployment and maintenance costs but also may incentivize consumers to engage with utilities beyond bill payment. As most utility companies have databases that relate distribution transformers to the customers connected to them, power-flow analysis could be updated with high frequency or on demand as needed. Cybertampering can be a major concern due to potentially malicious customers altering the metering values [28].

Although new smart meter devices provide an opportunity for consumers to reduce their monthly utility charges, utilities may not realize near-term profits from their use due to maintenance and installation costs. Hardware upgrade would affect the finance of new technology and the concern of cost recovery. In addition, some consumers may avoid smart meter installation due to concerns regarding the breadth of information recorded.

The total cost of an IP-based smart meter is approximately $566 including hardware, installation, and maintenance. This relatively high cost is a primary hindrance to the wider deployment of IP-based metering. Many consumers upgrade their mobile devices on a two-year cycle with their old devices available for repurposing. The use of repurposed mobile devices means that the primary cost of the IE approach would be the mounting hardware with an estimated expense of $140.

III. CAMPUS TESTBED

An AMI deployment was commissioned on ten buildings out of a 35-building campus in January 2012 at Michigan Technological University. This provided approximately half of the total campus power consumption and load information in real time at an installation cost of $60 000. A low-cost solution was to capture the remaining campus load with a similar bandwidth. Although the upgraded infrastructure provides a high percentage coverage of system observability today, it may not in the future due to shifts in energy consumption as building usage changes. Thus, a flexible method for acquiring load information is desirable.

Within the campus intranet, subnets of different buildings are connected and are routed through the campus-wide communication backbone network to other internal networks for real-time information sharing. This demonstration project is to increase a greater number of metering points for the lower priority buildings by deploying mobile devices that acquire energy information from existing electromechanical analog meters instead of dedicated IP-based energy meters.

Fig. 1 depicts the mobile devices for transferring pictorial data between campus networks. The mobile devices are implemented to capture images from the analog meters and the image data are transferred to a centralized database. The IP-based energy meters accurately transmit the consumption data with other communication means. The figure also illustrates the basic architecture of the AX supervisor. Within the existing system, the IP-based meter data could be browsed and supervised using a web supervisor and browser through

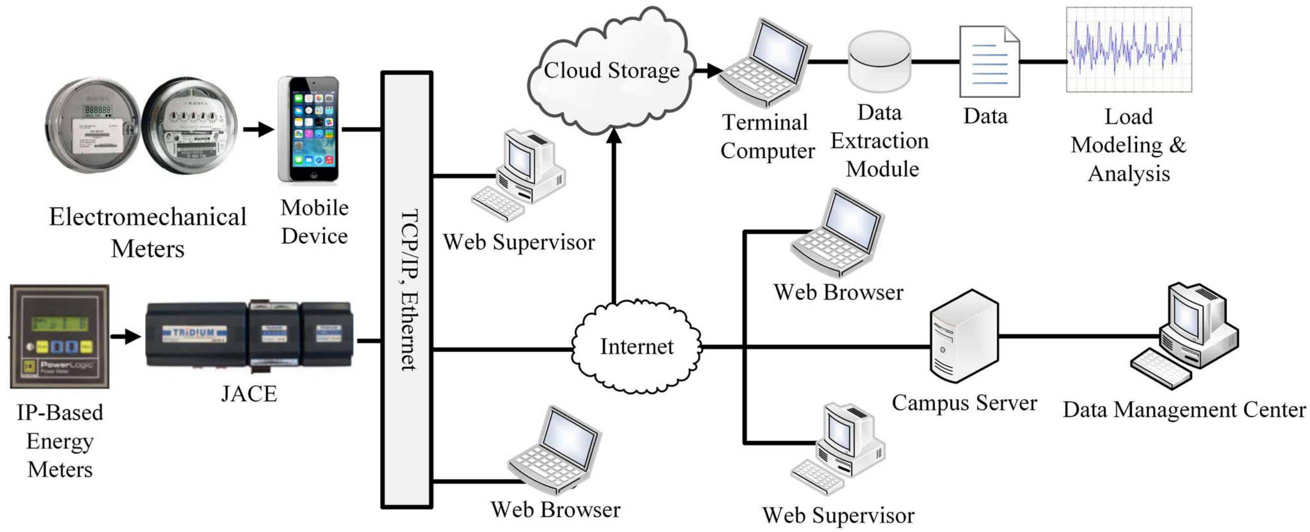

Fig. 1. IP-based metering infrastructure for campus distribution system.

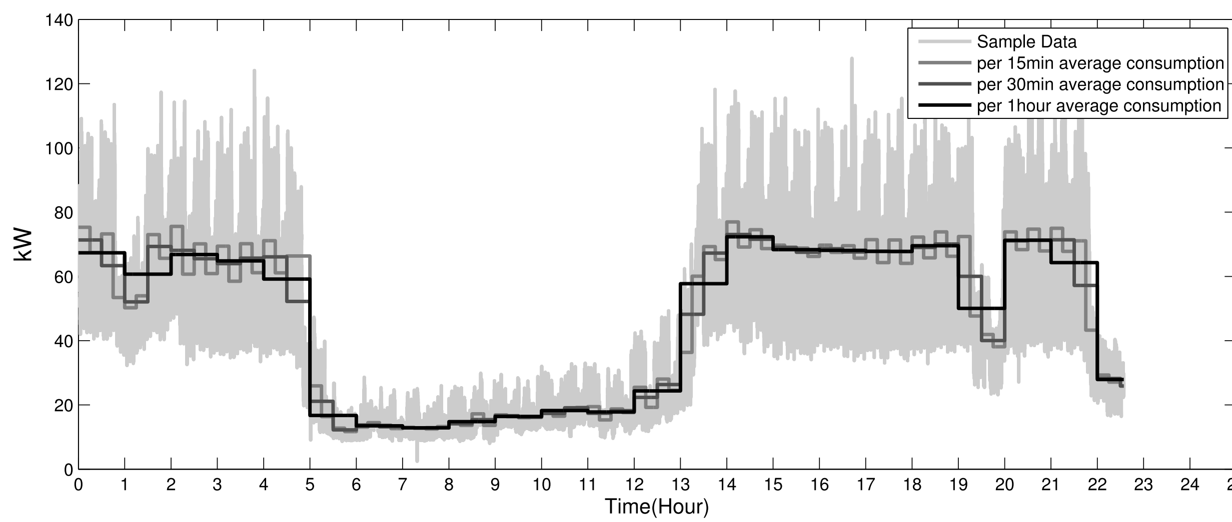

Fig. 2. Proposed simulation of energy consumption using sample data.

specific virtual private network (VPN) access and then saved to the campus data server. The proposed framework leverages two-way communication which means a one-side transmission delay would cause delay of image transfer to the cloud. Reliability can be increased if there exists a long-term evolution (LTE) network in addition to the Wi-Fi connection. This assumes the repurposed devices are LTE enabled. Both reliability and latency can be negatively impacted if there is poor wireless reception, which often increases with the distance between the mobile device and the hotspot. Additional communication latencies are introduced: 1) between the device and the cloud; and 2) between the cloud and the data center of the server performing the data extraction. In our experiments, the total latency was always less than 1 min.

A. Data Acquisition From IP-Based Energy Meters

The IP-based energy meters of the campus-wide distribution grid are monitored by the AX supervisor. It is a flexible network server where multiple Java application control engines can be networked together [29]. Real-time energy consumption information is displayed on the energy meter as well as uploaded to the internet through the IP-based internet link module [30].

For security reasons, ingress restriction and identification in communication protocols are configured for internet connection and access [31]. The users and supervisors are capable of executing operations with VPN verification together with a firewall [32], [33].

B. Pictorial Data From Electromechanical Meters

Unlike IP-based smart meters, the electromechanical analog meters do not establish network connection and require periodic manual reading. The typical analog meter has four pointers with different orders of magnitude to show scaled energy consumption.

The overall approach for real-time data extraction from the traditional mechanical meters is to apply live image transmission technology with the information uploaded to a private

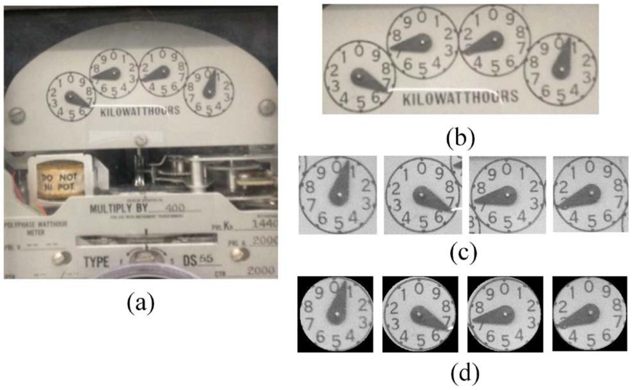

Fig. 3. (a)–(d) Image segmentation in four steps.

cloud storage [34] through the campus intranet with synchronization achieved at the download side. The operational approach is to have a mobile device with a timer camera application acquiring images every c minutes. The device is installed and placed in front of the dial plate with a stand support. The automatic upload function in the mobile device uploads the photo stream to the private cloud through the internet and then the photo appears at the monitoring terminal computer immediately for image processing and consumption data extraction [35].

Data samples of the IP-instrumented buildings were used to find a suitable value of c; trading off frequency resolution, and phase lag with the size of datasets. Fig. 2 is an example that illustrates average value time-activity curves of sample data acquired from an IP-based meter with three different time durations. The estimated power in kW is determined based on a first-order finite difference of the two image snapshots

$$P_{\text{est}} = \frac{E_{\text{mec}}(t) - E_{\text{mec}}(t-1)}{c} \tag{1}$$

where $E_{\text{mec}}(t)$ and $E_{\text{mec}}(t-1)$ are the latest image snapshots of the electromechanical analog meter. If we restrict the interval to be every 10 min, then $c = 1/6$ using an hourly base.

IV. Image Data Extraction

A. Image Segmentation

Fig. 3(a) shows an image of a four-dial plate electromechanical meter. The processing area is formed using a rectangular crop shown in Fig. 3(b). To deploy a modular pointer extraction algorithm, a strategy was developed to extract each of the circular dials shown in Fig. 3(c), with elimination of the background shown in Fig. 3(d)

$$\Theta = \begin{cases} \tan^{-1}\left(\frac{|X_{\text{mid}}-X_{\text{center}}|}{|Y_{\text{mid}}-Y_{\text{center}}|}\right) + \theta_0, & \theta_0 = \begin{cases} 0, & \text{quadrant 1} \\ \pi, & \text{quadrant 3} \end{cases} \\ \tan^{-1}\left(\frac{|Y_{\text{mid}}-Y_{\text{center}}|}{|X_{\text{mid}}-X_{\text{center}}|}\right) + \theta_0, & \theta_0 = \begin{cases} \frac{3\pi}{2}, & \text{quadrant 2} \\ \frac{\pi}{2}, & \text{quadrant 4.} \end{cases} \end{cases} \tag{2}$$

Fig. 4. Exported images after segmentation and preprocessing.

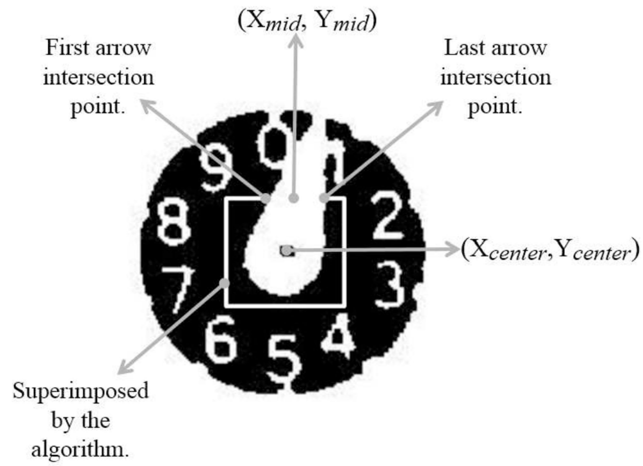

Fig. 5. Intercepted square box with a dial plate arrow within an image.

B. Digital Image Preprocessing

The change in lighting conditions can lead to color and contrast variance. In order to avoid the identification error generated from this situation, we first produce parallel grayscale images from segmented areas. Discerning grayscale images directly is often accompanied by random noise as well as diverse shade degrees in a focused zone of images. Here, we utilize grayscale image binarization to acquire analyzable outcomes with little identification error. It is noted that the threshold value for binarization of 0.6 was used to magnify the contrast ratio of the white pixels.

To further improve the resolution of the binary image, we applied morphological operations, dilating, and corroding [36], to simplify the image data structure. The dilating operation expands and enhances the edge of the object to dislodge or cover blank spots while the corroding operation eliminates external pixels to reduce edge "burrs." The preprocessed, inverted image is shown in Fig. 4 and is ready for pointer extracting.

C. Pointer Extraction Algorithm

Fig. 6 demonstrates the flowchart of overview process of image data extracting. The image data are transferred: 1) between mobile devices and the cloud this is presumed to be sent from consumers to the cloud and 2) data transfer between cloud and customer billing center this is received at the customer billing center. The flowchart includes security verification, which includes the following steps.

1) Estimated latitude and longitude position of the mobile device based on Wi-Fi or assisted global positioning system (GPS) information.
2) Each photo taken has the geotagging information that includes latitude and longitude. The geotagging feature must be enabled on the mobile device.

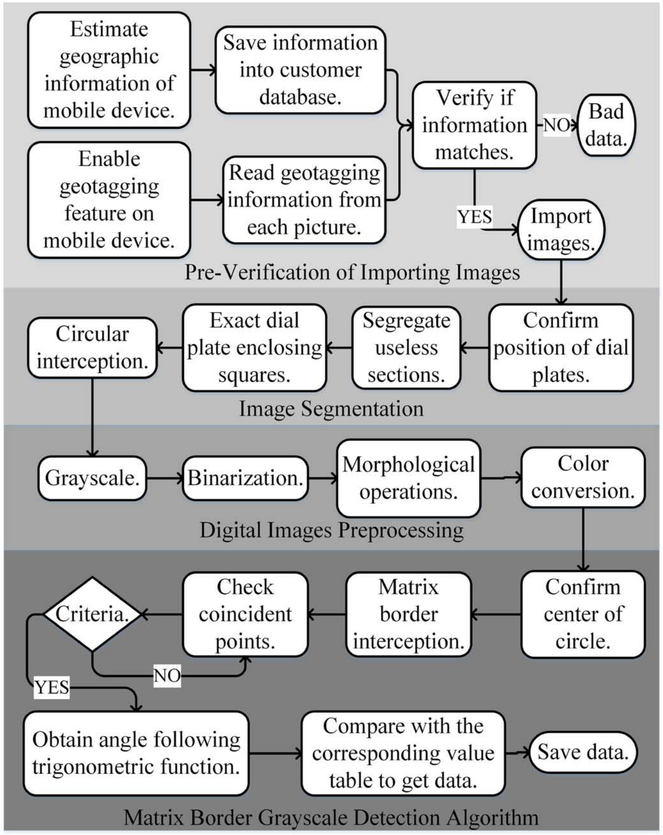

Fig. 6. Flowchart of matrix border grayscale detection algorithm.

Fig. 7. Campus-wide distribution system with 35 buildings.

3) Images are transferred to the database of customer billing center. Before the data extraction begins, the geotagging information is verified together with username and address of the customers database.
4) If they match, then the data extraction algorithm starts processing. If some images violate the criteria that are expected, then those will be disregarded and the data points will be indicated as bad ones as a result not to be considered.

An AMI system is expected to last between 15 and 20 years [37], while the life cycle of proposed IE approach could vary significantly based on the device used. Similarly, the IE cost is also highly variable depending on the availability of repurposed devices. The time interval setting of transmitting the image datasets was set to be every 10–15 min. The internet today has the bandwidth sending pictures through Wi-Fi. Furthermore, the geotagging features from assisted GPS devices only shows the location of the device rather than the position of the customer (since this is a repurposed unit). These pictorial datasets do not include the name of the customer or their billing information.

Our pointer extraction algorithm is based on the characteristics of the binary image matrix and is designed to intercept a square border within an image as illustrated in Fig. 5. The angle Θ is found by superimposing a square onto the extracted image as shown in Fig. 5. The first and last intersections of the square with the boundaries of the arrow pixels are used to find the arrow's midpoint, also indicated on Fig. 5. Finally, the arrow angle is computed by the line segment connecting the circle center to the arrow midpoint.

When traversing the square to find the arrow intersection points sometimes spurious pixels are found that can give a false positive intersection. These are filtered out if their surrounding pixels are inverted. Depending on the midpoint and the center of a circle, the offset angle, Θ is calculated based on the pointer position in each quadrant using the appropriate quadrant-dependent version of (2), where X_{mid}, Y_{mid} and X_{center}, Y_{center} present the coordinate of midpoint and center of circle, respectively.

The goal of the pointer extraction algorithm is to find the value, d, indicated by the pointer. This is accomplished by first finding the angle the pointer makes with the dial plate, Θ and then using (3). For the fastest moving dial (right most) the resolution of the algorithm is 3.6° which indicates n is equal to 2. For the first three dial plates, the accuracy is integer bit that n should be equal to 1. Under certain circumstance, the adjacent pointers on traditional electromechanical analog meters may have an inverse numerical plate, i.e., clockwise and anticlockwise

$$d = \begin{cases} \text{trunc}\,(\Theta/\,(2\pi/10^n)), & \text{clockwise} \\ 9 - \text{trunc}\,(\Theta/\,(2\pi/10^n)), & \text{anticlockwise.} \end{cases} \tag{3}$$

V. Case Study

The IE approach was validated on a test case using the existing electromechanical analog meters in a building connected to part of the Michigan Tech distribution system. The evaluation of time-activity curves is discussed in this section.

A. Test Case Description

Fig. 7 is the geographical map of the campus distribution network with numbered buildings. There is one substation and

Fig. 8. Actual timer camera device in operational mode.

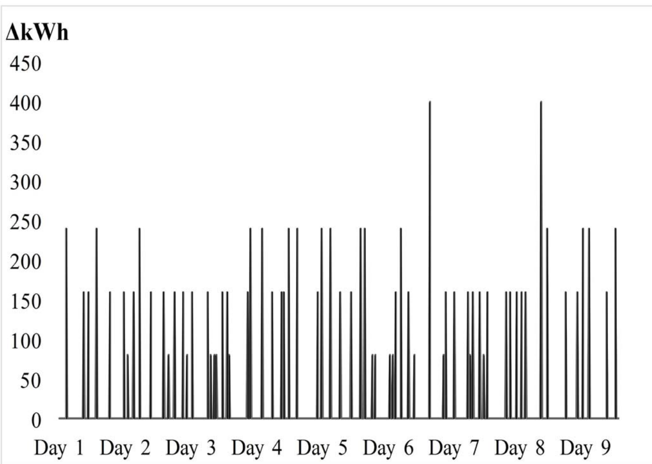

Fig. 9. Energy consumption of building-20 208 V circuit between 3/22/2014 and 3/30/2014.

four generating units in building 41 which is also the facilities management site. There are three existing distribution feeders and each building is connected to a primary feeder and a backup feeder. The dark gray circles are the ten buildings deployed with IP-based electricity meters. The IE system was tested in the unmetered building 20. This building was selected because of its relatively high consumption relative to the other unmetered buildings. Additional criteria considered for the study are to ensure that the location is equipped with outlets and Wi-Fi availability. Building 20 had all of them. As the 120 V supply near a meter is pretty rare, a power cord is necessary to connect the wall outlet with the device charger. In addition, the implementation of the proposed framework was secured in the electrical room of building 20 and thus weather protection of the device was not considered.

Two different types of electromechanical analog meters were present in building 20's electrical room: 208 and 480 V. The 208 V meter monitors low power-driven equipment such as lighting and electronic locks while the 480 V meter detects high-power machinery loads. The case study was based on both meters and the datasets obtained from meter readings were recorded for nine days.

Two IE systems were deployed with the timer-camera application placed in front of the dial plates as shown in Fig. 8. The captured images were automatically and wirelessly uploaded to the server every 15 min and were also displayed on an attached computer. The umbilical shown in the figure was for power only.

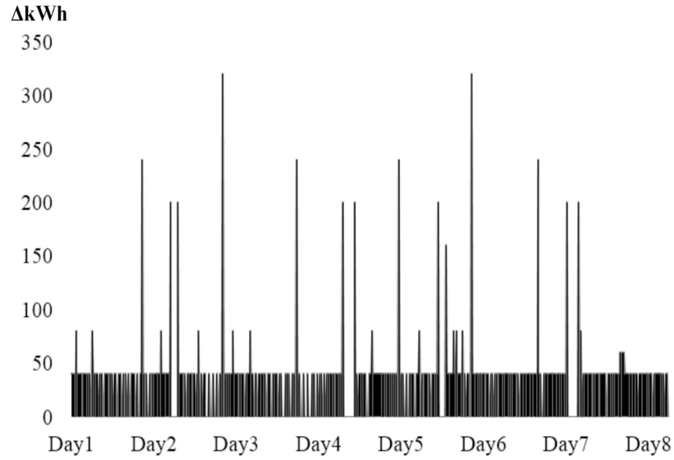

Fig. 10. Energy consumption of building-20 480 V circuit between 3/22/2014 and 3/29/2014.

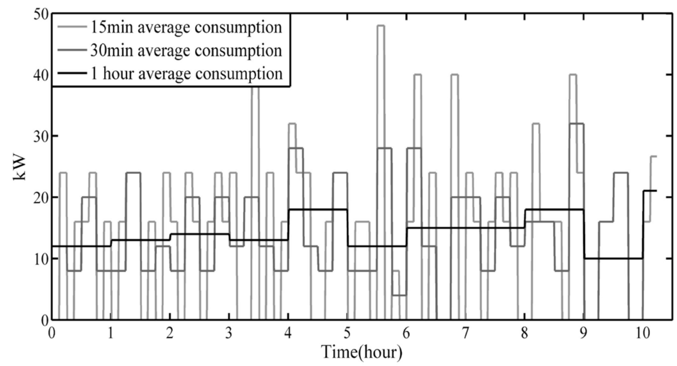

Fig. 11. Average power consumption for building-20 208 V circuit.

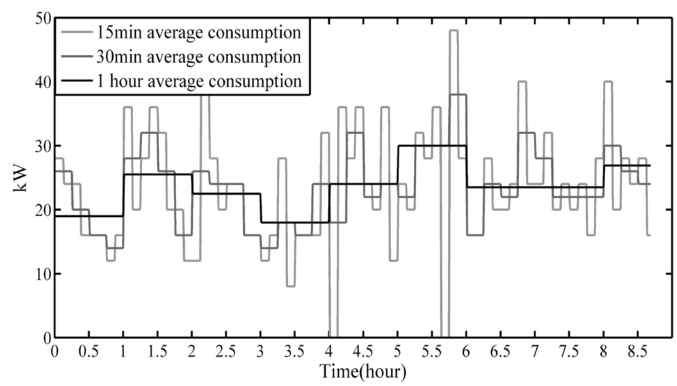

Fig. 12. Average power consumption for building-20 480 V circuit.

B. Study Results

Converted meter readings were saved in an text file for subsequent analysis. The change in power usage, extracted from the 15-min sampled images and averaged to hour increments, is shown in Figs. 9 and 10 for both the 208 and 480 V circuits. The curve of actual image extracted data from the 208 V

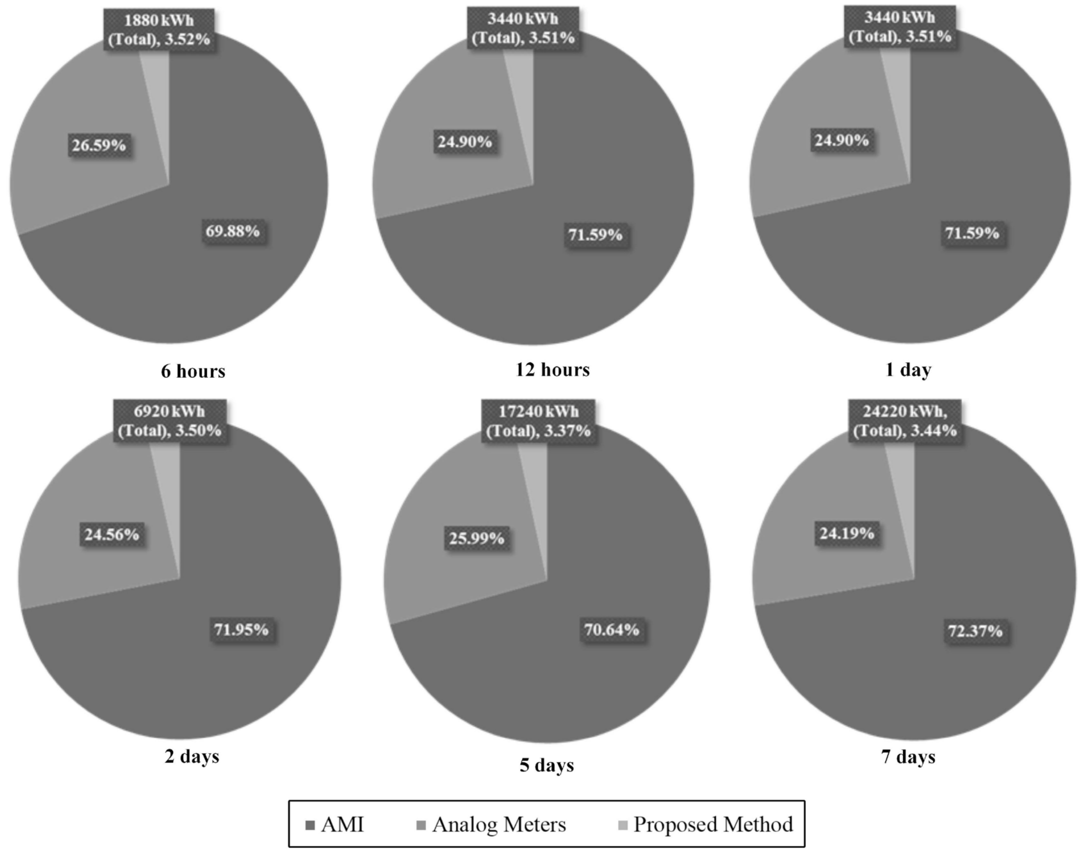

Fig. 13. Consumption percentage piecharts for buildings with AMI, analog meters, and analog meters with proposed method (number 20).

TABLE II
ERROR RATE ANALYSIS

Number of days	Image taken time stamp	IE approach (kWh)	Manual reading timestamp	Actual consumption (kWh)	Error rate (%)
1	6:06pm	3,440	6:00pm	3,431	0.26
2	6:06pm	6,920	6:00pm	6,888	0.46
5	6:06pm	17,240	6:00pm	17,189	0.30
7	6:06pm	24,220	6:00pm	24,134	0.36

circuit is similar to a bar chart rather than the typical line chart because the energy consumption variability of the low power devices was small between 15-min updates.

From (1), the energy information (in kWh) on those analog meters can be translated into average power (in kW). As the rotation of the electromechanical blade can be slow (scale of 800), considering average consumption time-activity curves with 15-min, 30-min, and an-hour timescale can help to estimate and predict energy consumption over a longer period of time. The initial experimental outcome of the datasets is divided by three different time intervals and the corresponding power estimates are shown in Figs. 11 and 12. This illustrates the ability of the IE approach to produce power usage trends over varying time windows.

Table II illustrates the error rate analysis between the IE approach and manual reading. Four time intervals for 1, 2, 5, and 7 days are shown and corresponds to the range of dates 3/22/2014–3/23/2014, 3/22/2014–3/24/2014, 3/22/2014–3/27/2014, and 3/22/2014–3/29/2014. Since the manual reading time stamp was 6:00 P.M. (± 5 min), the nearest IE time stamp of 6:06 P.M. was chosen. The error between the IE approach and manual reading was always less than 0.5%.

Fig. 13 compares the IE-based penetration on the total campus consumption with respect to the ten building's smart meters and the rest of the unmetered buildings. Time intervals of 6 h, 12 h, 1 d, 2 d, 5 d, and 7 d are shown.

Building 20s consumption (labeled "proposed method" in the figure) is approximately 3.5% of the total (35 buildings) throughout the six time intervals from March 22, 2014 to April 1, 2014. In March 2014, the monthly consumption percentage of building 20 is with the average values of 3.51%. This consistently indicates the estimation of energy consumption from the unmonitored building via the IE system is reasonable. The energy consumption of building 20 is apparently higher than the average consumption of each of the 25 unmetered buildings (labeled as "analog meters"), which are the campus insignificant loads.

The statistics of the AMI are the accumulation values that sum up all ten buildings with smart meters. About one-fourth of the total consumptions, which is the remainder of the 25 buildings, does not have smart meters nor implemented with the IE approach. Through the observation of those six piecharts, the proportion of energy usage on those ten-building smart meters is estimated to be about 70% of total campus consumption, which is considered the heavy loads of campus.

VI. Conclusion

The IE approach is designed to automatically extract data from images of electromechanical analog meters without smart IP-based energy meters. It requires a wireless network and a continuous power supply in close proximity to the existing electromechanical analog meter's location. The IE algorithm includes image segmentation, digital image processing, and matrix border grayscale detection analysis. Note that there are a few error points during the process of matrix boarder grayscale detection. Setting a criterion for restricting the extraction region decrease the number of errors whereas the accuracy rating of these arranged images will be influenced slightly. The analysis in this algorithm is based on the four sub-dials rather than the whole plate surface. The algorithm will keep working when the sub-dials retain circle shapes without considering the shape, size, diameter, or configuration of the whole plate. The primary step in this algorithm is to binarize the original picture from colors to black and white only. The IE approach was tested on an unmetered campus building which has reasonably large consumptions among all buildings. Simulation results show that the IE system provides periodically extracted data to generate power usage time-activity curves. We make a comparison between extracted data and actual data to prove the accuracy. In addition, the energy usage estimation ability of the IE approach is illustrated. Although this approach is in the experimental stage, it offers an alternative to improve observability of the distribution network. It is important to implement Wi-Fi reception for meter locations or replace the mobile device to ensure images can be transferred as well as with outlets in order to provide continuous power supply. In the future, additional circle recognition algorithms should be considered to compensate for camera position shift. Considerations to enumerate other types of analogy meters would include in the studies and adaptation of existing modules in meeting a manufacturer-specific requirement of their analog devices would be necessary.

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