Emerging Technologies for Improved Plug Load Management Systems: Learning Behavior Algorithms and Automatic and Dynamic Load Detection

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ABSTRACT

Plug loads are responsible for a significant portion of the energy consumed in commercial buildings, yet their distributed and ever-changing nature makes them one of the most challenging building end uses to manage. Plug load management systems exist today that use smart plugs to meter and control devices at the outlet level, but their uptake has been relatively slow in part because of the significant labor required for installation and maintenance. Learning behavior algorithms and automatic and dynamic load detection are two technology areas that could accelerate the adoption of plug load management systems by reducing these labor demands and providing additional energy efficiency and nonenergy benefits. Learning behavior algorithms learn occupant behavior and adjust plug load management systems accordingly, allowing for the automatic creation of optimized control schedules. Automatic and dynamic load detection allows a plug load management system to identify devices as they are plugged in to a building and keeps the system up to date as devices are moved throughout a building. In this paper, we present our findings on the current state of these two technologies based on a review of existing research and patents as well as a series of interviews with companies working in the plug load space. We found that no commercialized solutions currently exist for these plug load technologies, and more work is needed to bring them to market. In addition, we summarize our findings related to the technology challenges and market barriers, drivers, and opportunities for these technologies moving forward.

Introduction

Plug and process loads (PPLs) represent more than 40% of the total energy use in U.S. commercial buildings and this percentage is projected to increase during the next 30 years (EIA 2020). PPLs are challenging to manage and control given that they are distributed throughout a building and can consist of numerous loads, many of which are relatively small. To help with PPL reductions, building standards (e.g., California Title 24, ASHRAE 90.1, and the International Energy Conservation Code) are adopting plug load energy management mandates that require a portion of the outlets in a building to be controlled. Controls allow devices to be turned on and off automatically via set schedules or based on occupancy, reducing equipment power consumption when not in use. Controlling individual pieces of equipment can yield up to 30% savings on PPL energy consumption (Langner and Christensen 2018).

Currently, there are solutions available that offer both PPL control and metering capabilities down to the socket level. Often referred to as "smart plugs," the hardware in these technologies collects power consumption data from individual devices and can turn devices on or off by controlling the flow of electricity to the device. In some cases, this is accomplished with hardware located between the outlet and the equipment plug; in others, the hardware is integrated into the outlet itself. These smart plugs are often part of a greater plug load management (PLM) system. The smart plugs will often transfer information to a gateway wirelessly using ZigBee, Wi-Fi, or another communication protocol. The gateway then communicates with a cloud-based system that aggregates the data from the smart plugs and allows building managers to monitor individual device energy consumption and control the smart plugs remotely.

Setting up these types of PPL metering and control technologies requires labor, time, and expertise. During installation, a human will often have to map each smart plug to the device it is metering (i.e., labeling the outlet with serial number 109 as a "printer"). In residential settings, where there are relatively few devices, homeowners can typically complete this process themselves by naming each smart plug with a mobile application. Smart home platforms, such as Google Home, Amazon Alexa, and Apple HomeKit, allow some plug-in devices to integrate directly into their existing home automation platforms.

In commercial settings, however, installations are more labor intensive due to the large number of devices. A well-planned naming system must be established to keep track of the monitored devices and their locations. If a device is moved to a different outlet, this change will often go undetected, which could compromise the metering data for that outlet or the control of the device itself. To maintain proper operation, the PLM system must be regularly updated as the building is reconfigured and as occupants move devices around. As a result, the labor cost for the management of the PLM system could be higher than the energy savings from the control opportunities (Kandt and Langner 2019). In addition to the installation and management challenges, determining appropriate control schedules for several individual devices can be difficult. As a result, controlled devices are often all on the same schedule. In this case, the schedule must be relatively conservative to avoid inconveniencing building occupants, which may leave important energy-saving opportunities on the table.

Addressing some of these challenges, such as long setup and maintenance times, would help accelerate the adoption of PLM systems in commercial buildings. Langner and Trenbath (2019) broadly described the current state of smart plug technologies and pathways to integration with whole-building energy management information systems. They also identified emerging technologies that could enable faster uptake of PLM systems, two of which are further investigated in this paper:

- Learning behavior algorithms (LBAs) are machine learning algorithms used to identify patterns in behavior and make predictions about future behavior based on these patterns. These algorithms could assist building managers in determining optimum schedules for devices based on how individual devices are used. This technology would not only reduce the labor required for system management but would also allow more targeted schedules that could capitalize on otherwise unrealized savings opportunities.
- Automatic and dynamic load detection (ADLD) allows a building's PLM system to automatically recognize when a device is plugged into an outlet, identifying both the type of device and its location (Langner and Trenbath 2019). This shortens PLM system installation time and drastically reduces issues arising from moving devices around.

Both technologies can streamline plug load controls for building owners, reducing PLM system set-up and maintenance time. Although they don't currently have a significant market presence, the development of PLM systems with these technologies could speed market uptake.

The purpose of this paper is to address the following questions:

- What is the current state of LBA and ADLD technologies in PLM systems?
- What are the technology challenges and market barriers for LBAs and ADLD?
- What are the drivers and opportunities for the further development of these technologies?

By addressing these questions, this paper will inform readers about the current state of these technologies and their potential to help reduce plug load energy consumption.

Methods

To address our research questions, we performed literature reviews for LBA and ADLD technologies and conducted interviews with companies either actively pursuing these technologies or working in the PLM space. In the literature reviews, we investigated journal publications, technical reports, and patents to understand what plug load-related research has been conducted on these two technologies. We reviewed 4 LBA publications and 16 ADLD publications. Although LBAs have been well studied in the context of buildings, LBA research specific to plug loads has been limited. The ADLD review included papers related to nonintrusive load monitoring (NILM), which has been researched for more than 25 years.

Companies developing plug load control products that incorporate ADLDs, LBAs, or both were targeted for interviews. Companies referenced in research papers and market reports were added to a preliminary list and further researched to determine their relevance. We ultimately reached out to 14 companies to request interviews, of which seven responded. Five of those companies have worked with LBAs and four have investigated topics related to ADLD.

We developed a semistructured interview protocol and conducted individual phone interviews with representatives from six of the seven companies. One company chose to email their responses to the interview questions. The interview protocol included sections for both LBAs and ADLDs and the interviewer tailored the questions to the specific company's expertise. We coded notes from the interviews using grounded theory (Glaser and Strauss 1967) and categorized these codes to summarize the technology challenges and market barriers and drivers.

The interviewees we spoke with all hold relatively senior roles within their companies and have more than 80 years of collective industry experience. The companies represent a broad range within the industry with respect to their age and size, technologies and services, and clients. One company is only 4 years old while another has been around for more than a century, and company sizes vary from 5 to more than 35,000 employees.

All companies offer some form of hardware. The services they provide vary, however, and include smart home and building automation, power quality metering and correction, manufacturing, NILM, and demand response control. The companies work with clients from both the residential and commercial sectors, including contractors, utilities, and consumers from around the world, with the largest sales concentration in North America. Although the seven interviews only capture a portion of the work being done in the plug load space, the diverse portfolio of companies along with the vast experience of their employees offer a valuable snapshot of where the industry stands with respect to LBAs and ADLD.

Learning Behavior Algorithms

LBAs allow technologies to adapt based on how people use them. Plug load energy consumption is often a reflection of human interaction with devices and therefore power data from plug load devices offer a unique opportunity to employ LBAs. Applying LBAs to plug load data, and potentially combining data from other types of sensors (e.g., occupancy sensors) could improve the usability of PLM systems and create new, untapped applications for these systems. In the plug load world, however, the technology is young and mostly in the development stages.

Literature Review

In our review of prior research on plug load related LBAs, we found that a few different approaches have been taken to apply machine learning to plug load data but the research has been relatively limited thus far. The research includes both residential and commercial applications and has targeted a variety of potential benefits of LBA development. Table 1 summarizes the sectors and targeted benefits of each of the four reviewed publications.

Table **1**. Learning behavior algorithms research sectors and targeted benefits

	Sector		Targeted Benefits of LBA Research				
Author and Year	Residential	Commercial	Energy Savings	Convenience	Health and Wellness	Building Performance	Fault/ Abnormality Detection
Zhao et al. 2014		x	x	x		x	
Wong 2015 (patent)	x		x	x			
Alam et al. 2016	x			x	x		x
Vafeiadis et al. 2017	x		x			x	

Two of the studies used LBAs with device energy consumption data to predict occupancy. Zhao et al. (2014) metered 28 appliances in an office building and used wristwatch-like pedometers to track the location of the occupants. They used these data to train a handful of data mining algorithms to classify the occupants' behavior. They found that the C4.5 decision tree algorithm was most successful at classifying occupant behavior, with an average classification accuracy of 90% for ten individuals. Vafeiadis et al. (2017) employed LBAs for predicting occupancy in the residential setting based on appliance electricity consumption and occupant water consumption data. They trained machine learning algorithms using occupancy data from an infrared door sensor and found that the random forest technique was most successful at predicting occupancy, with an accuracy of just over 80%.

Alam et al. (2016) investigated using LBAs for monitoring at-risk patients (elderly, mentally ill) who live at home. They used energy consumption data from the patient's residence to detect appliance energy usage anomalies and correlate them to the patient's behavior abnormalities. Upon detection, the system could alert responsible parties to the changes in a patient's behavior. The authors metered 32 total appliances in two residential settings and were able to achieve a 97% accuracy in detecting days with anomalous energy use using the Mixture of Gaussian Mixture Model. They achieved an 87% accuracy with predicting the behavioral cause (i.e., insomnia, changed eating habits, increased social isolation) of the anomalous day using the Gaussian Latent Dirichlet Allocation algorithm.

Wong (2015) filed a patent with Oracle that laid a framework for automatically controlling smart devices based on historic user and device behavior. The patent encompasses a variety of appliances and suggests methods for identifying patterns in building data collected from multiple sources to develop and send control signals to connected devices. The patent lays out a systems-level approach to using LBAs to control smart appliances.

The prior published research articles focus on predicting occupant behavior, but none of the publications we reviewed document the effectiveness of applying LBAs for plug load controls. Wong (2015) describes a technology that could achieve this, but this technology has not been validated with further research. More work is needed to develop advanced algorithms and validate their effectiveness to improve the commercialization success of LBAs in PLM systems.

Interview Findings

Current state of learning behavior algorithms and uses. Across many industries, machine learning has been used to better understand and predict user behavior, and the buildings industry is no exception. Smart thermostats, for example, have garner significant attention for their ability to learn occupant behavior and adjust a building's temperature throughout the day to both meet the occupants' needs and save energy. We have found that behavior-based machine learning algorithms have been more heavily applied to HVAC and lighting end uses than to plug loads. Still, some companies are actively investigating LBAs for plug load applications.

Five of the seven companies we interviewed are developing or already offering products with behavior-based machine learning technologies. Table 2 is a snapshot of the capability, end use, and sector that each of the five companies is targeting, along with the status of their product.

Table 2. Snapshot of companies developing learning behavior algorithms technology for plug load management

Company	End Use Control	Primary Sector	Capability	Status
1	Lighting	Commercial	Sensor-based auto-commissioning	Used today
2	Lighting	Residential	Lighting catered to occupant activity	Under development
3	HVAC	Residential	Demand response signals catered to user history	Used today and under development
4	Plug Loads	Residential and Commercial (in-home healthcare)	Elder care abnormal behavior detection via device usage anomalies	Under development
5	Plug Loads	Commercial	Custom schedules based on individual device usage	Under development

Although all the companies are working on products to control plug loads, some are focusing their LBA work on other end uses. Companies 1 and 2 are using LBAs for lighting applications. Company 2's goal is for lighting to respond to user behavior. They are interested in learning how users interact both with lighting directly and with plug load devices, to cater the lighting to the user's activities. This is one example of how these two end uses can be tied together with LBAs.

Company 3 is using LBAs to understand how users of window air-conditioning units respond to demand response events. They are looking at how individual users have historically responded to demand response signals and are adjusting their future signals accordingly, such that the users are more likely to respond in a beneficial manner.

Companies 4 and 5 are investigating LBAs for plug loads specifically. Company 4 is interested in detecting abnormalities in device usage, especially in the case of elder care, to identify abnormal behavior and send alerts when there may be an issue with the occupant. For example, if a device starts being turned on regularly in the middle of the night, it may indicate changes to an occupant's sleep habits. This technology is currently in the development phases for simple applications. Company 5 is using LBAs to learn when occupants use individual devices and to create schedules for each device based on this information. Their method takes much of the labor and uncertainty out of the schedule making process, allows for schedules to be regularly updated based on device usage, and capitalizes on energy savings. They are also working to incorporate data from other sensors, including occupancy sensors, into the LBAs to make more accurate scheduling predictions.

Interviewees provided insights on technology challenges and market barriers, drivers, and opportunities for LBAs in the plug load space, which we summarize here.

Technology challenges and market barriers. Machine learning has opened new opportunities for building energy savings, but there are still significant challenges.

Barrier: Device power consumption patterns may not display regular use patterns. Identifying reliable patterns in device power consumption data can be difficult, and the patterns can change drastically from device to device. A refrigerator's power may follow a relatively regular pattern through its compression cycles, whereas a water boiler's power is completely dependent on when occupants desire hot beverages, which will likely change with the seasons.

Barrier: Difficulties in expanding beyond simple cases and single building types. Building type can have a substantial effect on behavior prediction. What may work in a bank, where there is a structured workday schedule, may not work in a university laboratory where people are potentially entering and leaving the space at irregular times. These complexities have made it difficult for companies to expand the use of LBAs beyond simple applications.

Barrier: The market demand is focused on cost. Building managers often are interested in solutions with the least labor and cost requirements. Although occupancy sensor-based plug load controls may not have all the functionalities that an LBA-informed PLM system would have, occupancy-based controls may meet most of a building manager's needs at a lower cost. Therefore, LBA-informed PLM systems compete with simpler and less expensive solutions for market share. There are nonenergy benefits to LBA technology but building managers may not see value in these benefits until they reach cost parity with current systems.

Drivers and opportunities.

Driver: Convenient solutions reduce human input. The companies' clients are looking for solutions that will require as little human input as possible. With the current PLM offerings, building managers must spend time setting up device schedules. As they are developed further, LBAs could generate schedules for devices without the need for significant human intervention.

Driver: Learning behavior algorithms can predict anomalies in elderly behavior, flagging possible issues. In the elder care sector, there is interest in providing independent living while at the same time offering a means for monitoring daily activity. LBAs that analyze device usage patterns could provide this functionality, but more work is needed for LBAs to become a reliable and trusted method for detecting abnormal behavior.

Driver: Energy efficiency is a potential driver, yet none of the interviewees listed it as the primary driver. Multiple interviewees suggested that energy efficiency tends not to be a primary driver for their residential clients. Energy efficiency can, however, be an important driver in the commercial setting when a client is looking for a return on their PLM investment. Had we interviewed more companies that offer plug load scheduling for the commercial sector, we might have found a stronger emphasis on energy savings as a driver.

Opportunity: Target niche markets while LBA technology gains traction. Technology developers could avoid direct competition with occupancy sensor-based plug load control by targeting a niche market, from which they could expand. One use case that was highlighted by Alam et al. (2016) in a company interview is the ability to remotely detect anomalous occupant behavior with LBAs. Product manufacturers, therefore, could break into the market by focusing their development on similar niche applications.

Opportunity: Learning behavior algorithms could encourage integration of plug load data with data from other sources. These additional sources of data could be from, for example, water consumption meters, door sensors, occupancy sensors, cell phones, or even wearable devices. Incorporating additional sources of information could lead to improved LBA prediction capabilities.

Summary. When fully developed for PLM technologies, LBAs could reduce set-up time, making plug load controls more convenient to implement and, in turn, reducing energy use. The technology is not yet commercialized for PLM systems. Work is needed to improve LBAs for specific device types and to understand how users will interact with algorithm-based controls. The latter is a potential future research area and could be broadened to include occupant behavior studies to improve algorithms.

Automatic and Dynamic Load Detection

ADLD allows a PLM system to automatically identify devices when they are plugged into building outlets. This capability provides a much more straightforward PLM installation process and more accurate and dynamic plug load energy metering and control. In the LBA section, we began with a fundamental technology (LBAs) and investigated various applications that have been proposed for the technology. In this section, we begin with an end functionality (ADLD) and investigate various technological methods that are being explored to arrive at this functionality. We identified two principal technology pathways in which ADLD can be implemented, namely via implicit identification and explicit identification. Implicit identification leverages algorithms to determine a device's identity by analyzing measurements of the device's electrical characteristics (voltage, current, harmonics, etc.). Explicit identification uses either wired or wireless communication technologies to directly communicate a device's identity or location between the device and its corresponding outlet. To provide context for the literature review and interview findings, the following paragraphs summarize these technology pathways.

Implicit Identification

The most well-studied and commercially available method for load identification is through the analysis of a device's electric signals to determine its device type. The two main avenues for implementing this technology include:

1. NILM, which disaggregates loads from a building's main electrical power readings.
2. Intrusive load monitoring (ILM), which meters individual devices or small groups of devices via smart plugs and identifies associated electric signals without disaggregation.

NILM's potential to provide insight into device-level power consumption through a single meter has generated significant interest in the technology. It is used by some homeowners, commercial building owners, and utilities today, however, the technology's load identification accuracy is still limited. This is especially true when there are many devices in a building and when many of the loads are small, which is often the case with plug loads (Kazmi et al. 2014). Although NILM has the potential to identify loads, it is currently incapable of identifying a device's location and is therefore only a partial solution for ADLD. ILM, on the other hand, could be used for location identification because the individual meters needed to perform ILM are tied to specific locations throughout a building. Many implicit identification methods have demonstrated relatively high accuracy in research settings, but because device identities are in fact determined implicitly, uncertainty is inevitable with this method.

Explicit Identification

Another method for ADLD is to communicate device identity and/or location directly between the device and a smart plug or wall outlet. This type of direct communication would remove the uncertainty involved in device identification based on electrical signal analysis. There are many different configurations in which this communication could be accomplished, each requiring different inputs from device manufacturers and PLM system providers.

Tags and Readers: Previous research and patents have proposed a tagging approach in which a tag is applied near the prongs of the device's plug that stores information about the device's identity. The smart plug could read the tag and know which device has been plugged in. If the smart plugs are mapped with their location within the building, they could communicate device type, location and energy information back to a main hub for the PLM system. The tags themselves could be in the form of bar codes, quick response codes or, even more likely, radio-frequency identification (RFID) technology. Each device in the building would have a tag adhered to it or, once standardized, the tags could be built into the devices by manufacturers. This approach is a relatively low-cost solution that would require the least input from device manufacturers. At the same time, this would limit the device to sharing only static information with the PLM system (e.g., it could not share its operating mode) because the tag itself is static.

Short Distance Communication Protocols: An alternative to using tags and readers would be to take advantage of short distance communication protocols such as near field communication (NFC). In this case, the device and the smart plug could communicate directly when they are brought in close proximity to one another. This technology is similar to the tags and readers approach but would allow sharing of dynamic information between the device and the smart plug. To be implemented, it would require a sizable, coordinated effort from device manufacturers and PLM system providers.

Wired Electrical Connection: A final potential approach to explicit identification would be to communicate between the device and the smart plug directly through the wired electrical connection. Powerline communication is an established technology that uses a building's existing electrical infrastructure to communicate data throughout the building. A similar technology could be implemented to allow a device to communicate its identity and any additional dynamic information to a smart plug. Furthermore, many devices are now powered from a USB connection (e.g., phones, laptops, and many other rechargeable devices), which can transmit both electrical power and data. As device connection protocols become more standardized, such as the current standardization toward USB-c, and if building-level direct current distribution becomes more popular, many future devices could be powered directly via USB connections. In this case, device manufacturers and PLM system providers could use the data communication capabilities of USB connections to perform ADLD. Commercializing this approach to ADLD would likely require a significant effort from device manufacturers, PLM system providers, and building electrical engineers at large.

Literature Review

Implicit Identification

Many of the papers we reviewed developed methods for identifying devices based on power consumption data. Some authors conducted their own data collection to test their methods, while others tested their classification methods with existing plug load data sets. The Plug Load Appliance Identification Dataset (PLAID), for example, is one of the most commonly used data sets and contains voltage and current measurements for more than 200 appliances (11 different appliance types) sampled from 55 homes.

One significant difference among the reviewed studies was the data sampling rates. The four studies from before 2014 used a sampling rate of 1 Hz or less, while the four more recent studies used sampling rates from 3 kHz to 30 kHz. All of the studies with longer timescales used real power characteristics for identification, while studies with higher sampling rates tended to investigate combinations of voltage and current characteristics. Publicly available data sets like PLAID make high frequency analysis more accessible to the research community. Table 3 summarizes the characteristics of the studies related to implicit identification.

Table 3. Summary of literature focused on implicit identification approaches to automatic and dynamic load detection

Author and Year	Data Set (data source; # of devices, # of device types, sampling rate)	Electrical Characteristics Considered/Features Extracted	Best Performing Algorithm (Identification Accuracy)
Zufferey et al. 2012	Collected data; 30 devices, 5 types, 0.1 Hz	Real power, reactive power, root mean square (RMS) current, phase	k-nearest neighbor (85%)
Reinhardt et al. 2012	Collected data; 122 devices, 31 types, 1 Hz	Real power	Random committee (95.5%)
Ridi, Gisler, and Hennebert 2013	ACS-F1[†] database; 100 devices, 10 types, 0.1 Hz	Real power, reactive power, RMS current, RMS voltage, frequency, phase	Gaussian mixture model (93.6%)
Barker et al. 2014	Collected data; several dozen devices, 15 types, ~1 Hz	Real power	Naïve Bayes (60%)
Gao et al. 2015	PLAID data set; >200 devices, 11 types, 30 kHz	Current, real and reactive power, harmonics, voltage-current binary image, principal component analysis, combined feature	Random forest (86%)
Du et al. 2016	Previously collected data; >40 devices, 23 types, 30 kHz	Voltage-current trajectories	Supervised-self organizing map (99%)
Barsim, Mauch, and Yang 2018	PLAID data set; >200 devices, 11 types, 30 kHz	Raw voltage and current	Neural networks (89%)

Makkinje 2018	PLAID data set; >200 devices, 11 types, down-sampled to 3 kHz	Current	Long short-term memory recurrent neural network (92%)

†ACS-F1: Appliance Consumption Signature-Fribourg 1 database

The reviewed studies tested a variety of machine learning algorithms to identify devices, such as k-nearest neighbor, Gaussian Mixture Model, random forest, and neural networks. Each study had a unique methodology for classifying performance, with reported identification accuracies ranging from 60% to 99%. Ultimately, these studies provide a strong basis for implicit device identification, but more work is needed to better establish best practices.

Explicit Identification

The publications related to explicit identification we reviewed tended to focus on the residential setting, but some of the technologies could be adapted to the commercial setting. The study authors used all three explicit identification configurations although most by far used tags and readers. Most of the tags and readers configurations used RFID technology to communicate device identity, although Morsali et al. (2012) used 4-bit magnetic tags. The publications typically include energy metering as part of the technology, although Kumar, Louzir, and Naour (2018) proposed a lower-cost solution that simply captured a devices on/off state and its identity. Table 4 summarizes recent papers and patents on explicit identification of plug loads.

Table 4. Summary of literature focused on explicit identification approaches to automatic and dynamic load detection

Author and Year	Explicit Identification		
	Configuration	Identification Technology	Intended Use
Elzabadani et al. 2005	Tags and Readers	RFID tag on device plug and RFID reader on outlet	Simple convenient method for setting up and maintaining self-sensing spaces
Morsali et al. 2012	Tags and Readers	4-bit magnetic tag on device plug and magnetic reader in outlet	Residential energy management systems; automatically identify/categorize devices to facilitate peak shaving
Hung et al. 2013	Tags and Readers	RFID tag on device plug and RFID reader on outlet	Improved management of home lighting devices through better energy monitoring, brightness control, and overload detection
Stubbs and Roman 2013 (patent)	Tags and Readers or Short Distance Communication	RFID or NFC tag on device plug and RFID or NFC reader on outlet	Improved methods for energy metering and PLM
Allen et al. 2014 (patent)	Tags and Readers	Tag on device plug and reader on outlet (many possible configurations described)	Improved methods for energy metering and PLM
Naaman 2014 (patent)	Tags and Readers	Tag on device plug and reader on outlet, sensor to detect when device is plugged in	Improved safety controls for potentially harmful devices that are left on and reduction of standby power consumption
Chung, Lee, and Lee 2016 (patent)	Direct Electrical Connection	Smart socket and smart plug with pins that can communicate via an electrical connection when plugged in	Improved energy monitoring for electric appliances

Kumar, Louzir, and Naour 2018	Tags and Readers	3-axis magnetometer for on/off detection attached to power cord and coupled with RFID tag for identification	Low-cost solution for communicating device on/off state and identification within a household for improved energy monitoring

Four of the reviewed publications were patents that employed an explicit identification approach to ADLD. Stubbs and Roman (2013) filed a patent for a system containing power strips that identifies a device and determines its energy usage via RFID or NFC tags and readers. When a device with a tag is plugged into the power strip, the reader registers the device, assesses the amount of energy used, and sends the tag's identifier to the centralized system. Naaman (2014) filed a patent for a similar tag and reader technology that focused on the safety benefits of turning off potentially hazardous devices (e.g., irons) if they are accidentally left on and mentioned the energy benefits of reducing standby loads. Allen et al.'s (2014) patent includes tags on the plugs of devices and transceivers in the sockets to relay device identity information to a centralized system and control the power supply to specific devices. Chung, Lee, and Lee (2016) filed a patent for a smart plug, outlet, and adaptor that use wired communication for ADLD. When a device is plugged into an outlet, the proposed components form a circuit and pass a device identification code directly via the electrical connection. The smart adaptor can be used to connect a normal plug to the smart outlet.

Interview Findings

Current state of automatic and dynamic load detection and use cases. At the time of this writing, there is no well-vetted technology in which a building management system can automatically identify the type and location of a device when it is plugged in to an outlet. The companies we interviewed have only investigated implicit identification through electrical signal analysis, which we will discuss in the following paragraphs.

Three of the seven companies interviewed have worked in the NILM space. One company offers NILM as one of their main products together with power quality metering, another company focuses on power correction but can offer NILM capabilities as an ancillary service, and a third company intended to develop NILM technology but instead pivoted to working on utility-focused demand response technology. All three companies used different methods for identifying devices. Some methods looked at device behavior over minute timescales using relatively low-cost meters, while others used more advanced meters to measure many parameters at high frequencies to identify devices based on distinct component behaviors.

One company suggested a hybrid approach to NILM and ILM in which inexpensive sensors communicate when devices change state (turn on or off) and this information could aid disaggregation. Another company is developing an ILM approach in which individual devices are metered with smart plugs and identified directly based on their electronic signatures. This method also identifies device location and avoids the difficulties associated with disaggregation. The distributed approach does, however, introduce computational challenges. Performing classification analysis in the cloud causes undesired latency, while performing analysis at the edge requires high computational power within smart plugs themselves, which may increase cost. For this reason, the company is investigating resource-constrained artificial intelligence, which they believe will prove critical in addressing these challenges.

In our online investigation, we found one company that was developing an explicit identification method for ADLD using RFID technology. However, they have likely gone out of business as they have not had an online presence since 2009. From our research, it seems clear that ADLD is a nascent technology that has yet to gain significant market traction. The following paragraphs summarize some of the key findings from the interviews regarding the technology challenges and market barriers that have slowed ADLD's commercialization, as well as some of the drivers and opportunities for ADLD may help to increase its market traction.

Technology challenges and market barriers.

Barrier: High development costs. Some companies pointed toward a lack of a business case for ADLD technology given its high up-front hardware and software costs. The companies that offer some form of device identification also tend to offer other, more lucrative services.

Barrier: Nonintrusive load monitoring technology is not fully automated. The interviewees suggested that nearly all NILM technologies still require human input from the end user or the service provider in order to accurately classify devices. The accuracy of implicit identification will continue to improve with advances in metering capabilities, computing power, and machine learning technologies, but the required labor limits implicit identification's broad market adoption.

Challenge: Integrating new loads as more electric devices are added to the market. Identifying loads based on electric signals is further complicated by the fact that it is an evolving challenge. In some cases, the load profiles from new devices entering the market are harder to identify via electrical signal analysis than older equipment with more distinct power profiles. With more electronic devices coming on the market, there is a need for more comprehensive load profile data sets to allow implicit identification to keep up.

Challenge: Combined loads are difficult to individually identify. Regardless of the method used for load identification, properly identifying devices plugged into power strips and powered furniture is challenging. Workstation devices, especially laptops and monitors, are often powered via docking stations, which presents a similarly complicated challenge.

Drivers and opportunities. Despite the market and technical challenges, companies and researchers will likely continue to investigate ADLD, as its realization could significantly improve PLM in modern buildings. Here are some drivers and opportunities identified from the interviews for pushing this technology forward.

Driver: Consumers want a convenient system that is "plug and play." Convenience is a key driver for ADLD, as consumers want a system that is "plug and play" or one that can self-set up as soon as it is turned on. ADLD technologies have the potential to make PLM systems much more automated, which is critical for these types of systems to become widely adopted.

Opportunity: Explicit identification takes the guesswork out of identifying devices and enables a plug and play system. Implementation of this technology will take a coordinated effort from device manufacturers and PLM system providers to embed the technology—tags and readers, for example—into their products directly and to ensure standardization across products.

Driver: Ease of installation and implementation. The "nonintrusive" aspect of NILM is a significant market driver for the technology, as it suggests the technology will cause limited disruption to normal building operation. Even for more "intrusive" ADLD solutions, efforts to make their installation process as seamless as possible will likely increase market adoption.

Opportunity: Nonenergy benefits. Many companies mentioned that most consumers are not motivated solely by energy savings. Therefore, companies have suggested targeting nonenergy benefits, such as improved asset performance through power quality metering and improved asset management through ADLD-based utilization tracking. One company even mentioned the potential safety benefits of ADLD as one of their selling points, similar to the work presented in Makkinje (2018) and Naaman (2014).

Summary. Given the current state of implicit identification, commercializing a fully automated implicit identification-based product will require significant research to improve identification accuracy and computational demands. Explicit identification, on the other hand, is not held back by accuracy and computational constraints, but instead is challenged because current infrastructure does not have the described capabilities (e.g., RFID technology is not already built into devices or outlets). There is a need to demonstrate this technology as a potential solution for streamlining plug load controls because market awareness is relatively limited.

Challenges for Emerging Technologies

In addition to the information specific to ADLD and LBA technologies, interviewees shared insights on challenges applicable to both technologies. The following is a summary.

Challenge: Reducing plug load management system costs. Although users are constantly seeking additional features, more than anything they are looking for lower costs. Today, smart plugs are generally seen as an expensive technology, especially in the commercial setting, where the number of smart plugs required for a comprehensive PLM system can be large. Consumers are motivated by energy saving strategies if they are cost-effective; otherwise there must be other benefits associated with the technology, such as convenience or safety.

Challenge: Developing reliable products and coming to market wisely. Consumers have become accustomed to technology that works with relatively little effort on their part. As a result, reliable functionality and easy operation are of paramount importance for any new technology in this space. If users are first exposed to faulty PLM technologies because they were rushed to market, they will have a negative perception of the technology in general and it will push back the market adoption of fully functional products.

Challenge: Scaling up technology for market readiness. Both ADLD and LBAs have demonstrated success in early development phases, but face challenges in scaling up to become market-ready. ADLD becomes more difficult due to the ever-growing variety of devices found in today's buildings. When many additional devices and more sporadic, real-world behaviors are introduced to LBAs, it becomes much harder to understand, quantify, and predict user behavior. More computing power is needed to address these challenges, but that introduces new issues with regard to where that computing takes place. There is a trade-off between having localized computing at the smart plug level, which can drive up hardware costs, and having the computation take place in the cloud, which can create latency issues. Many commercial customers are interested in integrating PLM systems with their building management systems, but most building management system platforms are not built to have the same type of plug load control functionality that these PLM companies can offer with their own proprietary system. There is a need for building management and PLM system development to take place in a coordinated fashion to meet the integration desires of the customers.

Challenge: Access to funding resources for hardware start-up companies. Hardware start-ups can be much more challenging to fund than software start-ups. All the companies we spoke with offer some form of hardware, and most PLM systems require hardware as a part of their solution. A lack of access to funding resources makes it difficult for hardware start-ups to get off the ground and challenging to fund the development of new technologies. Of the companies we spoke with, however, we noticed a general trend that the younger, smaller companies were more actively developing market changing technologies, such as ADLD and LBAs, whereas the more established companies were mostly focused on providing the tried and true solutions with which they have been successful.

Challenge: Addressing data privacy and cybersecurity concerns. The installation of new technologies often sparks privacy concerns from the residential market and cybersecurity concerns from the commercial market. The interviewees pointed out that if new PLM technologies are going to come to market effectively and safely, their products must thoroughly address privacy and cybersecurity concerns.

Conclusion

LBAs and ADLD are promising solutions for PLM systems due to the "plug-and-play" nature of both technologies. They can potentially help building owners save energy and reduce installation and maintenance costs, although there are challenges associated with the technologies' development, implementation, and market uptake. More research and development is needed to improve algorithms, scalability, and cybersecurity and behavioral and market research is needed to inform product design and determine price points.

The percentage of whole-building energy use from PPLs is expected to increase during the next 30 years (EIA 2020) and technologies that better control plug loads could become critical to improving building energy efficiency. That said, energy savings are only one of the drivers for emerging PLM technologies, as LBAs and ADLD could enable better "plug-and-play" functionality and provide nonenergy benefits such as and improved asset management. These new technologies could target niche markets focusing on safety as a nonenergy benefit, such as elderly monitoring for the healthcare sector. Collaborative, nonproprietary work is needed for companies to benefit from data integration and interoperability, which would standardize device communication. Future research to improve LBAs and ADLD for PLM systems will help the advancement of plug load controls by providing a fundamental technology basis from which companies can develop commercialized products.

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