

Load modelling and non-intrusive load monitoring to integrate distributed energy resources in low and medium voltage networks

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ABSTRACT

In many countries distributed energy resources (DER) (e.g. photovoltaics, batteries, wind turbines, electric vehicles, electric heat pumps, air-conditioning units and smart domestic appliances) are part of the 'Green Deal' to deliver a climate neutral society. Policy roadmaps, despite providing a framework and penetration targets for DER, often lack the network planning strategies needed to transition from passive to active distribution networks. Currently, DER's dynamic performance parameters and location identification techniques are not fully standardised. In fact, it can be very *ad hoc*. Standardised distributed load modelling and non-intrusive load monitoring (NILM) for equipment manufacturers, installers and network operators is critical to low and medium voltage network management in order to facilitate better balancing, flexibility and electricity trading across and within the power system for mass DER deployment. The aim of this paper is to fill this load modelling and NILM knowledge gap for DER to inform the 'Green Deal' transition and support standardisation. In the paper, existing load modelling techniques and NILM methodologies are critically examined to inform and guide research activity, equipment development and regulator thinking, as well as network operators. Seven key findings that need urgent attention are identified to support a smooth power system reconfiguration.

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Nomenclature

DER	Distributed energy resources
DG	Distributed generation
EV	Electric vehicle
ILM	Intrusive load monitoring
NILM	Non-intrusive load monitoring
PMU	Phasor measurement unit
PV	Photovoltaic
ZIP	Load model of constant impedance, current and/or power

1. Introduction

Distributed energy resources (DER) are small-scale, embedded generators, which include photovoltaic (PV) systems, energy storage systems, wind turbines, and electric vehicles (EV). Other smart loads and low-carbon technologies, such as electric heating, air conditioning units, combined heat and power, among others are also considered as DER [1]. Distributed energy resources are key enabling technologies in transitioning away from fossil fuel-based electric power generation technologies to less pollutant electrical systems [2]. In recent years, DER have experienced a mass-deployment globally, as a consequence of the implementation of global strategies related to decarbonization of energy and power sectors and the electrification of transportation and heating [3]. Nevertheless, the deployment of these renewables systems worldwide has brought along technical issues on electrical networks caused by the variation of conventional dynamics of the electrical network.

Technical challenges have arisen on distribution networks due to inadequate planning and management in the DER integration, which will become more severe as the installed capacity continues increasing [4]. The effect of DER on the network depends on factors such as network characteristics, weather conditions, geographical location, economic models, end customer usage patterns, and the type of DER. These new challenges for distribution network operators have motivated the creation of innovative strategies to increase hosting capacity of DER systems in distribution networks. In Table 1, several studies from different countries are analysed. These research studies investigated DER impact in distribution networks from economic or technical perspectives.

Several measures have been proposed to tackle DER negative impacts in distribution networks. For instance, curtailment of renewable energy generation, electrical equipment upgrade, robust optimization [12], active management systems, variable pricing schemes, vehicle to grid (V2G), vehicle to home [13], and so on. The mentioned strategies create a high interaction between utility companies and end users, who become active customers (also called prosumers), through internet-connected devices (e.g. smart appliances) and requires of smart metering and intelligent devices. Less adapted and existing electrical networks presenting an increase on DER penetration require network reinforcement, advance planning and monitoring [6]. However, it is required an urgent improvement of the observability of low voltage distribution networks to facilitate the implementation of proposed and future innovative strategies. This contributes with the effective integration of DER obtaining a more sustainable, flexible and resilient electrical sector. Load modelling and load monitoring approaches have been identified as potential techniques to understand DER performance, and to quantify, control and mitigate DER negative impacts especially on distribution networks [14].

Load modelling is a technique based on load forecasting commonly used at high and medium voltage levels. It consists on describing mathematically the behaviour of a load or group of loads for state estimation, demand response, and frequency control, among other purposes [15]. *Load identification* methods are mostly applied on low voltage networks for distribution networks analysis [16]. Based on actual measurements acquired from the electrical system under analysis, load identification is often considered a function of load monitoring techniques.

Intrusive load monitoring (ILM), sometimes called ‘component-based’ load monitoring or distributed sensing, operates by monitoring and acquiring electrical consumption data from each individual device or appliance separately. Thus, ILM requires installation of distinct end-load monitoring devices. *Non-intrusive load monitoring* (NILM) consists of obtaining measurements representing several devices and appliances aggregated together in an electrical system [17]. Feature identification techniques are applied to disaggregate those measurements, identify and monitor individual load profiles of specific devices that are in operation on the network. In this way, the NILM approach requires fewer measurement devices. Fig. 1 illustrates a distribution network with conventional and DER loads. If ILM methods were applied, then all DER would need to all be monitored individually. On the contrary, using the NILM approach it is only required to place one measurement

Table 1
Issues and strategies proposed for the effective adoption DER in distribution systems.

Location	What the author(s) studied?	Approach	Key Findings	Limitations	Recommendations	Ref
United States of America	Analysed the rebound effect of increasing DER penetration at customer level. This to determine if it can cause a future damage to the environment. The rebound effect is defined as the change in consumer electricity consumption or the change in the customer consumption behaviour when acquiring a new technology such as a DER.	Two years of 1-min power consumption from 409 households were considered from the “Pecan Street - Dataport” Dataset. Here several factors including electricity consumption, physical conditions of the houses and DER usage behaviour (independent, dependent and control variables) were considered to determine the change in electricity consumption after installing a DER.	- Consumption of prosumers is affected depending on the meter they have installed: conventional or bidirectional. - Social aspects such as motivation to get a DER, salaries and education playing an important role to define DER power load profile. - Restrictions imposed to customers could be evaluated to create policies and incentives for a higher DER adoption at customer level. - Economic benefits and/or environmental reasons as main motivation to install a DER. - Profits based on strategies for prosumers to sell electricity, contribute to reduce power consumption. - Higher level of education is correlated to higher energy consumption from the electrification of sectors such as transport and heating.	- Sustainable power consumption is a complex and very dynamic characteristic. - Instead of subsidies, electricity prices are constantly increasing for the use of DER. - Low education in terms of reducing energy consumption. - Effect of power generation in the consumer incomes are not known. - Only electrical energy consumption is analysed. Other power sources such as gas or fuel should be analysed. - Before studies are not carried out. This means the authors do not considered the change from passive to active consumers.	- Inefficient policies are needed to be replaced to increase DER integration in Distribution Networks. - Further education is required to remove bad habits and save more energy. - Behavioural factors are needed to provide a more complete study to understand how energy efficiency is affected by the installation of DER at household levels.	[5]
Germany	Consulted with 10 distribution network operators their experience of integrating solar PV systems.	Interviewed 10 large-scale distribution network operators in Germany. The distribution network operators are among the top 30 in terms of DER installed on their network.	- Grid renovation measures are primarily focused on complying voltage and thermal limits (reached by overloading transformers or power lines). - Optimization techniques provide the most cost-effective solution for initial expansion. Subsequently, conventional techniques can be applied to upgrade the infrastructure. - Improved grid-planning contributes to maximise resources available of a low voltage DN. - Network reconfiguration, reinforcement and expansion are valid techniques to avoid	- Although, there have been proposed several technical ways to reduce DG impacts in low voltage networks, the authors emphasise the lack of connection between the proposed measures and their applications in a realistic environment - Planning and monitoring are not analysed on this paper.	Advanced expansion technologies can be implemented after testing them in pilot projects.	[6]

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Table 1 (continued)

Location	What the author(s) studied?	Approach	Key Findings	Limitations	Recommendations	Ref
Spain	A method to evaluate upgrading costs of a real LV network to allow more PV generation in a long-term frame including installation, operation, maintenance, and losses costs.	Load flow solvers are used to eliminate uncontrolled technical constraints violations. Smart meters hourly data from a network of 80,000 households and solar irradiation are used. Base case is set as no PV generation and then a 10% PV increase scenario is analysed until 100% PV. Five steps are used 1) Energy balance of each feeder; 2) Load flow analysis to eliminate mild and severe constraints/violations with Length-cumulated Section Saturation Index (LSSI) and Energy-cumulated Voltage Violation Index (EVVI); 3) Definition of the degree of the constrain; 4) Selecting and prioritising the reinforcement action needed at the lowest price; 5) Economic evaluation of the solution	PV issues in low voltage DN. - Expansion, optimization, and reinforcement of the electrical network plus advance network planning are key steps taken by main distribution network operators (DNO) in Germany for the integration of DG in low voltage networks. - Ampacity congestions and voltage violations are proportional to PV penetration. - Costs associated to the reinforcement grow in a higher slope than constraints. 30% PV penetration is a threshold for higher losses compared with the base case. When the LV network with 0% PV is reinforced, this percentage is moved to 40%. - Costs increasing 2.73 €/kWp for 30% PV integration and 10.18 €/kWp for a 50% PV scenario. After 30% the investment needed increases quadratically. 18% PV penetration provides profits to the network and reduces losses due to lower power flowing in the network.	Other technical constraints are not considered in the study such as fast voltage changes, increased harmonic distortions, system imbalances, reverse power flow, coordination of protections issues, network component faster aging.	- To solve unconsidered issues measurements such as digitization, monitoring and automation are needed. - Utility companies could set additional charges to those prosumers with PV systems where the PV penetration is higher than 30%.	[7]
Sweden	Authors carried out an investigation of key aspects regarding the challenges due to the increasing integration of DER on distribution networks.	- Output oriented regulatory models. - Infrastructure reinforcement. - Automatic tap changing transformers. - Enhanced grid monitoring. - Improved grid planning. - Smart metering.	DER ISSUES mainly caused by distributed PV and EV home charging. - Overload - Transformers and electrical infrastructure thermal constrain. - Network congestion - Voltage and frequency fluctuation Proposed solutions - Output oriented regulatory models. - Infrastructure reinforcement. - Automatic tap changing transformers. - Enhanced grid monitoring. - Improved grid planning. - Smart metering	- Complexity and uncertainty on funding for output-oriented models. - Current policies, directives and layered regulations. - Projects being implemented in isolation from the grid. - Immature technologies. - Lack of knowledge and fear to fail in changing. - Funding.	- Using energy storage systems (BESS or Heat pumps) to minimise technical issues. - Cooperation withing grid operators. - Increasing technical competences to allow DER integration. - New business models. - Dynamic pricing.	[8]
Australia						[9]

Table 1 (continued)

Location	What the author(s) studied?	Approach	Key Findings	Limitations	Recommendations	Ref
	A distributed AC optimal power flow (DOPF) for DER coordination with volt VAR control and fair PV curtailment method is proposed. It considers reactive power compensation as variable of the model for fairly curtail of PV generation. It is a realistic and scalable method which considers network constraints and protects customer privacy. Opposite to convex relaxation methods, the approach is based on interior point methods (IPM) which leads to feasible solutions.	Using a 50-prosumers test system, 50 simulations are carried out. Seven scenarios with uncoordinated and coordinated prosumer interaction were analysed for low, medium, and high PV penetration. One day of data from a smart grid in Australia was used (data recorded every 30 min).	- Uncontrolled PV generation lead to violate voltage operational limits. - Introduction of Voltage VAR Control (VCC) reduces voltage range violations, but curtailment is not fair among prosumers. - Prosumers located in the end of the network tend to be more penalised with conventional methods.	- Few data used to do several simulations. - Telecommunications requirements are proportional to the number of prosumers in the electrical network.	- Other methods based on volt-VAR control need to consider network constraints. - Proposed Volt-Var controlled methods should look for feasible solutions.	
China	A nonlinear model is proposed to analyse factors with an impact on DER growth in China from an economical perspective.	A nonparametric additive regression model is developed with backfitting. It efficiently computes nonlinear effects of six economic factors for the DER adoption. A dataset of 14 years (including 30 regions in China) is used.	- Technological advance and government policies contribute to the increase of DER acquisition. However, the rate of new DER slows down afterward. - Energy consumption has an n-shape relationship with DER adoption. - Overall price of an Oil barrel, exportations of Oil and urbanization have a positive effect on DER increase.	There were not evaluated economical aspects of network reinforcement depending on the percentage of DER influence in a specific area.	A few recommendations are given for the Chinese policies to help increasing DER adoption. - Government and industries to increase support for DER R&D. - Provide long term incentives for the installation of new PV or wind generation farms. - Promote the investigation of cleaner sources of energy. - Reduce usage of coal and increase gas extraction. - Decarbonization of highly pollutant industries.	[10]
Sri Lanka	A methodology to create general low voltage distribution network models and analyse PV penetration impacts is proposed.	- The DN model is created using a Monte Carlo based stochastic technique and considering other factors such as size of PV systems, phase of connection, location. - Real data is collected from a distribution network. The dataset includes electrical and technical variables as well as location. - A set of 10,000 simulations were computed in 10 distribution network topologies.	Distributed generation causing - Voltage oscillation - Violation of voltage limits - Violation of thermal limits - Reverse power flows - Power quality issues - Three phase system imbalances In the study it was found: - Total momentum of PV size linearly proportional to increased low voltage feeder magnitude. - Imbalance voltage factor is linearly proportional to the mean absolute deviation of PV capacities.	The fact this study is focused on Sri Lanka, plus the dependency of PV on weather conditions, might reduce the proposed model as general approach for other distribution networks. Ambient temperature, clouds, dust, and other conditions of each area are needed to make this model transferable to other countries with strong seasons.	The developed model is advised to be replicated to other LV networks	[11]

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Table 1 (continued)

Location	What the author(s) studied?	Approach	Key Findings	Limitations	Recommendations	Ref
			• After 10,000 simulations to analyse 10 correlated DN, it was found a framework to define if it was either not needed an intervention, needed conventional control techniques or the system required severe intervention from the DNO.			

device on the low voltage side of the distribution transformer to monitor all DER from the aggregated measurements.

Both ILM and NILM are important approaches that enhance energy management systems, yielding increased energy consumption efficiency, and distribution networks stability, improving electrical system reliability [18]. Non-intrusive load monitoring techniques, in particular, offer opportunities to encourage active participation of customers [19]. Despite several research studies have been developed during recent decades to improve observability of the distribution network, few of them have presented a base approach focused on DER load modelling or identification. Load modelling techniques have been recently studied to forecast the impact of individual DER such as PV systems or wind turbines in distribution and transmission networks. On the low voltage side of distribution networks, there are a number of research articles distinguishing conventional loads at the end user distribution board (i.e. within the customer's property boundary) rather than DER identification on the low voltage side of the service transformer (supplying several customers).

The research question addressed in this paper is what is needed of smart meters and the distribution network to decarbonise and integrate DER, which is pertinent issue when considering the future

smart grid. To this end, part of this challenge is standardising load modelling and NILM methodologies in order to effectively coordinate and operate DER in real time to facilitate better electrical network management and reduce carbon emissions. Considering DER growth projections and their impacts on conventional distribution networks, standardised load modelling and NILM techniques focused on DER become critical to ensure stability and flexibility of the electrical system. Hence, the aim of this paper is to fill the gap regarding load modelling and NILM knowledge for DER.

The remainder of the paper is structured in seven sections. In section 2 a description of the implemented methodology to find knowledge state and gaps of load modelling and non-intrusive load monitoring on distribution networks is described. Sections 3 and 4 the existing load modelling and load monitoring techniques are critically examined to inform and guide research activity, equipment development and regulator and network operator thinking. Section 5 reviews existing load modelling and NILM methods for DER identification on distribution networks. Section 6 evaluates and discusses, in the wider context, the challenges and opportunities to facilitate DER integration in the distribution section of the electrical network. Finally, conclusions are drawn in Section 7.

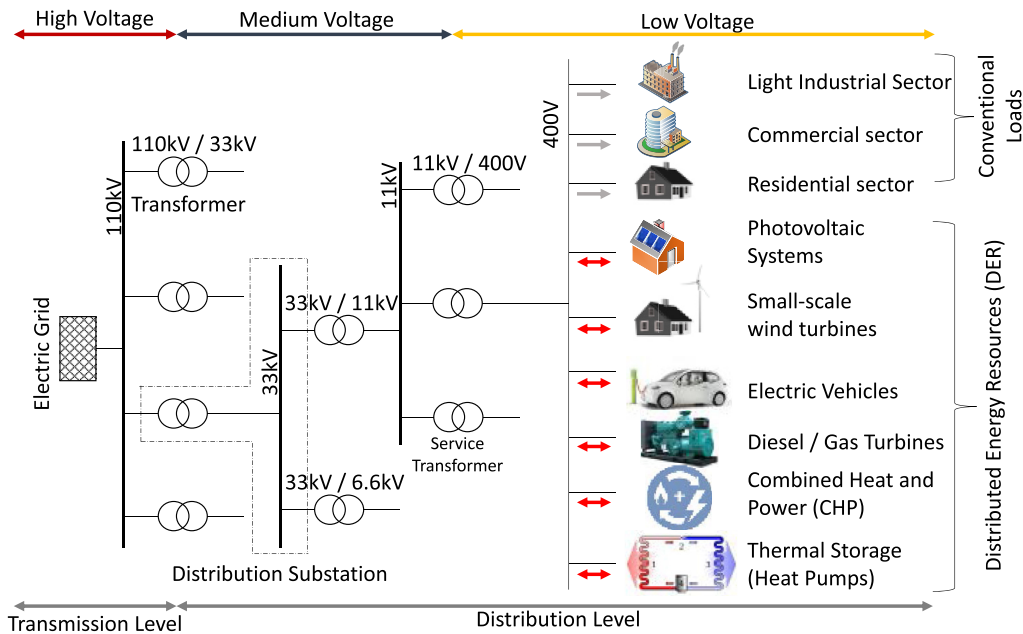


Fig. 1. Model distribution network including conventional loads and DER.

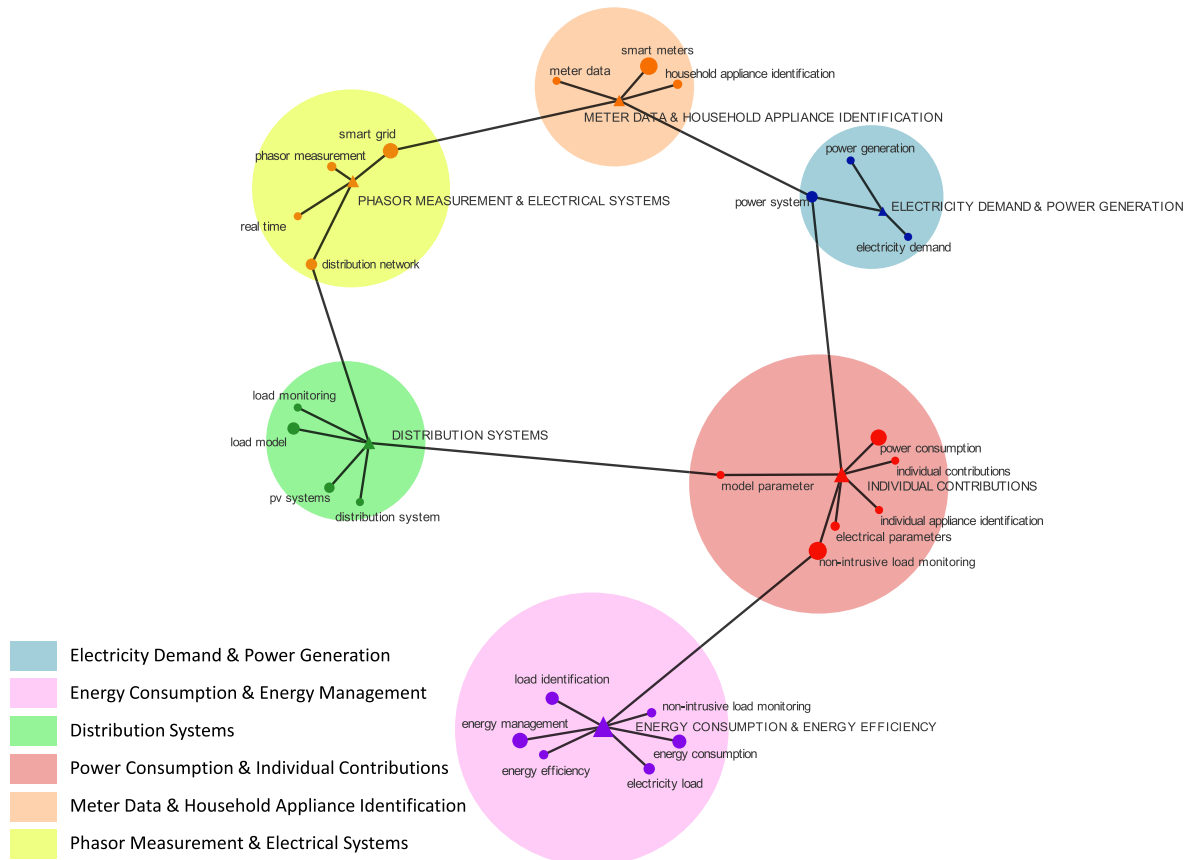


Fig. 2. Network map from "Cortext Manager".

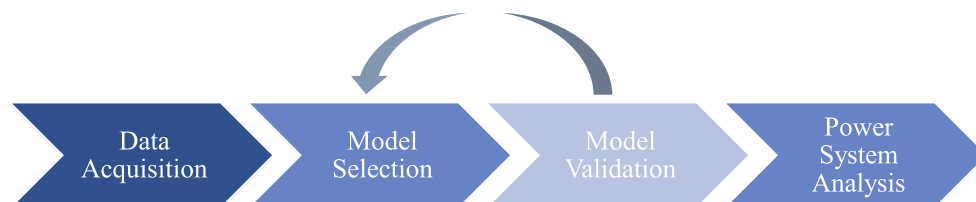


Fig. 3. Structure of load modelling process (Adapted from Ref. [21]).

2. Methodology

A systematic review was developed to establish the state of the art regarding load modelling and non-intrusive load monitoring techniques on distribution networks. The method involved analysing the most relevant primary research studies in the mentioned fields with the objective of finding possible knowledge gaps in the literature. The developed systematic review consisted of two main steps: 1) Identifying key research subtopics within load modelling and NILM concepts to create a Cortext database from the web of science; and 2) Generating a network map using key terms from relevant abstracts.

The first step consists of identifying key research studies to summarise the state of the art and discover knowledge gaps in the fields of load modelling and non-intrusive load monitoring techniques. The advanced search tool for research publications from the Web of Science was used for this study using the terms 'load

modelling' AND 'non-intrusive load monitoring' as inputs. To limit the number of studies, only those manuscripts highly cited in the field of Electrical and Electronics Engineering published between the years 2011 and 2021 were considered. This returned 243 articles, which contained information such as academic journal paper title, abstract and other information from the journal. The obtained list of documents was manually scanned to refine the search and considered most relevant studies in the field, obtaining 167 publications. The information was downloaded as a comma separated values (".csv") file, known as text corpus. The database was used as input of the second step of the systematic literature review process.

The achieved text corpus data was parsed using a tool called "Cortext Manager" to create an "sqlite" database. The "sqlite" database is portable and more accessible version of the data saved in the ".csv" format, which can be used in the Cortex Manager to provide a graphic interpretation of the correlation of key words in the main sources. Subsequently, key terms from the compound of

article abstracts were identified automatically. These terms were used to generate a network map to comprehend the correlation of the key words and frequency of occurrence as shown in Fig. 2.

The last step of the systematic review was focused on filtering the most important research studies from the list of papers achieved in the text corpus database. Literature was primarily collected from two locations, namely Science Direct and The Institute of Electrical and Electronics Engineering digital library IEEE Xplore. As a result, 127 papers were finally selected after completing the eligibility scanning.

3. Load modelling

The aim of load modelling at transmission and distribution levels is to represent aggregated characteristics of a group of loads to plan, predict and control them to match power demand with power generation [20]. These methods make use of specific features of the electrical network such as busbar voltages and phase angles to calculate unknown electrical features such as active and reactive power of an electrical network. This provides utility companies with an understanding of network performance, and correlation of loads with voltage or frequency variations. In general, load modelling-based techniques follow the four-step structure consisting on the acquisition of the electrical data, selection of the model applicable to the load, model validation and power system analysis as shown in Fig. 3.

3.1. Data acquisition

Load modelling (and load identification) requires various data from the electrical network. In modern microprocessor instruments, the AC voltages and currents are sampled by an analog-to-digital converter, and mathematical models and functions are applied to the sampled values to derive other measurements [22] such as root-mean-squared voltage and current magnitude [23], power, reactive power [24], harmonic content, frequency and phase angle. Measurement instruments installed at consumer voltages (i.e. 230 V/120 V) may apply the phase voltages and currents directly to their terminals, while those installed in substations will use instrument transformers to step down the high line voltages (in the kV range) and currents (in the kA range) to standard substation instrument ranges, i.e. 110 V and 1 A or 5 A [25].

Utility companies have conventionally used slow scan telemetry supervisory control and data acquisition systems, yielding system information such as root-mean-squared voltage and current magnitudes, power flow, and Boolean circuit breaker position status at regular intervals (usually 10–30 s between updates) [25]. Power quality meters and phasor measurement units (PMUs), provide data at higher reporting rates, usually at the system nominal frequency yielding 50 or 60 reports per second [26].

It is important that measurement instruments are applied correctly if the data yielded is to be meaningful [27]. PMUs provide synchro phasors which express the magnitude and phase angle of the fundamental of voltage and current. Caution must be used if those voltages and currents contain significant harmonic content or are non-periodic, these being attributes the PMU is not designed to measure [28]. Additionally, while some measurements are well described, such as active power, some measurements have many interpretations, such as reactive power [24]. Therefore, caution must be used when comparing datasets to ensure that measurement methods are consistent.

3.2. Tools, techniques & methods for load modelling

A wide variety of load modelling techniques have been designed

for analysis, planning and control of power systems. The main objective is to mathematically describe aggregated and complex loads as equations which can be used in models. The models themselves can be described as static, dynamic, composite load, low voltage, active distribution networks and machine learning-based models [29], and they are described in this section.

Static models represent steady state characteristics of a load as a function of the bus bar voltage, considering active and reactive power components independently [30]. Here, one can find methodologies such as ZIP, exponential, frequency dependant and the Electric Power Research Institute (EPRI) models. ZIP models are used to represent a load in terms of active and reactive power demand, based on bus bar voltage and three variables describing the load as constant impedance (Z), constant current (I) and/or constant power (P). Exponential models also represent the load in terms of active and reactive power as function of bus bar voltage, but using polynomial equations as described by M. Leinakse et al in Ref. [31]. Frequency dependent models implement either exponential or ZIP models multiplied by a factor defined in terms of the frequency of the system. The EPRI model combines ZIP, induction motor, load bus capacitor and static load models to find active and reactive power of the system [32].

Dynamic models are based on analysing electrical signals in time and space domains using derivative equations as a common characteristic. They can be divided into mathematical approaches and physical approaches. Mathematical approaches are based on representing active and reactive power as a function of voltage, frequency and time, while physical-based approaches describe power in terms of machine components such as induction motor models [21]. Another dynamic method called exponential recovery load model is a mathematical approach which focuses on transient responses to a step changes in active and reactive power [29]. The Induction Motor model, considered a physical approach, represents active and reactive power of a bus bar based on the voltage and frequency of a system using the equivalent circuit of an induction motor [29].

Constant power and ZIP models are preferred amongst other methods in the industrial sector for steady state and dynamic active and reactive power analysis [29]. However, ZIP models as well as exponential and polynomial models present considerable deviations to represent non-linear electronic loads, which is not desirable in a network with increasing DER penetration [33].

Composite load models are based on representing loads at the customer side from electrical substations, considering their variations over time [34]. These models were introduced by the Western Electricity Coordinating Council, which have been applied to monitor induction motors and static loads. It is a more advance technique than conventional static and dynamic models, but further research is required to improve some models such as single-phase induction motors and distributed generation. Composite load models require the definition of nearly 130 parameters, which can be defined by default, but they can be time consuming and problematic to solve non-converging issues [35].

Low voltage models consist of modelling components on the low voltage side of a distribution network such as transformers, voltage regulators, overhead and underground cables, unbalanced systems caused by unequal end-users location, and so on [33]. Analytical models using measurements as well as equivalent models to represent sections or individual parts of the system are commonly applied on this technique.

Active distribution networks models consider generation and demand projection in the distribution network, dealing not only with conventional load changes but also DER variations [36]. Based on the representation of technical and economic uncertainties of the network, the main methodologies applied to active distribution

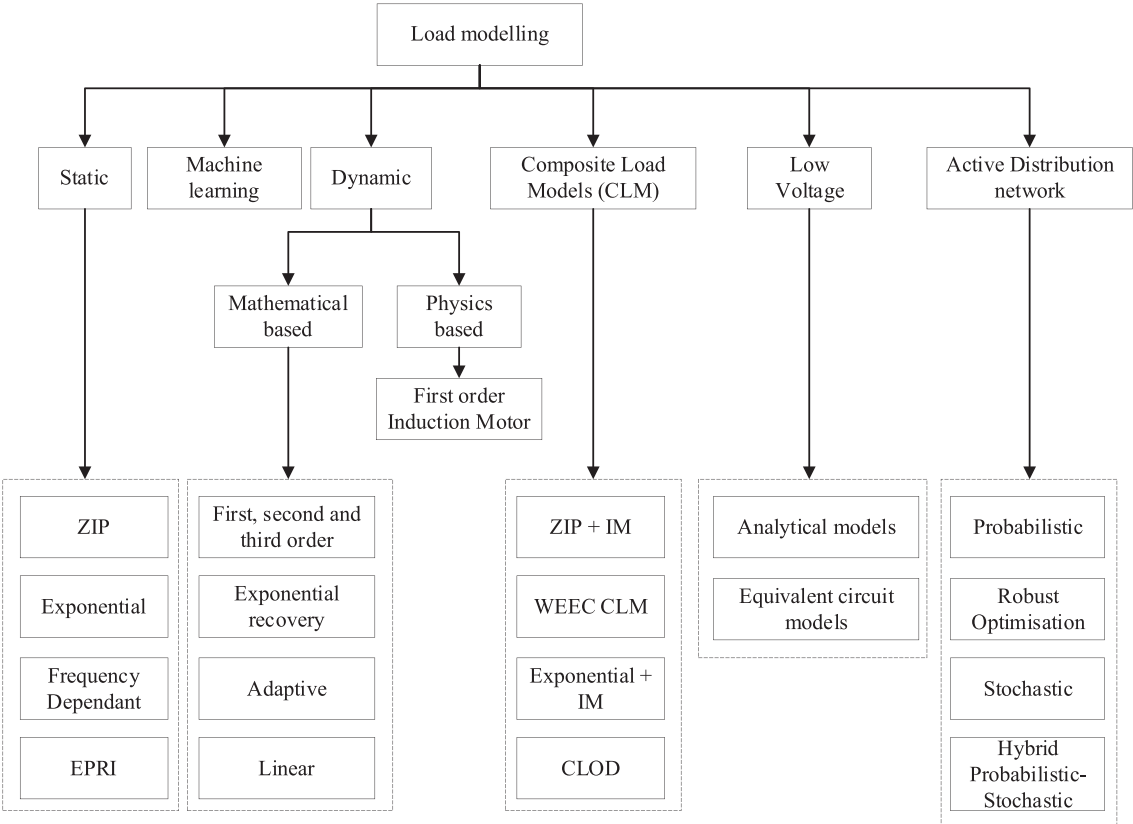


Fig. 4. Diagram of load monitoring classification.
(Source: Own elaboration from data in Refs. [21,29,36]).

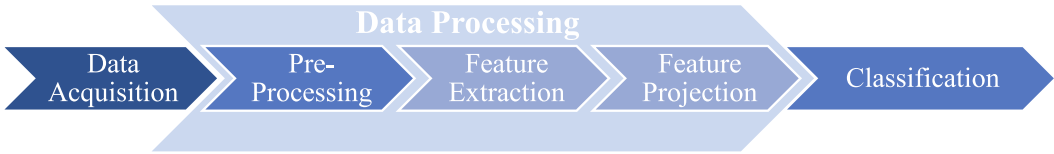


Fig. 5. NILM process structure (Adapted from Ref. [49]).

networks are probabilistic techniques, stochastic methods, combined probabilistic and stochastic approaches, robust optimization and information gap decision theory. These methods are further expanded in Ref. [36].

Machine learning techniques have been implemented in several areas of investigation, including load modelling for power systems analysis [37]. Therefore, supervised and unsupervised techniques are applied to forecast loads in distribution networks. The modularity of these techniques is reflected on the usage of conventional methods and advanced machine learning algorithms applied to load modelling. Some examples include regression methods, support vector machines, Artificial Neural Networks, Genetic Algorithms, Ant Colony and particle swarm optimization, just to mention but few [38].

A schematic diagram of the most common load modelling methods used for research and industrial purposes are shown in Fig. 4.

3.3. Model validation

The third stage of the load modelling process consists in validating the obtained model. At this stage the output of the algorithm is compared with the real load, providing a percentage of efficacy. If this validation is not satisfactory, the second stage is repeated to recalculate the model. Parameter optimization before the model is used to predict loads is a common approach applied to this section as described by Somu N., Raman G. and Ramamritham K. in Ref. [39]. Models are evaluated under specific metrics, testing the

correct description of the electrical system using the obtained parameters. Metrics such as mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean squared error (RMSE) are highly used by researchers to evaluate the quality of the models [40].

4. Load monitoring

Load monitoring methods are typically related to efforts in energy management, that is methods to reduce power consumption by using electrical devices efficiently [41]. These techniques can be categorized as invasive (ILM) or non-invasive (NILM) attending to the number of monitoring sensors deployed. ILM methods require the installation of sensors on each particular load to obtain its electrical characteristics [42], thus providing high quality analysis of individual loads. However, ILM is costly in terms of equipment and the labour involved in installing all the recording devices. Despite its benefits, it is often rejected by the customer [43]. Therefore, in this section we will mainly focus on NILM techniques.

Non-Intrusive load monitoring methods are based on disaggregating electrical measurements representing many loads which are connected to a common power supply. Their main objective is to classify individual loads from electrical networks [44]. Several research studies have been focused on aggregated load identification at the distribution board in residential, commercial and industrial sectors. As an example, authors in Ref. [45] describe an NILM method applying an unsupervised algorithm. It is design using a high-resolution machine learning technique based on clusters to identify electric load signatures and low power events. Electric loads are categorized analysing energy power quantities as well as harmonic content for non-residential electrical installations. Comparatively, studying voltage and electric current load signatures, a multilevel load classification algorithm based on energy power quantities, current total harmonic distortion and a correlation coefficient is used in Ref. [46] to distinguish residential loads.

Advantages of NILM are related to their scalability, cost reduction, less maintenance and the minimization of intrusiveness when compared with ILM methods. Moreover, NILM techniques also contribute to improve the observability of the electrical system. It reduces the risk of supply failure due to equipment constraints in times of increasing demand for electricity [47]. Additionally, simpler and shorter installation times are required comparing NILM with ILM, making NILM methods a feasible option for energy management systems [19], planning and operation of electrical networks [41]. However, there is a compromise between accuracy and complexity of these methodologies.

Although elementary NILM techniques do not require significant computational resources, their accuracy is relatively low when compared with complex methodologies. Sophisticated methods

involve advanced algorithms and higher development times due to more elaborated training processes and parameter configuration [47]. Non-intrusive load monitoring methods also depend on the reliability of the input data and metering reporting rates. Low frequency measurements reduce noise impact in designed methods and provide an accurate identification of resistive loads, being usually implemented in offline systems. In contrast, high resolution data requires accurate measurement instruments, often increasing complexity, programming times and implementation costs but enabling harmonic and transient analysis [48], two important electrical characteristics for DER load identification.

Non-intrusive load monitoring methods can be summarised in three main stages, which are illustrated in Fig. 5 and are: (i) data acquisition; (ii) data processing and (iii) classification. The nature of the aggregated loads is captured during the data acquisition process where raw measurements are recorded. Subsequently, divided into pre-processing, feature extraction and feature projection, data processing focuses on getting a clean load signatures to be used as input of the last stage known as classification.

A key step on the design of NILM methods consists of the creation of independent training and test datasets. Both are created in the processing stage. During the classification stage, training data is implemented to teach the machine learning algorithm the main characteristics of system. Subsequently, to evaluate the efficacy of the designed method, an independent set of data unknown by the classifier and called test data, is used to obtain predictions. Obtained results are compared with expected values using evaluation metrics.

4.1. Data acquisition

4.1.1. Tools

Several data acquisition instruments are used to measure and record electrical variables. Commercial Energy management systems and off the shelf solutions are commonly used, including PowerScout 24 [50], eGauge energy monitoring systems [51], EnviR energy aggregator [52], and oscilloscopes [53]. Alternatively, some researchers have developed their own experimental data acquisition systems using devices such as a Raspberry Pi 3 and a Arduino Mega 2560 [54] or the modular open-source phasor measurement unit called OpenPMU [55].

4.1.2. Data types

Understanding the nature of the electrical load is a key step to develop NILM methods. Load profiles can be categorized in four groups depending on their power consumption: 1) on-off, 2) regularly variable, 3) continuously variable devices and 4) constant loads [56]. On-off loads are appliances having two step changes in their operation such as electric kettles, incandescent lamps, toasters, fridges, air-conditioning, central heating pumps, electric

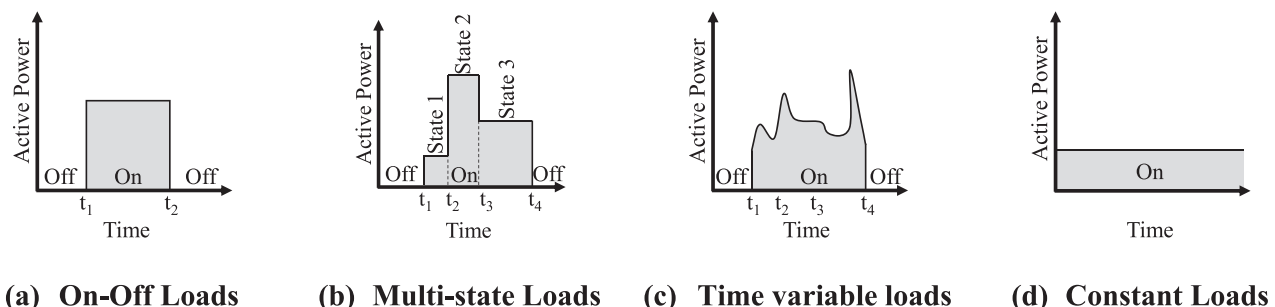


Fig. 6. Types of loads (Adapted from Ref. [57]).

Table 2
Common public datasets used for NILM methods (Adapted from Refs. [57,59]).

Dataset	Location	Frequency	Number houses/ loads	Evaluated Time	Variables	Ref.
AMPDS	Canada	1 min	1 house (19 loads)	2012–2014	V, I, f, P, Q, S and PF	[60]
BLUED	USA	12 kHz	1 house	8 days	V, I, switching events	[61]
COOLL	France	100 kHz	42 loads	June 2016	V, I	[62]
DRED	Netherlands	1 Hz, 1 min, 1 h	1 house	July–Dec 2015	Electrical, environmental, occupancy, household data	[63]
ECO	Switzerland	1 Hz	6 houses	8 months	V, I, phase shift	[64]
GREEND	Austria and Italy	1 Hz	8 houses (9 loads/house)	1 year (3–6 months)	P	[65]
HELD1	—	4 kHz	18 loads	3 s per event	V, I	[66]
HFED	Delhi (India)	5 MHz	24 loads	Few ms	power line EMI	[67]
Pecan	Texas, Colorado, California, others in the USA	1 min to 1 Hz	750 houses	6 years*	P, S, I, V, THD, phase to phase angle	[51]
Street PLAID	Pittsburgh, USA	30 kHz	65 houses (17 loads)	Summer 2013, Winter 2014, 2017	V, I	[68]
REDD	USA	15 kHz, 1 Hz, 0.5 Hz	6 houses (24 loads)	3–19 days	V and P	[69]
REFIT	UK	8 s	20 houses (11 loads)	2 years	P	[52]
Smart*	USA	1 Hz	3 houses, 400+ houses	2012–2016	Power consumption, power generation (solar, wind), indoor and outdoor weather data, switching events	[70]
Tracebase	Germany	1–10 s	15 houses (158 loads)	—	P	[59]
UK-DALE	UK	16 kHz, 6 s	5 houses (54 loads)	499 days, 2.5 years	P, event labels	[71]
WHITED	Germany, Austria, Indonesia	44.1 kHz	110 loads	5 s per event	V and I transients	[72]

Notes: Definition of acronyms listed on this table.

Time-frequency: Frequency (f); Hours (h); minutes (min); seconds (s); milli seconds (ms).

Electrical Features: Electromagnetic interference (EMI); Current (I); Active power (P); Power factor (PF); Reactive power (Q); Apparent power (S); Total harmonic distortion (THD); Voltage (V).

ovens and electric space heaters. Regularly variable, finite state or multi-state loads are those appliances with several power states when turned on, which are repeated through their operational conditions such as washing machines. Another group of loads is called continuously variable devices such as desktop computers, laptops and televisions [57], while constant loads are those appliances in continuous operation such the standby base load of electronic appliances, fans, continuously operating pumps (e.g. aquariums). Some authors consider loads such as fridges or television as constant loads, but these devices present several operational states, thus they better fit into the multi-state group of loads. A graphical representation of the types of loads here described is shown in Fig. 6.

4.1.3. Datasets

Machine learning-based techniques are highly dependent on training data to effectively learn load characteristics and create accurate models [58]. The acquired data to implement NILM methods is a compound of aggregated measurements from loads of an electric system. To do so, three different options are usually available for research studies to acquire data from: private, experimental and public datasets.

Studies based on private datasets may be of value, but the results are not reproducible due to institutional policies for sharing data and privacy laws. Thus, researchers often consider creating their own data acquisition system, thereby being able to choose specific reporting times, select desired variables to be monitored and define the length of the dataset, among others. Buddhahai et al. [50] used an experimental dataset consisting of data taken every minute acquired from 19 different loads. Five electrical variables (current, voltage, power factor, active and reactive power) for a period of 5 weeks where measured, splitting data into 20% training, 40% testing and 40% for validation purposes. Reliability of experimental

datasets is the main advantage for scientist because each researcher sets up the experiment with the needed conditions to obtain the required system information. However, its main drawbacks are the recording costs and the time involved in the data acquisition activity. It also presents a concern in terms of external reproducibility of the research work, and thus public datasets have an advantage in that regard. Public datasets represent an accessible source of data for academic research purposes. The most common open databases available used in research studies applying NILM techniques are presented in Table 2. The main benefit of public sources relies on the availability of considerable amount of data from various appliances and different electrical features during specific periods of time. Additionally, it provides a common test bench for comparison purposes, facilitating the evaluation and optimization of proposed methods with similar objectives. However, researchers need to evaluate as an initial step if data characteristics fulfil their requirements. Reporting times, number of loads, type of loads, measured electrical variables and sampled times are key features needed to select a dataset and develop a NILM model.

4.2. Data processing

Optimal processing of the input data increases the efficacy of NILM algorithms. Mitigating measurement noise, discarding uncorrelated values as well as maximizing information from the input signal are the main objectives of this section [73]. Three main stages can be defined in this process: (i) pre-processing; (ii) feature extraction and (iii) feature projection.

4.2.1. Pre-processing

The pre-processing stage is required to prepare the raw data in an appropriated format to use it in the contiguous stages. Normalization, thresholding and filtering techniques are applied to

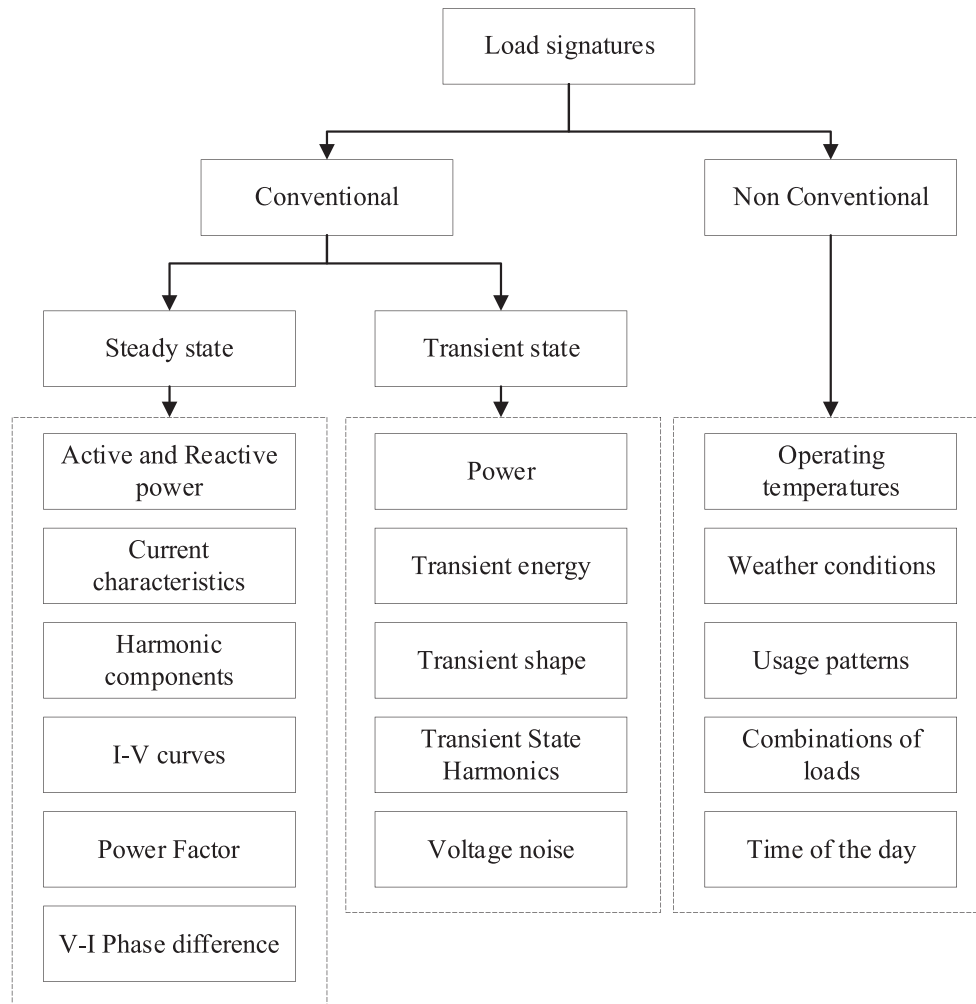


Fig. 7. Load signature classification (Adapted from Refs. [47,50,80,81]).

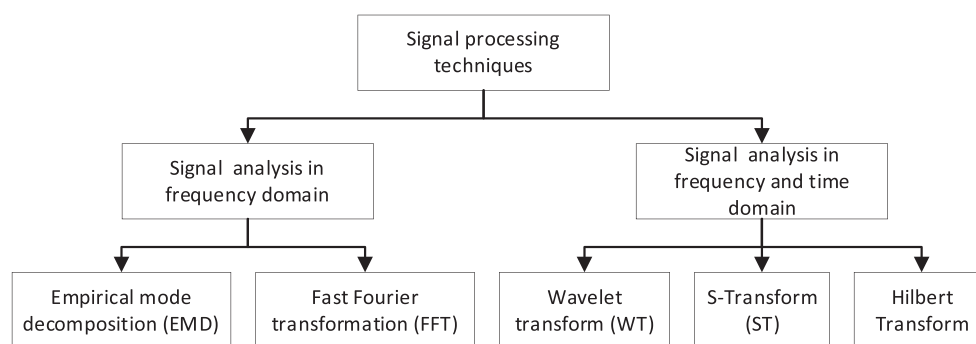


Fig. 8. A taxonomy of signal processing methodologies.

replace missing values, discard noisy samples, avoid nonsense measurements and re-organise the input data [74]. Additionally, sliding windows [75], centring and whitening methods [76] are also commonly applied at this stage. As an example, Drechtny standardizes the input data to achieve zero mean and unity standard deviation in Ref. [77]. Additionally, Lin et al. presented in Ref. [78] an NILM algorithm based on variable sliding windows to identify load events of several electrical variables.

4.2.2. Feature extraction

This step is based on analysing electrical loads behaviour by metering means, which varies depending on the type of load. Non-intrusive load monitoring methodologies are focused on obtaining one or more unique electrical attributes, also called electrical signatures. This is to identify specific load features from aggregated measurements [79]. Conventionally, steady or transient states are selected to obtain load characteristics, but other non-electrical features can be implemented as is presented in Fig. 7.

Table 3

List of relevant NILM methods applied in the customer side.

Features	Pre-processing	Feature Extraction	Feature Projection	Classification Algorithm	Supervised	Event based	Sampling rate	Dataset	Evaluation Metric	Result (%)	Ref.
P, Q	FL	—	—	FL	Y	N	—	Experimental	$\delta_{\max}$	—	[47]
P, Q, THD, PF	CUSUM	K-means	—	GA	Y	Y	50 kHz	REDD	Acc	>76.5	[49]
I, P, Q, PF, V	—	RAkEL	—	DT	Y	Y	1 min	Experimental	F1 Score	>59.0	[50]
P	—	DFT	PCA	k-means	N	N	30 min	CER Ireland	Acc	>92.0	[86]
		WT	PAA	Hierarchical					MSE, SIL,		
			SAX	SOM, GMM, FCM					DBI, MIA,		
P	SW	—	—	RF k-NN	Y	Y	—	Experimental	WCBCR, Di	89.0	[54]
									Acc	85.0	
VI	—	Binary images	CNN	DBSCAN	Y	Y	30 kHz	PLAID	RI	99.0	[89]
							44 kHz	WHITED	F ₁ score	85.0	
P	Centering	HSID	—	FHMM	Y	Y	1 min	AMPds	F ₁ score	95.0	[90]
				ISDTW				REDD	PCE	>2	
									R2 score	~1	
PQ	Threshold	Mean Values	—	CNN	Y	Y	1 Hz	Experimental	Precision	87.0	[53]
I_{THD}	—	FFT	—	FFNN	Y	Y	2 kHz	Experimental	MSE	—	[91]
PQ, Harmonics	—	FFT	—	k-NN	Y	Y	4 kHz	HELD1	Acc	90.8, 88.9	[93]
FIT-PS				SVM						68.3	
				Bayes							
Z, P	—	—	—	Multilayer FFNN	Y	Y	1 min	Experimental	MAPE	19.09	[94]
P	Median filtering	SW	—	PF-FHMM	N	Y	1 Hz	REDD	Error	89.0	[95]
P	SW		PCA	RF	Y	Y	1 min	Pecan Street	Precision	92.3	[96]
									Acc	92.7	
									Recall	93.0	
									F1 Score	92.7	

Notes: Definition of acronyms listed on this table.**Electrical Features:** (FIT-PS); Current (I); Active power (P); Power factor (PF); Active and Reactive power (PQ); Reactive power (Q); Apparent power (S); Total harmonic distortion (THD); Voltage -Current (VI).**Pre-processing:** Cumulative sum (CUSUM); Sliding windows (SW).**Feature extraction:** Discrete Fourier transform (DFT); Fast Fourier transform (FFT); Hybrid Signature-based Iterative Disaggregation (HSID); RANdom k-labelSets (RAkEL); wavelet transform (WT).**Feature projection:** Convolutional neural networks (CNN); Principal component analysis (PCA); Piecewise Aggregate Approx. (PAA); Symbolic Aggregate approXimation (SAAX).**Classification:** Density-Based Spatial Clustering of Applications with Noise (DBSCAN); Decision trees (DT); Fuzzy C-means (FCM); Feed forward neural networks (FFNN); factorial hidden Markov models (FHMM); Fuzzy logic (FL); Genetic algorithm (GA); Gaussian mixture model (GMM); Iterative Subsequence Dynamic Time Warping (ISDTW); k- Nearest Neighbours (k-NN); Particle filtering - FHMM (PF-FHMM); Random forest (RF); Self-Organizing Maps (SOM); Support vector machines (SVM).**Metrics:** Accuracy (Acc); Davies-Bouldin Indicator (DBI); Distance (Di); Mean squared error (MSE); Mean Index Adequacy (MIA); Power contribution error (PCE); Rand index (RI); Silhouette index (SIL); Ratio of within-cluster sum of squares to between-cluster variation (WCBCR).

Table 4
Scenarios for a two categories based problem.

Feature	Expected Value	Predicted Value
True positive (TP)	On	On
False positive (FP)	Off	On
True negative (TN)	Off	Off
False negative (FN)	On	Off

Steady state conditions are observed analysing electric load features during the ON and OFF states. This commonly requires low frequency data acquisition, which simplifies the general algorithm. A common approach is based on active and reactive power graphs, which are simple to use presenting high accuracy for loads with different electrical signatures and constant steady state characteristics [44]. However, they lack precision to identify loads with similar, variable or low power characteristics. Therefore, other features such as current harmonics, averages, Root Mean Square values and voltage-current waveforms, among others, are also implemented as electrical signatures in NILM [78].

The analysis of transient states focuses on observing the electrical changes from one steady state to another one, passing from the OFF to ON state or vice versa [82]. Data sampling frequencies fulfilling the Nyquist-Shannon sampling theorem are used to adequately represent the signal during transient events. At this stage, the needed high sampling frequencies are feasible relying on modern instruments. However, it presents constraints regarding data storage and communication for remote locations [81]. Despite

a higher complexity, elevated cost and increased time in comparison with steady state features, electrical loads generally present unique transient states. Thus, loads presenting similar electrical signatures and low power consumption can be better identified using transient analysis instead of steady state analysis [81]. Transient power, current, voltage noise and harmonics are some examples of transient characteristics frequently monitored with NILM algorithms.

Complex loads present non-linear and variable load profiles, being easy to confuse them in aggregated measurements with other load signatures. Thus, non-conventional features have been included in recent studies as alternatives to correlate loads with external factors, complementing steady state and transient based load signatures [59]. As an example, heating and cooling loads can be correlated with operating temperatures, weather conditions, usage patterns, combinations of other loads, the season of the year, time of the day and so on.

As another alternative to deal with similarities across loads in the time domain, many research studies use signal processing techniques to extract hidden characteristics from the selected electrical features. Conventionally, frequency domain methodologies such as Fast Fourier transformation [83] or empirical mode decomposition are used to filter the signals and discard meaningless values in the time domain [80]. Other techniques allowing time and frequency domain analysis have been also implemented [84] in order to provide more information to improve the efficacy of NILM based on signal processing. Methods such as wavelet transformation, S-transformation and Hilbert transformation are

Table 5
NILM evaluation metrics (Adapted from Ref. [97]).

Metric	Type of problem	Mathematical Equation	Parameters
Accuracy (Acc)	Classification	$A_{cc} = \frac{TP + TN}{TP + FP + TN + FN}$	TP, FP, TN, FN
Precision	Classification	$P_r = \frac{TP}{TP + FP}$	TP, FP
Recall	Classification	$R = \frac{TP}{TP + FN}$	TP, FN
F1-Score	Classification	$F_1 = \frac{2 * P_r * R}{P_r + R} = \frac{2 * TP}{2 * TP + FP + FN}$	TP, FP, FN
Mean average error (MAE)	Regression	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \bar{y}_i $	y_i : actual measurement $\bar{y}_i$: median value n: number of samples
Mean average percentage error (MAPE) [94]	Regression	$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{(y_i - \hat{y}_i)^2}{y_i}$	y_i : target value $\hat{y}_i$: predicted value n: number of samples
Mean squared error (MSE) [39]	Regression	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y}_i)^2$	y_i : actual measurement $\bar{y}_i$: median value n: number of samples
Root mean squared error (RMSE)	Regression	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y}_i)^2}$	y_i : actual measurement $\bar{y}_i$: median value n: number of samples

Table 6
DER load modelling in distribution networks existing research.

DER	Method	Dataset	Metric	Result	Ref.
Smart Grids	Multi-Factor Back-Propagation Neural Network	Pecan Street	Accuracy	>90.0%	[102]
			MSE	<0.15	
	Conventional neural networks, Neural Network based Genetic Algorithm (NNGA), Neural Network based Particle Swarm Optimization (NNPSO)	Pecan Street	MSE	<0.54	[103]
PV	Long Short-Term Memory (LSTM) neural network	Pecan Street	RMSE	<24.42	[104]
	Contextually Supervised Source Separation (CSSS)	Pecan Street	RMSE	3.5	[101]
	Analytical	Experimental	—	—	[105]
EV	Long Short-Term Memory (LSTM) neural network	Pecan Street	RMSE	<0.62	[106]
	Monte Carlo	Pecan Street	RMSE	0.065	[107]
	M ₁ /M ₂ /∞/N _{MAX} queue model (Stochastic model)	Pecan Street	G	−0.0064	[108]
			Sg	0.5109	

frequently explored. A taxonomy of these techniques is presented in Fig. 8.

4.2.3. Feature projection

Feature projection, also called dimensionality reduction, is used to transform the data into a different subspace. This is made keeping relevant information to correctly represent the input signal into a different domain to facilitate the classification of the load [85]. Its main advantage relies on automatically reducing noise or redundant variables (dimensions) from the original data. Transformations are applied to find a smaller or equal dimensional subspace where valuable information can be consistently separated to improve the load identification. Methods such as linear discriminant analysis, independent component analysis [43], symbolic aggregate approximation [86], piecewise aggregate approximation and principal components analysis are some techniques applied at this level [87,88].

4.3. Load classification

Due to diverse types of loads presenting constant patterns, numerous states and non-linear electrical behaviour, accuracy and flexibility of load identification methods are required [41]. Therefore, several techniques have been developed in order to improve the efficacy of the designed methods, which can be classified in function of the used machine learning algorithm [59]. Generally, machine learning techniques can be grouped as supervised and unsupervised methods, as well as event or non-event-based methodologies.

Supervised methods depend on a set of labelled data, requiring time to adequately configure the system parameters to train the machine learning algorithm [81]. Online and offline approaches during a specific window of time to train the algorithm. This contributes reducing processing times and data storage required capacity. Conventional algorithms such as decision trees, random forest, support vector machines, k-nearest neighbour and Naïve Bayes belong to the list of supervised NILM methods [54]. In contrast, unsupervised systems provide an automatic learning process of the algorithm without user interaction [86]. These types of methods do not require previous knowledge of the dataset to generate the model and classify the loads. The operational principle

is based in clustering the input data into groups of individuals presenting similarities. Therefore, they do not provide labels in the output data but clusters. Techniques such as K-means clustering, hierarchical clustering, self-organizing map, fuzzy c-means [86], as well as Markovian models (hidden Markovian model, factorial hidden Markovian model and others) are commonly implemented as unsupervised methods [81].

Alternatively, NILM algorithms can be also classified as event or non-event-based methodologies. Event based techniques are focused on identifying time-based changes. Low sampling frequencies event base methods require small size datasets, being simpler to implement. However, these methods are susceptible to measurement error arising from sudden transient changes in the signals and low sampling rates. This represents an inconvenient to identify loads with similar electrical characteristics. Therefore, event-based algorithms need high measuring rates to properly record the transient characteristics to achieve high performance of complex loads. In contrast, non-event based methodologies analyse the signal in every iteration, depending on the database to identify patterns or electrical signatures to train them [73]. To apply non-event based NILM, researchers can use a wide range of sampling frequencies. Fast recording systems (hundreds of Hz) or low sampling frequency rates (seconds or minutes) are designed as presented by L. De Baets et al. in Ref. [89] and A. Cominola et al. in Ref. [90] respectively.

Advanced techniques based on deep learning are also used to develop NILM. Representing the operation of the human brain by defining evaluating nodes as neurons and weighted connections as axons, neural networks have been implemented in several areas of investigation [59]. Convolutional neural networks [53] and feed-forward neural networks [91] represent the most common deep learning techniques used for NILM. Using these types of methods, considerable high performance is commonly achieved. However, computational requirements, non-availability of large annotated datasets and high complexity are common reasons for researchers to first analyse conventional methods [92].

A compilation of some representative NILM developed methodologies, including their main characteristics is presented in Table 3. It is demonstrated the wide variety of methodologies and possible combinations to be considered to design NILM algorithms.

Table 7
DER identification in distribution networks existing research.

DER	Method	Dataset	Metric	Result	Ref.
PV	Support Vector Machines (SVM)	OpenPMU	Precision	99.04%	[55]
			Accuracy	96.27%	
			Recall	93.44%	
			F1 Score	96.16%	
	Piecewise Aggregate Approximation (PAA), Agglomerative clustering, K-means, Self-organizing maps (SOM)	Pecan Street	Accuracy	98%	[88]
			F1 Score	95%	
EV	Analytical	Pecan Street	RMSE	~ 0.41	[100]
			Accuracy	>90%	
	Karhunen Loève expansion	REDD	A _{PD}	84%	[110]
		Tracebase			
	Deep neural network (DNN)	Pecan Street	MAPE	3.98%	[111]
	Modified independent component analysis (ICA)	Pecan Street	F1 Score	93%	
	Random Forest + Principal Component analysis (PCA)	Pecan Street	Precision	92.34%	[96]
			Accuracy	92.66%	
			Recall	93.03%	
			F1 Score	92.69%	
	Convolutional neural networks and recurrent neural networks (RNN)/long short-term memory (LSTM)	Pecan Street	F1 Score	67%	[98]
		Eidsiva DNO	Precision	58–68%	
	Mean sliding window (MSW) and support vector machines (SVM), k-NN, decision trees (DT) and regression	Pecan Street	Precision	83%	[109]
			Recall	100%	
			F1 Score	91%	

4.4. Performance evaluation

Metrics are used to evaluate the efficacy of the developed methodologies, providing a better understanding of the performance of each method under the developed conditions. Different metrics are implemented to assess NILM methods among research studies. They are usually based in four parameters: true positive, true negative, false positive and false negative. For example, in a two-classes (On-Off) problem, these metrics would be defined as function of the predictions and their expected values would be those shown in Table 4.

Accuracy (Acc), Precision (Pr), Recall (R) and F₁-Score (F₁) are defined as function of the fundamental metrics. They are normally used by authors to evaluate the performance of the NILM in a classification/identification setting. Additionally, other methods based on error measurements such as mean average error and root mean squared error are frequently used in different approaches [59]. In particular, the last ones are used to evaluate the performance of NILM methods for regression problems. Equations for the most used evaluation metrics are presented in Table 5.

Although, the above metrics depicts the performance of each NILM, misunderstandings might be found during the interpretation of results. Unbalanced datasets might project a good efficacy if either true positive or true negative values are predominant. As a result, the classification system is not very well trained for a general case but a specific one [98]. Therefore, it is also recommended using a confusion matrix to get a better picture of the achieved predictions [99]. This is particularly relevant to multi-class identification. A problem defined by identifying m types of loads, will have an $m \times m$ confusion matrix, where the main diagonal represents the correct classifications and the other values represent misclassifications. The advantage of using this metric to evaluate a classification algorithm is the clear identification of the deviations in the algorithm or biases towards some of the classes regarding the others.

5. State-of-the-art of load modelling and NILM methods for DER identification on distribution networks

Up to date research studies focusing on DER load modelling in distribution networks (summarised in Table 6) have placed an emphasis on algorithms applied on the medium voltage and low voltage customer side of the electrical network. These methods were designed following similar taxonomy as that explained in sections 2 and 3. In low voltage networks, distributed generation modelling has been developed in order to obtain individual system response of a particular source. Here, renewable sources such as PV and wind turbines are classified as inverter-connected distributed generation (DG), while others such as diesel or gas generators and heat pumps are considered as directly connected DG [29]. Those models are categorized as both static models, where all DG are defined as negative loads, and dynamic models. Dynamic models consider variations for directly coupled DG that are frequently represented by motor models. Inverter-connected DG that omit mechanical dynamics but include quicker control loops due to governing of power electronic converters. Examples of static and dynamic DG models are carried out by Arif et al. in Ref. [29].

In terms of applied methodologies for DER load monitoring, researchers have been mostly focusing on EV identification and PV systems modelling. A predictive model to obtain PV generation was developed by Tabone et al. [100]. In this study, solar PV generation from a residential area was predicted using smart meter data registered every 15 min. The electrical variables were obtained from a historical public dataset called the “Pecan Street – Dataport” (hereafter “Pecan Street”) and real-time data. The real-time input

data was obtained from actual systems generating in the area, called proxies. Obtaining an root mean squared error of 3.5%, it was found that the number of proxies negatively affected the predictions whenever their number was higher than 3. Additionally, Vrettos et al. [101] proposed a methodology to identify PV systems' power generation at a distribution network feeder. Using an online irradiance measurement as a reference, aggregated active and reactive power were modelled to analyse solar PV farms and distributed generation scenarios.

In a previous research study, an NILM method was proposed to identify EV from aggregated measurements of household load profiles as explained in Ref. [96]. Using principal components analysis as feature projection method and support vector machines as classification algorithm, authors recognised EV in charging state. It was designed considering sliding windows of 10 min using the Pecan Street dataset obtaining an overall efficacy of 92.68%. To improve the method, further research is required not only to obtain a Boolean indicator of EV state but to provide active power consumption of this considerable high residential load. For this, an adequate understanding of the DER dynamics is needed to initiate an appropriated algorithm capable of recognizing them from aggregated signals. Electric vehicles connected on the low voltage side of the electrical network present variable charging patterns due to increasing, steady and decreasing charging stages. This involves not only the identification of the load in one single stage but in all the charging process. This fact is demonstrated in the work undertaken by A. Munshi and Y. Mohamed in Ref. [43], where a NILM methodology was developed based on EV charging patterns identification. Using ICA and low frequency sampling rates, authors achieved a 93% efficacy identifying EV load charging profiles. Different databases were used to train, test and validate the algorithm. In addition, Rheman et al. presented in Ref. [109] a supervised event-based NILM for EV and air conditioning systems identification. Using low sampling-rate measurements, transient analysis was carried out to extract electrical features such as peak power and transient's duration. These features were used as inputs of a k-nearest neighbour classifier achieving an overall efficacy of 95%. A summary of available publications related to DER load identification in distribution networks is presented in Table 7.

6. Discussion

Optimal DER integration on low voltage distribution networks require real time awareness of the electrical system as well as active management of sources and loads [112]. Load modelling and identification techniques allow distribution network operators to identify system faults, control them and contribute to identifying critical sectors of the network requiring infrastructure intervention [35] and effective and efficient power consumption. There are however several aspects to be considered in order to effectively implement monitoring methodologies for DER identification on low and medium-voltage distribution networks, which are discussed below.

6.1. Lack of information about low voltage distribution networks

Methodologies to model and predict aggregated loads on distribution networks, which enable state estimation analysis, switching control, and management operation of the electrical system are commonly used for power system analysis. Real-time load modelling and load identification techniques are required when transitioning from unidirectional to active distribution networks. To that end, using non-invasive approaches to acquire individual load signatures from aggregated measurements, NILM methods have been extensively developed since it was proposed by

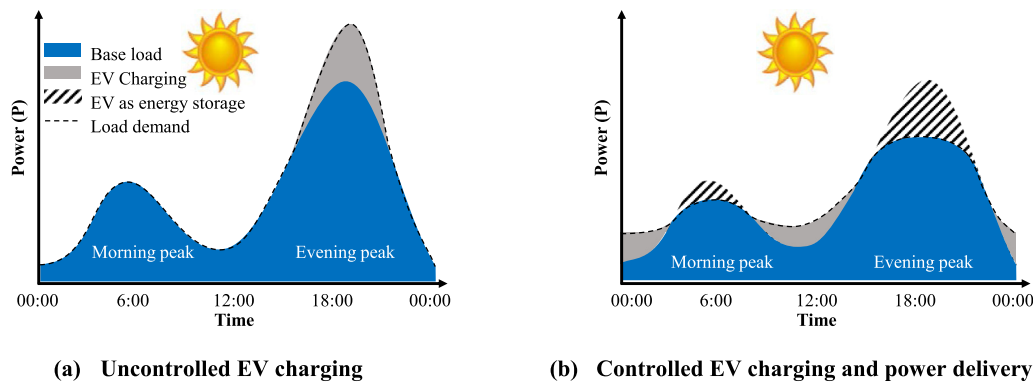


Fig. 9. EV role in active management systems (Adapted from [126]).

Hart et al., in 1986 [113]. Although, DER data are vital for distribution networks operation, the lack of a correctly mapped distribution networks is an issue identified worldwide for distribution control centres [100]. This makes difficult the integration of new, low-carbon loads and distributed generation in the electrical system. Therefore, it is required to face this problem by implementing real-time identification and modelling techniques to generate appropriated control responses in accordance with the fast-changing variations in voltage, frequency, among others caused by DER.

6.2. Smart metering

Smart metering has been identified as an enabling technology for DER integration and active control of loads on low voltage distribution networks [114]. However, smart meter deployment challenges such as conventional meter replacement, customer engagement, scalability, processing capability, data interpretation as well as communication protocols, installation and maintenance standards are some of the main obstacles for the mass use of these meters [115]. Several challenges utility companies have been facing include lack of synchronized measurements, poor communications infrastructure, security concerns as well as issues integrating new and old technologies, were summarised in 2011 by Depuru et al in Ref. [116]. Many of the mentioned issues still remain in place.

Advance metering infrastructure has been increasing in countries such as the United States of America where 43% of the residential sector has had smart metering since 2014 [16]. Projections of 780 million smart meters by 2020 installed globally [86] provide an opportunity to include NILM techniques and inform with real time data distribution control centre operators. In the future it is likely to have intelligent sensors provided with physical and logical addresses connected to the Internet or any other mean of data transmission such as power line communications for billing, demand response and other utility services [117]. These are important characteristics needed to implement monitoring methodologies and to effectively integrate DER on distribution networks. However, new regulations, the technical and commercial compatibility of the different smart meters available are required to enable the roll out of these technologies.

6.3. Data storage

Real-time NILM methods increased complexity should be considered. This includes higher data storage requirements due to the considerable amount of information obtained at high reporting rates (reporting rates above 1 Hz) [43]. It also involves advanced

communication systems with increased bandwidth and lower latency times. However, these conditions are not a barrier anymore for NILM techniques due to rapid technological development that increases the accessibility to computational power, data storage, and precise measurements. As an example, a low-cost phasor measurement unit called the OpenPMU has been presented in Ref. [118], being able to record voltage and current magnitudes, phase angle, frequency, and rate-of-change of frequency every cycle in 50 Hz or 60 Hz electrical networks. This sensor also allows the researchers to record point on wave data (oscillography) at 12.8 kHz in 50 Hz or 15.36 kHz in 60 Hz electrical systems.

6.4. Cyber security

Active distribution networks are at risk from cyber-attacks [119] and advanced security measures are needed to secure existing communication systems [120]. Cyber security attacks have been increasing side-by-side with the internet of things. Malicious attempts to get access to the electrical network are not a rare event and concerns about data management is also presented as a challenge regarding security and privacy of both large and small systems. As an example, the largest Indian nuclear power plant was attacked with malware in September 2019 [121]. A type of 'DTrack RAT' targeted the Kudankulam Nuclear Power Plant financial system. The virus objective was extracting administrative information but also had potential to cause control system disruptions. Electronic vulnerabilities of vehicles connected to the Internet have been also targeted for malicious purposes such as stealing vehicles, illegally acquiring data, denial-of-service attacks, frauds and vehicle ID modification. In accordance with the 2020 Global Automotive Cyber Security report, 367 publicity attacks were informed since 2010, with 155 of them occurring from 2018 to 2019, presenting a 94% increase during that period [122].

Internet of things inner characteristics in DER provides better opportunities to increase the efficiency of the electrical system but also increases the number of possible entries for malicious attacks, also known as 'the attack surface'. Using NILM in the context of real-time operations of the power system, cyber-attacks could cause potential maloperation of energy management systems and destabilisation of the power system. Attacks targeting NILM data manipulation can involve smart loads such as EV and heat pumps as well DG systems causing generation-demand mismatch. Therefore, load modelling and DER identification techniques require reliable and high security communications standards for safer communication platforms. This will help to avoid cyber-attacks that can target not only data acquisition devices such as smart meters, data storage and servers but also smart loads such as EV.

6.5. Active energy management systems

The balance of electricity generation and load demand is crucial for electrical networks stability. Microgrids [123] and demand side management techniques present an opportunity to manage stochastic load profiles and unpredictable generation from DER [124]. This is an action that is required in the near term. In the United Kingdom alone, it is calculated that migration of residential heating systems (currently power by natural gas boilers) to cleaner technologies will involve around 20 million dwellings in the coming years [125]. Using remote control of new and smart loads contribute to maximizing electrical network flexibility and efficiency [126]. As an example, uncontrolled charging of EV can generate high load peaks during the evening. Using “vehicle-to-grid” technologies contribute not only to reducing peak load demand but flattening the load demand curve, as shown in Fig. 9. One of the main advantages in vehicle-to-grid schemes is the reduction of investments to cover network renovations. In the United Kingdom, BloombergNEF has estimated that about 16% of the nation's energy demand could be covered from vehicle-to-grid schemes by 2040 [126]. Synchronization of generation and loads, bidirectional communication systems and active end customer participation are crucial in this scenario. Thus, real-time based load modelling and load identification methods present an opportunity to make this happen.

6.6. Available up to date DER data for research purposes

Optimal DER load monitoring techniques rely on updated high-resolution data for the management of active distribution networks. However, out-of-date network models incapable of forecasting DER load profiles as well as a majority of public databases focused on load profiles of conventional loads [29], expose a different reality. Only few available datasets contain information about one or more DER, often PV or EV systems. Thus, interaction between researchers and industry is key for the development of these new methods for academic, commercial and most importantly practical purposes. The development of accurate and novel load monitoring algorithms requires real data from industry. This to design methods applicable not only to analyse historical datasets but to test them under realistic conditions. It is also needed from the academic perspective to know and understand specific challenges in the industrial sector to allow methodologies to be benchmarked. The availability of these large public dataset will be of particular interest to develop and train deep learning methodologies, currently state of the art in the machine learning field, but of scarce application to DER load monitoring.

This will help distribution network operators to recognise DER variable load profiles through all seasons, which can be different depending on customer preferences, geographical location, brands, technologies, and many more factors that make energy demand a local task [18]. Having high resolution datasets allows the implementation of several methodologies such as supervised, non-supervised and event or non-event identification methods, using a combination of conventional and new techniques designed for specific DER characteristics [48]. In case of EV, PV, battery energy storage systems and small-scale wind turbines, NILM online identification presents better options for their identification. In contrast, load modelling techniques including user patterns, seasonal variations in demand and temperature profiles could lead to an accurate representation of electric heating systems.

6.7. Research focus

Load identification on the utility side has become important during recent years due to DER integration, requiring further

advances to properly deal with modern loads and DG. The main challenges are created due to the presence of several types of loads, stochastic customer usage patterns, weather conditions, time variations and the lack of accurate information on distribution networks. Particularly on this sector of the electrical network, reducing power losses and covering efficiently the electrical demand are key motivations [127]. Although extensive research has been carried out on load modelling and NILM at both utility and customer side, most of the literature have been focused on developing modelling and monitoring techniques applied to conventional loads in the utility, commercial and residential sector. Although these methods work properly for conventional loads, projecting in general metrics of above 80%, they do not consider the inner properties of DER such as highly variability and non-linear characteristics. As a consequence, new and advanced methodologies are required to properly follow and comprehend DER electrical characteristics.

Considering the increase of DER installation on distribution levels, real-time load monitoring methodologies are important methods to correctly make the transition from conventional to bidirectional power flow distribution networks. This will enable distribution network operators to use online control techniques and appropriately mitigate DER undesirable impacts on electrical networks. However, a reliable and clear evaluation of the proposed methods ensuring their reproducibility is also required to facilitate further studies not only to learn from old models but to improve them [59]. The main advantage of having clarity on proposed methods consists of increasing the already fast development of new techniques, working in conjunction and collaboration instead of doing it as separated islands.

6.8. Recommendations

There are five main recommendations.

- i Projects such as “The Pecan Street Dataport – Dataset”, REFIT, REDD, Tracebase and other public datasets contain electrical measurements of several household appliances available for researchers. However, there is a clear need for public datasets that include several electrical features of different DER recorded in low (minutes, days) and high frequencies ($f > 1$ Hz).
- ii A few public datasets contain either PV generation or EV power consumption, while none of them having information of small-scale wind generation, battery storage or other systems such as heat pump or electric heating load demand profiles.
- iii Other variables such as wind speed, solar irradiance, and outdoor temperature among others, could contribute correlating DER electrical profiles to non-conventional variables. This contributes to obtain more accurate load monitoring and forecasting models.
- iv Public DER datasets are needed to provide researchers with a key tool for the development of precise techniques to improve the observability of low voltage distribution networks around the world. This cannot be a singular effort from one institution due to the different variables modifying the effect of DER on distribution networks (such as weather, usage patterns, location, customer preferences, and so on). The effective integration of several stakeholders such as universities, utility companies and customers are key for an effective creation of a high-quality dataset.
- v Research studies are also required to be precise and replicable to provide with strong basis new developments in this area of knowledge. Data manipulation to achieve publications should be under no reason carried out by any researcher and a complete result analysis including

deviations should be provided for future studies to complement and improve previous techniques. To reach this, the usage of conventional metrics could contribute to provide a better understanding of the performance of load modelling and load monitoring methods. Using only one evaluation metric could provide a false sense of high efficiency of a proposed technique, while other metrics can illustrate weakness of the proposed method for other factors.

6.9. Future trends and perspectives

The increasing penetration of DER in low voltage distribution networks from distributed generation systems and the electrification of transport and heating sectors is a fact that system operators need to consider in the near future for daily management of electrical systems. The implementation of localised control techniques such as demand side control strategies are needed to integrate increasing load carbon loads such as EV load demand. At the same time, these loads could be used as dynamic storage systems to reduce the variability of distributed generation such as roof top PV systems connected in the same network. With this, low voltage distribution networks migrate from conventional static loads towards not only to a more efficient electrical systems with constant technological renovation of electrical appliances but to dynamic networks, making the grid smart [114]. This increases the interaction between utility companies and active consumers requiring a more developed platforms in terms of communication, monitoring and data storage systems.

7. Conclusion

The aim of this paper was to present the first systematic review of load modelling and identification techniques applied to DER on distribution networks. Load modelling of conventional loads was provided with a short description of its mechanism. Load identification focused on non-intrusive load monitoring steps was equally presented. Proposed DER methods were summarised providing the analysis of the most relevant studies and a discussion regarding seven aspects required for the massive integration of DER on distribution networks was provided.

Load modelling and NILM are methodologies which contribute to improving distribution network observability, particularly in the low voltage side of power networks where a lack of information has been found to be a general issue for distribution network operators. Load modelling and NILM contributes real-time data informing not only utility companies, but also government, consumers and manufacturers. Implementing these methodologies on distribution networks for voltage and stability control will help in making a smooth transition to DER rich electrical systems. Thus, online time-synchronized measurements represent a feasible solution in the current technological era to improve distribution network observability, reliability and flexibility in order to produce valid responses in light of the modified system dynamics.

Online DER modelling and identification at distribution levels provide a new challenging research area, which should be further investigated focusing not only on the development of effective methodologies, but also implementing precise and real-time measurements under strict communications standards. These techniques are needed to effectively identify non-linear devices among aggregated load measurements with considerable variety of electrical appliances, involving significant amounts of data. This should be processed in short periods of time and therefore require advanced, safe and reliable communication platforms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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