Vol. 22, n.°4, pp. 93-102, 2023
Revista UIS Ingenierías
Página de la revista: https://revistas.uis.edu.co/index.php/revistauisingenierias

New data-based load modeling for active distribution networks

Modelizado de carga basado en datos para redes de distribución activa

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Received: 23 July 2023. Accepted: 19 October 2023. Final version: 2 November 2023.

Abstract

Electric systems are experiencing fast development, mainly motivated by the carbon reduction policies in the energy sector and the technological developments that introduce new elements and processes. The transition to active distribution networks (ADNs) represents a significant technological advancement in this ever-evolving context. Accurate models for each device present in ADNs are crucial for adequately representing their dynamics; however, load modeling poses challenges due to the vast diversity of load components, variations over time, and dependence on several factors. Despite these challenges, understanding load behavior is fundamental for efficient planning and operation of ADNs. Therefore, precise load models are indispensable for conducting preventive and forensic studies. This paper analyzes various scientific documents from the most relevant scientific databases, explicitly focusing on the challenge of measurement-based load modeling in ADNs. The main contribution of this document lies in enhancing the representation and understanding of loads in ADNs through the analysis of current approaches, challenges, and measurement-based modeling strategies. Additionally, it serves as a reference for future research in the field of load modeling.

Keywords: active distribution network; data-based models; distributed energy resources; dynamic models; load modeling; measurement-based models' parameterization; static models.

Resumen

Los sistemas eléctricos están experimentando un rápido desarrollo, impulsado principalmente por las políticas de reducción de carbono en el sector energético y los avances tecnológicos que introducen nuevos elementos y procesos. En este contexto en constante evolución, la transición hacia redes de distribución activas (ADNs) representa un significativo avance tecnológico y tener modelos precisos para cada dispositivo presente en las ADNs es crucial para una representación adecuada de su dinámica. Sin embargo, el modelado de la carga presenta desafíos debido a la gran diversidad de componentes de carga, las composiciones que varían en el tiempo y la dependencia de varios factores. A pesar de estos desafíos, comprender el comportamiento de la carga es fundamental para la planificación y operación eficiente de las ADNs; por lo tanto, disponer de modelos de carga precisos es indispensable para realizar estudios preventivos y forenses. En este artículo, se presenta un análisis de diversos artículos provenientes de las bases de datos científicas más relevantes, centrándose específicamente en el desafío del modelado de carga basado en mediciones en las ADNs. La principal contribución de este documento radica en mejorar la representación y comprensión de las cargas en ADNs, a través del análisis de enfoques actuales, desafíos y estrategias de modelizado basado en mediciones. Además, busca servir como referencia para investigaciones futuras en el campo del modelado de carga.

ISSN Printed: 1657 - 4583, ISSN Online: 2145 - 8456.

How to cite: D. Osorio-Vásquez, S. Pérez-Londoño, J. Mora-Flórez, "New data-based load modeling for active distribution networks," *Rev. UIS Ing.*, vol. 22, no. 4, pp. 93-102, 2023, doi: https://doi.org/10.18273/revuin.v22n4-2023009

Palabras clave: modelizado de carga; modelos basados en datos; modelos dinámicos; modelos estáticos; parametrización de modelos basados en mediciones; recursos energéticos distribuidos; red de distribución activa.

1. Introduction

1.1. Motivation

The significant increase in electricity consumption in recent years has led to a greater integration of distributed energy resources (DERs) in distribution networks and microgrids [1]. These resources, such as small-scale solar and wind power generation, have proven to be highly efficient in reducing carbon emissions associated with the electricity sector [2]. As a result, implementing DERs is considered a promising solution to reduce dependence on fossil fuels and move towards a more sustainable energy matrix.

However, this growing adoption of DERs and the incorporation of emerging technologies, such as controllable loads, intelligent loads, and loads with power electronic components, have brought about significant transformations in the conventional electrical system. These advancements have driven the transition towards active distribution networks (ADNs), characterized by their ability to dynamically manage and optimize distributed resources [3]. In this context, obtaining accurate models of each element within ADNs is crucial for proper system representation.

A key element in ADNs is load, which exhibits random and time-varying behaviors, implying that their active and reactive power response exhibit dynamic behavior. Additionally, incorporating new technologies in distribution networks has made loads increasingly sensitive to system fluctuations and external disturbances, adding complexity to their modeling [4]. Nevertheless, it is recognized the need for accurate models to characterize modern loads [5]. These models are fundamental for analyzing, planning, and controlling the electrical system; moreover, these are useful for conducting forensic studies that ensure reliable, secure, and efficient operation [6].

Load modeling aims to accurately represent the behavior of loads in an electrical system, both under steady-state conditions and in response to various disturbances. There are two common approaches to load modeling: component- and measurement-based.

The component-based approach involves obtaining detailed information about each load component and their mathematical relationships to represent their combined effect on the system [7], [5], [8]. However, this approach may have limitations due to the difficulty of obtaining specific information for each load component.

On the other hand, the measurement-based approach utilizes data obtained from measurement devices to accurately and aggregately represent the dynamic characteristics of loads [9], [5], [8]. This approach is more practical and widely used due to the availability of measurement devices in electrical systems. It allows for developing reliable and representative load models, facilitating forensic and predictive studies.

Various techniques have been implemented in the measurement-based approach to develop load models. For example, optimization techniques have been employed to construct load models using static and dynamic structures [5]. Additionally, machine learning techniques have been applied to develop black-box models that capture load characteristics without requiring knowledge of their internal structure [10], [11]. Statistical techniques have also been used to develop probabilistic models, allowing for considering uncertainty in load behavior prediction [12], [13].

1.2. Contributions

Load modeling in ADNs is a subject of ongoing study and development. Additional efforts are required to obtain reliable models that enable forensic and predictive studies. In this regard, this document aims to contribute to the field of load modeling, serving as a reference for future research. The challenges and modeling strategies through the measurement-based approach are analyzed to enhance the representation of loads in ADNs and gain a better understanding of their dynamics in these systems.

1.3. Document structure

This paper is ordered as follows. Section 2 presents some models used to represent loads in ADNs. Section 3 presents the approaches to load modeling. The analysis of load modeling in ADNs and recommendations are represented in section 4. Finally, section 5 presents the most critical highlights derived from this paper.

2. Conventional and Current Load Models

In electric system analysis, well-defined and accurate models have been developed for elements such as lines, transformers, generators, and compensation devices. However, load modeling presents a unique challenge (Rodríguez, Pérez, & Mora, 2015)due to the inherent complexity and temporal variability of loads, as well as factors such as weather conditions and the diversity of load types connected to a single source [9]. The task of modeling loads in electrical systems becomes even more complex due to the diversity of users and their different needs.

Significant research has been conducted in load modeling over the past decades. Different mathematical expressions have been proposed to represent load characteristics, which classify models into static and dynamic models based on their form. Static models establish that the relationship between load power, voltage, and system frequency remains unchanged for any given instant. On the other hand, dynamic models define load powers as a function of voltage magnitude at past and present time instants [14].

Load modeling has gained greater importance with the transition to an active distribution network (ADN). These networks encompass various loads, including resistive, motors, electronic, and other loads. Both conventional models and more advanced and updated approaches have been employed in the field of load modeling to accurately represent these loads' behavior.

2.1. Conventional load models

2.1.1. Exponential load model (EXP)

This model is characterized by expressing the active power (P) and reactive power (Q) at each instant t, as a function of the magnitude of the voltage (V) at the bus and the frequency (f) of the system, as shown in equations (1) and (2).

$$P_{EXP,t} = P_0 \left(\frac{V_t}{V_0}\right)^{k_{pv}} (1 + k_{pf}\Delta f) \tag{1}$$

$$Q_{EXP,t} = Q_0 \left(\frac{V_t}{V_0}\right)^{k_{qv}} (1 + k_{qf}\Delta f) \tag{2}$$

V_0, P_0, and Q_0 correspond to the load bus's nominal voltage, active power, and reactive power, respectively. The exponents k_{pv} and k_{qv} represent the response characteristics of active and reactive power to changes in voltage magnitude. Additionally, the exponents k_{pf} and k_{qf} are considered, representing the response characteristics to variations in frequency Δf. These exponents are essential for understanding how active and reactive power are modified concerning changes in voltage magnitude and frequency variation in the system.

2.1.2. Polynomial or ZIP load model

The ZIP model is commonly used to represent static loads in electrical systems. This model includes components of constant impedance (Z), constant current (I), and constant power (P), which describe the relationship between power and the voltage of interest. The mathematical equations of the ZIP model are expressed in equations (3) and (4).

$$P_{ZIP,t} = P_0 \left[a_p \left(\frac{V_t}{V_0}\right)^2 + b_p \left(\frac{V_t}{V_0}\right) + c_p\right] \tag{3}$$

$$Q_{ZIP,t} = Q_0 \left[a_q \left(\frac{V_t}{V_0}\right)^2 + b_q \left(\frac{V_t}{V_0}\right) + c_q\right] \tag{4}$$

In these equations, $P_{ZIP,t}$, and $Q_{ZIP,t}$ represent the active and reactive power at the specific node of interest at a given time t. V_0 is the rated system voltage, while P_0 and Q_0 are the model's base active and reactive powers. V_t indicates the magnitude of the voltage at time t.

Parameters a_p, b_p, and c_p determine the contribution of each component of the ZIP model to the active power and must satisfy the constraint $a_p + b_p + c_p = 1$. Similarly, the parameters a_q, b_q, and c_q define the contribution of each component to the reactive power and satisfy the constraint $a_q + b_p + c_q = 1$.

2.1.3. Exponential recovery load model (ERL)

This model represents the exponential load response of active and reactive powers after a step-type disturbance in the voltage of the load bus [15]. This behavior is modeled through the first-order nonlinear differential equations shown in (5), (6), (7) and (7).

$$T_p \frac{dx_p}{dt} = -x_p + P_0 \left(\frac{V_t}{V_0}\right)^{N_{ps}} - P_0 \left(\frac{V_t}{V_0}\right)^{N_{pt}} \tag{5}$$

$$P_{ERL,t} = x_p + P_0 \left(\frac{V_t}{V_0}\right)^{N_{pt}} \tag{6}$$

$$T_q \frac{dx_q}{dt} = -x_q + Q_0 \left(\frac{V_t}{V_0}\right)^{N_{qs}} - Q_0 \left(\frac{V_t}{V_0}\right)^{N_{qt}} \tag{7}$$

$$Q_{ERL,t} = x_q + Q_0 \left(\frac{V_t}{V_0}\right)^{N_{qt}} \tag{8}$$

The active power, denoted as $P_{ERL,t}$, and reactive power, denoted as $Q_{ERL,t}$, represent the power consumption of the load bus. The state variables x_p and x_q are associated with the active and reactive power respectively. Time constants of the exponential recovery response are represented by T_p and T_q. Parameters such as N_{ps}, N_{qs}, N_{pt}, and N_{qt} are related to the steady-state and transient responses of the load. Additionally, V_0, P_0, and Q_0 correspond to the load bus's rated voltage, active power, and reactive power respectively.

2.2. Conventional load models

2.2.1. Electronic load model

The electronic load model in PowerWorld software has specific characteristics. When the voltage at the terminal exceeds the threshold V_{d1}, the electronic load maintains a constant active power (P) and reactive power (Q). If the voltage is between the thresholds V_{d1} and V_{d2} (where V_{d1} is greater than V_{d2}), the active and reactive power of the electronic load linearly decreases to zero. The parameter α represents a fraction of the electronic load. If α is greater than zero, the load will gradually reconnect as the voltage recovers.

The electronic load model in the WECC composite load system is like the model in PowerWorld and is expressed by the equations (9) and (10).

$$P_{E,t} = c_t P_{E,0} \tag{9}$$

$$Q_{E,t} = c_t Q_{E,0} \tag{10}$$

Where $P_{E,t}$, and $Q_{E,t}$ represent the active/reactive power of the electronic load, while $P_{E,0}$, and $Q_{E,0}$ correspond to the base active/reactive powers, respectively. The coefficient c_t is related to the bus voltage and is listed in Table 1. The operating modes depend on the terminal voltage. In Table 1, V_{d1} and V_{d2} are two threshold values, and α represents a fraction of the electronic load that recovers from a low voltage drop. $V_{min,t}$ is a value that tracks the lowest voltage but is always greater than or equal to $V_{min,t}$. It is a known value for each sample. The calculation of $V_{min,t}$ is expressed in equation (11).

$$V_{min,t} = max\{V_{d2}, min\{V_t, V_{min,t-1}\}\} \tag{11}$$

Table 1. Coefficient of Electronic Load

Value of c_t	Condition	Mode
0	$V_t < V_{d2}$	1
$\frac{V_t - V_{d2}}{V_t - V_{d2}}$	$V_{d2} \leq V_t < V_{d1}$, $V_t \leq V_{min,t}$	2
$\frac{V_{min,t} - V_{d2} + \alpha(V_t - V_{min,t})}{V_t - V_{d2}}$	$V_{d2} \leq V_t < V_{d1}$, $V_t > V_{min,t}$	3
1	$V_t \geq V_{d1}, V_t \geq V_{d1}$	4
$\frac{V_{min,t} - V_{d2} + \alpha(V_{d1} - V_{min,t})}{V_t - V_{d2}}$	$V_t \geq V_{d1}, V_t < V_{d1}$	5

Source: [16].

2.2.2. Composite load model (CEZL)

The composite load model is obtained as the combination of the ZIP model and the electronic load model. The equations (12) and (13) are presented below, representing the composite model.

$$P_t = (1 - \beta_p)P_{ZIP,t} + \beta_p P_{E,t} \tag{12}$$

$$Q_t = (1 - \beta_q)Q_{ZIP,t} + \beta_p Q_{E,t} \tag{13}$$

Where β_p and β_q are the coefficients representing the portions of electronic loads in the total active and reactive power, respectively. P_t and Q_t represent the active and reactive power of the composite load, respectively.

Detailed information about this model can be found in [16], where further insights and explanations can be obtained.

2.2.3. Constant power load model (CPL)

The constant power load exhibits an attractive characteristic in terms of its impedance. While the instantaneous impedance is positive $V/I > 0$, the incremental change in impedance is negative $\Delta V/\Delta I < 0$. This means that even though the load shows a positive resistance at a given moment, its increase in resistance is negative. This property can be mathematically explained through the relationship between voltage and current, expressed as $P = VI$, where P represents constant power. The mathematical structure of this model can be found in [17] and [18].

3. Load Modeling Approaches

The proposed methodologies for developing load models can be classified into two main approaches: component-based and measurement-based approaches. The component-based approach involves constructing individual models for each electrical component, which are then combined into an aggregate load model. Applying this approach requires knowledge of the load composition, that is, the percentage of load consumed by each component type. On the other hand, the measurement-based approach relies on leveraging data obtained from devices such as PMUs (phasor measurement units), and smart meters, among others. These data are used to characterize and model the electrical load.

3.1. Component-based approach

The component-based approach, also known as the knowledge-based approach, represents an aggregate load model structure that fully considers the categories or classes of load, their compositions, and proportions, as illustrated in Figure 1.

Individual load components can be depicted using either static or dynamic models. For example, resistive elements like cooking appliances and water heaters can be represented as constant impedance; whereas loads such as switch-mode power supplies (SMPS) are characterized as sources of constant power [5].

The component-based approach follows three main steps. First, a precise categorization of connected loads is performed. Four types of loads are grouped on a distribution bus: residential load, commercial load, industrial load, and public infrastructure load. Each type of load may require different power supply standards and has different modeling requirements. Modeling typical load classes can be challenging due to the natural distribution of load across different classes and the potential need for comprehensive data.

Second, the structure and composition of each load category are carefully considered. For example, in residential loads, appliances such as air conditioning, washing machines, clothes dryer, dishwasher, refrigerator, cooling or heating pump, lighting, and other home electronic devices must be considered. The specific composition of the load is tailored to practical situations, as end-users may have different appliances in use.

Third, each load category's typical characteristics and proportion are clearly estimated. For example, in residential loads, different appliances have different power characteristics, and their performance may vary based on customers' electricity consumption habits. Identifying the percentage contributions of each load component within a given load category is challenging as it requires conducting extensive customer surveys, which can be costly in terms of time and money [8].

On the other hand, the advantages and disadvantages of the component-based approach are presented in Table 2.

3.2. Measurement-based approach

The measurement-based load modeling approach involves gathering data at the load bus or substation. This data comprises measurements of voltages, active powers, and reactive powers during voltage or frequency disturbances in the system. Utilizing these measurements, the load model parameters are estimated through strategies that minimize the disparities between the measured data and the response of the estimated model, as presented in equation (14).

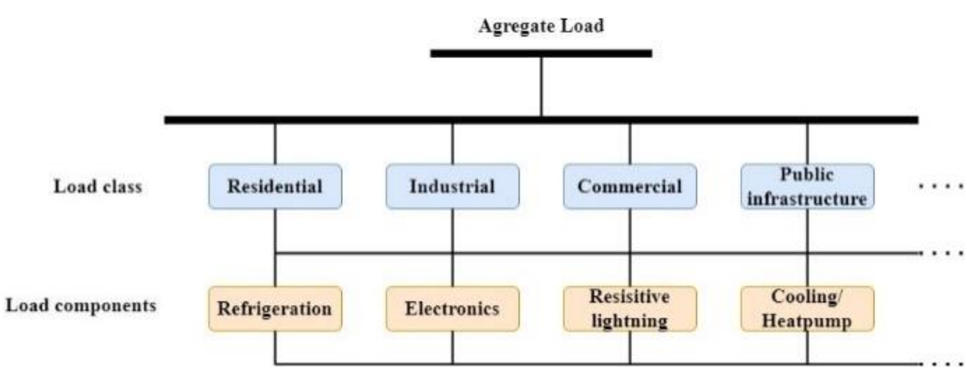

Figure 1. Component-based modeling approach. Source: [5].

$$min \frac{1}{N} \sum_{i=1}^{N} [(p_i{}^m - p_i{}^s)^2 + (q_i{}^m - q_i{}^s)^2] \qquad (14)$$

T
able 2. Advantages and disadvantages of the component-based approach

Component-based approach	
Advantages	**Disadvantages**
Correlate the mathematical formulation to the physical characteristics of the load components	Difficulty in handling temporal load variation
The load sector data are generally available	The load structure data is substation specific
No need for field measurements	Error in modeling the newly connected load components
Adaptable to different systems and conditions	The model parameters can vary greatly with age, the manufacturer, and so on
Flexibility in load/demand control	Difficult for transmission system operators to apply

Source: [8].

Where $p_i{}^m$ and $q_i{}^m$ represent the measured active and reactive powers, respectively, $p_i{}^s$ and $q_i{}^s$ are the estimated active and reactive powers by the model, respectively, and N is the number of data points for the model estimation. The parameter estimation is not limited to the use of a particular optimization technique, and various techniques can be employed, such as genetic algorithms (GA) [19], Kalman filter (KF) [20], Levenberg-Marquardt algorithm [21], particle swarm optimization (PSO) [9], support vector machines (SVM) [16], constrained least squares (CLSQ) and sensitivity-driven constrained optimization (SDCO) [22], among others.

Figure 2 illustrates the process for applying the measurement-based approach in load modeling.

The process consists of the following steps:

Step 1: Collect and process disturbance data. This involves taking measurements of voltages for each phase, frequency, as well as active and reactive powers.

Step 2: Select an appropriate load model structure. An initial load model structure is chosen, which can be modified in Step 4 if the parameters are not adequate.

Step 3: Execute the optimization process to obtain the parameters using equation (14).

Step 4: Validate the derived load model. The model is compared with additional measurements, and a minimum error threshold is established. Cross-validation techniques can also be employed to validate the model [23]. If the model does not meet the validation criteria, the procedure is repeated with a new set of initial parameters or even a different load model structure.

Step 5: If the final parameters of the load model are suitable, they are selected. However, if they do not meet the necessary requirements, it is possible to return to Step 2 and select another model. When obtaining an appropriate load model is not feasible, the collected data may not be suitable for this measurement-based methodology.

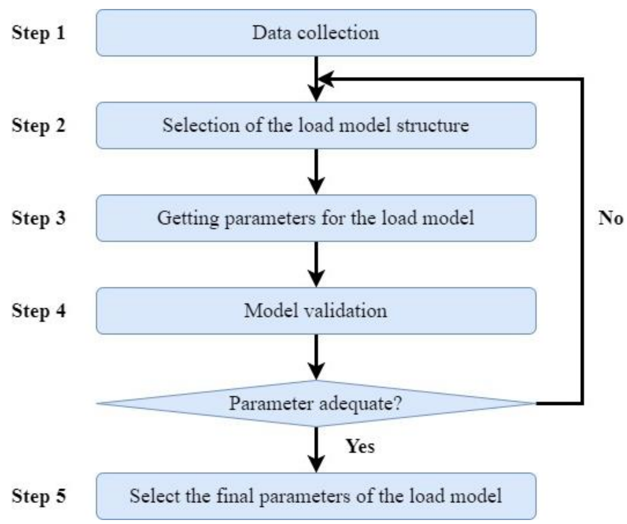

Figure 2. Measurement-based modeling approach.
Source: [8].

Like the component-based approach, the measurement-based approach also encompasses advantages and disadvantages, which are presented in Table 3.

4. Analysis and Recommendations of Dynamic Load Modeling in ADNs

In the context of proposed strategies for load modeling in ADNs, a predominance of conventional load models has been observed [24], [25], [26], [27]. However, these models have significant limitations in capturing the dynamic complexity and real-time variability inherent in the new types of loads present in ADNs. Some loads may exhibit notable changes in behavior due to multiple factors such as system conditions, time of day, and user activities. Furthermore, the non-linear nature of electronic loads or loads with power electronic interfaces can generate harmonics, voltage fluctuations, and abrupt changes in power demand [8].

Table 3. Advantages and disadvantages of the measurement-based approach

Measurement-based approach	
Advantages	**Disadvantages**
Collects dynamic responses from an actual system	Low frequency of disturbances
Provides a generic method applicable to model any load	Lack of generalizability due to specific data collection location and time
Captures temporal changes in connected loads	Divergence in the performance of the objective function, resulting in suboptimal parameters

Source: [8].

To accurately address these dynamic aspects, sophisticated and flexible models need to be developed to accurately reflect loads' real-time behavior. Currently, some proposals consider the measurement-based approach to represent the variability and complexity of loads. Some of these proposals focus solely on individual load modeling, while others consider an aggregated model of the ADN that includes the interaction between loads and other system components. Table 4 provides a review of current approaches, highlighting the techniques used in each case.

Table 4. Comparison of Measurement-Based Dynamic Load Modeling Approaches in ADNs

Ref	Modelling		Applied Technique
	Load	Aggregate ADN	
[10]		✓	Machine Learning
[11]		✓	Machine Learning
[12]		✓	Gaussian Process
[13]		✓	Gaussian Process
[18]	✓		Hybrid Algorithm
[22]	✓		CLSQ SDCO
[28]		✓	Machine Learning
[29]	✓		Iterative Algorithm
[30]		✓	Machine Learning
[31]		✓	Machine Learning

Source: Own elaboration.

As noticed, there is a predominance of aggregated ADN modeling, then it is crucial to highlight the importance of considering load models independently. These specific load models are necessary for conducting detailed studies on stability, resilience analysis, and protection coordination, among other relevant analyses [8].

In terms of stability, load models allow for precise evaluation of limits and understanding of the impact of load on system dynamics [26]. Furthermore, regarding network resilience, critical areas can be identified where demand may exceed generation capacity or transmission and distribution infrastructure limitations [27].

On the other hand, to ensure a more accurate representation of load models, it is recommended to consider relevant exogenous variables, such as temporal demand variability and consumption patterns [13]. In this regard, the availability of advanced measurement equipment like PMUs and smart meters offers a significant advantage by enabling the acquisition of precise and real-time data for adequate load characterization. This availability of detailed and up-to-date information is essential for achieving a more accurate and comprehensive representation of load models.

Additionally, in terms of protection coordination, individual load models provide a more precise representation of current flows during faults and short circuits. They also allow for tracking the value of load impedance, which is crucial for optimal adjustment and configuration of protection devices, avoiding unnecessary supply interruptions and minimizing impacts on the network.

5. Conclusions

Transition from conventional electric distribution networks to ADNs entails the need for continuous studies on the modeling of the involved elements. This shift towards a more dynamic and decentralized infrastructure highlights the importance of understanding and accurately representing complex elements such as loads. The proper load representation is crucial for comprehending and predicting network behavior, especially in an environment where distributed generation and variations in consumption play a crucial role. Accurate load modeling enables reliable system operation and stability evaluation and understanding of the impacts of distributed generation resources and interactions among network components. Load characteristics can vary over time and exhibit stochastic behaviors, so it is essential to conduct continuous and up-to-date studies on load modeling in the context of ADNs.

Modeling involves collecting and analyzing relevant data, developing suitable techniques, and validating proposed models through measurements and real-world tests.

The state-of-the-art review of load modeling in Active Distribution Networks using measurement-based approaches analyzed in this paper focuses on applying machine learning techniques, Gaussian processes, and general learning-based algorithms. However, most research considers loads within an aggregated ADN model, highlighting the need to consider loads individually. Although significant progress has been made, challenges still need to be solved in achieving satisfactory model generalization, where factors such as computational burden, load diversity, and system disturbances increase this difficulty. Therefore, further research is required to improve the accuracy and generalization of load modeling approaches, enabling more reliable and precise predictions of consumption behavior in response to system disturbances. It is essential to consider loads individually and develop methods that capture their specific characteristics for a more accurate and comprehensive representation.

Funding

This research result is funded by the Colombian Science Ministry (Minciencias) young researchers program, the research program INTEGRA2023, and the Master's Program in Electrical Engineering from Universidad Tecnológica de Pereira (UTP). This product was obtained by the ICE[3] research group at the UTP.

Autor Contributions

D. Osorio-Vásquez: state-of-the art, investigation, methodology, writing-original draft, writing-review & editing, results, visualization. S. Pérez-Londoño: conceptualization, methodology, validation, formal analysis, investigation, writing-review & editing, visualization, supervision. J. Mora-Flórez: conceptualization, resources, data curation, writing-review & editing, formal analysis, supervision, project administration, funding acquisition.

All authors have read and agree to the published version of manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

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