# A Review of Smart Meter Data Analytics for Distribution Network Applications

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***Abstract*—As digital transformation progresses, smart meters with enhanced monitoring and communication capabilities gradually replace the old-generation metering infrastructure. Their large-scale deployment enables innovative and advanced data-driven services. In this paper, an overview of the state-of-the-art of distribution network-oriented applications using smart meter data is conducted. The most recent developments are summarized and discussed with a focus on six key areas, i.e., load forecasting, non-technical losses, asset management, power system planning, topology identification, and power system operational analysis. It is expected that the taxonomy and the associated applications, as evaluated and discussed in this work, will assist utilities, service providers, and distribution system operators to identify future technological trends regarding the utilization of smart meter data.**

***Index Terms*—Data analytics, distribution networks, smart meters.**

## I. Introduction

Digitalization is nowadays emerging as a necessity for energy utilities and companies globally. One of the most important milestones of this transformation is the extensive smart meter (SM) roll-out. For example, the numbers of SMs installed in the U.S. and China reached by the end of 2016 70 million, and 96 million, respectively, [1]. At its first step, SM technology was deemed useful solely for automatic readings by the energy provider aiming to facilitate accurate billing and reduce labor costs of on-site visits. However, since SMs can generate and communicate various kinds of energy data between the consumer and the energy provider at much more fine-grained spatial and temporal resolutions, the benefits are numerous for all energy stakeholders, e.g., operators, retailers, consumers, and aggregators. In particular, distribution system operators (DSOs) and utilities have access to more data and information from thousands of internet-of-things (IoT) endpoints within the smart grid (SG) creating new opportunities for energy services and data-driven business models, e.g., non-intrusive load monitoring (NILM), grid operation and maintenance, fault detection, detection of non-technical losses (NTLs), and load forecasting [2].

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In the literature, there is a significant number of research activities accompanying the global SM roll-out, seeking to exploit and create value from the collected data to the fullest extent through SM data analytics [3], [4]. According to [1], in recent years, there is a vast number of funded projects on SM data analytics worldwide. However, most academic works are end-user-oriented [3] or conduct generic analysis on various SM use cases [1], [4]. Unlike these works, in this paper, a comprehensive overview is conducted regarding the new applications being enabled by the use of SM data from the distribution network (DN) perspective. Based on the outcome of the literature review, the various applications are grouped into six key categories, namely, load forecasting, NTL detection, asset management, power system planning, topology identification, and power system operation and analysis, as depicted in Fig. 1.

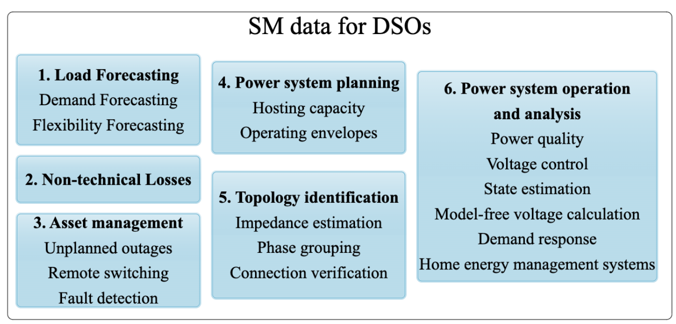


Fig. 1. Taxonomy of SM data analytics for DSOs.

## II. Load Forecasting

### A. Demand Forecasting

Demand forecasting is one of the most useful tools in modern power systems. To support the production-demand equilibrium, energy participants, such as balance-responsible parties, rely significantly on short-term demand forecasting. DSOs use forecasts at the feeder level to support operations and planning processes, and at the same time, electricity providers can make more educated decisions about pricing, procurement, and hedging based on knowledge of their customers' future needs [1].



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Aggregated forecasting on the substation level has been extensively researched in the literature [5]. However, fine-grained SM and demographic data can be utilized to improve the forecasts of aggregated models by extracting valuable information from clusters of households with similar characteristics. These characteristics may be demographics, appliance information, household information [6], energy consumption [7] and geographical location [8]. Once the clusters are formed, multiple cluster-specific forecasting models are employed using SM consumption, weather, and calendar data. Eventually, the forecasts are aggregated to form the substation-level forecast.

### B. Demand Flexibility Forecasting

With the evolution of the SG, demand response (DR) has been envisioned as one of the potentially cost-effective options for operating the power system. SMs unlock new opportunities for residential DR. For example, high-granular SM data can provide advanced end-user behavior profiling with regard to the usage of individual appliances [9].

In this context, the DR potential, i.e., flexibility, of an aggregated group of residential users is quantified and analyzed in [9]. Several households own SMs with sub-metering capabilities meaning that measurements of specific appliances are available. All monitored appliances are grouped into controllable and uncontrollable loads; controllable loads are related to space/water heating and laundry activities. An artificial neural network (ANN) is trained to calculate the participation of controllable loads in the total aggregated consumption of the monitored households. Eventually, the trained model is used for the day-ahead forecast of controllable loads projected to the whole customer base.

## III. Non-technical Losses

NTLs correspond to the non-billed energy injected into the network that is neither measured nor allocated to technical losses (TLs) and may arise from electricity theft, measurement errors, metering faults, etc. The most common source of NTLs is electricity theft which refers to malicious measurement manipulation by consumers or other parties. As NTLs can have a large impact on the optimal operation and management of DNs, their detection is of utmost importance. According to the comprehensive and thorough review of [10], NTL detection techniques can be classified into two main categories, namely data-oriented and network-oriented.

### A. Data-oriented Methods

Data-oriented methods utilize SM and end-user-related data, e.g., personal, spatial, or financial information. They are divided into supervised and unsupervised based on the existence of labels (known positive/fraud and negative/not-fraud classes) or not, respectively. These methods are usually applied on end-user level, characterizing each one independently as fraudulent or not. This is achieved by taking into account various features such as maximum power usable by the client, geographical location of end-user, contract status, and more.

The most common supervised approaches rely on machine learning (ML), deep learning [11]–[14], and fuzzy logic approaches [15]. Additionally, unsupervised methods have been proposed that do not require labeled samples, i.e., datasets with known energy thieves, presenting inferior performance compared to supervised. Such approaches rely on game theory [16] and the expertise of inspectors [17].

### B. Network-oriented Methods

Besides SM data, network-oriented methods utilize additional DN information, e.g., topology and additional measurements from remote terminal units and observer meters, i.e., meters on the secondary side of the medium voltage (MV)/low-voltage (LV) transformer. These methods are based on power flow analysis, state estimation, and sensor placement.

In power flow methods, TLs are initially calculated and subsequently, NTLs are estimated by subtracting TLs from the total losses in the DN [18]. State estimation approaches [19], [20] have been applied to calculate the loading of MV/LV transformers from three-phase voltage, current, active, and reactive power measurements. In case of a mismatch between measured and estimated values, NTLs may be considered. The use of dedicated sensors for detecting fraud is also proposed by comparing the measurements of a sensor with the aggregated measurements of SMs behind the sensor [21].

## IV. Asset Management

Asset management is one of the most important chapters in the operation of power systems. Poor asset management can lead to increased costs and unreliability at the level of production, transmission, and distribution. In this section, three groups of asset management applications using SM data analysis are discussed: outage management, remote switching, and fault detection.

### A. Unplanned Outage Management

An unplanned power outage is defined as an electricity supply failure caused by short circuits, station failure, or distribution line damage [1]. Outage management is the most significant SM data application behind billing. SM can enable automatic outage notifications by last-gasp messages enabling utilities to be informed about outages without the need for sufficient end-user calls. Moreover, SMs allow outage confirmation, i.e., verifying that there is an actual outage and not single light-out problems, and restoration verification.

Several works in the literature focus on identifying the outage location. The basic idea in [22] is the usage of multiple SMs in a neighborhood. For a single service outage, neighbor meters should operate normally. However, all meters can not transfer metering data in case of a mass power outage. In [23], additional measuring devices at the lines of the DN are considered. Given the DN tree structure, an outage detection method is developed by combining the use of real-time power flow measurements on the edges with load forecasts at the nodes.

The large-scale penetration of distributed renewable energy sources (DRESs) in DNs is considered in [24]. According to the authors, outage detection methods relying on end-users' reports and SM last-gasp signals present poor performance since DRESs provide power even during an outage. To this end, a data-driven outage monitoring approach is proposed based on the hypothesis that voltage measurements exhibit significant statistical changes after outages.

### *B. Remote Switching*

Besides remote reading, SM can offer to DSOs the possibility of remote switching. By sending a remote signal to the breaker of the SM, DSOs can connect/disconnect end-users from the grid without the need of on-site personnel [25]. This feature can be cost-efficient reducing labor costs. For example, the DSO can remotely disconnect end-users that have delayed their payments or do not have any contract and reconnect them as problems have been resolved.

In [25], possible future applications are proposed. For example, the DSO can disconnect selected end-users during peak load crises avoiding overloading of the network lines. Moreover, during cases of faults, reinforcement, or upgrading of the network, the DSO needs to disconnect power from the substation, and thus, all end-users under that substation lose power supply. By remote switching, the disconnection of the end-users is easier and it is even possible to supply a portion of the affected ones from other available substations.

### *C. Fault Detection*

SM data can be used to detect and locate specific types of faults. For example, in [26], a high-impedance fault detection method is developed based on the even harmonics present in the high-frequency voltage data of SMs. In [27], inter-turn winding faults in single-phase distribution transformers are detected. Instead of measuring the transformer secondary voltage by sensors, the proposed method uses SM measurements. Results obtained from simulations as well as experimental data show that SM measurements can be utilized to achieve very high detection accuracy while maintaining low costs.

## V. Power System Planning

Power system planning in developing countries has become more difficult due to the ever-increasing penetration of DRESs and electric vehicles (EVs) into LV DN posing unprecedented technical challenges and jeopardizing the reliable operation of power systems. SM can play a pivotal role in aiding DSOs prepare for future challenges and plan their network development. In this section, works focused on PV/EV hosting capacity and operating envelopes [28] are presented.

### *A. Hosting Capacity*

As solar PV penetration continues to grow, technical challenges, such as overvoltage and congestion are expected to occur. To this end, approaches to estimate PV penetration limits for the long-term planning of the power system have been investigated [29]. The extent to which LV DNs can host solar PV is the hosting capacity.

In [29], a SM-driven method is introduced for the fast estimation of the hosting capacity requiring no complex and detailed network studies. Using SM data, a regression model is trained to estimate the additional PV capacity that can be hosted without causing voltages outside an upper limit. In [30], [31], probabilistic tools are used to perform power flow analyses for possible future PV integration scenarios. As long as operational constraints are not exceeded, more PV units are added to the DN. In this way, hosting capacity is determined.

Besides DRESs, EV hosting capacity has also been investigated since the expected increase in peak demand poses significant technical challenges, such as asset congestion or voltage drop issues [32]. The EV hosting capacity is assessed in [32] by exploring multiple EV scenarios and considering their time-varying behavior during the peak demand day.

### *B. Operating Envelopes*

The high penetration of residential DRESs in DNs has enabled households to provide bottom-up services through aggregators. The use of operating envelopes, i.e., individualized, time-varying import/export limits, has been proposed to better facilitate such services while ensuring network integrity and allowing more efficient short-term planning of the DN [33]. The work of [28] proposes a framework for operating envelopes in the presence of prosumers that operate their assets using control schemes outside the self-consumption operation. The prosumer's intended operation is periodically submitted and power flow analysis is performed by the DSO to check for possible operational violations. If any violations occur, dynamic operating limits are imposed on the prosumers.

## VI. Topology Identification

Topology identification and parameter estimation form the basis for the operation and control of the DN with little or no observability. Parameters, such as line impedance, and phase grouping, are necessary for thorough analysis as well as for applied control schemes, e.g., voltage regulation. However, such information is sometimes not known or inaccurate in DNs. Various methods utilizing SM data have been proposed to tackle these issues.

### *A. Impedance Estimation*

To enhance the observability of DNs, several methods focus on impedance estimation of DN lines using SM data. In [34], particle swarm optimization is utilized given the network topology and active/reactive power measurements, whereas in [35], a non-linear and non-convex optimization problem is formed. Decoupled linear power flow equations are formulated in [36] and a total least squares regression method is used. In [37], the impedances of a three-phase LV feeder are determined by assuming the knowledge of additional information, e.g., feeder topology, service cable parameters, etc. Eventually, a multi-linear regression technique is used to exploit historical SM time-series measurements to calculate the self and mutual impedances of an LV feeder segment.

### B. Phase Grouping

Phase grouping is the process of determining the phase connection of end-users to obtain accurate DN models. Several data-driven approaches based on SM data have been introduced.

Mixed-integer programming (MIP) has been widely used. In MIP approaches, optimization problems are formed. Specifically, SM measurements and the distribution transformer supply are required. On the basis of the law of conservation of power the connection phase of each end-user is determined, as the load measured at a feeder level must be equal to the aggregated consumption of all SMs connected to that feeder plus the unmetered load, i.e., street lights, and TLs. The optimization aims to minimize the difference between the total feeder demand and the transformer supply [38], [39].

Voltage measurements are also used for phase grouping. In [40], [41], the Pearson correlation between an end-user's voltage time series and a reference voltage time series, i.e., the voltage of the transformer, is calculated. The end-user is assigned to the reference phase with the highest correlation. A similar approach is followed in [42], but instead of using measurements at the substation downstream, the voltage of a three-phase end-user is used as reference. This avoids using additional measuring devices at the transformer level, but the connection of a three-phase end-user must be known.

### C. Connection Verification

The last topic concerns connection verification and detection of switching actions/reconfigurations based on known topology information that can be obtained through the geographic information system (GIS).

A MIP-based topology identification model is proposed in [43] to determine the topology configuration with weighted least squares (WLS) using active power, reactive power, and voltage measurements at each node. In [44], a generalized state estimation approach for the identification of topology changes is proposed. In [45], an algorithm for correcting connectivity errors in the GIS representation of the DN topology is developed that leverages SM measurements. This algorithm is based on voltage correlation to identify neighboring meters and predict end-users' upstream and downstream locations.

## VII. Power System Operation and Analysis

Operational analysis applications refer to methods of examining and improving the performance of power systems, reducing costs, and facilitating better data-driven decision-making for proper day-to-day management. In this section, the following concepts are analyzed: power quality, voltage control, state estimation, model-free voltage calculation, DR, and home energy management systems (HEMSs).

### A. Power Quality

Power quality refers to the degree to which the voltage characteristics of the power supply system, e.g., voltage magnitude, frequency, harmonics, etc., conform to established specifications. Poor power quality means that there are non-stationary disturbances that can cause significant malfunctioning of the electrical equipment, financial losses, interruption of production lines in industrial environments, and low quality of the electricity that is delivered to consumers. SM data can be valuable in the detection and classification of these disturbances.

In [46], the authors use feature extraction and ML models, such as ANN and decision trees, to classify a number of disturbances, e.g., voltages sags, swells, etc. The overall system is developed to run on the edge inside SMs. Similarly, in [47], a real-time power quality monitoring system for SM level is proposed to detect and classify any type of disturbance. Discrete wavelet transform is used for feature extraction and a support vector machine (SVM) for segregation between regular and abnormal data. The classification of disturbances is based on a multi-class SVM.

### B. Voltage Control

Since SMs allow two-way communication, enabling sending and receiving commands in real-time, voltage monitoring and control is one of the most likely new applications. SM data can be used to detect in real-time if voltage regulation should be applied to mitigate overvoltage/undervoltage violations. Such control strategies could be on-load tap-changer (OLTC) Volt-VAr control or capabilities of modern inverters.

In [48], the potential use of SM data as part of an OLTC voltage control strategy is theoretically discussed aiming to solve voltage problems caused by DRES. The SMs can provide the necessary voltage measurements from all end-users to a control center within a short time period to establish near real-time control. Using these measurements, the voltage set point for OLTC voltage control can be determined by means of optimal power flow.

In [49], a new control scheme is developed, which applies the voltage stability margin as the control objective, instead of the traditional voltage magnitude. The voltage stability issues are solved at the end-user side by reactive power support using both utility-scale and residential DRESs.

### C. State Estimation

State estimation is a digital processing scheme which provides an estimation of the power system condition. The estimator processes the available imperfect information and produces the best possible estimate of the true state of the system enhancing the observability of DNs.

In [50], a combination of WLS and the Levenberg-Marquardt algorithm with an integrated power flow formulation is used. The methodology is applicable for real-time state estimation and uses information provided only by SMs already installed at LV DNs. WLS is also used in [51], where a cloud-based SM architecture allowing scalability and interoperability among different off-the-shelf meters is proposed. Moreover, a suitable design of the estimation algorithm using the uncertainty propagation theory is proposed to improve accuracy. To avoid inaccurate modeling due to measurement uncertainties, which can lead the state estimation algorithms to deviate from the true operating states, authors in [52] propose an interval state estimation approach.

### *D. Model-free Voltage Calculations*

Model-free voltage calculations refers to the process of calculating voltages at network nodes without the need of electrical models by capturing the nonlinear relationship, between historical data (demand and voltages) and the corresponding LV feeder. A model-free voltage calculation approach that uses a deep neural network (DNN) using single-phase SM data is proposed in [53]. The authors aim to replace the traditional power flow analysis (where the topology of the distribution network is known) with a DNN, since traditional power flow is allegedly expensive, time-consuming, and not 100% accurate due to errors in topology, phase grouping, impedances, neutral, grounding, etc. To this end, the input of the model is the active and reactive power measurements of all end-users and the outputs are the voltages. For training purposes, active/reactive power along voltage data are required. These can be obtained through power flow analyses or through SMs. Once the model has been trained, what-if scenarios can be evaluated by simulating cases of interest, e.g., PV, battery energy storage (BES) units, or EV penetration.

### *E. Demand Response / Home Energy Management Systems*

DR refers to a change in the power consumption of a user to match the demand with supply. Typically, a signal is broadcasted by a utility to the user containing a price change or a command for load shedding [54]. Based on this, the end-user can adjust the power demand by postponing selected activities that require large amounts of electric power. A HEMS combines hardware and software components to efficiently manage home energy under DR strategies.

Residential DR and HEMS have been widely investigated in the literature. Various approaches rely on direct appliance control by programming the set-points of heating, ventilation, and air-conditioning units and water heaters to provide thermal and hot water comfort [55], [56]. Appliance scheduling under day-ahead pricing has also been investigated [57] to plan the operation of specific appliances for the next day aiming to minimize the cost and maximize thermal comfort. To extract end-user habits and provide optimal day-ahead scheduling, NILM has been integrated into HEMSs. In [58], SM data are analyzed via a multi-task DNN, and appliance-level information regarding consumption and operating status is extracted. The results are integrated into a HEMS to create an efficient and user-centered system by scheduling the appliance usage.

Similar energy management systems have been developed for residential microgrids [59], [60] where DRESs, EVs, and thermostatically controlled loads are adjusted aiming to reduce the electricity bills for end-users without affecting their comfort levels and also reduce the operation cost of the microgrid and avoid new peaks that may appear after appliance scheduling.

## VIII. Conclusions

In this paper, a comprehensive overview of possible use cases of SM data analytics for DN applications is conducted. Aside from automated energy consumption metering, which is the main application of SMs, there are more use cases for new services and businesses. From the literature review, six key categories for DN-oriented applications using SM data have been identified, i.e., load forecasting, NTLs detection, asset management, power system planning, topology identification, and power system operation and analysis; the latest developments for each case have been reported and discussed. As the number of installed SMs increases globally, it is expected that DSOs will utilize SM data for new fields outside their core business function.

## References


[1] Y. Wang, Q. Chen, T. Hong, and C. Kang, “Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges,” *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3125–3148, 2019.

[2] C. L. Athanasiadis, T. A. Papadopoulos, and D. I. Doukas, “Real-time non-intrusive load monitoring: A light-weight and scalable approach,” *Energy Build.*, vol. 253, p. 111523, 2021.

[3] B. Völker, A. Reinhardt, A. Faustine, and L. Pereira, “Watt’s up at Home? Smart Meter Data Analytics from a Consumer-Centric Perspective,” *Energies*, vol. 14, no. 3, 2021.

[4] N. Efkarpidis *et al.*, *Smart Metering Applications*. Cham: Springer International Publishing, 2022, pp. 13–124.

[5] A. A. Mamun *et al.*, “A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models,” *IEEE Access*, vol. 8, pp. 134 911–134 939, 2020.

[6] B. Goehry, Y. Goude, P. Massart, and J.-M. Poggi, “Aggregation of Multi-Scale Experts for Bottom-Up Load Forecasting,” *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 1895–1904, 2020.

[7] Z. A. Khan and D. Jayaweera, “Smart Meter Data Based Load Forecasting and Demand Side Management in Distribution Networks With Embedded PV Systems,” *IEEE Access*, vol. 8, pp. 2631–2644, 2020.

[8] S.-H. Lai and T. Hong, “When One Size No Longer Fits All – Electric Load Forecasting with a Geographic Hierarchy Executive Summary,” 2013.

[9] J. Ponoćko and J. V. Milanović, “Forecasting Demand Flexibility of Aggregated Residential Load Using Smart Meter Data,” *IEEE Trans. Power Syst.*, vol. 33, no. 5, pp. 5446–5455, 2018.

[10] G. M. Messinis and N. D. Hatziargyriou, “Review of non-technical loss detection methods,” *Electr. Power Syst. Res.*, vol. 158, pp. 250–266, 2018.

[11] S. Y. Han, J. No, J.-H. Shin, and Y. Joo, “Conditional abnormality detection based on AMI data mining,” *IET Gener. Transm. Distrib.*, vol. 10, pp. 3010–3016(6), September 2016.

[12] I. U. Khan, N. Javaid, J. Taylor, and X. Ma, “Data Driven Analysis for Electricity Theft Attack-Resilient Power Grid,” *IEEE Trans. Power Syst.*, pp. 1–1, 2022.

[13] M. N. Hasan *et al.*, “Electricity Theft Detection in Smart Grid Systems: A CNN-LSTM Based Approach,” *Energies*, vol. 12, no. 17, 2019.

[14] B. Kabir *et al.*, “Detection of Non-Technical Losses Using MLP-GRU Based Neural Network to Secure Smart Grids,” in *Complex, Intelligent and Software Intensive Systems*. Springer International Publishing, 2021, pp. 383–394.

[15] K. V. Blazakis, T. N. Kapetanakis, and G. S. Stavrakakis, “Effective Electricity Theft Detection in Power Distribution Grids Using an Adaptive Neuro Fuzzy Inference System,” *Energies*, vol. 13, no. 12, 2020.

[16] T.-S. Zhan *et al.*, “Non-technical loss and power blackout detection under advanced metering infrastructure using a cooperative game based inference mechanism,” *IET Gener. Transm. Distrib.*, vol. 10, pp. 873–882(9), March 2016.

[17] J. I. Guerrero *et al.*, “Improving Knowledge-Based Systems with statistical techniques, text mining, and neural networks for non-technical loss detection,” *Knowl. Based Syst.*, vol. 71, pp. 376–388, 2014.

[18] M. Tariq and H. V. Poor, "Electricity Theft Detection and Localization in Grid-Tied Microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1920–1929, 2018.
[19] W. Luan *et al.*, "Energy theft detection via integrated distribution state estimation based on AMI and SCADA measurements," in *2015 5th Int. Conf. on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, 2015, pp. 751–756.
[20] S. A. Salinas and P. Li, "Privacy-Preserving Energy Theft Detection in Microgrids: A State Estimation Approach," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 883–894, 2016.
[21] Y. Zhou *et al.*, "A Dynamic Programming Algorithm for Leveraging Probabilistic Detection of Energy Theft in Smart Home," *IEEE Trans. Emerg. Topics Comput.*, vol. 3, no. 4, pp. 502–513, 2015.
[22] K. Kuroda, R. Yokoyama, D. Kobayashi, and T. Ichimura, "An Approach to Outage Location Prediction Utilizing Smart Metering Data," in *2014 8th Asia Modelling Symposium*, 2014, pp. 61–66.
[23] R. A. Sevlian *et al.*, "Outage Detection Using Load and Line Flow Measurements in Power Distribution Systems," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2053–2069, 2018.
[24] Y. Liao, Y. Weng, C.-W. Tan, and R. Rajagopal, "Quick Line Outage Identification in Urban Distribution Grids via Smart Meters," *CSEE J. Power Energy Syst.*, vol. 8, no. 4, pp. 1074–1086, 2022.
[25] Y. Arafat, L. Bertling Tjernberg, and P.-A. Gustafsson, "Remote switching of multiple smart meters and steps to check the effect on the grid's power quality," in *2014 IEEE PES T&D Conf. and Exposition*, 2014, pp. 1–5.
[26] S. Chakraborty and S. Das, "Application of Smart Meters in High Impedance Fault Detection on Distribution Systems," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3465–3473, 2019.
[27] K. Ashok, D. Li, N. Gebraeel, and D. Divan, "Online Detection of Inter-Turn Winding Faults in Single-Phase Distribution Transformers Using Smart Meter Data," *IEEE Trans. Smart Grid*, vol. 12, no. 6, pp. 5073–5083, 2021.
[28] K. Petrou *et al.*, "Ensuring Distribution Network Integrity Using Dynamic Operating Limits for Prosumers," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 3877–3888, 2021.
[29] A. T. Procopiou *et al.*, "Smart meter-driven estimation of PV hosting capacity," in *CIRED 2020 Berlin Workshop (CIRED 2020)*, vol. 2020, 2020, pp. 128–131.
[30] V. Klonari, J.-F. Toubeau, J. Lobry, and F. Vallée, "Estimating the Photovoltaic Hosting Capacity of a Low Voltage Feeder Using Smart Meters' Measurements," in *Smart Metering Technology and Services*. IntechOpen, 2016, ch. 7.
[31] A. K. Jain *et al.*, "Quasi-Static Time-Series PV Hosting Capacity Methodology and Metrics," in *2019 IEEE PES Innov. Smart Grid Technol. Conf. (ISGT)*, 2019, pp. 1–5.
[32] J. Zhu, W. J. Nacmanson, L. F. Ochoa, and B. Hellyer, "Assessing the EV Hosting Capacity of Australian Urban and Rural MV-LV Networks," *Electr. Power Syst. Res.*, vol. 212, p. 108399, 2022.
[33] M. Z. Liu *et al.*, "Grid and Market Services From the Edge: Using Operating Envelopes to Unlock Network-Aware Bottom-Up Flexibility," *IEEE Power and Energy Mag.*, vol. 19, no. 4, pp. 52–62, 2021.
[34] S. Han *et al.*, "An Automated Impedance Estimation Method in Low-Voltage Distribution Network for Coordinated Voltage Regulation," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1012–1020, 2016.
[35] S. Iakovlev, R. J. Evans, and I. Mareels, "Low-Voltage Distribution Network Impedances Identification Based on Smart Meter Data," 2018. [Online]. Available: https://arxiv.org/abs/1809.06657
[36] J. Zhang, P. Wang, and N. Zhang, "Distribution Network Admittance Matrix Estimation With Linear Regression," *IEEE Trans. Power Syst.*, vol. 36, no. 5, pp. 4896–4899, 2021.
[37] Y. Wang, M. Z. Liu, and L. F. Ochoa, "Assessing the effects of DER on voltages using a smart meter-driven three-phase LV feeder model," *Electr. Power Syst. Res.*, vol. 189, p. 106705, 2020.
[38] V. Arya, T. S. Jayram, S. Pal, and S. Kalyanaraman, "Inferring Connectivity Model from Meter Measurements in Distribution Networks," in *Proc. of the 4th Int. Conf. on Future Energy Syst.*, ser. e-Energy '13. Association for Computing Machinery, 2013, p. 173–182.
[39] X. Tang and J. V. Milanovic, "Phase Identification of LV Distribution Network with Smart Meter Data," in *2018 IEEE Power & Energy Society General Meeting (PESGM)*, 2018, pp. 1–5.
[40] H. Pezeshki and P. Wolfs, "Correlation based method for phase identification in a three phase LV distribution network," in *2012 22nd Australasian Universities Power Eng. Conf. (AUPEC)*, 2012, pp. 1–7.
[41] B. K. Seal and M. F. McGranaghan, "Automatic identification of service phase for electric utility customers," in *2011 IEEE Power and Energy Society General Meeting*, 2011, pp. 1–3.
[42] H. Pezeshki and P. J. Wolfs, "Consumer phase identification in a three phase unbalanced LV distribution network," in *2012 3rd IEEE PES Innov. Smart Grid Technol. Europe (ISGT Europe)*, 2012, pp. 1–7.
[43] Z. Tian, W. Wu, and B. Zhang, "A Mixed Integer Quadratic Programming Model for Topology Identification in Distribution Network," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 823–824, 2016.
[44] G. N. Korres and N. M. Manousakis, "A state estimation algorithm for monitoring topology changes in distribution systems," in *2012 IEEE Power and Energy Society General Meeting*, 2012, pp. 1–8.
[45] W. Luan *et al.*, "Smart Meter Data Analytics for Distribution Network Connectivity Verification," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1964–1971, 2015.
[46] F. A. S. Borges, R. A. S. Fernandes, I. N. Silva, and C. B. S. Silva, "Feature Extraction and Power Quality Disturbances Classification Using Smart Meters Signals," *IEEE Trans. Industr. Inform.*, vol. 12, no. 2, pp. 824–833, 2016.
[47] I. Parvez *et al.*, "Online power quality disturbance detection by support vector machine in smart meter," *J. Mod. Power Syst. Clean Energy*, pp. 1–12, 2018.
[48] C. Gao and M. A. Redfern, "A Review of Voltage Control in Smart Grid and Smart Metering Technologies on Distribution Networks," in *2011 46th Int. Universities Power Eng. Conf. (UPEC)*, 2011, pp. 1–5.
[49] N. Duan, C. Huang, C.-C. Sun, and L. Min, "Smart Meters Enabling Voltage Monitoring and Control: The Last-Mile Voltage Stability Issue," *IEEE Trans. Industr. Inform.*, vol. 18, no. 1, pp. 677–687, 2022.
[50] E. B. Alzate, M. Bueno-López, J. Xie, and K. Strunz, "Distribution System State Estimation to Support Coordinated Voltage-Control Strategies by Using Smart Meters," *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 5198–5207, 2019.
[51] M. Pau *et al.*, "Low voltage system state estimation based on smart metering infrastructure," in *2016 IEEE Int. Workshop on Appl. Meas. for Power Syst. (AMPS)*, 2016, pp. 1–6.
[52] M. Huang *et al.*, "Interval State Estimation for Low-Voltage Distribution Systems Based on Smart Meter Data," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 9, pp. 3090–3099, 2019.
[53] V. Bassi, L. Ochoa, and T. Alpcan, "Model-Free Voltage Calculations for PV-Rich LV Networks: Smart Meter Data and Deep Neural Networks," in *2021 IEEE Madrid PowerTech*, 2021, pp. 1–6.
[54] P. Palensky and D. Dietrich, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," *IEEE Trans. Industr. Inform.*, vol. 7, no. 3, pp. 381–388, 2011.
[55] H. Mortaji, S. H. Ow, M. Moghavvemi, and H. A. F. Almurib, "Load Shedding and Smart-Direct Load Control Using Internet of Things in Smart Grid Demand Response Management," *IEEE Trans. Ind. Appl.*, vol. 53, no. 6, pp. 5155–5163, 2017.
[56] X. Kou *et al.*, "A Scalable and Distributed Algorithm for Managing Residential Demand Response Programs Using Alternating Direction Method of Multipliers (ADMM)," *IEEE Trans. Smart Grid*, vol. 11, no. 6, pp. 4871–4882, 2020.
[57] Y. Liu, L. Xiao, G. Yao, and S. Bu, "Pricing-Based Demand Response for a Smart Home With Various Types of Household Appliances Considering Customer Satisfaction," *IEEE Access*, vol. 7, pp. 86 463–86 472, 2019.
[58] H. Çimen, N. Çetinkaya, J. C. Vasquez, and J. M. Guerrero, "A Microgrid Energy Management System Based on Non-Intrusive Load Monitoring via Multitask Learning," *IEEE Trans. Smart Grid*, vol. 12, no. 2, pp. 977–987, 2021.
[59] P. Wang *et al.*, "Data-driven energy management in residential areas leveraging demand response," *Energy Build.*, vol. 269, p. 112235, 2022.
[60] H. Çimen *et al.*, "An online energy management system for AC/DC residential microgrids supported by non-intrusive load monitoring," *Appl. Energy*, vol. 307, p. 118136, 2022.