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SURVEY

Smart Meters for Smart Energy: A Review of Business Intelligence Applications

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ABSTRACT Smart Energy (SE) has emerged as a critical technology in tackling global challenges like climate change while addressing the rising energy demands driven by today's data-intensive industrial revolution. SE integrates information and communication technologies into energy systems, optimizing them to meet these challenges effectively. At the core of SE operations are smart meters, playing a fundamental role in ensuring efficient functionality. These devices collect data, which is then leveraged to derive Business Intelligence (BI) for operations across the entire spectrum, from the sensing infrastructure to the cloud, primarily utilizing the Internet of Things (IoT) technology framework. With the increasing complexity of operations and the growing demand for optimization and enhanced functionality, the SE technology stack is evolving to integrate across all layers and domains. This integration has led to the stratification of computational load across IoT layers, intensifying the dependence on smart meter data for BI. Consequently, smart meters themselves have evolved to become more functional and complex. This paper's novelty lies in its comprehensive exploration of the integration of BI with smart meter data. It delves into various aspects, including the different layers of intelligent operations within SE systems, the current state of the art, and diverse implementations of smart meters and their applications across operational locations, ranging from consumers to fog computing. The paper concludes by identifying research gaps and future directions, offering insights into the evolving requirements for the next generation of SE systems and the necessary adaptations in smart metering infrastructure to support these roles. This work contributes to a better understanding of the evolving landscape of data and computation in the context of SE, facilitating more efficient and effective energy management solutions.

INDEX TERMS Smart grids, smart meters, AMI, cloud, business intelligence, artificial intelligence, smart energy.

NOMENCLATURE

AI	Artificial Intelligence.
AMI	Advanced Metering Infrastructure.
BI	Business Intelligence.
CNN	Convolutional Neural Network.
DR	Demand Response.
DSM	Demand Side Management.
EV	Electric Vehicle.
FFNN	Feed Forward Neural Networks.
GBRT	Gradient Boosting Regression Trees.
HEMS	Home Energy Management System.
IoT	Internet of Things.
LSTM	Long Short Term Memory.
LTLF	Long Term Load Forecasting.
LV	Low Voltage.

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MILP	Mixed Integer Linear Programming.
NTL	Non-Technical Load.
PCA	Principal Component Analysis.
S2S-RNN	Sequence-to-Sequence Recurrent Neural Network.
SBCTL	Similarity Based Chained Transfer Learning.
SE	Smart Energy.
STLF	Short Term Load Forecasting.
SVM	Support Vector Machine.
V2G	Vehicle to Grid.
VSTLF	Very Short Term Load Forecasting.

I. INTRODUCTION

Modern technological world is computation-driven power house that has, in turn, driven the energy demands up by manifolds [1]. Not only the energy demand is on the rise it is so at an ever increasing rate. Increased demand has put severe constraints on natural resources risking depletion sooner than later along with heightened risks to environment [2]. This calls for better management of resources and integrating renewable energy, environmentally friendlier fuels and fuel technology to the energy mix. The energy mix is continuously being diversified with wind, solar, nuclear and other renewable sources which has greatly increased the complexity and functional dimensions of the energy grid. Along with the diversified mix more and more novel components are continually being added to the energy grid like grid storage, electrical vehicles, prosumers, distributed generation, energy management systems and inverter based loads producing non-sinusoidal currents and voltages in the grid which has made traditional grid functions as state estimation, load management, demand forecasting, fault prediction, location and isolation, frequency control and asset management more challenging along with adding more functionalities in terms of managing the energy mix, sensing of different energy resources, logistics and distribution etc. To make this feat manageable energy systems have integrated information and communication technologies and evolved into smart energy systems [3], [4]. In this context the term "smart energy" has evolved to signal the shift from single sector to multiple integrated sector managed as complex system of systems to scale up to grand challenges facing the energy sector both in terms of operations and environment.

Smart energy fundamentally, like typical smart system, consists of sensing [5], computation and communication functions for control and optimization. Smart meter is the core component of smart energy providing many contributions in the field. Traditionally they measured simple consumption parameters like voltage, current and power and reported to some central location. Due to increased complexity and functionality of SE, the requirements for the components vary greatly for different metrics such as latency, robustness, throughput, data granularity and data integration. These metrics varies for different functions of smart meters

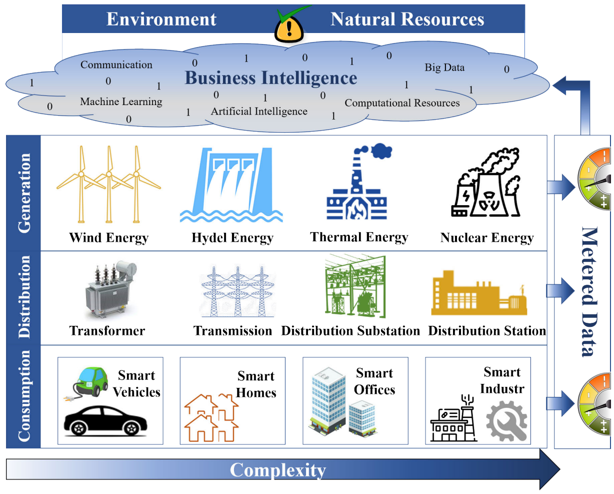

FIGURE 1. Illustration of the data collection of the energy meters at distinct levels of the power grid. Electricity data from the three domains i.e., consumption, distribution, and generation are collected by smart devices, the smart energy meters. The gathered data is sent to computing resources, where AI algorithms are used to make various business intelligent decisions. These choices ultimately contribute to addressing the environmental challenges and efficient deployment of natural resources.

like energy efficiency conservation, load balancing and grid management, demand response, predictive maintenance etc. For example frequency imbalance estimation requires faster response times then demand forecasting which requires more data. Similarly fault detection requires real time detection with lowest latency as compared to simple metering which has no stringent latency requirements. Such varied profiles have led to spreading of the sensing function across multiple layers in the network along with greater integration of function into the meter itself. Thus, smart meters now collect data at consumption, distribution, and generation as shown in **Figure 1** and process them for intelligent decision-making.

At the user node or consumption side, data is readily available, for example, information received from smart vehicles, smart infrastructures, and appliances [6]. The rate of information reception and dissemination through the communication network to the database is dependent on the volume of data being logged into systems along with distinct features such as the number of appliances, time of day, and weather conditions out of many to effectively represent the SE system. This data could directly be processed by consumer end smart meters for diverse functions such as demand side management, home energy management systems, dynamic tariff management and net metering etc. At the distribution level, smart meter data is consolidated from home area networks to the local area network and finally to the distribution centers. This data is further augmented by various measurements, such as Synchrophasors, for applications like fault isolation, fault classification, asset management and predictive maintenance of transformers and grid stations on a larger scale. Large amounts of data, generated and collected at the distribution level, contain details on pertinent events and activities during a specific period which helps in implementing advanced control strategies and optimization of the grid at a large scale. For example, power metering of the transformer for preventive maintenance [7]. Finally, the generation level of the data from the distribution and consumption layers is used for controlling real-time power output, energy consumption forecasting, optimizing energy mix, and voltage frequency monitoring for the distribution and generation components. The data typically measured at this layer is industrial, like process variables for thermal power plants and vibration of generators etc. Typically, voltage, current and frequency are monitored in greater detail at this level.

All the information from various levels together generates large volume of metering data which leads to big data management challenges. To cope with voluminous, veracious and versatile data Big Data technologies can be deployed at different computing levels. Each deployment option has its own set of benefits and drawbacks. Cloud-based big data technologies are typically hosted on a remote server and accessed through the internet. These solutions are typically easy to set up and can be accessed from anywhere. Fog and edge-based big data technologies work the same but are closer to the source of data providing quick processing and low latency respectively and are simpler In implementation and scope. Different AI approaches may be used to evaluate the data and get valuable insights from it once it reaches the desired computational level [8]. Additionally, the data can be visualized using dashboards, which allow for easy monitoring and analysis of the process.

The current state of the art in smart metering infrastructure has thus been varied in implementations and level of integrations. Lately smart meters have increasingly relied on (Internet of things technology) IoT technology for enhanced functionality and coverage. This has enabled data collection at various levels in the power distribution while oftentimes bringing computation closer to the data source to reduce latency and increase the effectiveness of power measurements. In view of this development, a review that encompasses different topologies of smart meter measurements and computations is necessitated but not adequately covered in the literature. This article aims to address this review gap. Thus, in this survey research article, we have presented a brief description of data collection at various levels of power systems followed by the role of big data in smart meters along with the different technologies involved and their advantages. To address the challenges of data processing and analytics different computational levels and their significance in the smart metering domain are explored. Afterward, a comprehensive review of applications and AI techniques are presented to make smart and intelligent decision-making for advanced energy-efficient systems which are more environmentally friendly. Finally, a review of different implementations of smart meter with respect to the measurements and functionalities is presented. **Figure 2** depicts the schematic diagram illustrating the flow of this research article. The introduction section covers the impetus

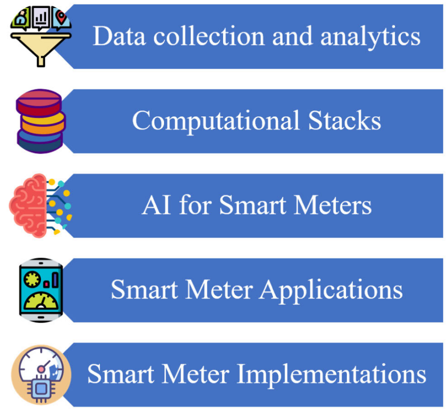

FIGURE 2. Sequential depiction of the research paper's methodology, analyses, and results, offering a comprehensive overview of the study's procedural flow.

and development of smart meters' implementations for complex smart energy systems which leads to differentiated implementations at various levels. These implementations are then segregated under the location in the power system where the smart meter operates, the computational stacks employed to carry out the different roles, and finally, different application domains employing the smart meter data. These aspects are covered in subsequent sections as detailed above.

II. DATA COLLECTION AND ANALYTICS FOR BI USING SMART METERS

Smart systems collect, transform, store, and process data for autonomous intelligent decisions [9]. Big Data and analytical technologies have now been universally deployed to manage and process the data for such intelligence. Using sophisticated data analytics, like predictive analytics, adds tremendous value to otherwise mundane data [10]. Smart meters now increasingly collect veracious and variable data at the measurement points and sometimes process data on location while at other times relaying the data to edge, fog, or cloud for different data analysis tasks. In this section, we review different sensing, collection, storage, and transformation techniques for smart meter data. The complexity of each technique largely depends upon the nature of the end goal.

Sensing is one of the core components of smart systems, and modern IoT-based implementations have spread sensing functions across different layers [17]. The dataset size for smart meter sensing varies based on the specific use case. For example, demand forecasting, which may require a large amount of data, typically involves collecting and analyzing data spanning several years. The list of different smart meter datasets is shown in **Table 1** indicating the different datasets and the type of data contained in each. These extensive datasets help in accurately predicting future energy demands. On the other hand, transmission parameter estimation, being a local problem with fewer data requirements, often deals with relatively smaller datasets covering a shorter time frame. Sensor values are transformed using fusion and advanced

TABLE 1. An overview of different smart meter datasets and a brief description of the data they contain.

Ref	Dataset	Description
[11]	Smart meter dataset	Contains the energy consumption (kW/hr) record of the 200 households over an entire year in 10-minute increments
[12]	Real dataset and reconstructed dataset	Obtained from real-time measurements (referred to as Real) and the other reconstructed from a signature profile (referred to as Rec)
[13]	New York Electricity Dataset	Real world electricity recorded from 25 houses in New York
[14]	Irish CER Smart Metering Project	Contains the load profiles of over 5000 Irish residential users and small and medium-sized enterprises for more than 500 days
[15]	SGCC Electricity consumption Dataset	Contains the electricity consumption data of 42372 electricity consumers within 1035 days.
[16]	Reference Energy Disaggregation Dataset (REDD)	Freely available dataset containing detailed power usage information from several homes.

analytics processing into derived values acting as virtual sensors for downstream systems. A preventive maintenance system is one example of such a scenario [18].

Collecting a wide range of data, including temperature, pressure, humidity, power consumption, and various environmental parameters, the specific data collected by the sensors depends on the application's requirements. These measurements are crucial for gaining insights into energy consumption patterns and ensuring the proper functioning and condition of equipment. Smart meters, in particular, go beyond these physical parameters. They also capture electrical data, including voltage, current, power flow, frequency, and phase of the electricity [19]. **Table 2** lists the different parameters being calculated by the smart meters along with the location of smart meters and their description in the application. Using advanced techniques, smart meters can even predict the remaining useful life of equipment, effectively functioning as virtual sensors. In industries such as process manufacturing, it's common to employ multiple sensors to monitor a single variable. These systems utilize sensor fusion techniques, among other methods, to ensure precise measurements of process variables. Similarly, smart electricity and energy networks apply similar techniques to derive a single sensed value from various measurements, such as cable impedance [20].

Smart meters, the sensing component of smart energy, measure voltage, current, power flow, frequency and phase of the electricity and report the data to the central location either in one hop or, now the usual case, in multiple hops to the cloud. These direct measurements are continually processed and transformed as they traverse through the energy network [33]. As described in Section I, each layer in the energy network aggregates the values from the layer beneath and adds its own set of data, which we consider smart metering data in the context of the current review. At each layer, the design of the smart meter also varies in terms of communication and computation capability, the type of software employed for processing and storing the data, and finally, the type of sensing circuit used, both in terms of technology and range of measurements.

Sensing, data fusion, and augmentation require communication systems for data transfer [34]. Smart meters come equipped with a range of data communication protocols tailored to their specific roles within the smart energy ecosystem. The choice of protocol depends on factors such as the network type, the meter's functionality, and its position in the hierarchy of the smart energy system [35]. In the realm of consumer nodes, where the focus is on home area networks, the protocols commonly in use include familiar names like Wi-Fi, 802.15.4, 802.11-based networks, and BLE (Bluetooth Low Energy) [36]. These networks are designed with efficiency in mind and may transmit data at different frequencies, such as real-time or daily intervals, depending on the application.

In the context of smart meters, the storage frequency refers to how often data is collected and stored regarding energy consumption and related parameters. Smart meters are programmed to record data at regular intervals ranging from hourly to 15-minute increments. This measurement period, or granularity, is an important feature of smart meter data management because it affects the level of detail accessible for analysis. Furthermore, smart meters frequently save past data for a set length of time, typically one to three years, allowing for trend analysis and long-term planning. In a recent study by [37] conducted in 2022, they undertook a comprehensive evaluation of various computational methods for forecasting next-day load using a dataset comprising half-hourly readings from 5,567 households. On the other hand, in 2018, [38] introduced an innovative approach involving unsupervised data clustering and frequent pattern mining analysis across three distinct datasets. Subsequently, they applied Bayesian network techniques for energy consumption forecasting, achieving an impressive accuracy rate of 81.89 percent. Worth noting is that the datasets utilized in these studies included high-frequency smart meter data, characterized by data resolutions of 6 seconds and 1 minute, respectively.

TABLE 2. Review of smart meter data and applications at power generation, distribution, and consumption levels.

Ref	Parameters	Location	Description
[21]	Power measurements	Distribution	Uses data augmentation to detect the failure of protection equipment
[22]	Synchronised voltage, current phasors, protection equipment status	Distribution	Uses random matrix theory to form an augmented matrix of power measurements to detect electricity theft
[23]	Phasor measurements	Distribution	Synchrophasor data is used to identify the fault type
[24]	Synchro phasor	Distribution	Voltage and current phasors are employed for fault identification
[25]	Phasor measurement units	Distribution	Phasor meter placement algorithm for enhanced modeling of power grid
[26]	Phase	Distribution	Uses smart meter aggregated data to asses phase
[27]	Phase	Distribution	Uses smart meter aggregated data to asses phase
[28]	Power metering	Distribution/ generation	Smart meters to assess future energy metering in co-generation model
[29]	Power metering	Distribution/ generation	Power consumption and generation metering and aggregation to predict electricity availability
[30]	Power factor	Distribution/ generation	Power factor metering using smart meter data for efficient grid and generation operations
[31]	Voltage	Grid	Using complex valued voltage measurements estimate the grid voltage and frequency
[32]	Voltage	Grid	Aggregation of smart meter data for voltage mapping at grid levels to identify the low voltage zones

These networks are designed with efficiency in mind, employing constrained energy protocols to keep overhead to a minimum and maintain a straightforward inter-networking structure. Moving up the hierarchy to the distribution layer, we encounter edge nodes that play pivotal roles in data management. Here, the emphasis is on local or wide-area networking, and the preferred protocols often include low-power WAN options such as 6LoPWAN and LoRaWAN [39]. These technologies are complemented by the deployment of single-board computers boasting multi-core, high-end systems on chips, ensuring the necessary processing power for data handling. Before the data from edge nodes reaches its final destination in the cloud, it may traverse a fog network, where several edge nodes collaborate. Eventually, all these streams of data converge in the cloud. The primary networking protocols utilized in this context are predominantly cellular, harnessing the capabilities of 4G and 5G networks. Details of these computing infrastructures will be presented in section III.

Smart meters use computing, storage, and transformation techniques to build intelligence from the data from sensors and the network [40]. These constitute the physical hardware running the smart meter program. As the complexity of metering algorithms has evolved, so have the physical platform capabilities. The smart meter algorithms at the consumer nodes have a range of hardware capabilities, from simple microcontrollers to single-board computers, depending upon the complexity. For example, simple metering and reporting systems employ a simple microcontroller equipped with a single communication interface, whereas complex home energy management systems use powerful single-board computers for communicating with individual appliances and local area networks or even with the cloud and use powerful multi-core processors, greater storage and memory for running complex analysis, inference and decision engines. For example, home energy management systems, which implement non-intrusive load monitoring, run a complex billing engine, and implement net metering, require a hardware platform with capable hardware and communication interfaces [41].

As the complexity at the consumption end increases, so do the hardware platform requirements. For example, a building energy management system uses edge computing hardware that might include multiple interacting platforms such as computer servers, modems, and sensing and actuation interfaces, implementing complex, scalable control and data acquisition (SCADA) systems [42]. The same edge computing infrastructure is implemented at distribution and fog levels with greater computing power to handle sub-grids and complex industrial loads metering [43]. Such a computational platform runs and derives metering variables used in complex control and optimization algorithms. For example, waveform analysis at the distribution level can reveal the power quality metrics used to control the complex interacting grid switches to minimize the losses.

Leveraging the synergy among the components described above, various algorithms, including demand-side management, electric load forecasting, anomaly detection, and innovative applications, have been enabled through the analysis of substantial data from smart meters. It is essential to consider the peculiarities of smart meter output to realize its maximum value because of the difficulty in processing and evaluating the enormous amount of smart meter data and maintaining a real-time balance between energy supply and demand and instantaneity. Power providers must set up specialized data centers to store the data from these high-dimensional smart meters. Data is exponentially increasing due to technological advances and population increase. Fast data processing is crucial for short-term demand forecasting, power system fault identification, and other decisions. Therefore, it is necessary to assess information from large-scale electricity manufacturing and utilization relatively quickly. This characteristic is known as velocity. ICTs have quickly advanced and are frequently used in smart grids. Modern smart meters are commonly utilized in smart grids and, in general, come with clever processing software and the ability to collect data almost instantly, hence enhancing data transmission capabilities. Due to the combination of user data, business data, and data on power generation with the voltage, current, and frequency of measurement nodes, the data is incredibly complex and has huge data dimensions. The diversity of data is further expanded by meteorological information and geographic location data, enhancing the data's contribution to grid efficiency and developing new commercial energy models. In addition, smart meters' technical capabilities have recently improved, allowing them to deliver finer-grained data to a greater extent and thereby boosting variety and volume.

III. COMPUTATIONAL STACKS FOR SMART METER ANALYTICS

The data collection at various levels and locations of the smart energy system by the smart meter needs intelligent decision-making for processing and monitoring the data from smart meters has its advantages, but because of the huge data load, it would take a lot of computing power to run the training models on it. As pointed out earlier, the metering infrastructure is now spread across the energy and IoT stack to reap the benefits of allowing greater computational resources to integrate and calculate advanced metering parameters for the smart energy system. To avoid cost and complexity increases, smart meters at the consumption end are kept as simple as possible, while for management of more complex consumption entities, such as offices, buildings or factories, smart meters with more hardware and software resources are employed. As the data consolidation, augmentation, and processing get more complicated, the metering functionality is distributed further up the computational stack into the edge, fog and, finally, the cloud. The previous section reviewed different metering functions distributed across the smart energy layers but only provided brief hints about the corresponding complexity of the computational stack. This section reviews different computational models used by the metering functionality, which are crucial for implementation. The concept is depicted in **Figure 3**. The smart meter function

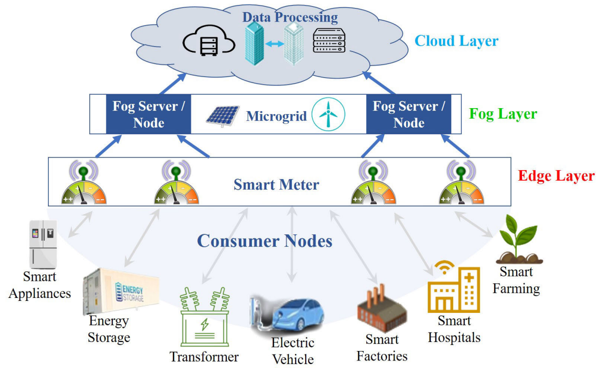

FIGURE 3. Depiction of the various technological stacks. Data from consumer nodes is collected and then transferred to the edge layer. Three layers are shown that are present according to the data available sources. The use of each layer solely depends on the application. Edge being the closest take the least time but cannot carry a large amount of calculation due to resource constraints. On the same pattern fog and cloud work.

is spread across different computational layers, edge, fog, and cloud dealing with different metering functionality depending upon the application. In the following sub-sections, we review different computing stack and their application domain for smart meter functionality.

Cloud Computing: Cloud computing allows flexible computational resources on demand, often without constraints on limits from an application standpoint of view [44]. Cloud computing is becoming more prevalent for smart metering functionality, offering features suitable for smart metering software applications in integrating information, evaluation, and programs like flexible assets and support functions [45]. Cloud computing can be public, private, and hybrid based on various factors such as privacy, security, complexity and cost [46]. Public clouds are a good option for the general processing and visualization of metering data; for example, simple home energy monitors and energy auditing interfaces for buildings [47]. Such solutions require very low cost but need connectivity and design resources that might be prohibitive for private implementations. Thus public clouds are mostly employed to implement consumption-related metering facilities. On the other hand, when data security, privacy and functional uniqueness are important factors, such as for large companies, private clouds are deployed in the smart energy network. Generation facilities and distribution networks often employ private cloud deployments for performing metering functions like power quality measurements, transmission line parameter estimations, alarming, efficiency, asset management parameter estimation and monitoring. Most often, however, hybrid implementation is employed, where private and secure functionalities are performed on private clouds, whereas the public cloud is used for data consolidation, augmentation and visualization. Another important function of the public cloud is to train the neural networks used by smart meters at various levels to implement intelligence. Training a neural network for smart metering parameter estimation and calculation is expensive and requires large computational resources that are most often used only once. The public cloud is an ideal candidate in this scenario because that allows renting the computing, communication and storage facility at a much lower CAPEX cost. Competition is fierce, so the public clouds often provide software tools to program the data ingestion, neural network programming and training, which also leads to reduced OPEX.

Cloud computing benefits smart meters by lowering maintenance costs, providing easily scalable resources to meet demand, and adopting a pay-as-you-go pricing model to invest in infrastructure, making smart meters an important component and pervasive of smart energy system [48] and allowing power system's efficient, intelligent, and optimal operation. Researchers are primarily focusing on integrating the energy infrastructure, cloud technology, and intermediate communication provider domains to maximize their benefits while upholding the same degree of security, confidentiality, and safeguard standards as the conventional system for managing energy.

However, while cloud computing provides numerous advantages, there are also significant challenges that need to be addressed, as highlighted by various studies [49]. One major concern is cybersecurity. Data stored on cloud servers is vulnerable to hacking and misuse, which can have severe consequences. In the context of smart grids, maintaining the privacy and dependability of users' data in cloud services becomes paramount. As the number of users grows, the challenge of ensuring data security becomes even more complex. Additionally, data security often relies heavily on the cloud service provider, which may hinder the application of tighter security protocols desired by operators [50], [51], [52].

Another challenge is the increased infrastructure cost associated with cloud integration. While cloud resources offer scalability, they come at a cost, which can add to the overall expenses of implementing and maintaining smart metering systems [53]. This financial aspect requires careful consideration and cost-benefit analysis. Furthermore, high-speed internet access, while essential for efficient data transmission, can introduce technological problems under heavy load. Issues related to network congestion and bandwidth limitations need to be addressed to ensure seamless data flow between smart meters and cloud servers [54].

Data segregation is another concern where many customers' virtual computers are co-located on the same hard drive. This setup can potentially lead to data access and security issues if not managed properly [55], [56]. Additionally, delayed recovery procedures in cloud environments can prove to be a major setback, impacting the availability and reliability of data in critical situations.

Edge Computing: In the edge computing paradigm, the data is processed locally without being transmitted over the internet. Smart meters are replacing conventional electricity meters to improve the precision, transparency, and effectiveness of measurements and usage patterns. The majority of smart meters, however, merely digitally capture and transmit power data to service providers. Numerous applications, including demand side management and energy savings through customer load detection and irregularity detection, could make use of the data supplied by smart meters.

TABLE 3. Review of smart meter data and applications at the edge, fog, and cloud levels.

Ref	Location	Description
[57]	Cloud	Service-oriented data aggregation for cloud service provisioning for smart meters
[58]	Cloud, Fog, Edge	A reference architecture for smart metering functionality for smart grid
[59]	Cloud, Fog	Harmonic source location using distribution level phase measurements and power measurements of smart meter
[6]	Cloud	Review of smart meter data analytics
[60]	Cloud	Socio-Demographic information estimation using smart meter data
[61]	Cloud	Cluster analysis of smart meter data
[62]	Cloud	Energy demand behaviour modelling using smart meter data
[63]	Cloud, Fog	Non-technical loss and theft detection using smart meters' data
[64]	Edge	Event detection and classification on the smart meter
[65]	Edge	Anomaly detection on the smart meter
[66]	Edge	FFT based micro-services for harmonic analysis of non-linear loads on the smart meter
[67]	Edge	Commercial, state-of-the-art open embedded edge computing capabilities designed for both 5G wireless public and private cellular networks.
[68]	Cloud, Fog, Edge	Generalized patterns of edge, fog and cloud applications using smart meter data. Implements device control at edge for energy efficiency and perform load forecast and direct load control at the fog
[69]	Cloud, Fog, Edge	Edge intelligence for implementing smart functionalities using Fog and Cloud layers. Implements federated learning use case.
[70]	Cloud, Fog, Edge	Mixed signal processor for arc-fault detection using Edge, Fog and Cloud layers

High sampling rate requirements, a lack of transmission bandwidth, and resource limits in analyzing a massive volume of data demand high computational resources given by cloud and fog resources. However, edge computing tries to provide those resources at the device level. Integrating data analytics into smart meters significantly reduces the accuracy, latency, and bandwidth requirements for smart grid applications [71].

Edge computation uses high powered computational platform capable of forming a small network of nodes distributed locally for appliance monitoring and control. Such meters find extensive usage in load power quality metering, energy quality metering for energy auditing, peak demand metering for energy saving, net metering for pro-consumption and energy storage metering etc. Edge computers also form computational nodes for fog computing.

Fog computing: As mentioned in the previous section, edge devices are becoming increasingly powerful and capable of executing advanced features. However, advanced metering functionalities require still greater computational resources, communication networks and data to execute advanced metering functionalities. Cloud computing, on the other hand, has security, privacy, delay and cost issues. Fog computation is fast emerging as an alternative to strike a balance between the cloud and the edge. While edge computers might be too constrained for traditional cloud-centric functionalities, these devices still possess computation and communication resources that might be under-used for edge metering functionalities. The fog computing model uses edge resources and executes some of the functionalities attributed to cloud computing, reducing costs and communication benefits while providing benefits such as security, privacy, reduced latency and costs.

The fog computing model uses edge nodes for performing more extensive tasks than are possible using simple edge computation. Several edge nodes are grouped together and controlled via a single master server. The server aptly called a fog server, manages data storage, distribution, distributed processing and visualization. By coordinating a set of nodes for external sources, greater control and metering functionality could be achieved. This model also is resilient to attacks and latency.

This model has been used for federated learning to incorporate non-intrusive load monitoring-based metering of appliance load, power quality metering for neighborhood area electrical networks, theft metering, synchronous phase metering for fault detection and load metering for behavior analysis etc.

The above-mentioned computation paradigms are used for the processing of the generated data from the smart meters. In this regard, **Table 3** shows the literature review related to the smart meter data and applications at edge, fog, and cloud levels. The specific use of a particular paradigm depends upon the application. The quality of energy services is increased thanks to the disposal of a sizable amount of smart meter data and computing resources at various levels, which allows for the optimization of energy efficiency and maintenance of the stability and dependability of a smart grid using advanced metering algorithms available at different levels of energy grid and computational stacks. For instance, a variety of smart meter applications, such as electric load monitoring and anomaly detection of electric power, have been developed using the resources discussed above to create effective smart grids.

IV. AI FOR SMART METER ANALYTICS

While the computational load is spread across the modern IoT stack the key enabler for the application of such huge data is artificial intelligence(AI). AI is the driving force behind the modern Data revolution and is extensively involved in smart grid and smart metering functionality. Modern AI uses technologies like neural networks and machine learning enabling autonomous intelligence and allowing machines to comprehend and act on data independent of human intelligence. AI is one of the most promising technologies of the modern information revolution besides communications and computing. AI is being used as the main technology in many modern technological fields, and smart energy, consequently metering, is one of them. The primary source of the staggering amount of high-dimensional, multi-type data about smart grids is smart meters implemented at different levels. With so many benefits offered by AI, this data offers an incredible chance for smart energy to scale up to global challenges. AI allows rapid and precise decision-making in diverse scenarios and allows smart meters to derive and sense parameters beyond the ones sensed directly.

AI for smart energy and smart metering lists various case studies and techniques. Modern AI implementations are usually categorized as supervised and unsupervised learning. Supervised learning uses labeled data to train the inference engine and includes deep learning, neural network, classification, and regression techniques. Convolutional neural networks (CNN), recurrent neural networks, autoencoders and deep belief networks are some of the popular deep learning methods. Popular neural networks include extreme learning machines, back-propagation neural networks, multilayer perceptron and probabilistic neural networks. Classification techniques include, among others, support vector machines, nearest neighborhood method, decision trees and logistic regression. Finally, regression techniques include linear, Gaussian and support vector regression and multivariate adaptive regression splines etc. Unsupervised learning automatically detects patterns in the underlying data but cannot learn a label for the patterns. Unsupervised learning can use neural networks, such as relevance vector machines, variational autoencoders, clustering techniques, such as K-means, hierarchical clustering etc., and dimensionality reduction techniques, such as principal component analysis, linear generalized discriminant analysis and non-negative matrix factorization. Besides supervised and unsupervised learning techniques, the current AI system uses reinforcement learning such as deep-Q networks, generative adversarial

TABLE 4. AI techniques for smart meters.

Ref	Aim	Methodology	Results
[72]	Load forecasting by correlating lower distinctive categorical levels (season and day of the week) and weather parameters	Random forest regression, k-nearest neighbor regression, linear regression	Mean absolute percentage error (0.86), short-term/long-term load prediction
[73]	Anomaly detection for power system forecasting, mitigating the risk of data corruption and improving forecasting performance	Variable Auto-encoder	Mean absolute percentage error (0.85), F-Score (0.58)
[74]	High-accuracy phase identification method single-phase meters in low-voltage distribution networks using time sequence voltage data	Principal component analysis, k-nearest neighbor regression, non-negative matrix factorization	Correlation Analysis (0.97), PCA+CKM (0.97) and NMF+Label Propagation (1)
[75]	Effectively address non-technical losses and electricity theft challenges in electric distribution utilities	Random forest regression, convolutional neural networks	
[76]	Cyber intrusion protection system for Advanced Metering Infrastructures, employing SVM-based intrusion detection and TFPG analysis to identify cyber attacks	Support vector machine	NN (MLP) (0.982), SVM (RBF) (0.987)
[77]	Prediction of voltage distribution in Low-Voltage networks with partial smart meter coverage, addressing challenges arising from incomplete data and privacy restrictions	Deep learning neural network	Identification of key customer connection points
[78]	Highly accurate fault detection, classification, characterization, and location within smart grids, achieving a precision rate of 99.9	Fuzzy logic, neural networks	ANFIS model for fault detection (0.99)
[79]	Develop an advanced model-agnostic framework for theft detection in smart grids, improving accuracy and practical aspects of detection.	Gradient Boosting Machine	OPF (0.9), NN (0.53), SVM (Gauss) (0.89), SVM (Linear) (0.45), Decision Tree (0.99)

networks and deep enforcement learning etc., and ensemble methods such as bagging, boosting and stacking, as well.

These methods have been used in power quality metering to detect in-stability and faults, phase metering for detecting irregularities in power flow, waveform monitoring for fault classification, asset monitoring, preventive maintenance, synchronous phase metering for fault location, load metering for power flow assessments, load prediction, storage calculations, power factor metering for frequency dis-balance detection, consumption metering for detecting consumer. patterns, nontechnical losses, and line parameters [80]. A brief overview is presented for AI use cases in the following passage.

An auto-encoder (convolutional sparse) is described in [81] for the detection of faults and classification in transmission lines. The transformation of high dimensional data into low dimensional known as dimensional reduction plays a crucial role in smart meter data which often contains redundant features. Smart meters are poised to independently manage energy consumption, interact with households and suppliers, and enhance the quality of the power supply using AI algorithms soon [82]. A thorough analysis of potential AI methods that can be applied to smart metering in numerous applications is also provided [83]. Machine learning on smart meter data is a classification of nonresidential power flow metering [84]. Non-technical load (NTL) detection using a smart meter is reported in [85] which implements SVM on multiple meters' data for triangulation. While collecting smart meter data, missing values are commonplace, leading to errors in downstream functions. An algorithm to impute the missing values using autoencoders for smart metering is reported in [86]. A high-resolution metering data reconstruction framework using CNN is proposed in [87]. Anomaly detection method for smart metering data use clustering and support vector machine is reported in [88]. With increasing capabilities of AI and availability of behavior detection datasets and algorithms, privacy is a growing concern in energy metering application. The electricity consumption data could be used to detect the activities [89] possibly for malicious intent. A privacy boundary detector is designed in [90] using AI techniques. Moreover, **Table 4** lists down some of the most important AI techniques utilized in smart meters showcasing results from advanced AI implementations with the normalized accuracy provided in the brackets.

Authors in [91] reported a game theoretic AI approach to determine amount and content of the data that can be shared with the grid. Authors in [92] used adversarial machine learning to avoid occupancy detection AI for preserving privacy. On the other hand, consumption data can be used by authorized entities for beneficial usage of activity detection. Authors in [93] used AI-based algorithms on smart meter data to detect frailty in the elderly population. An overview of health applications using smart sensor data, including smart meters, using AI frameworks is provided in [94]. In case of cyber-attacks, smart meters can become effected and remain effected even after the attack. An AI-based method using extreme learning machines is proposed in [95] to detect the effected meters by comparing the power measurements with predicted power measurements. The tampering detection algorithm for smart meters using decision trees is reported in [96]. Federated learning is novel AI technique that uses distributed learning paradigm minimizing the data that needs to be shared with the network allowing greater privacy. A federated learning based instruction detection for smart meters is reported in [97]. Fault detection using deep belief networks using smart metering data is reported in [98]. Smart meters can generate large volumes of data that can be difficult to analyze. Singular value decomposition is employed to extract patterns from sparse measurements of power meters in [99], which can be used in intelligent decision making. Smart meter intelligence opportunities for greener homes is an important avenue with great prospects. Such possibilities in terms of smart homes is discussed in [100]. Short term load forecasting can be used for load management for peak consumption scheduling in buildings. Gradient boosting regression trees (GBRT), support vector regression (SVR), feed forward neural networks (FFNN) and long short term memory networks (LSTM) are used for future energy consumption metering in [101]. In co-generation model power metering predictions, using AI tools, are used to optimize the energy mix in [28]. Authors in [102] have used knowledge discovery protocols based AI to incrementally perform pattern metering of consumption data from smart meters. Kernel SVM based consumption cluster metering using smart meter data is reported in [103]. A reinforcement learning based pricing engine for smart meters is developed in [104]. A comprehensive review of application of advanced AI techniques like reinforcement learning, deep learning and deep reinforcement learning in smart grid, including smart metering, is given in [105].

V. APPLICATIONS OF SMART METERS

In previous sections we have reviewed data measurements, computations and processing by various smart meter technologies. This section reviews the different application domains enabled by the combination of sensing and processing empowered by smart meters. Smart meters are employed in several smart domain applications because of their high level of measurement accuracy and capacity to multitask. They are capable of measuring both electrical and non-electrical variables for example temperature, pressure, water and gas consumption, etc., in addition to energy [106]. They have the potential to help with energy conservation and efficiency efforts. The primary benefit of smart meters is that they may help with energy efficiency conservation. Following are the applications of smart meters.

A. ELECTRIC LOAD FORECASTING

For power systems to operate economically, safely, and reliably, electric load forecasting is crucial [107]. Traditionally, system-level information (e.g., total power consumption, weather conditions, or economic indicators) has been utilized to anticipate load, while lower-level (e.g., substation, transformer, or household levels) power consumption characteristics have not been reported. Utilizing high voltage data for load forecasting is a common practice among both researchers and industrialists, as found in studies such as [108], [109], and [110]. On the contrary, the use of information from smart meters was previously limited due to a lack of available household data, as reported in [111] and [112]. Smart meters, due to their location at the point of consumption, can be grouped together in various ways using different criteria or shared characteristics examples of which include the geographical location of the meters, the type of connection they have, or their association with a specific service category [113]. This allows for a more in-depth analysis of power consumption patterns and helps utilities and system operators make more informed decisions about generation, transmission, and distribution.

Incorporating lower-level data, such as smart meter data, into electric load forecasting models can provide a more detailed and accurate picture of power consumption patterns. This allows for a more in-depth analysis of power consumption and can help utilities and system operators make more informed decisions about generation, transmission, and distribution. This type of data can be used to improve the accuracy of very-short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF) and long-term load forecasting (LTLF), as described in [111], [114], [115], [116], and [117], which correspond to hourly, single-day, monthly and annually predicting load respectively and support the evolution of an electric power system's power-generating planning. **Figure 5** is a pictorial depiction of how data is utilized for forecasting in the above described scenario.The addition of AMI data gives load forecasting for the aforementioned categories at many levels,

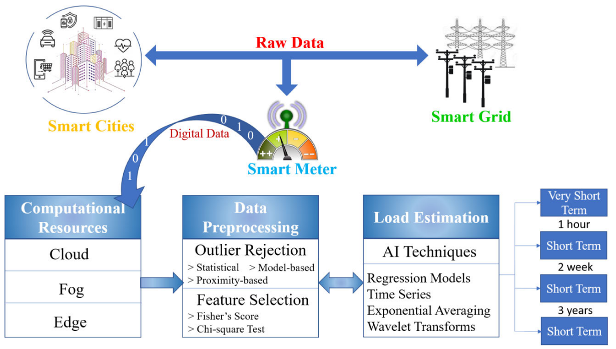

FIGURE 4. **Electric load forecasting. Raw data is collected by smart meters from smart cities and grids. The digital data is then preprocessed through different techniques two of which are mentioned. The processed data is then sent to the compute resources where different AI techniques are utilized for data preprocessing and processing to estimate the load.**

including system, feeder, and even customer level, a new perspective.

The utilization of various techniques, including univariate methods, as described in [114], is necessary to effectively forecast electric load using the data provided by Advanced Metering Infrastructure (AMI) and to improve the accuracy and reliability of load forecasting models. Utilizing distinct neural networks (NNs) to load data that had been wavelet decomposed, [118] combined the data to create a final forecast consisting of the prediction of loads 1 hour in the future in 5-minute stages in a moving window fashion. Regression models, exponential averaging, weighted repetition, and other sophisticated methods like stochastic time series and adaptive prediction have all been used for forecasting electric load. Neural networks and genetic analysis have also been extensively used for the forecasting of electric load. A technique for estimating electric load that incorporated selection and manipulation of weather parameters with fuzzy polynomial regression, which enhances short-term load forecasting's precision and efficiency, is proposed in [119]. Past data from readings from smart meters was used in [120] to train a neural network to forecast the present electric load. Energy providers and operators of the distribution system can utilize the forecasting model to create the best power distribution plans. A hybrid prediction method for forecasting electric load utilizing wavelet transform and a neural adaptive model is suggested in [121]. Smart meters have gathered a significant amount of reliable data that serves as the basis for projecting energy load. However, it is quite challenging to directly forecast electric load using high-dimensional smart meter data. Additionally, customer grouping is the foundation of load profiling, but clustering such high dimensional data has its challenges as described in [122], necessitating the compression of big data from smart meters to reduce dimensionality.

While machine learning techniques, as discussed in studies such as [123], [124], [125], and [126], have achieved high accuracy in load forecasting, it's worth noting that there's a growing need to optimize these models, especially when dealing with a large number of smart meters. In this context, researchers have also explored innovative approaches like federated learning and shared machine learning frameworks, as introduced in [127], to tackle these challenges.

Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN) as mentioned earlier, has gained significant traction in the field of electric load forecasting. Its ability to capture long-term dependencies and intricate patterns in time series data has made it a popular choice. Researchers have explored LSTM-based models to predict electrical load demand, and several notable studies stand out: In reference [128], the authors introduce a short-term load forecasting method utilizing LSTM-based RNNs with historical load data as inputs. This approach has shown promise in accurately predicting load demand for shorter time horizons. In another study discussed in reference [129], researchers delve into an LSTM-based sequence-to-sequence (S2S) architecture for load forecasting. They compare the results with a standard LSTM-based approach and find that the S2S architecture outperforms when forecasting high-resolution load data. Reference [130] presents a unique approach by combining Feedforward Neural Networks (FFNN) with LSTM-based RNNs for load forecasting. This hybrid method aims to leverage the strengths of both techniques to improve accuracy. In a different vein, reference [131] introduces a load forecasting technique centered around LSTM-RNNs. The authors compare its accuracy with Support Vector Regression (SVR)-based load forecasting and find that the LSTM-RNN approach excels in forecasting electrical loads using only historical load data as input. Machine Learning (ML) methods extend beyond load forecasting. In reference [132], authors present a robust framework that explores various LSTM-based deep neural networks. Their research demonstrates that deep neural networks can effectively forecast electrical loads in different commercial buildings, regardless of their geographical location. To anticipate load, the Sequence-to-Sequence Recurrent Neural Network (S2S-RNN) with an attention mechanism is presented. Similar to the approach used in [24], which also uses S2S-RNN to scale the process of forecasting load for several smart meters, the Similarity-Based Chained Transfer Learning (SBCTL) is proposed in [26].

B. DEMAND SIDE MANAGEMENT (DSM)

DSM optimizes power consumption and encourages customers to utilize reduced electricity around prime time and more electricity during the off-prime time. Targeting its three distinct types-energy efficiency, DR, and strategic load growth-is the main goal of this application. The work is accomplished using a variety of techniques, as indicated in **Figure 6**.

Utilizing techniques and strategies, DSM aims at managing and reducing electricity consumption [133]. This is achieved by actively engaging and empowering consumers to make changes in their energy usage patterns through the use

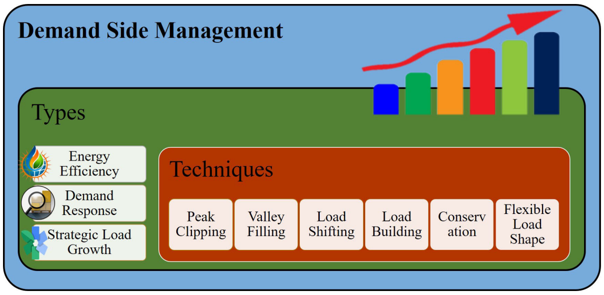

FIGURE 5. The categories and DSM-related procedures. There are three different DSM types' energy efficiency, DR, and strategic load growth. Moreover, various technologies related to DSM are also demonstrated.

of incentives, pricing mechanisms, and other techniques. Different pricing schemes and incentives are the main topics of the most recent DSM research [134] including Time of use (TOU) price, spot price, and crucial peak price, day-ahead price. Depending on when you use electricity, TOU pricing will charge you a different amount. The cost of electricity rises as the load grows. DSM encourages customers to use power during times when the grid is not at peak demand, hence lowering peak loads. The best pricing scheme for electricity systems is thought to be spot pricing. Based on supply and demand, utilities adjust energy prices in real-time to encourage customers to utilize electricity during times of reduced demand. Peak load reduction can be combined with peak load shifting. If used fairly, it keeps the grid stable while saving users money on their electricity bills [135]. Critical peak pricing represents short-term market costs and is based on TOU tariffs plus a spike rate [136]. All supply and demand bids are examined to determine the day-ahead price [137]. For financial markets, supply is then chosen from the maximum supply bid, and demand is chosen from the minimum demand bid. It is applied for the charging and discharging synchronization. A decentralized system is suggested by [138] to efficiently manage electric vehicle charging and disposal (EV). Customers adjust their charging and discharging schedules in response to changing prices over time, which helps them save money on their electricity bills and maintains the distribution network's working limits.

Mixed integer linear programming (MILP) is utilized in [139] to address the issue of household DR. Renewable energy sources with electric storage systems are also discussed in terms of the benefits provided to the demand side management. The development of HEMS to establish the optimum load schedule is discussed in [140]. Under DAP, DR is used to optimize load-shaping and lower customer power bills. In terms of incentive programs, users receive rewards when they follow the rules set forth by electricity companies. Different types of incentives have been suggested, such as the use of discount vouchers [141]. Smart meter monitoring has been widely used to assess customer DR in connection to this type of DSM strategy [142]. DSM can support users in taking an effort to improve their usage patterns by encouraging and assisting them. It helps the EPS be more dependable and stable. Demand Side Management is based on the notion that power providers can predict how much electricity users will require at a specific moment by utilizing vast amounts of data from smart meters.

Load scheduling is a key concept for DSM and plays a vital role in its implementation to manage load according to demand at different times. Many optimization techniques are developed for its implementation. The proposed HEMS (Home Energy Management System) based on DR (Demand Response) in [143] aims to reduce household electricity bills while enhancing user comfort in the domestic sector. Applications of inclination block rate (IBR) systems and ToU for pricing are ensured through the proper scheduling of households. Domestic appliances' scheduling is optimized using interval number optimization by categorizing different appliances, as proposed in [144]. A method for household power scheduling to synchronize appliances and decentralized energy supplies is presented in [145]. To reduce daily energy usage, [146] employs Automated Demand Response and utilizes mixed integer non-linear programming to solve the price reduction problem. The possibility of energy trading, where surplus energy can be sold by the utilizer to others, is discussed in [147]. The exchange of energy and load scheduling was discussed. DSM through peak clipping is discussed in [148]. The authors suggest a smart meter and describe the method for implementation in which, after exceeding the designated use of peak hour needs, the smart meter generates a warning before eventually cutting off or turning off the power supply for one minute. Artificial neural networks were used as implementation algorithms.

C. ELECTRICITY THEFT DETECTION

Smart meters have improved the frequency of data collection on domestic energy use, enabling effective detection of energy theft through modern data analysis. To find criminal activity, data manipulation, and tampering, smart meter data on electricity use can be collected and examined.

As described by [149], there are four major categories of smart grid energy theft detection classification-based, neural network-based, ensemble learning-based, and statistical techniques based. Different types of classifiers have been used such as support vector machines [150], [151], [152], which use a collection of mathematical operations to implicitly map clients with specific features into large-scale spaces. Class imbalance and inconsistent information in smart meter data are addressed using a classification technique based on deep neural networks [153]. To categorize the clients into truthful or dishonest classifications, a mix of CNN and a particle swarm optimization-gated recurrent unit model is given in [154]. Long short-term memory NN is utilized along with the concept drift process to develop contextual anomaly detection technique as proposed in [155].

Regarding ensemble machine learning models, a concept related to meta-algorithms is utilized to detect energy theft as done in [156]. For real-time fraud monitoring in smart grids, an algorithm that uses three different LSTM

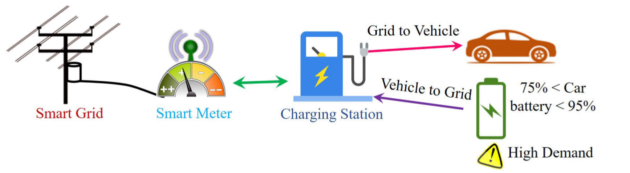

FIGURE 6. Electricity from the grid is provided to the charging station through a smart meter. Keeping the track of the utilized energy by EVs also helps provide electricity to the grids when there is a high demand for batteries of EVs when fully charged.

techniques namely, ST-Links, AlexNet, and peephole is designed in [157]. An algorithm aimed to detect theft on the transformer level using the combination of the autoencoder, gate recurrent units, and feed-forward NN is proposed in [158].Higher-order statistics of electric usage patterns are utilized by [159] to identify theft. Multiple pricing schemes for hidden electric theft attacks were used to propose a novel algorithm [160]. Along with the aforementioned techniques, statistical inferences are used to analyse electric theft such as Bayesian models, Markov Models, Bollinger bands, Pearson correlation coefficient, Kullback-Leibler divergence, and Likelihood ratio as described in [161].

Anomaly detection is essential for preventing financial losses and securing consumers' data on electricity use [162]. Smart meters frequently feature built-in advanced sensors that, in the event of a power outage, may transmit problem info to the issue management platform. To pinpoint the reasons and places of defects, spatial data, meteorological data, and place of failure data can all be employed. If many grid failures are occurring simultaneously, it can be determined through communication between the Energy meter and controllers.

D. ELECTRIC VEHICLES AND SMART METERS

Due to numerous programs aimed at electrifying transportation, the adoption of electric vehicles (EVs) has risen quickly. Additionally, EVs and distributed solar photovoltaic (PV) systems are becoming more popular among customers. Pollutants from gasoline-powered vehicles can be reduced and greenhouse gas emissions can be mitigated through the widespread adoption of EVs and a cleaner electric grid. Less fossil fuel-generated electricity will be needed if EVs can charge using renewable solar energy.

Many studies concentrate on this application and how smart meter data may help electric vehicles. A probabilistic approach for fusing data from electric vehicles and smart meters to analyse the implications on the distribution system is proposed in [163]. Different EV charging patterns show that, as discussed in [164] and [165], they proved to be harmful to dispersed systems. Therefore, important insights about the impact on the distribution network were discovered together with the smart meter data. Using data from smart meters to examine how adding distributed solar panels to homes affects how much electricity EV owners use from the power grid is described in [166].

Moreover, as discussed in [167], the infrastructure development of electric vehicle charging systems with smart meters having features such as digital payment systems and connection to the internet is proposed. Other than the infrastructure, an algorithmic perspective is provided in [168]. Electric vehicles can also integrate with smart grids with the implementation of one of the applications through the smart meters as mentioned in [169]. Emphasis is laid upon the benefits involved with the integration of smart grids and EV charging points. Smart meter utilization for optimizing the speed of the charging EV according to the overall electricity consumption of the appliance in the house [170]. The concept of integration of EV with the smart grid is depicted in **Figure 7**, where not only the device is consuming electricity from the grid but at the time of high demand and with sufficient battery charged it can provide electricity to the grid using the smart meters, the concept named as Vehicle to Grid (V2G) [171].

E. LOW-VOLTAGE (LV) NETWORKS

Carrying electricity from distribution transformers to final clients is what this network of electric power distribution is all about. It supplies the primary voltages to the end electric appliances used in home settings while operating at low voltage. Depending on the country, two popular AC-rated voltages are 100-127 V and 220-240 V, with frequencies of 50 Hz and 60 Hz, respectively. This network has several topologies and configurations depending on the necessary dependability, the number of phases, and the operating voltages. Smart meters can be helpful in this area since their data can be analyzed to create LV Network models that are helpful for phase balancing and network planning along with many others.

Numerous studies have been conducted on utilizing smart meter data for finding different topologies of low-voltage networks, as proposed in [172] and [173]. A solution for real-time LV-Network monitoring by integrating measurements from secondary substations and smart meters data for a more realistic view of the LV network is proposed by [163]. An algorithm for identifying the topology of LV networks when the customers are not equipped with smart meters, referred to as nodes, is proposed by [174] and [175] and further verified by evaluating its performance on several customers with or without smart meters. Wavelet reduction-based clustering is suggested by [176] to accurately categorize clients. A model that builds the LV system while removing load distortion, or the variation in voltage from the feeder to the smart meter at the connecting point, is proposed by [177]. The information from smart meters is used by [178], [179], and [180] to establish secondary distributed factors.

Optimization techniques for estimating connection in phase and network architecture using time series of power measurements are discussed in [181]. For the secondary circuit architecture and parameterization of radial distribution systems, [182] proposes a useful and computationally

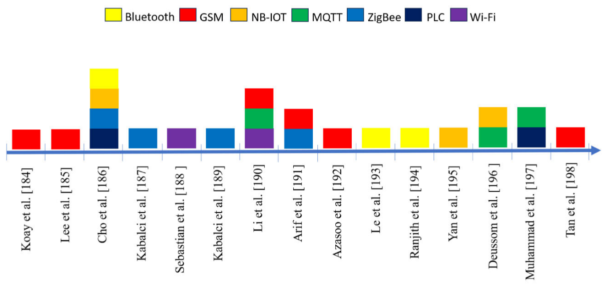

FIGURE 7. Internet protocols reported in smart meters.

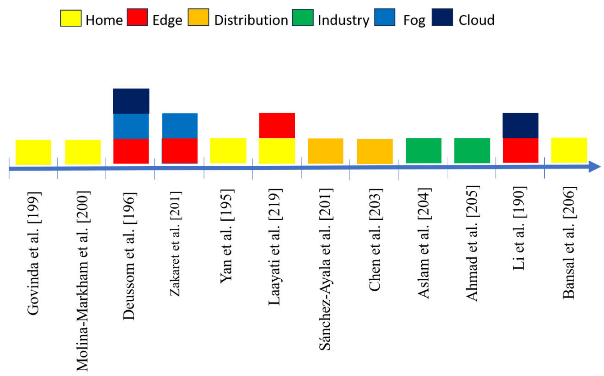

FIGURE 8. Locations reported in the literature where the smart meters are deployed.

effective technique. This investigation also confirms if the topologies of the two secondary circuits are the same.

VI. SMART METER IMPLEMENTATIONS

The paper provides a comprehensive overview of different techniques used in smart meter analytics, various topologies for data processing and analytics, and the wide range of applications enabled by smart meters in the energy sector. It emphasizes the potential of AI and machine learning algorithms in harnessing the rich data from smart meters to optimize energy management, improve efficiency, and enhance grid operations. This section reviews different implementations of the smart meter reported in the literature and compares them across the different characteristics reviewed in different sections.

The smart meter has been applied and reported on in a variety of methods, some of which were covered in the section above. Highlighting the uses and situations that smart meters can benefit from in the previous section, we shift our focus to the deployment of smart meters in different locations, exploring the innovative ways they are utilized based on factors such as usage locations, internet protocol usage, deployment locations, and measurements taken. By examining these aspects, we aim to highlight the diverse and creative applications of smart meters across various scenarios.

Although there are numerous measurement techniques employed in industry to guarantee the robustness of a smart meter, these approaches are typically not discussed in the literature, therefore in this case, we are focusing on those that are. The following discussion is based on the literatures [53], [183], [184], [185], [186], [187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200], [201], [202], [203], [204], [205], [206], [207], [208], [209], [210], [211], [212], [213], [214], [215], [216], and [217] that we have completed for this purpose and in relation to the other categories.

A. INTERNET PROTOCOL LANDSCAPE

The plot in **Figure 7** illustrates the protocols utilized by smart meters as reported in the paper. The analysis reveals that the majority of smart meters are equipped with a single protocol. However, modern smart meters have multifaceted functionalities that necessitate communication at various levels, including device level, local area, and wide area communication. At the device level, smart meters employ internal communication to facilitate their primary function of accurately measuring and monitoring energy usage. This enables the meter to gather data and perform calculations for billing and other purposes. Local area communication pertains to interactions within a specific location, such as a home or building. In this context, smart meters establish connections with in-home displays and home energy management systems. This enables consumers to access real-time information about their energy usage, set energy-saving preferences, and receive alerts and notifications regarding their consumption. On the other hand, wide-area communication is crucial for establishing connections with utility or energy provider systems. Through this form of communication, smart meters can transmit energy consumption data, receive instructions for load management, and contribute to overall grid management and control. It is important to note that each level of communication requires specific protocols to enable seamless and efficient data exchange. While the figure highlights that most reported smart meters utilize a single protocol, it is evident that modern smart meters possess the capability to support multiple communication protocols. By employing different protocols at each level of communication, smart meters can effectively collect, transmit, and receive data, facilitating better energy management, improved customer engagement, and enhanced grid operation. The integration of multiple protocols empowers smart meters to connect with diverse systems and devices, enabling a wide range of functionalities and interactions within the energy ecosystem

B. SMART METER ROLLOUT LOCATIONS

Different locations of smart meters have been reported in multiple papers, as depicted in **Figure 8**. The analysis reveals that the majority of reported smart meters are installed in residential homes. However, smart meters can be deployed in various locations within the energy infrastructure, including the edge, industry, distribution, fog, or cloud environments. Distribution-level smart meters are reported

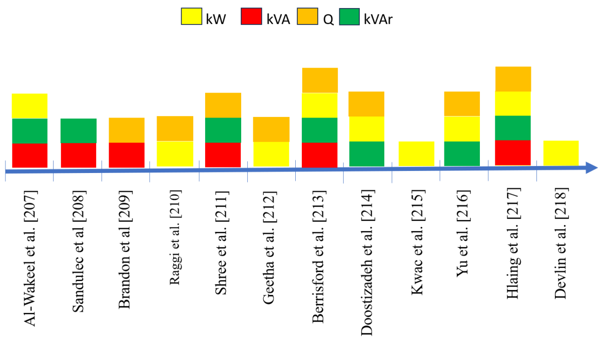

FIGURE 9. Measurement quantities reported for smart meters.

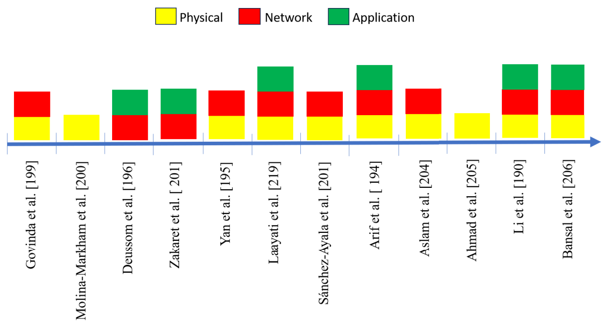

FIGURE 10. Smart meters reported at different application layers in the literature.

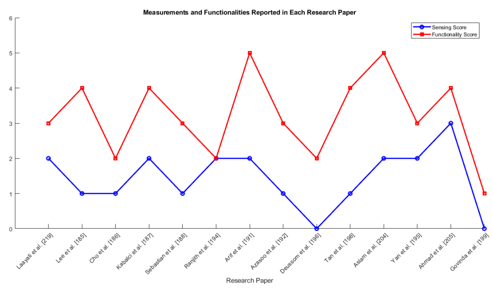

FIGURE 11. The graph rates different research papers on the reported measurements and functionalities of the smart meters according to the depth and width covered in them.

that are positioned throughout the electricity distribution network, typically at substations. These meters aid in grid monitoring, fault detection, and system optimization. Fog and cloud-based smart meters offer scalability, data aggregation capabilities, and advanced analytics for large-scale energy management applications. Each location of smart meters brings unique benefits and serves specific purposes within the energy ecosystem. The choice of deployment depends on the specific use case, objectives, and requirements of the energy management system. By strategically situating smart meters in various locations, stakeholders can gather comprehensive data, optimize energy usage, enhance grid performance, and enable effective energy management across different domains.

C. DATA METRICS CAPTURED BY SMART METERS

Most of the measurements recorded by smart meters that are commonly discussed in the literature primarily focus on simple domestic meters, which typically provide basic measurements such as active power, reactive power, and apparent power as shown in **Figure 9**. However, as smart grid technology advances, modern smart meters are designed to encompass more sophisticated sensing techniques across various network strata. These advanced sensing techniques in modern smart meters enable the collection of a wide range of measurements that provide a deeper understanding of the electrical system. Some of the notable techniques include Phase and Magnitude, Synchro-Phasor, Relative Phase Angle, Voltage Harmonics, and Crest Factor [106]. These are just a few examples of the advanced sensing techniques that modern smart meters are capable of. While discussions and implementations of these advanced techniques may be relatively sparse in comparison to the more common domestic meter techniques, they are gaining increasing attention as researchers and practitioners recognize their potential for enhancing grid operations, improving power quality, and enabling more advanced analytics and control strategies.

D. SMART METER APPLICATIONS ACROSS VARIOUS LAYERS

Figure 10 shows the multidisciplinary nature of the function that smart meters play. On a physical level, it concerns the hardware elements that serve as their foundation for communication and data transfer. The metering device itself, sensors, communication connections, and physical wiring are only a few of the components. The precise measurements of energy use are made by this layer. Smart meters and other devices inside a network may communicate with one another more easily thanks to the network layer. It manages the transmission and routing of data packets among devices. This layer makes sure that data is sent between linked devices like smart meters securely and reliably. The interface between smart meters and higher-level systems is controlled by the application layer. including various APIs and protocols that allow for the processing of data, analytics, and interaction with energy management systems. The review of the literature indicated in the figure that there are different roles of smart meters being reported. Most frequently reported is a complete smart meter package that details each layer and how it functions within the application.

The realm of smart meter implementation studies reveals a captivating tapestry of diverse measurements and functionalities showcased in research papers. Each study unravels a unique thread, with some papers focusing on conducting an extensive array of measurements, graphically depicting the sensing score, while others delve deep into specific functionalities or explore intricate scenarios. This rich variation not only illustrates the vastness of research in the field of smart meters but also showcases the ingenuity of researchers in investigating this technology.

Within this **Figure 11**, the functionality score serves as a compass, guiding readers through the intricacies of each publication. A functionality score of 5 signifies a remarkable smart meter, encompassing a multitude of measurements, protocol stacks, and locations, and revealing its operational prowess across various layers. As the functionality score ascends, so does the magnificence of the smart meter under scrutiny, painting a picture of cutting-edge advancements and extraordinary capabilities.

These varying facets of smart meter research weave a captivating narrative, inviting readers on a journey of exploration and innovation. With every study, the boundaries of knowledge are pushed further, illuminating the limitless possibilities and inspiring the quest for smarter, more advanced metering technologies.

VII. CONCLUSION

The future of smart meter analytics holds immense promise with the convergence of cutting-edge technologies. Smart meters provide utilities the ability to more accurately assess and anticipate consumer behavior, which may help utilities make better decisions and operate more efficiently. Generative AI, integrated into computational stacks, will revolutionize data analysis through predictive modeling and anomaly detection, extracting actionable insights from the massive volumes of data generated by smart meters. This will allow utilities to optimize energy distribution and enhance grid resilience. Additionally, pricing model optimization and resource planning improvements may be made using the data gathered by smart meters. Simultaneously, advanced data collection methods will ensure the seamless flow of information from these devices, enabling real-time monitoring and grid management. New network protocols will underpin this ecosystem, ensuring secure and efficient data transfer. Innovative distribution techniques will further streamline the deployment of smart meters, making them more scalable and reliable than ever before. The many applications that are now in use are examined, forming the cornerstone of business intelligence in the energy sector. Together, these advancements promise a future where the smart grid is not just an energy distribution system but a dynamic and responsive energy ecosystem.

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