Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey

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Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey

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***Abstract*—Smart meters have been deployed in many countries across the world since early 2000s. The smart meter as a key element for the smart grid is expected to provide economic, social, and environmental benefits for multiple stakeholders. There has been much debate over the real values of smart meters. One of the key factors that will determine the success of smart meters is smart meter data analytics, which deals with data acquisition, transmission, processing, and interpretation that bring benefits to all stakeholders. This paper presents a comprehensive survey of smart electricity meters and their utilization focusing on key aspects of the metering process, the different stakeholder interests, and the technologies used to satisfy stakeholder interests. Furthermore, the paper highlights the challenges as well as opportunities arising due to the advent of big data and the increasing popularity of the cloud environments.**

***Index Terms*—Artificial intelligence, automated meter infrastructure, big data, cloud computing, data analytics, Internet of Things (IoT), machine learning, privacy, smart grids (SGs), smart meters.**

I. Introduction

SMART Energy has been an important conceptual paradigm for future energy use. Because of limited nonrenewable energy resources available on Earth and also high costs of acquiring renewable energies (REs), how to make energy use more efficient and effective is critical for future social and economic developments [1].

Smart grids (SGs) have been a key enabler for smart energy, which refers to power networks that can intelligently integrate the behaviors and actions of all stakeholders connected to it, e.g., generators, customers, and those that do both—in order to efficiently deliver sustainable, economic, and secure electricity supplies. While there are many definitions for SGs, one commonly used conceptual framework is that of the National Institute of Standards and Technology (NIST) which defines seven important domains: bulk generation, transmission, distribution, customers, service providers, operations, and markets.

Key technological challenges facing SGs include intermittency of RE generation that affects electricity quality; large scale networks of small distributed generation mechanisms, e.g., photovoltaic (PV) panels, batteries, wind and solar, plug-in hybrid electric vehicles (PHEVs), that result in high complexities. Another significant issue is how to use information and communication technologies (ICTs), advanced electronic and analytic technologies to enhance efficiency and cost-effectiveness of energy use.

Managing SGs to deliver smart energy require advanced data analytics for acquiring accurate information and automated decision support and handling events in a timely fashion. Significant progresses have been made for using field data obtained from intelligent devices installed in substations, feeders, and various databases and models across the utility enterprises. Some of the examples can be found in [2] and references therein. Typical information sources include market data, lighting data, power system data, geographical data, weather data which can be processed and converted into information and knowledge that can be used for state estimation, situational awareness, fault detection and forewarning, stability assessment, wind or solar forecasting. Information acquisition is a key for timely data sensing, processing, and knowledge extraction. So far, the most talked-about information about power network operations is from data collected from intelligent electronic devices installed in substations and various parts of the transmission and distribution networks.

In recent years, smart meters are being installed in homes and other premises in many regions of the world [3]. USA and Europe have been deploying smart meters for many years while other regions in the world such as Australia and Canada have also started deployment in the last few years. According to a recent report [4], due to deployments in 35 emerging countries from Central/Eastern Europe, Eurasia, Latin America, Middle East/North Africa, South Africa, and Southeast Asia, the smart meter numbers have more than doubled in 2013 compared to 2012. A report by Pike Research estimates the global smart meter installations to triple from 10.3 million in 2011 to 29.9 million units by 2017 [5]. Full deployment of smart meters has already been completed in Italy and Sweden, and mass rollout is ongoing in Finland and Spain [6]. This infrastructure, if used properly, can provide more than just recording consumption of electricity or a decision support tool to support energy usage by users. For example, advantages include easier processing of billing, automated meter reading (AMR) and data processing, detection of energy losses (possible fraud) and early warning of blackouts, fast detection of disturbances in energy supply, possible real-time pricing schemes, and demand–response for energy saving and efficient use of energy generated.

The research and development in smart meters and their applications have been progressed rapidly in recent years, and many methods and techniques have been developed. The technological scope relating to smart meters covers a diverse range of ICT technologies, such as electronics and communication,

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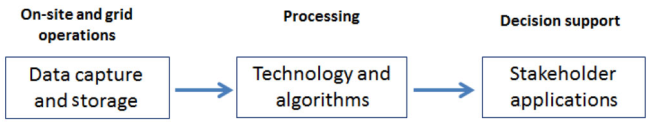
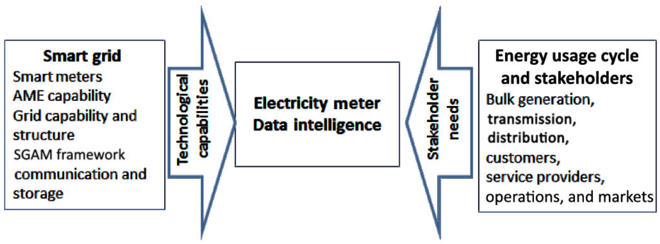


F1:1 Fig. 1. Key components of electricity meter data intelligence.



F2:1 Fig. 2. Environment for smart meter data intelligence.

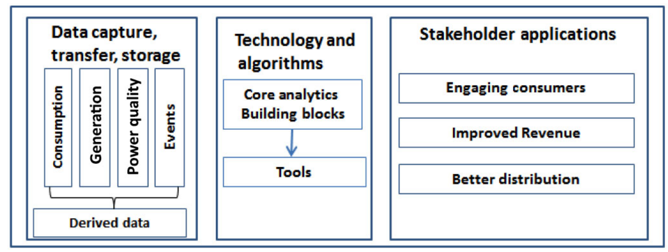


Fig. 3. Smart meter data intelligence framework. F3:1

and there have already been several surveys done, e.g., [7] looks into the different applications of SGs focusing on the communication needs and also on communication requirements of smart meters for integration into power grids. Reference [8] is a comprehensive survey of communication technologies for smart meters which could be used to satisfy the identified needs. Reference [9] introduces a novel smart meter communication technology, [10] examines the web and data service aspect of smart meter networks, and [11] proposes a framework for smart meter privacy. In this paper, we examine these developments from a holistic data analytic viewpoint. We will also outline potential future applications and challenges that lie ahead. As a foundation for our holistic approach, the key components of electricity meter intelligence are shown as in Fig. 1. The three key components capture the aspects of data, technology, and stakeholders. These aspects and the role they play in smart meter intelligence are discussed in Section II.

Section II describes the environment in which smart meter intelligence can occur. The key technology features in smart meters and their capabilities are also described, which are then used as a stepping stone in presenting a smart-metering framework. Sections III–V present each of the three key components of the framework where the data, technology, and stakeholder aspects are discussed in more detail. Section VI describes the key challenges in this area and suggests potential solutions. Section VII concludes the paper.

II. Smart-Metering Environment

To describe the components of smart meter data intelligence, it is necessary to understand the environment they exist. Fig. 2 highlights the main environmental factors being the SG, which provides the infrastructure and the stakeholders who generate the need for smart metering. Key elements which make up the environment are described below. The environmental factors presented in Fig. 2 provide the "bigger picture" for metering intelligence and positions the components presented in Fig. 1 within the smart-metering environment. The energy usage cycle and stakeholder information are based on NIST classification [12]. A further important factor is the recent push toward the integration and coupling of multiple systems and components within the SG and the understanding of the value of interoperability of such systems and components [13]. As highlighted in [13], it is desirable that multiple systems and components are interoperable under the three aspects of organizational, informational, and technical. It has been proposed that the smart grid conceptual model introduced by NIST can be extended to cater for the above requirements as well as the distributed energy requirements (DERs) especially in the European Union. The smart grid architectural model (SGAM) framework has been introduced to address these requirements [13]. With interoperability and the flexibility with technology independent systems and components, the environment is set for capturing data in near real time from multiple and diverse sources for generating data intelligence.

A. Framework for Smart Metering

The key components in Fig. 1 are further expanded as a framework in Fig. 3. A high-level view of the framework is presented as Fig. 3, where the relationships to the environment and the key components are highlighted. This framework is then further discussed in detail including the impact of these different components in Section III and illustrated in Fig. 5.

Types of data have been broken down in Fig. 3 into consumption or measurement, power generation, power quality, and events, such as power failures and meter status. These data types could be used as aggregates or combined with external data such as temperature to derive information for analysis. Capturing accurate and relevant data in a timely manner is essential for smart metering, which includes the collection, transfer, and storage (accumulation). Smart meters have resulted in a huge increase in the volume as well as types of data generated and collected, leading to many potential opportunities for generating value from such data. As mentioned under the metering process, there are several types of data-generated measurement or consumption data, generation information, power quality, and events data. Consumption data are the more predictable and regular consumption data. With smart meters, this could be time-interval consumption data as well as aggregated values for billing purposes. Time-interval data provide more granular data opening up possibilities of trend and cycle analysis and different time of day consumption analysis. Time-interval-based consumption also enables to profile consumer behavior and relate consumption to temperature changes. This requires the integration of smart meter data with external data such as weather, geography, and consumer information. Events and alerts are unscheduled and occur randomly due to unexpected situations.

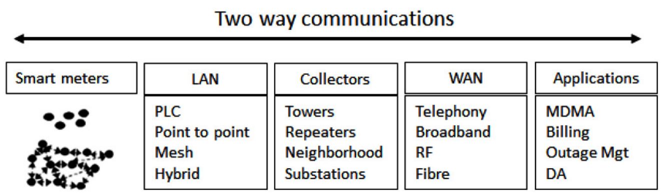


Fig. 4. Smart-metering process [16].

It could also be seen that the environment is dynamic and evolving. Technological capabilities change (improve), different types of data become available at faster rates and higher volumes and granularity. Stakeholders also become more demanding due to life styles, regulations, competition, etc. thus creating new applications and changing existing ones. It becomes imperative that data analytics technologies have to keep pace with this changing environment. Considering the above, the smart-metering framework is proposed as depicted in Fig. 3 based on a foundation described in Fig. 2. Each of the three components shown in Fig. 4 contributes significantly to smart meter data intelligence, and as such, each component is explored in more depth in the following sections.

B. Smart Meters

The term "smart meter" initially referred to the functionality of measuring the electricity used and/or generated and the ability to remotely control the supply and cutoff when necessary. It was called AMR that used one-way communication and capable of automated monthly reads, one way outage (or last gasp) and tamper detection, and simple load profiling. Over time, the AMR capability was extended into short-term interval (hourly or less) data capture, which on demand reads and linking and reading other commodities. A major upgrade of functionality occurred after integration of the meters with two-way communication technology which has been called advanced metering integrated (AMI). The upgrade included the incorporation of service switching, time-based rates, remote programming, power quality measure, and a dashboard-type user interface for real-time usage monitoring into the AMR. Although the term smart meter started to be used only after the SG initiatives, it can be seen that the features and functionality of the meters evolved from the manually read meters of the past to the AMI meters with dashboard interfaces and two-way communication capability. Therefore in the current metering environment, a meter is expected to have the following capabilities to be categorized as a smart meter [14]:

1) real-time or near real-time capture of electricity usage and possibly distributed generation;
2) providing the possibility of remote and local reading of the meter;
3) remote controllability of the meter enabling control and even cut off the supply;
4) possibility of linking to other commodity supply (gas and water);
5) ability to capture events such as device status (device measured by smart meter) and power quality (including voltage);
6) be interoperable within an SG environment (e.g., as specified by NIST and SGAM framework).

The smart meter is the measurement and information capture device and, in many instances, connected to the communication device called smart meter gateway to establish a secure energy-information network. The gateway could receive and communicate real-time information from supplier, be a point of control for appliances, start and stop energy supply, etc. It could also have a user interface called the "in-home-display" (IHD), which displays energy consumption, cost, tariffs with real-time updates, etc. The smart meter can be connected to the smart meter gateway which in turn communicates with different appliances (washing machine, refrigerator, etc), local generation as well as heating, ventilation, and air conditioning (HVAC). The measurements and information captured by the smart meter are displayed via the IHD. The smart meter could directly communicate the consumption information with the utility, but the gateway communicates with the next-level gateway in the SG infrastructure to pass information for aggregation, demand–response activities, as well as to utilities. As such, the system consisting of the smart meter, the gateway, and the IHD communicating in real time with appliances, HVAC subsystems and local generation become a key part of a smart home infrastructure. Smart meters need an environment where they are connected in appropriate structure, and also have the capacity to communicate and transfer the information captured to collection points. The architecture of the network, the capacity and speed of data transfer, and communication technology will determine whether smart meters can generate the anticipated value. The SG provides the necessary environment and infrastructure for the smart meters to function, and smart meters have been described as the key building block of the SG [15].

One of the key aspects of the SG architecture is to enable real-time decision making, which is possible only if data can be harnessed without latency as it is generated and applied toward a specific objective. This real-time or "active" data can be harnessed to make just-in-time decisions, such as automated outage detection through the last-gasp meter data for proactive customer service and proactive self-healing of the grid; detection of current load and critical peak conditions to initiate automated load-curtailment programs to curtail power at participating customer premises, or to perform air-conditioning load curtailment at participating retail households. Smart meters can add continuous communications if needed so that monitoring can be done in real time and can be used as a gateway to demand response-aware devices and "smart sockets" in the home. Within the grid, the smart meters may also simply replace the devices required at sensing points whose large number is not possible for cost and logistic reasons, by reporting, e.g., voltage and current measurements directly to a data acquisition system such as a smart-metering platform [16].

Smart electricity meter data analytics can assist in the distribution network operators in assessment and network management. For example, shorter time interval reading (e.g., 5 min) can help derive information of LV network topology reconstruction, which in turn help identify loading and voltage profiles, connectivity issues, and distributed energy resources (DER) impact measurement, which will help HV network and assessment operational monitoring. It can also help forecast future needs and trends of demand management, network tariff optimization, and asset maintenance requirements.

C. Smart-Metering Process

Although there are smart meters of varying technology and design, there is a common overall process for data collection, communication, and analysis leading to decision support. The smart-metering process in fact could be thought of as part of the activation and functioning of the SG.

There are some variations according to deployment in different countries and regions, but the general smart-metering process is shown in Fig. 4 [17]. The smart meter gathers data locally and transfers via a local area network (LAN) to a data collection point. There are two key categories of data collected as mentioned earlier. Usage or consumption data refers to the actual electricity usage measured in kilowatt hours (kWh), and this is read and transmitted in regular intervals. Depending on the particular deployment and region, the frequency of data collection can vary from 1 h to every 15 min. The issues faced with data collection and the implications and techniques for making use of this data are further discussed in detail in the following sections. In terms of the processing of data, some data processing could be carried out at the local collection points, but in most cases, the data are transferred to the utilities' central collection center via a wide area network (WAN). The data collected at the utility are used for a number of business purposes such as billing, network and service monitoring, profiling, prediction and planning.

D. Stakeholders

A simple classification is consumers, electricity companies (utilities), and environment [18]. In some literature, a further level of granularity has been added to the *electricity company* class by expanding to metering company (distributor), utility company, and supplier (retailer) [14]. However, a more comprehensive classification would be those by NIST, where the functionality of the whole energy usage cycle is defined to include bulk generation, transmission, distribution, customers, service providers, operations, and markets.

In terms of bulk generation, transmission, and distribution, which involve meter company and grid company, smart meters will complement well with existing infrastructure to provide a more accurate and timely view of the energy consumption by regions. Events such as suspicious usage areas and potential faults will be noticed more easily and on-time actions taken subsequently when necessary. It may also enable more accurate prediction of electricity flows enabling better network maintenance planning.

Smart meters can enable consumers to directly review their electricity usage, even down to the level of separate appliances [19], and thus adjust their behaviors to reduce energy cost. Customized rate plans are another key benefit to consumers. Although not a common practice at present, smart meters enable demand–response for consumers where limiting or even cutting off the supply depending on market situations is possible. When all consumers being aware of both consumption and production of energy, adapt their energy usage during a period of high demand, high pricing or lower supply, more reliable and stable supply, better energy awareness, savings and efficiency will be achieved. In combination, these activities have been called demand side management (DSM) which is essential to really benefit consumers [20]. Consumer awareness of the benefits from smart meters as well as their functionality will be a key factor in the successful adoption of this technology [21]. As discussed in [22], another key factor could be the use of disaggregation techniques to extract underlying end use and appliance-level information from an aggregated energy signal.

TABLE I
STAKEHOLDER INVOLVEMENT AND BENEFITS

Stakeholder	Type of benefit
Distributor/meter company	Accurate, timely view of consumption Capture suspicious usage, faults Better network maintenance
Consumer	Directly view electricity usage Monitor appliance use and consumption leading to awareness and better electricity usage planning Customized rate plans
Retailer	Understand and profile customers for targeted service for better loyalty Cut down peak usage Load control feature offer

Q4

For retailers, the availability of vast volumes of data which could be used to profile and understand customers, their needs and behaviors enable better service provision and build stronger loyalty. Better consumer awareness is expected to result in reduced energy consumption thus reducing the need for additional power plants which generate greenhouse gases. Restricting and reducing electricity usage during peak periods can result in cutting down on the need of using *peeker plants* [23] which generally make higher carbon emissions. Load control feature in smart meters enables switching individual appliances ON and OFF as required. Retailers could offer this feature to customers when the cost of power is very high, while distributors could use it when a section of the network is close to capacity.

For example, load control could be used to switch an air conditioner ON and OFF, which could reduce load on the network on a very hot day. The stakeholder involvement and benefits are summarized in Table I under each main stakeholder group.

For operations and markets, the information acquired from smart meters will be vital for planning operations, responding to market demands, and anticipating changes and disruptions to reduce risks to secure energy supply.

III. DATA FOR METERING INTELLIGENCE

A smart-metering framework has been proposed in the past, but it only looked at consumer characterization and not holistic view of the complete smart-metering process and environment [24]. The proposed framework is expanded and enhanced in this section and presented in Fig. 5 consisting of two key components.

1) The top part depicts the current smart-metering scenario: the data aspects, stakeholder needs-based applications,

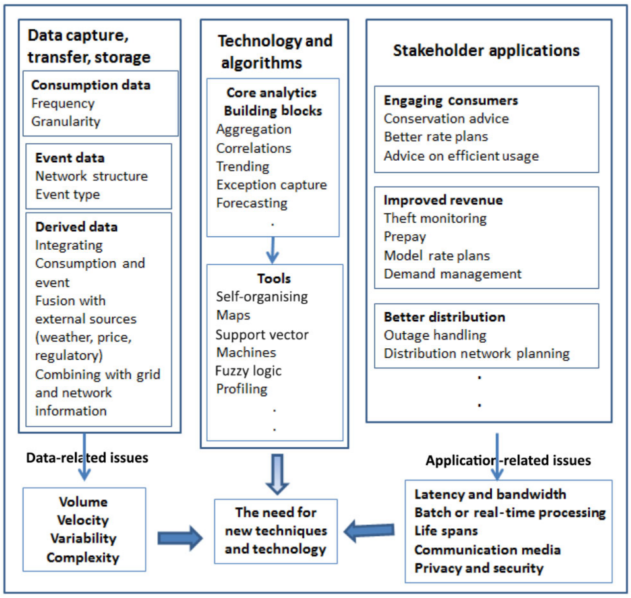


Fig. 5. Smart-metering framework and new impacts.

and technology tools and algorithms that attempt to support the application needs from the available or derived data. Current technologies and algorithms are shown as core analytics building blocks that are realized using different tools.
2) The bottom part depicts new requirements that have arisen due to reasons such as technological advancements, change in human behavior and expectations, competition, and better-informed consumers.

The new requirements and limitations of existing tools lead to new research and development needs.

AMI capability provides the base for collecting, transferring, and accumulating data and information. As shown in Fig. 3, types of data could be broken down into (power) consumption and generation data, power quality measurements, and event data. Out of these, the most widely used measurement data in smart-metering activities are the detailed consumption data consisting of time-based (15 min to 1 h), reading of electricity consumption. The other types of consumption data are as follows [25]:

1) *billing interval data*: readings at the beginning and end of billing intervals to enable variable pricing;
2) *aggregate statistical data*: monthly consumption, comparison with neighbors, usage history, etc.;
3) *broadcast data*: price change information, critical peak-time rebates, reliability status, etc., communicated to users.

Event data refer to information that is generated at the meters' end points and include real-time device status, power quality information, and meter status information. These can be made up of attributes such as source and proxy, severity level, and category. Source originates the event and the proxy captures and communicates. Main event categories include meter status, power quality events (voltage sag), meter tampering, and meter hardware events (low battery). Power quality data are generally used in fault analysis to help improve reliability. Both prefault and postfault analyses are considered as effective techniques of using power quality to improve the reliability of a distribution network. Generation data provide information such as solar usage which enables to identify patterns of electricity usage, effectiveness of alternative generation and profile households, and suburbs and regions. The integration of consumption, event, and other data categories could be useful to understand how the grid infrastructure stands up to usage. This can also provide insights into capacity planning and budgeting. The fusion of external data such as weather and geography with consumption can provide useful information for predicting power usage [26]. Data supporting such activities have been called derived data in Fig. 3.

Data analytics is the process of examining large amounts of data of a variety of types to uncover hidden patterns, unknown correlations, and other useful information. Data analytics is used to obtain value from such data captured and information derived such that stakeholder applications could be satisfied. The stakeholder applications in smart metering are grouped under several key categories in Fig. 3. With AMI and SG infrastructure for capturing and transferring data, opportunities for smart meter analytics have moved to a new dimension. But to make use of such opportunities, analytics technologies have to successfully face and resolve new data-related issues as shown in Fig. 5. The volume of data collected has increased massively due to collection of data in shorter intervals and the ability to store large volumes. The data capture at frequent intervals by smart meters and the infrastructure to transfer such data at high speeds results in streams of data. Due to the new technological capabilities of the smart meters as well as the increased demand from stakeholders including competition among utilities, different types of data are being collected to provide more value for stakeholders, which has been called variability issue in analytics. It is very difficult to measure the effectiveness of energy-efficiency programs. Many factors, such as weather, consumer profiles, seasons, geographic regions, infrastructure, type of homes and fittings, all contribute to the complexity. The combination of volume, velocity, and variability as well as different granularities, issues in integrating various types of data results in much more complexity needing to be addressed by analytics techniques.

The new technological capabilities have also resulted in increasing expectation from the stakeholders, and the different applications are highlighted in the right side in Fig. 5. Some of the key issues that have arisen due to such different applications are listed below [25].

1) *Latency and bandwidth*: Infrequent and low volume information (e.g., broadcasts) will require low bandwidth and probably low latency as well. Consumption data on the other hand will require high bandwidth and could tolerate higher latency.
2) *Batch or real-time processing*: Many event data and information for in-home displays will require real-time processing while batch processing will be suitable for consumption data.
3) *Life spans*: How long data need to be kept will depend on the usage. For example, billing and statistical data might

have regulatory requirements to be kept for certain periods, while detailed consumption data need only be kept for short periods.

4) *Communication media*: In-home display for real-time information such as prices and statistical data and aggregates could be displayed on a portal

5) *Privacy and security*: Prices are public information but consumption is confidential and sensitive.

IV. Technology and Algorithms

In smart-metering activities, the use of technologies and tools has been triggered from two main directions. The metering intelligence activities initiated based on the AMI capability could be called data-driven exploratory activities. Such activities are triggered mainly due to the availability of new AMI capability, e.g., new and more data being captured, better grid facilities enabling faster and more reliable transfer, and storage of data and appropriate skills and other resources being available in an organization. In such cases, the question could be asked: *how can this data and infrastructure be used to gain some benefit for various stakeholders?* Although the stakeholder needs are considered, they are not the drivers of these activities. In traditional data-mining tasks, this is called exploratory analytics and tools such as clustering, visualization, and unsupervised machine-learning techniques are utilized [27].

The second type is the application-driven directed activity. In contrast to the exploratory approach, this approach is triggered directly based on stakeholder needs. Current knowledge of stakeholder needs, business needs, government policies, social and environmental trends (privacy, green house effects, etc) will be the drivers for this approach. Compared to the exploratory approach, the activities initiated in this approach will have a *known* objective. In data-mining and machine-learning terminology, such activities are called directed, and use supervised learning tools such as classification, decision trees, and artificial neural networks [28].

The technologies and algorithms used for smart metering are presented in Sections IV-A and IV-B.

A. Core Analytics Building Blocks

Many statistical, machine-learning, data-mining and mathematical techniques have been used, separately as well as in different combinations for smart metering. Since different techniques could be used to achieve the same purpose in terms of analytics outcomes, we have presented these as analytics building blocks in Fig. 5. The building blocks of aggregations, correlations, trending, exception analysis, and forecasting are the key foundations of analytics in smart metering.

The meters connected to individual transformers can be aggregated together to identify transformer loading patterns. Combining homes or businesses into demand–response pools to deliver sizable demand reductions (or "negawatts") is another aggregation supported by smart meters.

Heat waves drive spikes in power consumption and statistical correlation using time-interval consumption data makes it possible to build algorithms that predict the size of demand spikes using forecast temperature. Cloud cover, humidity, and time of day can be added to further refine peak predictions. Correlations are generated by aligning data temporally, spatially, or across other attributes. This type of data is used to build analytical models to measure the energy efficiency of individual commercial properties.

A web site that shows a simple consumption data trendline can help customers relate power consumption to household activity. The ability to overlay multiple trendlines together is also valuable for purposes such as comparing consumption across similar seasons and times of day.

A missing meter read is an exception event. Analyzing exceptions over time may identify problems in communications and measurement infrastructure, as well as in the distribution grid. Component degradation or operational breakdowns can be captured by analyzing trends in exception events.

Forecasts are predictions of future events or values using historical data. A forecast of power consumption for a new residential subdivision can be created using historical data from similar homes.

B. Tools for Smart Metering

There are many mathematical and statistical techniques, machine learning, data-mining tools that can be used for smart metering as shown in Fig. 5. Widely used techniques include self-organizing maps (SOMs), support vector machines (SVMs), principle component analysis (PCA), and fuzzy logic (FL) [29].

The SOM [30] is an unsupervised learning algorithm which is widely used to project high-dimensional data vectors on to a summarized two- or three-dimensional space. Its key desirable features in exploratory data analysis are its ability to summarize the input space and visualize results for interpretation. This enables the visual inspection of the possible patterns and the structure of data which can then be used for clustering and other techniques to elicit useful information. In smart metering, SOM has been mostly used for exception capture and profiling [68], [83].

SVMs [31] are based on supervised learning with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. SVM-based analytics have been reported for appliance-type recognition from AMI data [32], [33] and electricity theft detection [34], [35].

PCA is a mathematical technique which generates an orthogonal linear transformation that converts the data to a new coordinate system such that the greatest variance by any projection of the data becomes the first coordinate (the first principal component), the second greatest variance the second coordinate, etc. [36]. PCA has been used for power usage data aggregation [37], a data reduction technique in consumption analysis [38] and the detection of anomalies due to malicious modification of network data [39].

FL is a form of reasoning that is approximate rather than fixed and exact which may have a truth value that ranges in degree between 0 and 1. In [29], FL has been used to create an automated decision-making platform in an SG, and in [36] and [40], it has been used to improve the reliability of clustering of smart meters, which is essential due to scalability problems. Integration of technologies and intelligence into the SG also makes it more open to cyberattacks. In [41], a FL-based technique for efficiently detecting cyberattacks was described.

The above are only some of the examples of how the existing techniques can be used. Bayesian and hidden Markov model techniques are being used in a variety of smart-metering applications, such as load disaggregation [42], appliance identification [43], and supply demand analysis [44]. Future applications will result in a broader range of needs which will see more and more methods applied and tailored for smart metering to bring out greater benefits.

V. Stakeholder Applications

The tools described above have been used separately and in combination to achieve metering intelligence. Majority of the metering-intelligence-related work reported uses time-varying power consumption data to generate consumption (or load) patterns showing usage behavior to the consumers. Clustering usage patterns makes it possible to identify typical behaviors called typical load profiles (TLPs) [45], [46]. TLPs could then be used for load forecasting [47], [48], load estimation [49], load control [50], abnormal electricity consumption detection [51], designing electricity tariff offers [52], developing market strategies [53], or demand side response policy [54]. Some of the most widely used metering intelligence activities are discussed below.

A. *Consumer Profiling, Segmentation, and Cluster Analysis*

Cluster analysis of smart meter data has been reported from a number of regions around the world. Cluster analysis aims at discovering structures in large data sets. The k-means algorithm and a combination of k-means and artificial neural networks, such as SOMs, are popular approaches for the clustering and have been used in load profiling [48]. A study of German electricity consumers by Flath *et al.* [55] highlights the advantages of cluster analysis in identifying consumer groups for targeted service innovation by utilities and retailers. They have also suggested the value of incorporating cluster analysis as part of the utilities business intelligence systems such that process innovation and customer portfolio management could be guided by the results. Cluster analysis has been conducted on data separated by season and by weekdays and weekends due to differing usage patterns. A study reported in [56] identifies customer signatures based on usage readings from 50 m. Daily energy-consumption plots yield information such as minimum, average, and maximum daily energy consumption, as well as changes in daily energy use from which one can derive information such as household occupancy and occupant activities. This highlights privacy as a key concern with profiling usage patterns. The key privacy concerns are occupancy detection and possibility of inferring appliance usage. It has been suggested that statistical representations of the data can be used rather than actual consumer information. Also aggregation, noise addition, and consumer signature flattening have been proposed as ways for privacy protection [11]. An SOM- [30] based clustering of 12 000 Finnish electricity consumers was reported in [57]. The study carried out using Viscovery SOMine tool suggested that understanding customer usage patterns can help design better demand–response tariffs schemes. The SOM has been used in several other studies as a tool for clustering electricity consumption data [58]–[60]. A study by Abreu *et al.* uses pattern recognition techniques to capture habitual behavior of consumers using smart meter readings [61]. The work, based on a new data-mining algorithm for finer profiling [62], proposed that such fine-grained profiling can be used to provide tailor-made forecasts for households. Zhang *et al.* [63] used clustering techniques to identify load profiles for large electricity uses in a Chinese province. This work differs from the previously stated as they compare three well-known clustering techniques, namely, k-means, fuzzy c-means, and SOM.

B. *Load Forecasting*

One of the most valuable analytics applications for the SG and the availability of time interval data have made it possible to forecast in the short term and with high accuracy. Accurate forecasts are important for deciding short-term operations as well as mid-term scheduling, but also decision makers need to have an understanding about the customers they have to supply for long-term planning. Many applications of load forecasting have been described in literature where several statistical and machine learning technologies have been utilized. For short- and medium-term forecasting, time-series analysis and neural networks have been used [64]–[66]. A problem with short-term forecasting models has been the loss of understanding about the bigger picture they require and understanding about the different categories of consumers. In [67], a PCA-based technique was used to identify the type of demand faced by such consumer categories. In [68], a hybrid system of SOMs and SVM was used to forecast mid-term electricity load. The SOM was used to separate electricity consumption data into two groups which are then fed into an SVM in a supervised manner for load prediction. In [48], Espinoza *et al.* report on short-term forecasting with hourly load data from a Belgian grid substation highlighting that forecasting and customer profiling are interrelated and proposed a unified framework which incorporates both. The initial modeling is based on seasonal time-series analysis, using the periodic auto-regression (PAR) model [69], which was used in the modeling of electricity prices [70]. The stationary properties obtained from these models are run through a k-means clustering process to capture different customer profiles.

C. *Pricing Intelligence*

Smart meters will enable to set up dynamic tariff structures to improve efficiency in electricity markets by better representing the costs of producing and delivering electricity at different times. Consumers could benefit from these if they choose more flexible tariff arrangements that better represent their electricity cost. To determine the price of electricity as well as the tariffs, retailers consider payments to distributors for services, wholesale electricity cost, retail services cost, as well as costs of any regulatory requirements. Smart meter data enable deeper analysis for understanding the dynamics of supply and demand resulting in better forecasting the needs, enabling pricing intelligence. Smart meter data can be used to analyze and plan different rate structures, without discriminating by demographics of low income, etc. This has been called "time of use" or dynamic pricing. Real-time stream analysis of consumption is required to make such a scheme practical. The benefits of dynamic pricing have been identified as demand reduction, cost reduction, and economic efficiency gain [52]. Prepay is another possible pricing intelligence technique with the advantages of being familiar to consumers and also helping utilities limit credit risk. Utilities can take a more opt-in approach where customers elect to select in a new rate plan, such as dynamic pricing. Customer demography segmentation related to consumption-based profiling has to be carried out in these approaches. Reference [57] describes work carried out using SOM tool Viscovery for clustering and visualization of consumer information from a utility in Finland. In addition to several consumption-based attributes, the type of residence was used for the segmentation.

D. Capturing Irregularities

Many load profile studies have used data-mining techniques, pattern recognition, and statistical techniques to obtain knowledge from customer load records. Knowledge of consumption behaviors is very important as it is very useful for formulating tariffs and developing marketing strategies, as well as allowing customized billing. Knowledge gathered from customers' load profiles could also be used to identify, detect, and predict behavior irregularities or abnormalities that ultimately may be due to faulty metering or human intervention and fraud [51], [71]. Potential theft or technical losses can also be identified by comparing smart meter data with measurements from sensors attached to transformers or feeders [14].

E. Metering Intelligence to Support Real-Time Operations

The rolling out of AMI makes it possible to acquire near real-time information of energy use, connect RE to grids, manage power outages and faster restoration, fault detection and early warning.

There are several levels of real-time responses. One level is at the actual control of machines and equipment which requires milliseconds response time. At this level, unless the infrastructure of smart meters and communication networks can be significantly upgraded to realize reliability and millisecond responsiveness required for real-time control (e.g., controlling transient responses of rotating machines in the gird), smart meters cannot necessarily provide adequate benefits. For those near real-time critical applications (5 min, quarterly hours, half hours, hourly intervals), such as fault identification and localization on MV and LV networks to ensure faster intervention and reduced outage duration, monitoring power quality, acting remotely, managing peak-saving, forecasting network conditions, facilitation of integration of RE and PHEVs into the grid, smart meters can help [6]. Examples include the measurement of voltage distortion (harmonic voltages and voltage unbalance) [72] using smart meter data to derive a dynamic model to improve volt-VAR control [73], as well as controlling congestion and stability in a power market [74]. Metering data can also be used to derive the knowledge of the power flows at and near the low-voltage end of the distribution networks so that the loading and losses of the network can be known more accurately. This can help to prevent overloading components (transformers and lines) and to avoid power quality deviations [75]. Another example is the state estimation using smart meter data which may provide an alternative economical way of estimating states of MV and LV networks [76], [77]. Smart meter data can also be used to enhance overcurrent protection [78] and load disaggregation [79]. The NOBEL project [80] has developed a smart-metering platform [81] that specializes in near real-time acquisition of metering information from the grid as it is reported directly by the smart meters. Data stream analysis [82] for capturing time-based usage patterns has also been reported in [83].

VI. Key Challenges and Future of Smart Metering

A. Issues in Smart Meter Data Analytics

To achieve metering intelligence as described in the previous sections, a number of technical issues need to be successfully addressed. The ability to work with very large volumes of data will be a key requirement. It is also essential that technologies be able to work with a variety of data such as weather information and consumer information, geographic data thus requiring techniques for efficient data fusion and integration. Such a big data integration and analytics engine are being developed by a C3 energy, where tasks such as voltage optimization, asset management, outage management, and fault detection to customer-focused services such as demand–response, load forecasting and customer segmenting, and targeting are to be integrated. Real-time monitoring and diagnostics-focused analytics would be an important requirement in such systems [84], [85].

To achieve real benefits of analytics outcomes, it is essential to gain consumer's acceptance and support for smart meters. A key requirement for such acceptance is transparency of the process which is currently being addressed by government regulators as well as utilities [86]. The availability of easy to understand and visual displays of information is also an important need. Making smart meter data and analytics outcomes available on the web and on mobile devices will make such information more readily available and also updates communicated to consumers in near real time [87]. Smart meter analytics will thus continue to evolve, making demands on the current knowledge and technology available.

The available big smart meter data will also present privacy and security concerns that are likely to become more prevalent as government-backed initiatives expand deployment of the meters to millions of homes across the country [88], [89]. These will have to be addressed within the regulatory regime of the particular country deploying smart meters. For example, obtaining permission from the customers to manage, use and create value from smart meter data is seen as a standard public service responsibility that already exists in all European countries [6].

The future of smart metering will also depend on several key technology revolutions currently in progress are discussed below.

B. Smart Meters and Big Data

"Big data" is a term that is currently being used widely with data analytics. Big data has many interpretations but there are three key features that are highlighted: volume, velocity, and variance. Data captured by smart meters clearly relate to all these features thus satisfying the definition for big data. For example, moving from one meter reading per month to smart meter readings every 30 min results in a massive volume of data to manage. The data are collected in frequent time periods, and if technology is available for near real time analysis, many advantages could be achieved. The analytics technologies will have to deal with not only consumption data but also consumer information, weather, and many grid-behavior-based readings. To manage and use this information to gain insight, utility companies must be capable of managing high-volume data and using advanced analytics to transform data into actionable insights [3]. Utilities that build up this capability can gain insight into their operations and assets and can become proactive in taking action based on analytics. Although the increase in volume, especially in consumption data, capture is the most prominent big data aspect with smart meters, and the other aspects of velocity and variance are equally important. Velocity refers to the need for collecting, processing, and using the data speedily and in time. Although analytical algorithms which can process huge quantities of data are available, many of these are not able to complete such activities in a sufficiently short time period to be of practical value. For example, overnight is not good enough for real-time tasks such as reliability monitoring of equipment, preventing outage, or security monitoring. Although several research techniques have been reported on analyzing streaming data, much work still needs to be done in making these commercially viable. Variety signifies the increasing array of data types, which are collected not only from traditional sources like industrial control systems but also from security cameras, weather forecasting systems, maps, drawings and pictures, and the web. The variety of data is likely to become increasingly important to utilities as they begin to analyze social media and call center dialogs and to integrate such information into smart meter and grid-generated data as part of their decision-making and planning processes [3].

C. Smart Meters and Cloud Computing

Although SG enables distributed and RE generation, controlling energy generation according to demand is still a problem. A new idea is aligning energy supply and demand using infrastructure such as a broadband network access, performance, scalability, and flexibility, which can be provided by a cloud platform [90]. Cloud computing is a paradigm in which services including computation, storage, and network are packaged and provided as metered utility services sold on demand both in terms of duration of use and utilization [91]. Benefits include on-demand self-service, resource pooling, and use of a cloud service on pay-per-use or charge-per-use basis. But this raises security and privacy issues with protecting the smart meter data from unauthorized usage [92]. Using smart meters to develop a dynamic pay-per-use pricing model for regulation and improvement of overall utilization of the cloud infrastructure is described in [91].

Denmark now has its first cloud-based smart-metering solution, targeted at small utilities and communities that previously could not afford such technologies. IBM and Cable & Wireless Worldwide are working to develop a new intelligent communications solution called U.K. Smart Energy Cloud to support the U.K.'s smart meter implementation program with expected roll-out of more than 50 million meters. The solution is expected to provide for more accurate billing, greater SG functionality, and other benefits.

Use of cloud platforms and technologies for smart metering and grid has resulted in the need of extended capabilities from analytics tools. A number of vendors have come up with tools such as IBM Coremetrics and Google BigQuery, and the cloud-based software platform for data-driven analytics described in [93] as part of the Los Angeles Smart Grid Project. The described system has attempted to incorporate several of the new advanced analytics requirements highlighted earlier such as real-time data analytics, scalable machine-learning techniques, and data integration demonstrating how the new advanced analytics techniques provide the base for future smart metering and SG systems.

D. Smart Meters and Internet of Things

The SG and the environment it creates have been called the Internet of Energy [94]. If there is an adaptation on the behavior of the prosumer devices based on the information that they receive such as electricity price, the energy-consuming/producing devices will not be black boxes but be able to adapt accordingly. Such an environment is called the Internet of Things (IoT) from an SG perspective [94], [95]. IoT are expected to grow to 50 billion connected devices by 2020 [95]. The connected SG provides a communication network that will connect all the different energy-related equipment of the future. From the transmission and distribution power infrastructure, electrical, water, gas, and heat meters to home and building automation. The first key step toward an SG that makes the IoT a reality will be the mass deployment of smart meters.

The connectivity and accessibility provided by the IoT brings further improvement of customer experience and efficiencies thus greater interaction and control. Additionally, the IoT enables manufacturers and utility providers to cut costs through diagnostics and neighborhood-based meter reading. As such IoT will result in building a more connected, cost-effective, and smarter SG.

VII. Conclusion

The paper has presented a comprehensive survey of smart metering and electricity smart meter data analytics. Although there has been much opposition to smart meters due to privacy and health concerns, it is obvious that smart meters are here to stay and that the SG and smart metering will be a "way of life" in the future. A number of different dimensions to smart meters have been highlighted including the smart meter technology and the process, the various stakeholders, existing analytics technologies and tools, and the current technological revolutions such as big data, cloud computing, and the IoT. The paper has also presented the current smart-metering space as the smart-metering landscape, and then, a framework has been established to relate smart meter data to stakeholders and applications created by their needs and the analytics tools and techniques required to achieve the stakeholder needs. The framework would help identify the current limitations in smart metering. Another contribution of this paper is the identification of smart meter analytics building blocks which enable to link the wide range of tools used for smart metering and identify the main analytics activities. The SG and smart meters will be part of a much wider IoT in the future integrating multiple aspects of human needs and services to satisfy such needs, and the analytics requirements discussed, such as big data, real time analytics, stream analytics, will need to be built into the processes and workflows for diagnostics in real time.

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Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey

Damminda Alahakoon and Xinghuo Yu, *Fellow, IEEE*

***Abstract*—Smart meters have been deployed in many countries across the world since early 2000s. The smart meter as a key element for the smart grid is expected to provide economic, social, and environmental benefits for multiple stakeholders. There has been much debate over the real values of smart meters. One of the key factors that will determine the success of smart meters is smart meter data analytics, which deals with data acquisition, transmission, processing, and interpretation that bring benefits to all stakeholders. This paper presents a comprehensive survey of smart electricity meters and their utilization focusing on key aspects of the metering process, the different stakeholder interests, and the technologies used to satisfy stakeholder interests. Furthermore, the paper highlights the challenges as well as opportunities arising due to the advent of big data and the increasing popularity of the cloud environments.**

***Index Terms*—Artificial intelligence, automated meter infrastructure, big data, cloud computing, data analytics, Internet of Things (IoT), machine learning, privacy, smart grids (SGs), smart meters.**

I. Introduction

SMART Energy has been an important conceptual paradigm for future energy use. Because of limited nonrenewable energy resources available on Earth and also high costs of acquiring renewable energies (REs), how to make energy use more efficient and effective is critical for future social and economic developments [1].

Smart grids (SGs) have been a key enabler for smart energy, which refers to power networks that can intelligently integrate the behaviors and actions of all stakeholders connected to it, e.g., generators, customers, and those that do both—in order to efficiently deliver sustainable, economic, and secure electricity supplies. While there are many definitions for SGs, one commonly used conceptual framework is that of the National Institute of Standards and Technology (NIST) which defines seven important domains: bulk generation, transmission, distribution, customers, service providers, operations, and markets.

Key technological challenges facing SGs include intermittency of RE generation that affects electricity quality; large scale networks of small distributed generation mechanisms, e.g., photovoltaic (PV) panels, batteries, wind and solar, plug-in hybrid electric vehicles (PHEVs), that result in high complexities. Another significant issue is how to use information and communication technologies (ICTs), advanced electronic and analytic technologies to enhance efficiency and cost-effectiveness of energy use.

Managing SGs to deliver smart energy require advanced data analytics for acquiring accurate information and automated decision support and handling events in a timely fashion. Significant progresses have been made for using field data obtained from intelligent devices installed in substations, feeders, and various databases and models across the utility enterprises. Some of the examples can be found in [2] and references therein. Typical information sources include market data, lighting data, power system data, geographical data, weather data which can be processed and converted into information and knowledge that can be used for state estimation, situational awareness, fault detection and forewarning, stability assessment, wind or solar forecasting. Information acquisition is a key for timely data sensing, processing, and knowledge extraction. So far, the most talked-about information about power network operations is from data collected from intelligent electronic devices installed in substations and various parts of the transmission and distribution networks.

In recent years, smart meters are being installed in homes and other premises in many regions of the world [3]. USA and Europe have been deploying smart meters for many years while other regions in the world such as Australia and Canada have also started deployment in the last few years. According to a recent report [4], due to deployments in 35 emerging countries from Central/Eastern Europe, Eurasia, Latin America, Middle East/North Africa, South Africa, and Southeast Asia, the smart meter numbers have more than doubled in 2013 compared to 2012. A report by Pike Research estimates the global smart meter installations to triple from 10.3 million in 2011 to 29.9 million units by 2017 [5]. Full deployment of smart meters has already been completed in Italy and Sweden, and mass rollout is ongoing in Finland and Spain [6]. This infrastructure, if used properly, can provide more than just recording consumption of electricity or a decision support tool to support energy usage by users. For example, advantages include easier processing of billing, automated meter reading (AMR) and data processing, detection of energy losses (possible fraud) and early warning of blackouts, fast detection of disturbances in energy supply, possible real-time pricing schemes, and demand–response for energy saving and efficient use of energy generated.

The research and development in smart meters and their applications have been progressed rapidly in recent years, and many methods and techniques have been developed. The technological scope relating to smart meters covers a diverse range of ICT technologies, such as electronics and communication,

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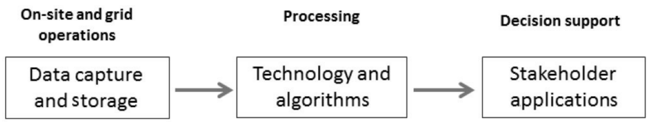
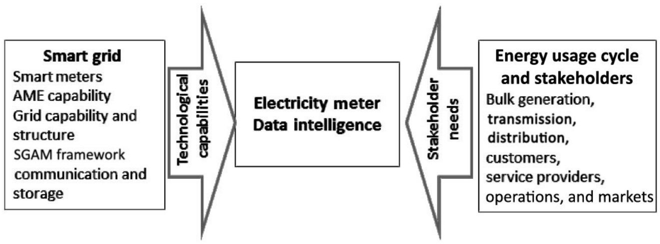


F1:1 Fig. 1. Key components of electricity meter data intelligence.



F2:1 Fig. 2. Environment for smart meter data intelligence.

and there have already been several surveys done, e.g., [7] looks into the different applications of SGs focusing on the communication needs and also on communication requirements of smart meters for integration into power grids. Reference [8] is a comprehensive survey of communication technologies for smart meters which could be used to satisfy the identified needs. Reference [9] introduces a novel smart meter communication technology, [10] examines the web and data service aspect of smart meter networks, and [11] proposes a framework for smart meter privacy. In this paper, we examine these developments from a holistic data analytic viewpoint. We will also outline potential future applications and challenges that lie ahead. As a foundation for our holistic approach, the key components of electricity meter intelligence are shown as in Fig. 1. The three key components capture the aspects of data, technology, and stakeholders. These aspects and the role they play in smart meter intelligence are discussed in Section II.

Section II describes the environment in which smart meter intelligence can occur. The key technology features in smart meters and their capabilities are also described, which are then used as a stepping stone in presenting a smart-metering framework. Sections III–V present each of the three key components of the framework where the data, technology, and stakeholder aspects are discussed in more detail. Section VI describes the key challenges in this area and suggests potential solutions. Section VII concludes the paper.

II. Smart-Metering Environment

To describe the components of smart meter data intelligence, it is necessary to understand the environment they exist. Fig. 2 highlights the main environmental factors being the SG, which provides the infrastructure and the stakeholders who generate the need for smart metering. Key elements which make up the environment are described below. The environmental factors presented in Fig. 2 provide the "bigger picture" for metering intelligence and positions the components presented in Fig. 1 within the smart-metering environment. The energy usage cycle and stakeholder information are based on NIST classification [12]. A further important factor is the recent push toward the integration and coupling of multiple systems and components

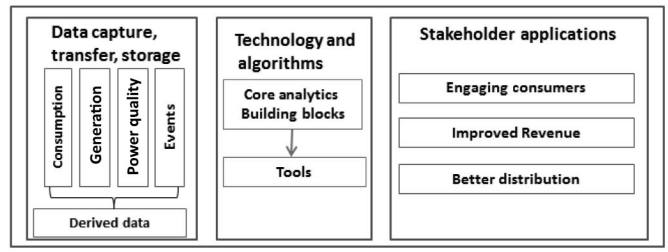


Fig. 3. Smart meter data intelligence framework. F3:1

within the SG and the understanding of the value of interoperability of such systems and components [13]. As highlighted in [13], it is desirable that multiple systems and components are interoperable under the three aspects of organizational, informational, and technical. It has been proposed that the smart grid conceptual model introduced by NIST can be extended to cater for the above requirements as well as the distributed energy requirements (DERs) especially in the European Union. The smart grid architectural model (SGAM) framework has been introduced to address these requirements [13]. With interoperability and the flexibility with technology independent systems and components, the environment is set for capturing data in near real time from multiple and diverse sources for generating data intelligence.

A. Framework for Smart Metering

The key components in Fig. 1 are further expanded as a framework in Fig. 3. A high-level view of the framework is presented as Fig. 3, where the relationships to the environment and the key components are highlighted. This framework is then further discussed in detail including the impact of these different components in Section III and illustrated in Fig. 5.

Types of data have been broken down in Fig. 3 into consumption or measurement, power generation, power quality, and events, such as power failures and meter status. These data types could be used as aggregates or combined with external data such as temperature to derive information for analysis. Capturing accurate and relevant data in a timely manner is essential for smart metering, which includes the collection, transfer, and storage (accumulation). Smart meters have resulted in a huge increase in the volume as well as types of data generated and collected, leading to many potential opportunities for generating value from such data. As mentioned under the metering process, there are several types of data-generated measurement or consumption data, generation information, power quality, and events data. Consumption data are the more predictable and regular consumption data. With smart meters, this could be time-interval consumption data as well as aggregated values for billing purposes. Time-interval data provide more granular data opening up possibilities of trend and cycle analysis and different time of day consumption analysis. Time-interval-based consumption also enables to profile consumer behavior and relate consumption to temperature changes. This requires the integration of smart meter data with external data such as weather, geography, and consumer information. Events and alerts are unscheduled and occur randomly due to unexpected situations.

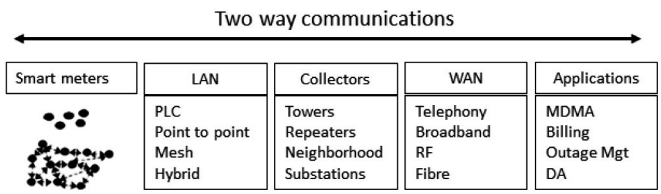


Fig. 4. Smart-metering process [16].

It could also be seen that the environment is dynamic and evolving. Technological capabilities change (improve), different types of data become available at faster rates and higher volumes and granularity. Stakeholders also become more demanding due to life styles, regulations, competition, etc. thus creating new applications and changing existing ones. It becomes imperative that data analytics technologies have to keep pace with this changing environment. Considering the above, the smart-metering framework is proposed as depicted in Fig. 3 based on a foundation described in Fig. 2. Each of the three components shown in Fig. 4 contributes significantly to smart meter data intelligence, and as such, each component is explored in more depth in the following sections.

B. Smart Meters

The term "smart meter" initially referred to the functionality of measuring the electricity used and/or generated and the ability to remotely control the supply and cutoff when necessary. It was called AMR that used one-way communication and capable of automated monthly reads, one way outage (or last gasp) and tamper detection, and simple load profiling. Over time, the AMR capability was extended into short-term interval (hourly or less) data capture, which on demand reads and linking and reading other commodities. A major upgrade of functionality occurred after integration of the meters with two-way communication technology which has been called advanced metering integrated (AMI). The upgrade included the incorporation of service switching, time-based rates, remote programming, power quality measure, and a dashboard-type user interface for real-time usage monitoring into the AMR. Although the term smart meter started to be used only after the SG initiatives, it can be seen that the features and functionality of the meters evolved from the manually read meters of the past to the AMI meters with dashboard interfaces and two-way communication capability. Therefore in the current metering environment, a meter is expected to have the following capabilities to be categorized as a smart meter [14]:

1) real-time or near real-time capture of electricity usage and possibly distributed generation;
2) providing the possibility of remote and local reading of the meter;
3) remote controllability of the meter enabling control and even cut off the supply;
4) possibility of linking to other commodity supply (gas and water);
5) ability to capture events such as device status (device measured by smart meter) and power quality (including voltage);
6) be interoperable within an SG environment (e.g., as specified by NIST and SGAM framework).

The smart meter is the measurement and information capture device and, in many instances, connected to the communication device called smart meter gateway to establish a secure energy-information network. The gateway could receive and communicate real-time information from supplier, be a point of control for appliances, start and stop energy supply, etc. It could also have a user interface called the "in-home-display" (IHD), which displays energy consumption, cost, tariffs with real-time updates, etc. The smart meter can be connected to the smart meter gateway which in turn communicates with different appliances (washing machine, refrigerator, etc), local generation as well as heating, ventilation, and air conditioning (HVAC). The measurements and information captured by the smart meter are displayed via the IHD. The smart meter could directly communicate the consumption information with the utility, but the gateway communicates with the next-level gateway in the SG infrastructure to pass information for aggregation, demand–response activities, as well as to utilities. As such, the system consisting of the smart meter, the gateway, and the IHD communicating in real time with appliances, HVAC subsystems and local generation become a key part of a smart home infrastructure. Smart meters need an environment where they are connected in appropriate structure, and also have the capacity to communicate and transfer the information captured to collection points. The architecture of the network, the capacity and speed of data transfer, and communication technology will determine whether smart meters can generate the anticipated value. The SG provides the necessary environment and infrastructure for the smart meters to function, and smart meters have been described as the key building block of the SG [15].

One of the key aspects of the SG architecture is to enable real-time decision making, which is possible only if data can be harnessed without latency as it is generated and applied toward a specific objective. This real-time or "active" data can be harnessed to make just-in-time decisions, such as automated outage detection through the last-gasp meter data for proactive customer service and proactive self-healing of the grid; detection of current load and critical peak conditions to initiate automated load-curtailment programs to curtail power at participating customer premises, or to perform air-conditioning load curtailment at participating retail households. Smart meters can add continuous communications if needed so that monitoring can be done in real time and can be used as a gateway to demand response-aware devices and "smart sockets" in the home. Within the grid, the smart meters may also simply replace the devices required at sensing points whose large number is not possible for cost and logistic reasons, by reporting, e.g., voltage and current measurements directly to a data acquisition system such as a smart-metering platform [16].

Smart electricity meter data analytics can assist in the distribution network operators in assessment and network management. For example, shorter time interval reading (e.g., 5 min) can help derive information of LV network topology reconstruction, which in turn help identify loading and voltage profiles, connectivity issues, and distributed energy resources (DER) impact measurement, which will help HV network and assessment operational monitoring. It can also help forecast future needs and trends of demand management, network tariff optimization, and asset maintenance requirements.

C. Smart-Metering Process

Although there are smart meters of varying technology and design, there is a common overall process for data collection, communication, and analysis leading to decision support. The smart-metering process in fact could be thought of as part of the activation and functioning of the SG.

There are some variations according to deployment in different countries and regions, but the general smart-metering process is shown in Fig. 4 [17]. The smart meter gathers data locally and transfers via a local area network (LAN) to a data collection point. There are two key categories of data collected as mentioned earlier. Usage or consumption data refers to the actual electricity usage measured in kilowatt hours (kWh), and this is read and transmitted in regular intervals. Depending on the particular deployment and region, the frequency of data collection can vary from 1 h to every 15 min. The issues faced with data collection and the implications and techniques for making use of this data are further discussed in detail in the following sections. In terms of the processing of data, some data processing could be carried out at the local collection points, but in most cases, the data are transferred to the utilities' central collection center via a wide area network (WAN). The data collected at the utility are used for a number of business purposes such as billing, network and service monitoring, profiling, prediction and planning.

D. Stakeholders

A simple classification is consumers, electricity companies (utilities), and environment [18]. In some literature, a further level of granularity has been added to the *electricity company* class by expanding to metering company (distributor), utility company, and supplier (retailer) [14]. However, a more comprehensive classification would be those by NIST, where the functionality of the whole energy usage cycle is defined to include bulk generation, transmission, distribution, customers, service providers, operations, and markets.

In terms of bulk generation, transmission, and distribution, which involve meter company and grid company, smart meters will complement well with existing infrastructure to provide a more accurate and timely view of the energy consumption by regions. Events such as suspicious usage areas and potential faults will be noticed more easily and on-time actions taken subsequently when necessary. It may also enable more accurate prediction of electricity flows enabling better network maintenance planning.

Smart meters can enable consumers to directly review their electricity usage, even down to the level of separate appliances [19], and thus adjust their behaviors to reduce energy cost. Customized rate plans are another key benefit to consumers. Although not a common practice at present, smart meters enable demand–response for consumers where limiting or even cutting off the supply depending on market situations

TABLE I
STAKEHOLDER INVOLVEMENT AND BENEFITS

Stakeholder	Type of benefit
Distributor/meter company	Accurate, timely view of consumption Capture suspicious usage, faults Better network maintenance
Consumer	Directly view electricity usage Monitor appliance use and consumption leading to awareness and better electricity usage planning Customized rate plans
Retailer	Understand and profile customers for targeted service for better loyalty Cut down peak usage Load control feature offer

Q4

is possible. When all consumers being aware of both consumption and production of energy, adapt their energy usage during a period of high demand, high pricing or lower supply, more reliable and stable supply, better energy awareness, savings and efficiency will be achieved. In combination, these activities have been called demand side management (DSM) which is essential to really benefit consumers [20]. Consumer awareness of the benefits from smart meters as well as their functionality will be a key factor in the successful adoption of this technology [21]. As discussed in [22], another key factor could be the use of disaggregation techniques to extract underlying end use and appliance-level information from an aggregated energy signal.

For retailers, the availability of vast volumes of data which could be used to profile and understand customers, their needs and behaviors enable better service provision and build stronger loyalty. Better consumer awareness is expected to result in reduced energy consumption thus reducing the need for additional power plants which generate greenhouse gases. Restricting and reducing electricity usage during peak periods can result in cutting down on the need of using *peeker plants* [23] which generally make higher carbon emissions. Load control feature in smart meters enables switching individual appliances ON and OFF as required. Retailers could offer this feature to customers when the cost of power is very high, while distributors could use it when a section of the network is close to capacity.

For example, load control could be used to switch an air conditioner ON and OFF, which could reduce load on the network on a very hot day. The stakeholder involvement and benefits are summarized in Table I under each main stakeholder group.

For operations and markets, the information acquired from smart meters will be vital for planning operations, responding to market demands, and anticipating changes and disruptions to reduce risks to secure energy supply.

III. DATA FOR METERING INTELLIGENCE

A smart-metering framework has been proposed in the past, but it only looked at consumer characterization and not holistic view of the complete smart-metering process and environment [24]. The proposed framework is expanded and enhanced in this section and presented in Fig. 5 consisting of two key components.

1) The top part depicts the current smart-metering scenario: the data aspects, stakeholder needs-based applications,

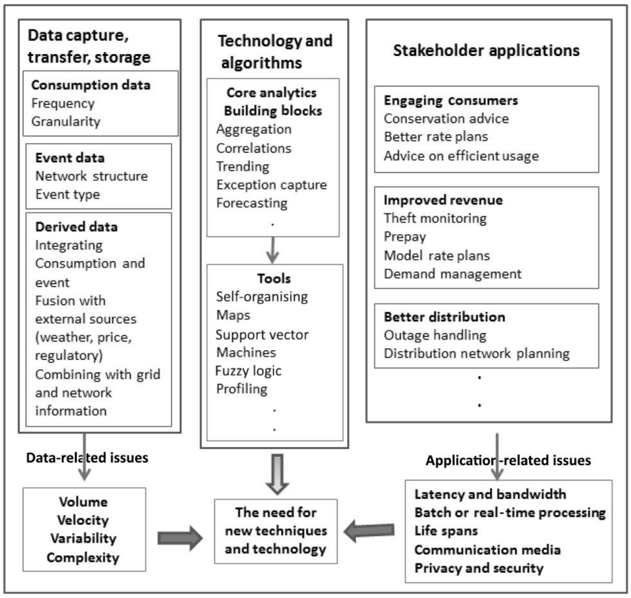


Fig. 5. Smart-metering framework and new impacts.

and technology tools and algorithms that attempt to support the application needs from the available or derived data. Current technologies and algorithms are shown as core analytics building blocks that are realized using different tools.

2) The bottom part depicts new requirements that have arisen due to reasons such as technological advancements, change in human behavior and expectations, competition, and better-informed consumers.

The new requirements and limitations of existing tools lead to new research and development needs.

AMI capability provides the base for collecting, transferring, and accumulating data and information. As shown in Fig. 3, types of data could be broken down into (power) consumption and generation data, power quality measurements, and event data. Out of these, the most widely used measurement data in smart-metering activities are the detailed consumption data consisting of time-based (15 min to 1 h), reading of electricity consumption. The other types of consumption data are as follows [25]:

1) *billing interval data*: readings at the beginning and end of billing intervals to enable variable pricing;
2) *aggregate statistical data*: monthly consumption, comparison with neighbors, usage history, etc.;
3) *broadcast data*: price change information, critical peak-time rebates, reliability status, etc., communicated to users.

Event data refer to information that is generated at the meters' end points and include real-time device status, power quality information, and meter status information. These can be made up of attributes such as source and proxy, severity level, and category. Source originates the event and the proxy captures and communicates. Main event categories include meter status, power quality events (voltage sag), meter tampering, and meter hardware events (low battery). Power quality data are generally used in fault analysis to help improve reliability. Both prefault and postfault analyses are considered as effective techniques of using power quality to improve the reliability of a distribution network. Generation data provide information such as solar usage which enables to identify patterns of electricity usage, effectiveness of alternative generation and profile households, and suburbs and regions. The integration of consumption, event, and other data categories could be useful to understand how the grid infrastructure stands up to usage. This can also provide insights into capacity planning and budgeting. The fusion of external data such as weather and geography with consumption can provide useful information for predicting power usage [26]. Data supporting such activities have been called derived data in Fig. 3.

Data analytics is the process of examining large amounts of data of a variety of types to uncover hidden patterns, unknown correlations, and other useful information. Data analytics is used to obtain value from such data captured and information derived such that stakeholder applications could be satisfied. The stakeholder applications in smart metering are grouped under several key categories in Fig. 3. With AMI and SG infrastructure for capturing and transferring data, opportunities for smart meter analytics have moved to a new dimension. But to make use of such opportunities, analytics technologies have to successfully face and resolve new data-related issues as shown in Fig. 5. The volume of data collected has increased massively due to collection of data in shorter intervals and the ability to store large volumes. The data capture at frequent intervals by smart meters and the infrastructure to transfer such data at high speeds results in streams of data. Due to the new technological capabilities of the smart meters as well as the increased demand from stakeholders including competition among utilities, different types of data are being collected to provide more value for stakeholders, which has been called variability issue in analytics. It is very difficult to measure the effectiveness of energy-efficiency programs. Many factors, such as weather, consumer profiles, seasons, geographic regions, infrastructure, type of homes and fittings, all contribute to the complexity. The combination of volume, velocity, and variability as well as different granularities, issues in integrating various types of data results in much more complexity needing to be addressed by analytics techniques.

The new technological capabilities have also resulted in increasing expectation from the stakeholders, and the different applications are highlighted in the right side in Fig. 5. Some of the key issues that have arisen due to such different applications are listed below [25].

1) *Latency and bandwidth*: Infrequent and low volume information (e.g., broadcasts) will require low bandwidth and probably low latency as well. Consumption data on the other hand will require high bandwidth and could tolerate higher latency.
2) *Batch or real-time processing*: Many event data and information for in-home displays will require real-time processing while batch processing will be suitable for consumption data.
3) *Life spans*: How long data need to be kept will depend on the usage. For example, billing and statistical data might

have regulatory requirements to be kept for certain periods, while detailed consumption data need only be kept for short periods.

4) *Communication media*: In-home display for real-time information such as prices and statistical data and aggregates could be displayed on a portal

5) *Privacy and security*: Prices are public information but consumption is confidential and sensitive.

IV. Technology and Algorithms

In smart-metering activities, the use of technologies and tools has been triggered from two main directions. The metering intelligence activities initiated based on the AMI capability could be called data-driven exploratory activities. Such activities are triggered mainly due to the availability of new AMI capability, e.g., new and more data being captured, better grid facilities enabling faster and more reliable transfer, and storage of data and appropriate skills and other resources being available in an organization. In such cases, the question could be asked: *how can this data and infrastructure be used to gain some benefit for various stakeholders?* Although the stakeholder needs are considered, they are not the drivers of these activities. In traditional data-mining tasks, this is called exploratory analytics and tools such as clustering, visualization, and unsupervised machine-learning techniques are utilized [27].

The second type is the application-driven directed activity. In contrast to the exploratory approach, this approach is triggered directly based on stakeholder needs. Current knowledge of stakeholder needs, business needs, government policies, social and environmental trends (privacy, green house effects, etc) will be the drivers for this approach. Compared to the exploratory approach, the activities initiated in this approach will have a *known* objective. In data-mining and machine-learning terminology, such activities are called directed, and use supervised learning tools such as classification, decision trees, and artificial neural networks [28].

The technologies and algorithms used for smart metering are presented in Sections IV-A and IV-B.

A. Core Analytics Building Blocks

Many statistical, machine-learning, data-mining and mathematical techniques have been used, separately as well as in different combinations for smart metering. Since different techniques could be used to achieve the same purpose in terms of analytics outcomes, we have presented these as analytics building blocks in Fig. 5. The building blocks of aggregations, correlations, trending, exception analysis, and forecasting are the key foundations of analytics in smart metering.

The meters connected to individual transformers can be aggregated together to identify transformer loading patterns. Combining homes or businesses into demand–response pools to deliver sizable demand reductions (or "negawatts") is another aggregation supported by smart meters.

Heat waves drive spikes in power consumption and statistical correlation using time-interval consumption data makes it possible to build algorithms that predict the size of demand spikes using forecast temperature. Cloud cover, humidity, and time of day can be added to further refine peak predictions. Correlations are generated by aligning data temporally, spatially, or across other attributes. This type of data is used to build analytical models to measure the energy efficiency of individual commercial properties.

A web site that shows a simple consumption data trendline can help customers relate power consumption to household activity. The ability to overlay multiple trendlines together is also valuable for purposes such as comparing consumption across similar seasons and times of day.

A missing meter read is an exception event. Analyzing exceptions over time may identify problems in communications and measurement infrastructure, as well as in the distribution grid. Component degradation or operational breakdowns can be captured by analyzing trends in exception events.

Forecasts are predictions of future events or values using historical data. A forecast of power consumption for a new residential subdivision can be created using historical data from similar homes.

B. Tools for Smart Metering

There are many mathematical and statistical techniques, machine learning, data-mining tools that can be used for smart metering as shown in Fig. 5. Widely used techniques include self-organizing maps (SOMs), support vector machines (SVMs), principle component analysis (PCA), and fuzzy logic (FL) [29].

The SOM [30] is an unsupervised learning algorithm which is widely used to project high-dimensional data vectors on to a summarized two- or three-dimensional space. Its key desirable features in exploratory data analysis are its ability to summarize the input space and visualize results for interpretation. This enables the visual inspection of the possible patterns and the structure of data which can then be used for clustering and other techniques to elicit useful information. In smart metering, SOM has been mostly used for exception capture and profiling [68], [83].

SVMs [31] are based on supervised learning with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. SVM-based analytics have been reported for appliance-type recognition from AMI data [32], [33] and electricity theft detection [34], [35].

PCA is a mathematical technique which generates an orthogonal linear transformation that converts the data to a new coordinate system such that the greatest variance by any projection of the data becomes the first coordinate (the first principal component), the second greatest variance the second coordinate, etc. [36]. PCA has been used for power usage data aggregation [37], a data reduction technique in consumption analysis [38] and the detection of anomalies due to malicious modification of network data [39].

FL is a form of reasoning that is approximate rather than fixed and exact which may have a truth value that ranges in degree between 0 and 1. In [29], FL has been used to create an automated decision-making platform in an SG, and in [36] and [40], it has been used to improve the reliability of clustering of smart meters, which is essential due to scalability problems. Integration of technologies and intelligence into the SG also makes it more open to cyberattacks. In [41], a FL-based technique for efficiently detecting cyberattacks was described.

The above are only some of the examples of how the existing techniques can be used. Bayesian and hidden Markov model techniques are being used in a variety of smart-metering applications, such as load disaggregation [42], appliance identification [43], and supply demand analysis [44]. Future applications will result in a broader range of needs which will see more and more methods applied and tailored for smart metering to bring out greater benefits.

V. Stakeholder Applications

The tools described above have been used separately and in combination to achieve metering intelligence. Majority of the metering-intelligence-related work reported uses time-varying power consumption data to generate consumption (or load) patterns showing usage behavior to the consumers. Clustering usage patterns makes it possible to identify typical behaviors called typical load profiles (TLPs) [45], [46]. TLPs could then be used for load forecasting [47], [48], load estimation [49], load control [50], abnormal electricity consumption detection [51], designing electricity tariff offers [52], developing market strategies [53], or demand side response policy [54]. Some of the most widely used metering intelligence activities are discussed below.

A. Consumer Profiling, Segmentation, and Cluster Analysis

Cluster analysis of smart meter data has been reported from a number of regions around the world. Cluster analysis aims at discovering structures in large data sets. The k-means algorithm and a combination of k-means and artificial neural networks, such as SOMs, are popular approaches for the clustering and have been used in load profiling [48]. A study of German electricity consumers by Flath *et al.* [55] highlights the advantages of cluster analysis in identifying consumer groups for targeted service innovation by utilities and retailers. They have also suggested the value of incorporating cluster analysis as part of the utilities business intelligence systems such that process innovation and customer portfolio management could be guided by the results. Cluster analysis has been conducted on data separated by season and by weekdays and weekends due to differing usage patterns. A study reported in [56] identifies customer signatures based on usage readings from 50 m. Daily energy-consumption plots yield information such as minimum, average, and maximum daily energy consumption, as well as changes in daily energy use from which one can derive information such as household occupancy and occupant activities. This highlights privacy as a key concern with profiling usage patterns. The key privacy concerns are occupancy detection and possibility of inferring appliance usage. It has been suggested that statistical representations of the data can be used rather than actual consumer information. Also aggregation, noise addition, and consumer signature flattening have been proposed as ways for privacy protection [11]. An SOM- [30] based clustering of 12 000 Finnish electricity consumers was reported in [57]. The study carried out using Viscovery SOMine tool suggested that understanding customer usage patterns can help design better demand–response tariffs schemes. The SOM has been used in several other studies as a tool for clustering electricity consumption data [58]–[60]. A study by Abreu *et al.* uses pattern recognition techniques to capture habitual behavior of consumers using smart meter readings [61]. The work, based on a new data-mining algorithm for finer profiling [62], proposed that such fine-grained profiling can be used to provide tailor-made forecasts for households. Zhang *et al.* [63] used clustering techniques to identify load profiles for large electricity uses in a Chinese province. This work differs from the previously stated as they compare three well-known clustering techniques, namely, k-means, fuzzy c-means, and SOM.

B. Load Forecasting

One of the most valuable analytics applications for the SG and the availability of time interval data have made it possible to forecast in the short term and with high accuracy. Accurate forecasts are important for deciding short-term operations as well as mid-term scheduling, but also decision makers need to have an understanding about the customers they have to supply for long-term planning. Many applications of load forecasting have been described in literature where several statistical and machine learning technologies have been utilized. For short- and medium-term forecasting, time-series analysis and neural networks have been used [64]–[66]. A problem with short-term forecasting models has been the loss of understanding about the bigger picture they require and understanding about the different categories of consumers. In [67], a PCA-based technique was used to identify the type of demand faced by such consumer categories. In [68], a hybrid system of SOMs and SVM was used to forecast mid-term electricity load. The SOM was used to separate electricity consumption data into two groups which are then fed into an SVM in a supervised manner for load prediction. In [48], Espinoza *et al.* report on short-term forecasting with hourly load data from a Belgian grid substation highlighting that forecasting and customer profiling are interrelated and proposed a unified framework which incorporates both. The initial modeling is based on seasonal time-series analysis, using the periodic auto-regression (PAR) model [69], which was used in the modeling of electricity prices [70]. The stationary properties obtained from these models are run through a k-means clustering process to capture different customer profiles.

C. Pricing Intelligence

Smart meters will enable to set up dynamic tariff structures to improve efficiency in electricity markets by better representing the costs of producing and delivering electricity at different times. Consumers could benefit from these if they choose more flexible tariff arrangements that better represent their electricity cost. To determine the price of electricity as well as the tariffs, retailers consider payments to distributors for services, wholesale electricity cost, retail services cost, as well as costs of any regulatory requirements. Smart meter data enable deeper analysis for understanding the dynamics of supply and demand resulting in better forecasting the needs, enabling pricing intelligence. Smart meter data can be used to analyze and plan different rate structures, without discriminating by demographics of low income, etc. This has been called "time of use" or dynamic pricing. Real-time stream analysis of consumption is required to make such a scheme practical. The benefits of dynamic pricing have been identified as demand reduction, cost reduction, and economic efficiency gain [52]. Prepay is another possible pricing intelligence technique with the advantages of being familiar to consumers and also helping utilities limit credit risk. Utilities can take a more opt-in approach where customers elect to select in a new rate plan, such as dynamic pricing. Customer demography segmentation related to consumption-based profiling has to be carried out in these approaches. Reference [57] describes work carried out using SOM tool Viscovery for clustering and visualization of consumer information from a utility in Finland. In addition to several consumption-based attributes, the type of residence was used for the segmentation.

D. Capturing Irregularities

Many load profile studies have used data-mining techniques, pattern recognition, and statistical techniques to obtain knowledge from customer load records. Knowledge of consumption behaviors is very important as it is very useful for formulating tariffs and developing marketing strategies, as well as allowing customized billing. Knowledge gathered from customers' load profiles could also be used to identify, detect, and predict behavior irregularities or abnormalities that ultimately may be due to faulty metering or human intervention and fraud [51], [71]. Potential theft or technical losses can also be identified by comparing smart meter data with measurements from sensors attached to transformers or feeders [14].

E. Metering Intelligence to Support Real-Time Operations

The rolling out of AMI makes it possible to acquire near real-time information of energy use, connect RE to grids, manage power outages and faster restoration, fault detection and early warning.

There are several levels of real-time responses. One level is at the actual control of machines and equipment which requires milliseconds response time. At this level, unless the infrastructure of smart meters and communication networks can be significantly upgraded to realize reliability and millisecond responsiveness required for real-time control (e.g., controlling transient responses of rotating machines in the gird), smart meters cannot necessarily provide adequate benefits. For those near real-time critical applications (5 min, quarterly hours, half hours, hourly intervals), such as fault identification and localization on MV and LV networks to ensure faster intervention and reduced outage duration, monitoring power quality, acting remotely, managing peak-saving, forecasting network conditions, facilitation of integration of RE and PHEVs into the grid, smart meters can help [6]. Examples include the measurement of voltage distortion (harmonic voltages and voltage unbalance) [72] using smart meter data to derive a dynamic model to improve volt-VAR control [73], as well as controlling congestion and stability in a power market [74]. Metering data can also be used to derive the knowledge of the power flows at and near the low-voltage end of the distribution networks so that the loading and losses of the network can be known more accurately. This can help to prevent overloading components (transformers and lines) and to avoid power quality deviations [75]. Another example is the state estimation using smart meter data which may provide an alternative economical way of estimating states of MV and LV networks [76], [77]. Smart meter data can also be used to enhance overcurrent protection [78] and load disaggregation [79]. The NOBEL project [80] has developed a smart-metering platform [81] that specializes in near real-time acquisition of metering information from the grid as it is reported directly by the smart meters. Data stream analysis [82] for capturing time-based usage patterns has also been reported in [83].

VI. Key Challenges and Future of Smart Metering

A. Issues in Smart Meter Data Analytics

To achieve metering intelligence as described in the previous sections, a number of technical issues need to be successfully addressed. The ability to work with very large volumes of data will be a key requirement. It is also essential that technologies be able to work with a variety of data such as weather information and consumer information, geographic data thus requiring techniques for efficient data fusion and integration. Such a big data integration and analytics engine are being developed by a C3 energy, where tasks such as voltage optimization, asset management, outage management, and fault detection to customer-focused services such as demand–response, load forecasting and customer segmenting, and targeting are to be integrated. Real-time monitoring and diagnostics-focused analytics would be an important requirement in such systems [84], [85].

To achieve real benefits of analytics outcomes, it is essential to gain consumer's acceptance and support for smart meters. A key requirement for such acceptance is transparency of the process which is currently being addressed by government regulators as well as utilities [86]. The availability of easy to understand and visual displays of information is also an important need. Making smart meter data and analytics outcomes available on the web and on mobile devices will make such information more readily available and also updates communicated to consumers in near real time [87]. Smart meter analytics will thus continue to evolve, making demands on the current knowledge and technology available.

The available big smart meter data will also present privacy and security concerns that are likely to become more prevalent as government-backed initiatives expand deployment of the meters to millions of homes across the country [88], [89]. These will have to be addressed within the regulatory regime of the particular country deploying smart meters. For example, obtaining permission from the customers to manage, use and create value from smart meter data is seen as a standard public service responsibility that already exists in all European countries [6].

The future of smart metering will also depend on several key technology revolutions currently in progress are discussed below.

B. Smart Meters and Big Data

"Big data" is a term that is currently being used widely with data analytics. Big data has many interpretations but there are three key features that are highlighted: volume, velocity, and variance. Data captured by smart meters clearly relate to all these features thus satisfying the definition for big data. For example, moving from one meter reading per month to smart meter readings every 30 min results in a massive volume of data to manage. The data are collected in frequent time periods, and if technology is available for near real time analysis, many advantages could be achieved. The analytics technologies will have to deal with not only consumption data but also consumer information, weather, and many grid-behavior-based readings. To manage and use this information to gain insight, utility companies must be capable of managing high-volume data and using advanced analytics to transform data into actionable insights [3]. Utilities that build up this capability can gain insight into their operations and assets and can become proactive in taking action based on analytics. Although the increase in volume, especially in consumption data, capture is the most prominent big data aspect with smart meters, and the other aspects of velocity and variance are equally important. Velocity refers to the need for collecting, processing, and using the data speedily and in time. Although analytical algorithms which can process huge quantities of data are available, many of these are not able to complete such activities in a sufficiently short time period to be of practical value. For example, overnight is not good enough for real-time tasks such as reliability monitoring of equipment, preventing outage, or security monitoring. Although several research techniques have been reported on analyzing streaming data, much work still needs to be done in making these commercially viable. Variety signifies the increasing array of data types, which are collected not only from traditional sources like industrial control systems but also from security cameras, weather forecasting systems, maps, drawings and pictures, and the web. The variety of data is likely to become increasingly important to utilities as they begin to analyze social media and call center dialogs and to integrate such information into smart meter and grid-generated data as part of their decision-making and planning processes [3].

C. Smart Meters and Cloud Computing

Although SG enables distributed and RE generation, controlling energy generation according to demand is still a problem. A new idea is aligning energy supply and demand using infrastructure such as a broadband network access, performance, scalability, and flexibility, which can be provided by a cloud platform [90]. Cloud computing is a paradigm in which services including computation, storage, and network are packaged and provided as metered utility services sold on demand both in terms of duration of use and utilization [91]. Benefits include on-demand self-service, resource pooling, and use of a cloud service on pay-per-use or charge-per-use basis. But this raises security and privacy issues with protecting the smart meter data from unauthorized usage [92]. Using smart meters to develop a dynamic pay-per-use pricing model for regulation and improvement of overall utilization of the cloud infrastructure is described in [91].

Denmark now has its first cloud-based smart-metering solution, targeted at small utilities and communities that previously could not afford such technologies. IBM and Cable & Wireless Worldwide are working to develop a new intelligent communications solution called U.K. Smart Energy Cloud to support the U.K.'s smart meter implementation program with expected roll-out of more than 50 million meters. The solution is expected to provide for more accurate billing, greater SG functionality, and other benefits.

Use of cloud platforms and technologies for smart metering and grid has resulted in the need of extended capabilities from analytics tools. A number of vendors have come up with tools such as IBM Coremetrics and Google BigQuery, and the cloud-based software platform for data-driven analytics described in [93] as part of the Los Angeles Smart Grid Project. The described system has attempted to incorporate several of the new advanced analytics requirements highlighted earlier such as real-time data analytics, scalable machine-learning techniques, and data integration demonstrating how the new advanced analytics techniques provide the base for future smart metering and SG systems.

D. Smart Meters and Internet of Things

The SG and the environment it creates have been called the Internet of Energy [94]. If there is an adaptation on the behavior of the prosumer devices based on the information that they receive such as electricity price, the energy-consuming/producing devices will not be black boxes but be able to adapt accordingly. Such an environment is called the Internet of Things (IoT) from an SG perspective [94], [95]. IoT are expected to grow to 50 billion connected devices by 2020 [95]. The connected SG provides a communication network that will connect all the different energy-related equipment of the future. From the transmission and distribution power infrastructure, electrical, water, gas, and heat meters to home and building automation. The first key step toward an SG that makes the IoT a reality will be the mass deployment of smart meters.

The connectivity and accessibility provided by the IoT brings further improvement of customer experience and efficiencies thus greater interaction and control. Additionally, the IoT enables manufacturers and utility providers to cut costs through diagnostics and neighborhood-based meter reading. As such IoT will result in building a more connected, cost-effective, and smarter SG.

VII. Conclusion

The paper has presented a comprehensive survey of smart metering and electricity smart meter data analytics. Although there has been much opposition to smart meters due to privacy and health concerns, it is obvious that smart meters are here to stay and that the SG and smart metering will be a "way of life" in the future. A number of different dimensions to smart meters have been highlighted including the smart meter technology and the process, the various stakeholders, existing analytics technologies and tools, and the current technological revolutions such as big data, cloud computing, and the IoT. The paper has also presented the current smart-metering space as the smart-metering landscape, and then, a framework has been established to relate smart meter data to stakeholders and applications created by their needs and the analytics tools and techniques required to achieve the stakeholder needs. The framework would help identify the current limitations in smart metering. Another contribution of this paper is the identification of smart meter analytics building blocks which enable to link the wide range of tools used for smart metering and identify the main analytics activities. The SG and smart meters will be part of a much wider IoT in the future integrating multiple aspects of human needs and services to satisfy such needs, and the analytics requirements discussed, such as big data, real time analytics, stream analytics, will need to be built into the processes and workflows for diagnostics in real time.

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