energies

Review

Applications of Electrical Load Modelling in Digital Twins of Power Systems

Hasith Jayasinghe [1,2,*], Kosala Gunawardane [1,*] and Robert Nicholson [3]

[1] School of Electrical and Data Engineering, Faculty of Engineering and Information Technology, University of Technology Sydney, Ultimo, NSW 2007, Australia
[2] Blue Economy Cooperative Research Centre, Launceston, TAS 7248, Australia
[3] Pitt&Sherry, North Sydney, NSW 2060, Australia; rnicholson@pittsh.com.au
* Correspondence: hasith.jayasinghe@student.uts.edu.au (H.J.); kosala.gunawardane@uts.edu.au (K.G.)

Abstract: Accurate electrical load modeling is crucial for both transient and steady-state power system studies. Although various load modeling techniques are documented in the literature, a comprehensive review of the latest advancements in these techniques is lacking. This manuscript addresses this gap by presenting a detailed review of load modeling techniques, emphasizing their applications, recent advancements, and key distinguishing characteristics. Additionally, it explores the role of Digital Twin Models (DTM) in power systems, which offers a virtual representation of the system to simulate diverse operational scenarios and inform future investment and operational decisions. The integration of load models into DTMs poses challenges, such as computational demands and microcontroller limitations, which can be alleviated by adopting advanced load modeling techniques. This work further examines the application of load modeling techniques in the design and development of DTMs for power systems, as well as strategies to enhance the performance of load models in DTM applications. Finally, the manuscript outlines future research opportunities for integrating load modeling within DTM-based power system applications.

Keywords: load modelling; digital twins; power systems

Academic Editors: José Matas, Ignacio Hernando-Gil, Ionel Vechiu and Chenghong Gu

Received: 12 November 2024
Revised: 31 January 2025
Accepted: 4 February 2025
Published: 7 February 2025

Citation: Jayasinghe, H.; Gunawardane, K.; Nicholson, R. Applications of Electrical Load Modelling in Digital Twins of Power Systems. *Energies* **2025**, *18*, 775. https://doi.org/10.3390/en18040775

1. Introduction

Electrical load modeling is essential for power system studies, forming the foundation for the analysis and planning processes critical to ensuring the reliability and stability of electricity networks. Accurate load modeling enables the prediction of electricity consumption patterns, supporting the optimal design, operation, and expansion of power systems [1]. By incorporating detailed representations of various load types—residential, commercial, and industrial—engineers can simulate real-world scenarios to evaluate the impact of different demand profiles on system performance. This process helps identify potential vulnerabilities and develop mitigation strategies to enhance grid resilience against disturbances such as extreme weather events and equipment failures [2]. Furthermore, with the growing integration of renewable energy sources and the electrification of transportation, precise load modeling has become increasingly important for assessing the dynamic relationship between generation and demand in modern power systems [3].

The significance of electrical load modeling extends beyond immediate operational considerations to support long-term planning and policy formulation. By accurately characterizing load behaviors, analysts can evaluate the effectiveness of demand-side management initiatives, energy efficiency programs, and grid modernization efforts, all of which promote sustainability in energy systems and contribute to the reduction of carbon emissions [4]. Load modeling techniques are particularly crucial in the context of electric vehicles, as they enable the assessment of grid integration challenges and the optimization of interactions with existing infrastructure [5]. In essence, electrical load modeling plays a vital role in both the planning and operation of smart grids.

Electrical load modeling plays a critical role in the successful implementation of DTMs on the demand side of power systems. In this study, we adopt precise definitions to ensure clarity in discussing digital twin (DT) concepts. A DT is a virtual representation of a physical system that dynamically updates based on real-time data and predictive models. It enables continuous monitoring, optimization, and decision-making by mirroring the physical asset's behavior and performance [6]. Figure 1 below illustrates the definition of a DT, where the green box represents the DT boundary, encompassing a virtual model of the physical system, storage, and associated services [7]. DTM is a computational or mathematical representation embedded within the DT. It may include physics-based simulations, machine learning algorithms, or hybrid models that characterize system behavior. While the DTM provides analytical insights, it is distinct from the DT itself, which encompasses real-time data integration and bidirectional communication with the physical asset [8]. Digital twin technology (DTT) refers to the suite of technologies that enable the implementation of digital twins. This includes sensor networks, IoT platforms, cloud computing, data analytics, and AI-driven modeling tools [9]. These technologies collectively facilitate data acquisition, processing, and visualization for effective DT operation [10]. Accurate load modeling serves as the foundation for DTMs, providing essential data and insights into electricity consumption patterns across various sectors and timeframes [11]. By incorporating detailed representations of diverse load types and behaviors, load modeling enables the creation of realistic virtual models that accurately replicate real-world conditions. These models form the backbone of DTs, facilitating the precise simulation and optimization of demand-side operations [12]. Furthermore, electrical load modeling is essential for validating and calibrating DTMs, ensuring that virtual representations closely align with actual system behavior. This alignment is critical for the effective use of DTM in decision-making processes, allowing stakeholders to confidently utilize simulations to inform energy management strategies and investment decisions [13].

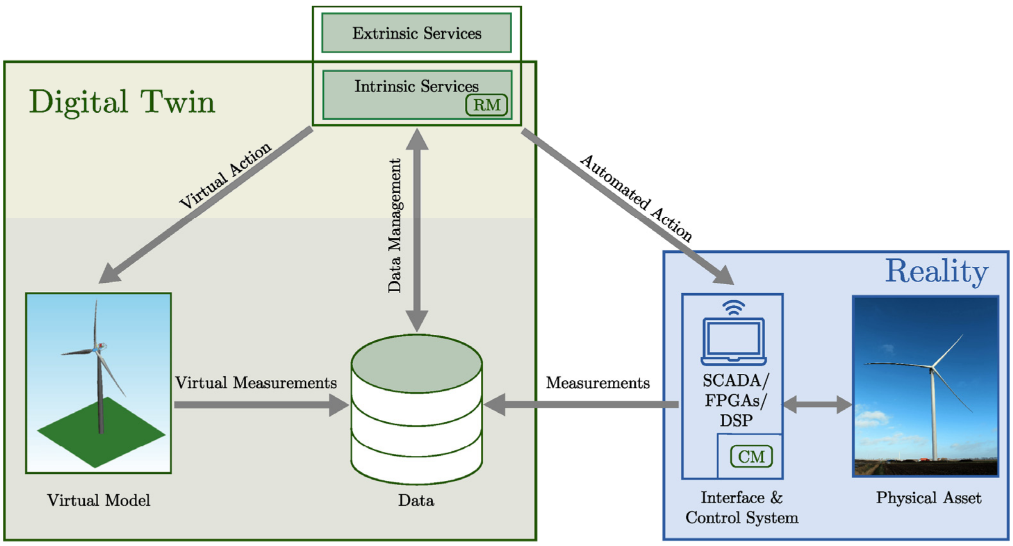

Figure 1. Representation of DT vs. Reality [7].

The application of DTM in power system modeling is an emerging research area. Accurate electrical load modeling is crucial for developing DTMs of power systems, enabling more efficient decision-making processes. However, only a limited number of review articles address the state-of-the-art literature on electrical load modeling and its applications. In [14], existing load modeling techniques are reviewed, with a focus on modeling distributed energy resources in power distribution networks. Similarly, ref. [15] discusses the characteristics of various load modeling techniques and their integration into larger power system networks. A classification of electrical load models in the context of smart grid design is provided in [16]. In [17], a comprehensive review of residential electrical load profile modeling techniques and their applications is conducted. The effects of static load models on power system transient stability studies are comprehensively analyzed in [18], with practical applications highlighted. Further, ref. [19] provides an overview of existing load modeling techniques and their applications in the modeling of distribution networks. In [20], modeling techniques for electric vehicle (EV) loads are discussed, considering load patterns and modeling methods. Load modeling techniques used to represent loads in distribution networks with distributed generation are thoroughly examined in [21]. Moreover, ref. [22] reviews modeling methods for nonlinear electrical loads in both time and frequency domains, as well as in state-space representations. Equivalent circuit load models for various types of loads are also presented in this study. The author in [23] reviews dynamic load models for nonlinear loads, proposing a simple model capable of capturing both the nonlinear behavior of loads in a steady-state operation and their overshoot and recovery dynamics.

While numerous review articles and manuscripts exist on load modeling techniques utilized in power systems, an evident research gap persists regarding the application of electrical load modeling techniques in the design of DTMs of power systems, as summarized in Table 1. Additionally, a dedicated review article focusing on the latest applications and developments in load modeling techniques has yet to be conducted in the literature. To address these research gaps, this manuscript provides a comprehensive review of electrical load modeling techniques, highlighting the latest advancements and applications. Furthermore, it explores the integration of DTT into advanced power system modeling, with a particular emphasis on incorporating electrical load modeling techniques for accurately representing demand-side dynamics. This work aims to bridge the identified research gaps and contribute to the state-of-the-art understanding in this field.

Table 1. Summary of review articles on electrical load modelling techniques for power systems.

Reference	Consideration of			
	Review of Load Modelling Techniques	Latest Developments of Load Modelling Techniques	Updated Applications of Load Modelling Techniques	Applications of Load Modelling Techniques in DTMs of Power Systems
[14]	✔	✗	✗	✗
[15]	✔	✗	✗	✗
[16]	✔	✗	✗	✗
[17]	✔	✗	✗	✗
[18]	✔	✗	✗	✗
[19]	✔	✗	✗	✗
[20]	✔	✗	✗	✗
[21]	✔	✔	✗	✗
[22]	✔	✗	✔	✗
[23]	✔	✗	✗	✗
This study	✔	✔	✔	✔

The structure of this manuscript is as follows: Section 2 presents the research methodology used to review the literature. Section 3 presents an overview of electrical load modeling techniques and their applications. Section 4 provides an overview of DTs and their role in the power system domain, particularly in energy management. Section 5 reviews the applications of load modeling in DTMs, with a focus on employing DTT for energy management in power systems. Section 6 discusses the overall contributions from the manuscript and future research directions. Finally, Section 7 summarizes the key insights and conclusions of the manuscript.

2. Research Methodology

The research methodology for this review manuscript involves a comprehensive literature review of electrical load modelling techniques and their applications in DTMs for power systems. The literature review adheres to the protocols outlined in [24], which consist of three key stages: planning, conducting, and documenting. The review process follows a structured methodology, beginning with the identification of the need for a comprehensive review, followed by the formulation of specific research questions to guide the study. Review protocols were developed and evaluated to ensure a systematic approach. Primary studies were selected based on predefined criteria, and data were subsequently extracted while assessing the quality of the studies. Finally, the extracted data were synthesized and interpreted to derive meaningful insights and effectively address the research questions.

The first step involved identifying clear research gaps in existing review articles through a detailed analysis of their content. To achieve this, relevant review articles were identified using databases such as Scopus, IEEE Xplore, ScienceDirect, and Google Scholar. Keywords used in the search included "Electrical Load Modelling", "Load Models", "Digital Twins", "Power Systems", and "Loads." A summary of the identified review articles is provided in Section 1. From this analysis, distinct research gaps were identified, leading to the formulation of the following research questions:

(a) What are the available load modelling techniques, and under what circumstances are they used?
(b) What are the key differences between various load modelling techniques, and what criteria should be used to select the appropriate technique for a given application?
(c) What are the latest developments in electrical load modelling?
(d) How is the DTT applied in power system modelling, and what are its benefits, challenges, and opportunities?
(e) How can electrical load modelling techniques be integrated into DTMs for more accurate modelling, and what are their potential applications?

To address these research questions, a comprehensive literature review was conducted. The search and screening process followed a systematic approach to ensure the identification of relevant and high-quality studies. Initially, keywords corresponding to each research question were identified and used to search major databases, including IEEE Xplore, Scopus, Google Scholar, and ScienceDirect. The results were refined by removing duplicates, non-English papers, irrelevant studies, articles with incorrect contexts, and publications lacking sufficient data or information. The final set of selected papers was summarized in accordance with a predefined structure to facilitate systematic analysis.

3. Electrical Load Modelling Techniques

The precision of electrical load models in power systems is essential for the thorough analysis of historical data, current conditions, and future scenarios. In recent years, the rise of renewable energy sources (RES) with stochastic behavior, alongside the development of smart grid technology, has further underscored the importance of accurate load modeling in power network design. Factors such as time dependency, seasonal variations, and sensitivity to weather conditions add to the complexity of load modeling [25]. Additionally, the lack of detailed information on individual system components and the scarcity of measurement data pose further challenges. The primary goal of electrical load modeling is to develop and refine simplified yet robust mathematical models that can effectively estimate load behavior under various conditions [14].

Load modeling involves two fundamental steps: (1) selecting the model structure and (2) identifying the parameters for the load model, which can be achieved through either a component-based or measurement-based approach. Component-based load modeling relies on the physical behavior of loads and uses mathematical expressions to describe the interactions between devices. However, obtaining complete physical information about all load components is often impractical. In contrast, measurement-based load modeling has gained prominence by utilizing actual system data to construct load models. It is important to note, however, that the applicability of measurement-based load modeling may be limited to the specific locations where the measurements were collected [15].

Electrical load models are typically categorized into two primary groups: (A) static models and (B) dynamic models [26]. Figure 2 illustrates the various load modeling techniques classified under these two categories.

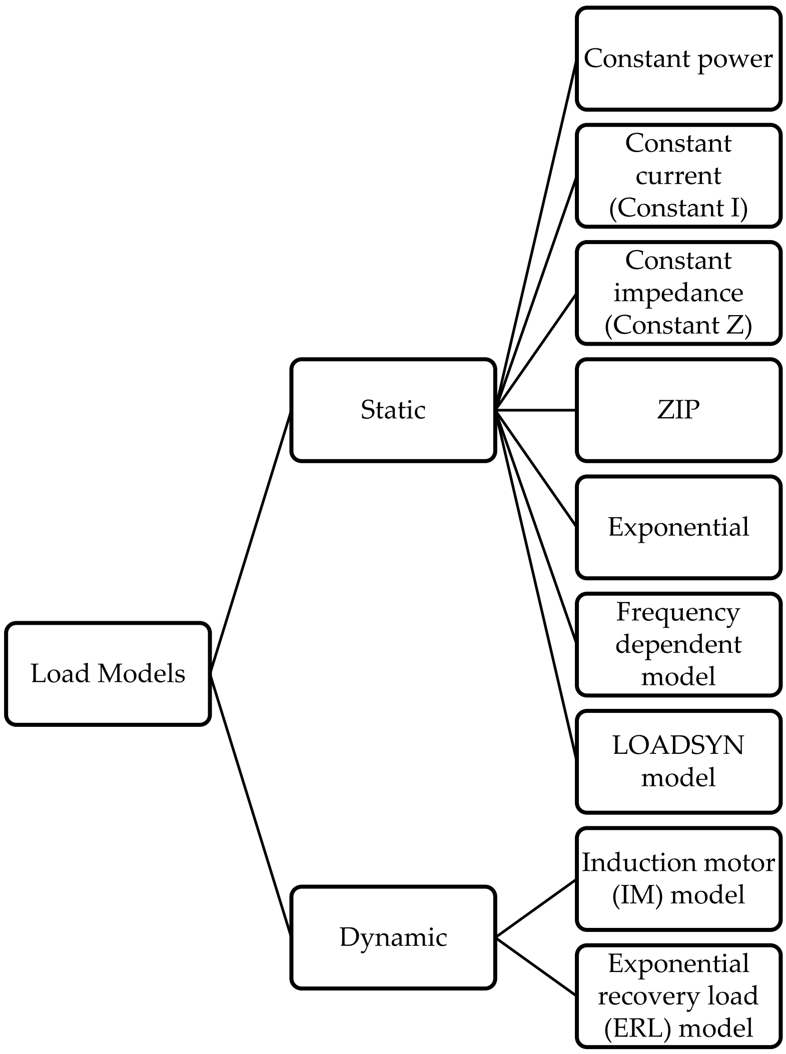

Figure 2. Classification of Load Modelling Techniques.

3.1. Static Load Models

Static load models are used to represent static loads and can also approximate dynamic loads. The fundamental static load models include constant power, constant current, and constant impedance models. Table 2 outlines the characteristics and applications of these three load modeling techniques.

Table 2. Characteristics and applications of fundamental load modelling techniques.

Load Modelling Technique	Characteristics	Applications
Constant power	Maintains a consistent level of power consumption regardless of changes in voltage or current.	Used in applications where maintaining a consistent power output is crucial for optimal performance (e.g., variable speed drives) [27].
Constant I	Ensures a stable current flow irrespective of fluctuations in voltage.	Suitable for applications where a constant current is essential for consistent operation and to prevent damage to sensitive components (e.g., LED lighting, battery charging) [28].
Constant Z	Maintains a fixed impedance regardless of changes in voltage or current.	Applied in scenarios where preserving constant impedance matching between components is critical (e.g., audio systems).

Advanced load models have been developed based on three fundamental static models. The ZIP load model is derived from a polynomial equation that combines these basic models and describes the relationship between active power, reactive power, and voltage [29]. Equations (1) and (2) represent the ZIP load model:

$$P = a_0 + a_1 V + a_2.V^2 \tag{1}$$

$$Q = b_0 + b_1 V + b_2 V^2 \tag{2}$$

In these equations, the scalars a_0, a_1, a_2, b_0, b_1, and b_2 are the coefficients representing the constant power, constant I, and constant Z components of the ZIP load model. ZIP load model is widely used in both transient and steady-state studies of power systems due to its ease of implementation and clear physical interpretation. A novel passivity-based controller capable of integrating ZIP loads was employed for transient analysis of a DC microgrid in [30]. In [31], the ZIP load model was used to derive a closed-form analytical solution for a second-order nonlinear differential swing equation, aiming to enhance power system dynamics. A consensus-based distributed control system for a DC microgrid incorporating ZIP load modeling was proposed in [32], to improve voltage regulation and ensure proportional current sharing.

The exponential load model represents the load using exponential equations to describe the relationship between power and voltage [33]. Equations (3) and (4) below represent the exponential load model.

$$P = P_0 \left(\frac{V}{V_0} \right)^{np} \tag{3}$$

$$Q = Q_0 \left(\frac{V}{V_0} \right)^{nq} \tag{4}$$

Here, P_0 and Q_0 are the initial active and reactive power conditions, while np and nq are parameters that characterize the load response. Additional exponential terms can be incorporated into the equations as required to better represent different load types. The exponential load model is typically used to represent mixed loads. In [34], the exponential load model was used to represent loads in a distribution network for the implementation of model predictive control-based voltage-var optimization. An exponential load model was employed for load flow analysis in a radial distribution network in [35], utilizing a network topology-based solver.

The frequency-dependent load model is derived by multiplying the ZIP or exponential model by a frequency-dependent factor k, as shown in Equation (5) below. In this equation, a_f represents the frequency sensitivity parameter, f_0 is the nominal frequency, and f is the bus frequency. This model is commonly used to represent the transient and steady-state behavior of frequency-dependent loads [36].

$$k = 1 + a_f(f - f_0) \tag{5}$$

The LOADSYN model, developed by the Electric Power Research Institute (EPRI), is integrated into the EPRI LOADSYN program and other software used for power system studies [37]. This model combines ZIP, exponential, and frequency-dependent load models, as illustrated in Figure 3 below. Bus voltage and frequency are measured using a root mean square (RMS) operator and a phase-locked loop (PLL). A moving average method is applied to address PLL inaccuracies during transient conditions.

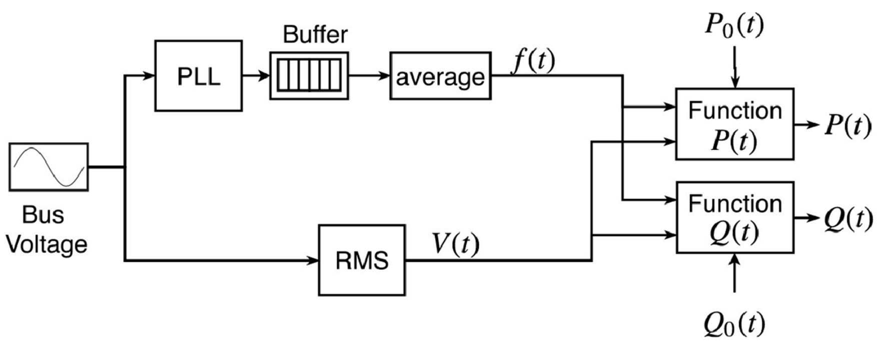

Figure 3. Diagram of EPRI LOADSYN model [38].

3.2. Dynamic Load Models

Dynamic load models are used to represent load behavior during oscillatory events. Accurately modeling load dynamics is essential for analyzing power system behavior under transient conditions, such as faults and sudden demand fluctuations. These models express active and reactive power as functions of both voltage and time.

The induction motor (IM) model is the most widely used dynamic load model in the literature [39]. This model is derived from the equivalent circuit of an induction motor, illustrated in Figure 4, where R_S and X_S are the stator resistance and reactance, R_r and X_r are the rotor resistance and reactance, X_m is the magnetizing reactance, and s is the state variable.

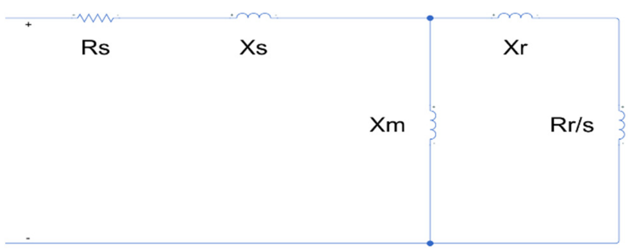

Figure 4. Equivalent circuit of the IM load model.

In [40], IM model was utilized to represent the dynamics of an isolated hybrid micro-grid for voltage stability analysis. The aggregated model, comprising first-, third-, and fifth-order IM models, was identified as the most accurate for estimating the dynamic response. Additionally, an interim dynamic IM model has been employed in stability studies by the Western Systems Coordinating Council (WSCC) in the USA to assess the effects of IM loads on highly stressed power distribution networks during peak demand periods [41].

The Exponential Recovery Load (ERL) model is used to represent the response of active and reactive power in loads following sudden disturbances. The ERL model is often applied to loads that exhibit slow responses to such disturbances. Derived from first-order nonlinear differential equations, this model effectively characterizes load dynamics. In [42], the ERL model has been extended to represent adaptive dynamic behavior by defining power as a function of the product of voltage and a state variable.

3.3. Latest Advances in Load Modelling Techniques

Building on the foundational categories of primary load modeling; static and dynamic load models, more advanced load modeling techniques have been developed to better represent loads in distribution networks and smart grids. These advancements address the challenges and limitations associated with the primary load modeling approaches. The following subsections outline some of the latest load modeling techniques and their applications.

3.3.1. Composite Load Modelling Techniques

By integrating static and dynamic load modeling techniques, composite load models have been developed in recent studies to achieve more accurate load representation for transient and steady-state analyses of power systems [43]. Table 3 provides an overview of some of the widely used composite load models.

Table 3. Configurations and applications of composite load modelling techniques.

Load Model	Description	Applications/References
ZIP + IM	Combines ZIP and IM models to represent both static and dynamic load behaviors.	Highly flexible in modelling loads for dynamic studies [44–46].
Exponential + IM	Integrates the exponential static load model with the IM model to capture both static and dynamic characteristics.	Applied in load modeling for frequency response studies [47,48].
Complex Load Model (CLOD)	Aggregates motors, discharge lighting, constant MVA loads, transformer saturation, shunt capacitors, tap ratios, and series impedance.	Integrated into Siemens Power System Simulator for Engineering (PSS/E) [36,49,50].
Western Electricity Coordinating Council (WECC) Complex Load Model	Developed in Western Systems Coordinating Council (WSCC) distribution system in the USA, assumes 80% static and 20% dynamic loads, with the IM model representing dynamic behavior.	Used for distribution networks with over 5 MW per load bus [51–53].

3.3.2. Machine Learning-Based Load Modelling Techniques

Machine learning-based load models lack physical interpretability but utilize artificial neural networks (ANNs) to predict outputs based on measurement data. An ANN comprises an interconnected set of processing units connected by weighted links, which are adjusted during training to optimize performance. The use of machine learning-based models for load modeling was first introduced in [54], employing ANN-based models to analyze static and dynamic voltage stability. ANN-based models have since been widely utilized to represent complex, nonlinear, and large-scale distribution networks in stability studies [55–57]. Although these machine learning-based models are powerful tools for representing complex systems, they face challenges in obtaining sufficient training data under various operating conditions. Furthermore, these models require periodic updates with newly acquired measurement datasets to maintain their accuracy and reliability.

3.3.3. Black Box and Grey Box Load Modelling Techniques

An active distribution network (ADN) is a power system characterized by a high penetration of distributed generation and controllable loads. A microgrid, whether grid-connected or operating in islanded mode, serves as an example of a simplified version of an ADN [58]. However, detailed modeling of all components within an ADN is challenging due to limited data availability and significant computational demands. To address these challenges, black-box and grey-box modeling approaches have been proposed in recent years [59]. These methods simplify the representation of the entire network, including generation and loads, while maintaining acceptable accuracy for analysis and operation.

In a black-box model, the relationship between input and output is established using a mathematical approach without accounting for the physical characteristics of the system [60]. Black-box models are particularly useful when limited information is available to develop a physically-based model [61]. For instance, a Prony analysis-based black-box model for a microgrid was developed in [62], focusing on dynamic studies involving frequency and voltage responses. Similarly, the voltage and frequency response of an islanded microgrid was modeled using a black-box approach in [63]. The effectiveness of black-box modeling for loads has been demonstrated in several recent studies [64–66] highlighting its potential for representing complex systems with minimal data requirements.

Grey-box models are developed by utilizing measurements from the actual system during the initial stages of parameter estimation. These models offer the advantage of incorporating physical meaning, unlike black-box models. For example, in [67], the authors developed a grey-box model representing a static equivalent of a distribution network integrated with a large number of solar photovoltaic (PV) systems. In this approach, the PV systems were modeled as separate entities rather than as negative loads, demonstrating superior performance compared to the latter method. Additionally, a grey-box modeling approach was proposed in [68] to maintain the balance between generation and load in interconnected networks through the economic dispatch of generators.

3.3.4. Analytical Load Modelling

Analytical load models first analyze load behavior using stochastic and time-series methods. Based on the analysis, loads are subsequently modeled using static and dynamic load modeling techniques. These analytical load models are particularly effective for modeling demand-side management applications in distribution networks and microgrids. In [69], a physical-based demand response (DR) enabled load model for residential appliances was developed, where individual appliance-level load models were aggregated to create load profiles for distribution networks. In [70], a residential low-voltage analytical load model was designed for price-based DR applications. This model employed a bottom-up approach using the Monte Carlo Markov Chain method. Analytical load modeling has proven effective in recent research for both transient and steady-state studies of demand-response-enabled power systems.

3.3.5. Equivalent Circuit Load Modelling

The equivalent circuit load modeling technique represents load behavior using an equivalent circuit based on specific load parameters, such as thermal properties. These models are commonly applied in DR applications for loads with well-defined behavioral changes. In [71], an equivalent circuit-based load model was used to evaluate the thermal profile of a room in a building with demand-response capabilities. Figure 5 illustrates the equivalent circuit of the room, considering the thermal applications of the heating and cooling system. Similarly, in [72], the equivalent circuit of an air conditioning unit was utilized to assess its performance under a DR program, enabling temperature control for improved energy management in buildings.

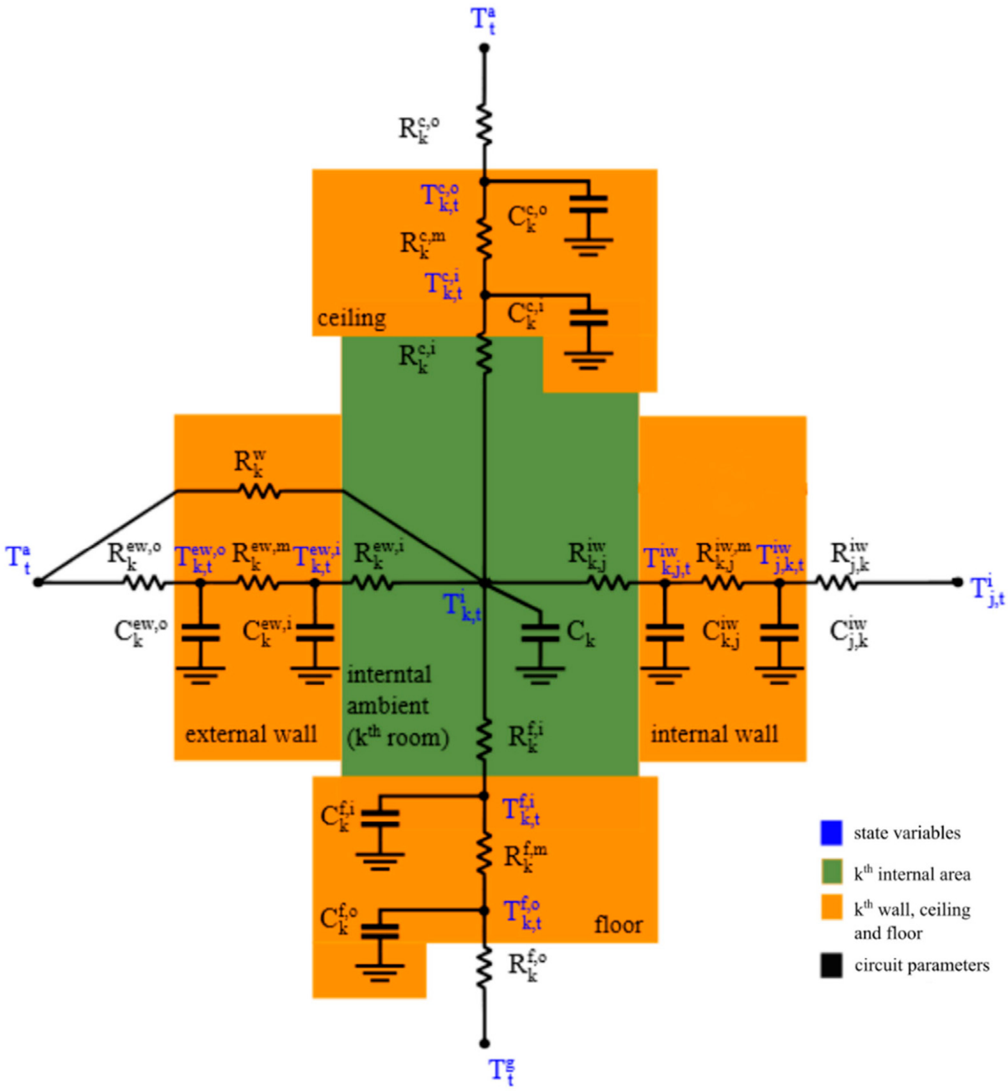

Figure 5. Equivalent circuit model of a room in [71].

3.4. *Comparison of Different Load Modelling Techniques*

Load modeling techniques discussed in the previous subsections are applied in various contexts. Table 4 provides a comparison of the characteristics and attributes of these techniques, offering a concise summary to aid in selecting the most suitable approach for a specific application.

Table 4. Comparison of Characteristics of different load modelling techniques.

Type	Load Modelling Technique	Physical Meaning	Ease of Implementation	Representation of Dynamic Loads	Accuracy	Detailed Modelling	Adaptiveness	Computational Burden	Inclusion of DSM	Measurement Data Requirement
Static	Constant P Constant I Constant Z ZIP Exponential Frequency Dependent (ZIP + Exponential) LOADSYN	Clear	Simple	Fail	Low	No	Low	Low	No	Low

Table 4. *Cont.*

Type	Load Modelling Technique	Physical Meaning	Ease of Implementation	Representation of Dynamic Loads	Accuracy	Detailed Modelling	Adaptiveness	Computational Burden	Inclusion of DSM	Measurement Data Requirement
Dynamic	IM Exponential Recovery	Clear	Simple	Yes	Low	No	Low	Low	No	Low
Composite	ZIP + IM Exponential + IM	Clear	Simple	Yes	Low	No	Low	Low	No	Moderate
	CLOD	Clear	Simple	Yes	Low	No	Low	Low	No	Low
	WECC CLM	Clear	Hard	Slow	High	Yes	Low	High	No	High
Machine Learning based		No	Moderate	Yes	Depends on data	No	High	High	Can Include	High
Black-box		No	Moderate	Yes	Moderate	No	High	High	Can Include	High
Grey-box		Partial	Moderate	Yes	High	No	High	High	Can Include	High
Analytical LV Models		Clear	Moderate	Yes	Moderate	No	Moderate	High	Yes	Moderate
Equivalent Circuit LV Models		Clear	Moderate	Yes	Moderate	No	Low	High	Yes	Moderate

4. DTs and Their Applications in Power Systems Domain

A DT is a virtual representation of a physical system, process, or asset that enables real-time monitoring, simulation, and optimization throughout its lifecycle. This concept integrates advanced data analytics, modeling, and Internet of Things (IoT) technologies to mirror the behavior and characteristics of its physical counterpart. DTs facilitate predictive maintenance, performance optimization, and informed decision-making by leveraging continuous data streams and advanced algorithms. In the context of engineering and renewable energy systems, DTMs are particularly valuable for simulating dynamic scenarios, improving system reliability, and reducing operational costs, making them indispensable tools for modern, data-driven system management and innovation.

DTMs enable the design, testing, and optimization of applications before real-world implementation, resulting in reduced costs and emissions while enhancing system efficiency and sustainability [73]. DTMs have been effectively employed in energy management across various sectors, including building management [74], transportation [75], electric vehicles [76], industrial processes [77], power grids [78], and microgrids [79]. In power and energy systems, DTMs are crucial for optimizing operations, increasing efficiency, and improving decision-making. By integrating diverse data sources, such as sensors, SCADA systems, and historical records, DTMs provide valuable insights into the performance of assets like generators, transformers, and transmission lines. They support predictive maintenance by continuously monitoring equipment health, identifying potential issues before they escalate, and enabling proactive maintenance scheduling. Moreover, DTMs facilitate scenario analysis and optimization, allowing operators to simulate different operating conditions and test strategies to maximize energy production while minimizing costs and environmental impacts [80].

A significant application of DTM is in the integration of renewable energy into power systems. With the growing penetration of renewable energy sources like wind and solar, managing their inherent variability and intermittency is essential. DTMs of renewable energy assets enable operators to forecast energy production accurately, optimize generation schedules, and coordinate seamlessly with conventional power plants for efficient grid integration [81]. Furthermore, DTMs support the development of advanced control strategies, such as predictive energy storage management and dynamic DR, to enhance grid stability and reliability [82]. DTMs can also be utilized across industries to improve energy management practices by simulating physical system performance under various scenarios, helping identify and address inefficiencies in energy consumption [83].

The implementation of DTM presents several challenges that require systematic strategies to address. One key issue is data acquisition, as accurate and reliable data is critical for creating a functional DTM. Ensuring seamless integration of sensors, IoT devices, and communication systems is essential for capturing high-fidelity, real-time data from physical systems [84]. However, the deployment of these technologies often encounters challenges related to sensor placement, data reliability, and cybersecurity vulnerabilities. To address these issues, robust data acquisition frameworks must be developed, incorporating redundancy, data validation algorithms, and secure communication protocols [85]. Additionally, advancements in edge computing can be leveraged to preprocess data locally, reducing the dependence on centralized systems and ensuring timely, accurate input for the DTM [86].

Another significant limitation lies in computational complexity, especially when embedding DTM functionalities in microcontrollers and integrating them with existing power systems. The high-fidelity modeling and real-time simulation of complex systems require substantial computational resources, which may exceed the capabilities of lightweight microcontrollers typically used in embedded systems [87]. This can be mitigated by employing model order reduction techniques, where simplified yet accurate models are developed to reduce computational demand without compromising performance [88]. Furthermore, the integration of DTMs with legacy power systems poses challenges in terms of interoperability and data exchange standards [89]. To overcome this, adopting open communication protocols, such as IEC 61850, and modular design principles can facilitate compatibility with existing infrastructure [90]. Collaborative efforts between industry stakeholders and academia are also vital to standardize practices, streamline integration processes, and ensure the scalability and reliability of DTM solutions in real-world applications. Multitime-scale modeling challenges, such as representing short-term energy storage behaviors alongside long-term phenomena like energy storage degradation, pose significant issues in the implementation of DTMs [91]. To address these challenges, various strategies can be employed, including multi-resolution modeling, parallel execution of models operating at different time scales, adaptive time-stepping methods, and replacing computationally intensive components with machine learning-based surrogates [92]. Figure 6 below presents the main challenges of implementing DTMs in the power system domain.

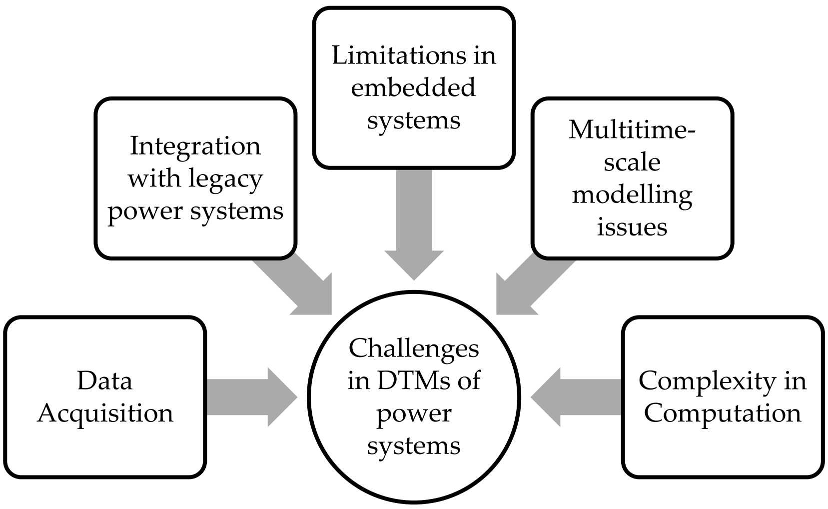

Figure 6. Challenges in implementation of DTMs in power system domain.

Electrical load modeling offers a viable solution to address many of the challenges associated with implementing DTMs of power systems. By accurately representing the dynamic behavior of electrical loads, load models reduce the computational complexity of DTM simulations without compromising system fidelity [93]. These models allow for the aggregation of data from various load types, simplifying the real-time simulation processes and making them suitable for microcontroller-embedded applications. Moreover, advanced load modeling techniques enable better prediction of system behavior under different operating conditions, thereby reducing the reliance on extensive real-time data acquisition [94].

This also mitigates integration challenges, as electrical load models can be designed to align with existing power system standards and communication protocols. Incorporating validated and standardized load models into DTMs not only enhances interoperability with legacy systems but also improves the robustness and efficiency of simulations, enabling more effective monitoring, control, and optimization of power systems [95].

5. Application of Load Modelling in DTMs for Energy Management

By accurately simulating and predicting the behavior of various loads within a system, DTMs offer valuable insights into energy consumption patterns, enabling proactive adjustments and informed decision-making. These insights are particularly beneficial in the context of smart grids, where load modeling assists in balancing supply and demand, optimizing grid operations, and reducing energy waste. Load modeling through DTMs also enables the identification of potential areas for improvement, allowing stakeholders to implement targeted strategies for load optimization and energy conservation.

Integrating load modeling within DTMs enables the development of sophisticated predictive analytics and optimization algorithms, enhancing energy management strategies across diverse applications. In contexts ranging from industrial facilities to commercial buildings and residential complexes, DTMs powered by advanced load modeling techniques provide a comprehensive understanding of energy usage dynamics. This enables stakeholders to devise tailored solutions for DR, peak load shaving, and load scheduling. By incorporating real-time data feeds and machine learning algorithms, DTMs can adapt to dynamic load conditions, offering responsive adjustments to fluctuations in energy demand and supply [96].

Table 5 summarizes the applications of load modeling techniques used to represent DTMs in current literature. These load modeling techniques have been effectively utilized to characterize load behavior within power system DTMs.

Table 5. Applications of load modelling techniques in DTMs of power systems.

Load Modelling Technique	Application in DTMs of Power Systems and Achievements	Reference
ZIP	Successfully fine-tuned ZIP load model parameters using a DTM approach based on the Bayesian inference method.	[97]
ZIP	Used DTMs to analyze the impact of weather patterns and environmental conditions on loads within microgrids.	[76]
ZIP + Machine Learning based	Identified time-varying load dynamics through a DTM by combining nonlinear optimization methods and ANNs, facilitating the integration of distributed energy resources (DER).	[98]
ZIP + Machine Learning based	Applied a DTM of a solar PV-based smart home to integrate a machine-learning-driven DR scheme, with scalability to additional smart homes for consistent benefits.	[82]
ZIP + IM	Conducted static and dynamic stability analysis for the Guayaquil area electricity network (Ecuador) using a DTM when disconnected from the national grid.	[95]
IM	An IM-based load model was utilized to develop a DTM of an internal combustion engine-based power plant integrated with a battery energy storage system (BESS). Real-time functions were tested and validated using actual data, with the model demonstrating a deviation of less than 5% compared to the actual power plant measurements.	[99]
IM	A novel method called the Digital Shadow was proposed for modeling the energy efficiency of IMs within the DT framework. A hybrid model, combining data-driven and physics-based approaches, was developed to effectively represent the DTM, addressing data discrepancies and accounting for losses associated with IMs.	[100]

Table 5. *Cont.*

Load Modelling Technique	Application in DTMs of Power Systems and Achievements	Reference
IM	IM load model was employed in a DTM for real-time determination of rotor temperature in an efficient and rapid manner. The minimum estimation error achieved using the DTM was within the standards specified by IEC 60034-2-1 [101].	[102]
CLOD	Utilized a DTM for real-time representation of the Australian transmission network, enabling integration of renewable energy, scenario analysis, and additional services.	[103]
Machine Learning based	Developed an effective sizing methodology for distributed BESS in a high solar PV penetration power distribution network using a DTM.	[104]
Machine Learning based	A convolution neural network (CNN) was utilized to model the loads in a reinforcement learning-based DTM of a distribution network. Analysis conducted through the DTM demonstrated a 50% reduction in investment costs during the transition of the power system for the winter period.	[105]
Machine Learning based	A reinforcement learning-based DTM was proposed for an electrical network, where the loads were modeled using ANN models. In this approach, an agent continuously interacts with the system to schedule power plants and optimize load scheduling using an optimal strategy.	[106]
Black box model	A black-box modeling approach was used to develop a load model for the powertrain of a vehicle, which was tested on a dynamometer test bed. The model was validated for a frequency range of 30 Hz to 1 kHz.	[107]
Grey box model	Employed a DTM using a grey box model to simulate the thermal profile of residential buildings, balancing the advantages of both white box and black box models. Identified pathways for improving building energy efficiency.	[108]
Analytical load model	An analytical load model was used to model loads in a proposed DTM for energy management in networked microgrids within a distribution system. The virtual model was represented by an ANN capable of providing real-time updates for scheduling generators and energy storage systems, accounting for demand changes across different networks.	[109]
Analytical load model	Analytical load models were integrated into DTM modeling in conjunction with non-intrusive load monitoring and smart meters to enhance DR. This approach was applied to an urban microgrid using various DR techniques, demonstrating its effectiveness in improving microgrid efficiency and strengthening cybersecurity.	[110]
Equivalent circuit load model	An equivalent circuit-based load model was utilized to analyze the degradation of power electronic converters over their operational lifespan using a component-level DTM. This approach is scalable and can be extended to a wide range of power electronic converters.	[111]
Analytical and Equivalent circuit LV models	Designed a novel urban building energy cyber-physical system (UBE-CPS) framework to connect physical and digital domains for real-time DR. Integrates sensor data from buildings into a DTM with a feedback loop to city utility administrators, aiming to automate and potentially control building-level demand for grid-level DR as part of city energy management.	[112]

From Table 5, it can be observed that most of the load modeling techniques described previously have been employed for DTMs in various power system applications. The ZIP load model has been the most commonly used, as it facilitates easier parameter estimation. Additionally, the IM model has been applied in dynamic studies where the DTM must represent the system's dynamic behavior. For integrating DR in power systems, DTMs have utilized analytical and equivalent circuit load models to simulate power system behavior under DR applications. To forecast uncertain loads, ANN models have been employed to identify load patterns and predict behavior using historical data. Grey-box and black-box models are applied in DTMs when load behavior is complex, difficult to represent with conventional load models, or when limited data is available to determine parameters for other load models.

IoT and Artificial Intelligence (AI) to Enhance the Performance of Load Modelling in DTMs

The integration of IoT, AI, and DTMs in power and energy systems is revolutionizing how energy is generated, distributed, and managed, with electrical load modeling playing a pivotal role in these advancements. Figure 7 below illustrates the techniques that can be employed to enhance the performance of load modeling in DTM applications. IoT devices such as smart meters, voltage sensors, and load monitors enable real-time data collection and monitoring of electrical loads, providing critical insights into demand patterns and grid performance [113]. Communication protocols like IEC 61850 and MQTT ensure seamless data transfer, while IoT platforms such as Schneider Electric EcoStruxure and Azure IoT Hub facilitate centralized data analytics and visualization of load behavior [114]. These tools empower energy operators to model load dynamics accurately, identify inefficiencies, and optimize energy usage in real-time.

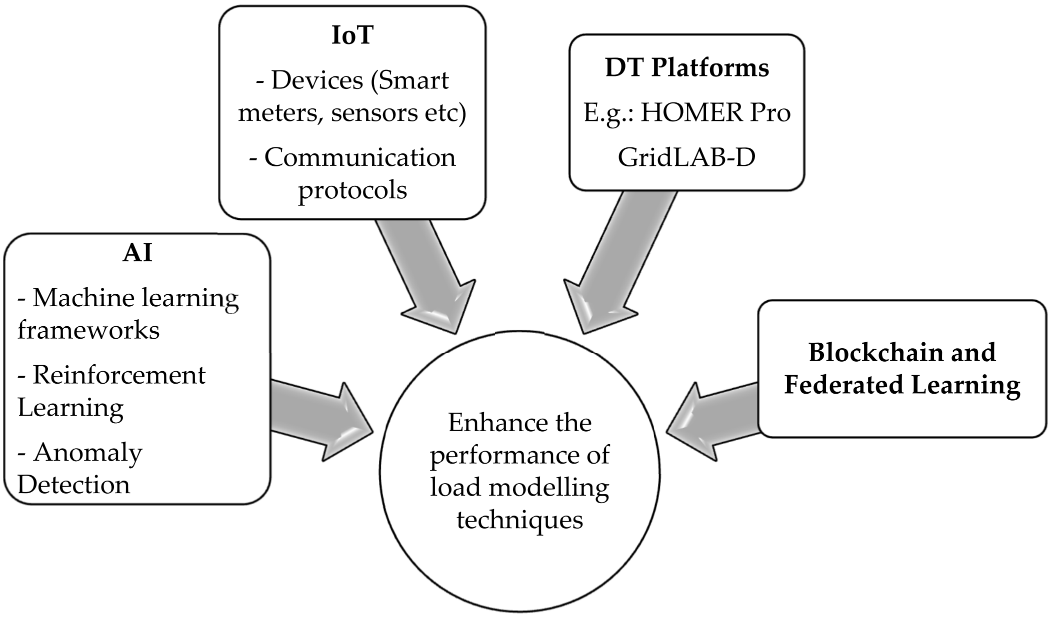

Figure 7. Techniques to enhance the performance of load modelling techniques in DTM applications.

AI significantly enhances electrical load modelling by enabling predictive, dynamic, and stochastic load analyses for grid optimization and planning. Machine learning frameworks like TensorFlow and PyTorch are utilized to develop predictive load models, forecasting electricity demand across various time horizons. These forecasts aid in better energy resource planning and operational scheduling [115]. Additionally, reinforcement learning frameworks such as OpenAI Gym and Ray RLlib optimize energy dispatch in microgrids, dynamically managing distributed energy resources (DERs) like solar PV, wind turbines, and hybrid energy storage systems (HESS). AI-based anomaly detection systems further contribute by identifying irregular load behaviors, preventing disruptions, and ensuring stable grid operations [116].

DT platforms like Siemens PSS®ODMS, Ansys Twin Builder, and Azure Digital Twins integrate IoT and AI with advanced electrical load modelling techniques to create virtual representations of energy assets and systems. These platforms enable the simulation of real-world scenarios, such as variations in electrical loads due to weather changes, renewable energy fluctuations, or demand-side management strategies [117]. By leveraging data-driven load models, DTMs allow operators to test grid configurations, analyze load flow dynamics, and predict the impact of renewable energy integration on overall grid performance. Tools like HOMER Pro and GridLAB-D combine these capabilities, providing a holistic view of load behavior, energy dispatch, and system optimization while reducing operational costs [118].

Emerging technologies such as federated learning and blockchain further enhance the integration of load modelling in DTMs [119]. Federated learning allows AI models to collaboratively train on distributed energy load datasets without sharing sensitive information, preserving data privacy and security [120]. Blockchain technology facilitates secure and transparent energy transactions, enabling decentralized energy markets to accommodate complex load-sharing mechanisms. The ultra-low latency and high reliability of 5G networks enhance the real-time capabilities of IoT devices, AI systems, and DTMs, enabling accurate and responsive load modelling across interconnected energy systems [121].

By adopting these technologies and advanced load modelling techniques, power systems can achieve higher efficiency, reliability, and adaptability to meet the demands of modern energy infrastructure. Whether optimizing renewable energy production, managing HESS, or ensuring stable grid operations, the integration of load modelling into DTMs is essential for shaping the future of sustainable energy management.

6. Discussion and Future Recommendations

The manuscript begins by discussing the basic categories of electrical load modeling. Advanced load modeling techniques have been derived from these foundational models, enabling the representation of both static and dynamic variations in power systems for transient and steady-state studies. However, due to the limitations of traditional load modeling techniques, especially in scenarios where component-level modeling is not feasible due to inaccessibility, researchers have explored more advanced techniques in recent studies. Machine learning-based models, including ANNs, as well as black-box and grey-box approaches, represent some of the latest developments in load modeling. These techniques are particularly useful for representing loads in complex systems that require adaptive load models. Additionally, analytical and equivalent circuit load modeling approaches have been developed for applications such as analyzing the transient and steady-state behavior of DR.

The review has revealed that different load modeling techniques possess distinct characteristics in terms of their physical interpretability, ease of implementation, ability to represent dynamic loads, accuracy, level of detail, adaptability, computational burden, measurement data requirements, and applicability to DR studies. The selection of an appropriate load modeling technique depends on the user's evaluation of how these characteristics impact the performance of the intended study. This review provides a comprehensive comparison of these characteristics, offering valuable insights to help readers choose the most suitable load modeling technique for their specific applications.

DTMs have been effectively utilized in power system studies to represent the actual behavior of a power system under various operational conditions. These computerized models enable the prediction of system behavior and the analysis of system actions under different scenarios. Although DTMs have been rapidly adopted in recent power system studies, several challenges remain in their implementation. These include issues with data acquisition, computational burden, integration of legacy components, and limitations of controllers used in DTM design. Integrating electrical load modeling techniques into DTMs for power systems can help address these challenges by reducing computational complexity, enhancing system fidelity, and improving real-time monitoring, control, and optimization through standardized and interoperable models.

Electrical load modeling techniques are extensively utilized in DTMs of power systems, as evidenced by recent research activities. These DTMs are primarily employed to represent power systems and analyze their behavior under various operational conditions.

They enable performance evaluation, testing of strategies to enhance efficiency, reduction of investment and operational costs, prevention of sudden failures, and extension of component lifespans. By accurately representing loads, electrical load modeling techniques have significantly contributed to improving the performance and applicability of DTMs across a wide range of power system applications. The applications of electrical load modeling techniques in DTMs are predominantly utilized for steady-state studies of power systems.

The integration of IoT, AI, and DTMs is transforming power and energy systems by enabling real-time monitoring, predictive analytics, and optimized operations. IoT devices such as smart meters and sensors, paired with platforms like Azure IoT Hub, facilitate seamless data collection and management. AI technologies, including machine learning and reinforcement learning frameworks like TensorFlow and OpenAI Gym, drive predictive maintenance, demand forecasting, and grid optimization. DTT platforms like Siemens PSS®ODMS and Ansys Twin Builder simulate energy assets and incorporate electrical load modeling to analyze consumption patterns, optimize load distribution, and improve energy efficiency. Emerging technologies like federated learning, blockchain, and 5G enhance data privacy, security, and communication, ensuring more resilient and sustainable energy systems capable of meeting modern demands.

The findings of this review indicate that electrical load modeling techniques are valuable for accurately representing load behavior in power system DTMs, which is beneficial for the design and analysis of power system components and scenarios. Although some literature exists on this topic, significant opportunities remain for researchers to explore electrical load modeling techniques and their applications in power system DTMs. Potential future research directions that could impact the development of power system design processes are outlined below.

- ✔ Electrical load modeling techniques have been used to represent loads in both static and dynamic studies of power systems. However, most DTMs have been applied primarily for steady-state studies. Future research should explore the use of DTMs for transient studies using dynamic electrical load models.
- ✔ Power system DTMs are primarily used for monitoring, visualization, analysis, and predictive maintenance. Electrical load modeling techniques, combined with real-time data acquisition, can offer a more accurate representation of load behavior under varying conditions. Further research could explore DTM applications with electrical load modeling to enhance system performance.
- ✔ IoT-based approaches and AI are increasingly popular in DTM design due to their potential to improve model accuracy. In power system DTMs, IoT and AI could enhance the accuracy of load models. Future research could focus on leveraging IoT and AI to optimize power system DTM performance.
- ✔ Accurately representing complex and large loads in power systems requires substantial effort to determine load model parameters. ANN-based approaches can be used to estimate load model parameters with high accuracy, reducing the need for extensive mathematical calculations. Future research could focus on using ANN techniques to determine load model parameters more efficiently.

7. Conclusions

Electrical load modeling techniques are widely used to represent loads in power systems for various transient and steady-state studies. These techniques are broadly categorized into static and dynamic load models. Advanced load modeling techniques have been developed from these foundational approaches to enhance accuracy and other key characteristics. However, challenges remain in modeling loads within complex power systems, particularly when component-based load modeling is not easily achievable. To address these challenges, recent research has introduced novel approaches, such as machine learning-based models, black-box and grey-box methods, and load models tailored for DR studies.

This manuscript presents a comprehensive literature review covering basic to advanced load modeling techniques, their applications, recent advancements, and practical utilizations. Additionally, it provides a detailed comparison of the available load modeling techniques, offering guidance for selecting the most appropriate technique for specific applications. This differentiation is intended to benefit readers and support their efforts in applying load modeling techniques effectively.

DTMs are utilized in power systems to represent the actual behavior of these systems under various operating conditions through computerized models. These models enable predictive analysis and support decision-making for investment and operational activities. However, implementing DTMs in power systems faces challenges such as computational burden, data acquisition issues, and controller limitations. Integrating electrical load modeling techniques into DTMs ensures accurate load representation, which can mitigate these challenges by reducing computational complexity and addressing controller limitations. All load modeling techniques can be integrated into DTMs based on the specific requirements of the application. This review manuscript explores the applications of electrical load modeling techniques in the context of DTMs for power systems. It highlights their effectiveness in enhancing the efficiency, performance, and applicability of DTMs for various power system studies.

This review highlights the importance of electrical load modeling techniques for accurately representing load behavior in power system DTMs which benefits the design and analysis of power system components. While existing studies focus mainly on steady-state applications, future research should explore dynamic load modeling for transient studies, leverage IoT and AI to enhance model accuracy, and utilize ANNs to efficiently estimate load parameters. These advancements could significantly improve the performance and application of power system DTMs.

Author Contributions: Conceptualization, H.J. and K.G.; methodology, H.J.; software, H.J.; validation, H.J., K.G. and R.N.; formal analysis, H.J.; investigation, H.J.; resources, H.J.; data curation, H.J.; writing—original draft preparation, H.J.; writing—review and editing, K.G. and R.N.; visualization, H.J.; supervision, K.G. and R.N.; project administration, K.G.; funding acquisition, K.G. All authors have read and agreed to the published version of the manuscript.

Funding: The authors acknowledge the financial support of the Blue Economy Cooperative Research Centre, established, and supported under the Australian Government's Cooperative Research Centres Program, grant number CRC-20180101.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: Author Robert Nicholson was employed by the company pitt&sherry. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Salimon, S.A.; Adebayo, I.G.; Adepoju, G.A.; Adewuyi, O.B. Optimal Allocation of Distribution Static Synchronous Compensators in Distribution Networks Considering Various Load Models Using the Black Widow Optimization Algorithm. *Sustainability* **2023**, *15*, 15623. [CrossRef]
2. Khan, M.R.; Haider, Z.M.; Malik, F.H.; Almasoudi, F.M.; Alatawi, K.S.S.; Bhutta, M.S. A Comprehensive Review of Microgrid Energy Management Strategies Considering Electric Vehicles, Energy Storage Systems, and AI Techniques. *Processes* **2024**, *12*, 270. [CrossRef]

3. Hashemi-Dezaki, H.; Hariri, A.-M.; Hejazi, M.A. Impacts of Load Modeling on Generalized Analytical Reliability Assessment of Smart Grid under Various Penetration Levels of Wind/Solar/Non-Renewable Distributed Generations. *Sustain. Energy Grids Netw.* **2019**, *20*, 100246. [CrossRef]
4. Lai, C.S.; Locatelli, G.; Pimm, A.; Wu, X.; Lai, L.L. A Review on Long-Term Electrical Power System Modeling with Energy Storage. *J. Clean. Prod.* **2021**, *280*, 124298. [CrossRef]
5. Karimi, M.; Shahriari, A.; Aghamohammadi, M.R.; Marzooghi, H.; Terzija, V. Application of Newton-Based Load Flow Methods for Determining Steady-State Condition of Well and Ill-Conditioned Power Systems: A Review. *Int. J. Electr. Power Energy Syst.* **2019**, *113*, 298–309. [CrossRef]
6. Juarez, M.G.; Botti, V.J.; Giret, A.S. Digital Twins: Review and Challenges. *J. Comput. Inf. Sci. Eng.* **2021**, *21*, 030802. [CrossRef]
7. Song, Z.; Hackl, C.M.; Anand, A.; Thommessen, A.; Petzschmann, J.; Kamel, O.; Braunbehrens, R.; Kaifel, A.; Roos, C.; Hauptmann, S. Digital Twins for the Future Power System: An Overview and a Future Perspective. *Sustainability* **2023**, *15*, 5259. [CrossRef]
8. Melesse, T.Y.; Pasquale, V.D.; Riemma, S. Digital Twin Models in Industrial Operations: A Systematic Literature Review. *Procedia Manuf.* **2020**, *42*, 267–272. [CrossRef]
9. Botín-Sanabria, D.M.; Mihaita, A.-S.; Peimbert-García, R.E.; Ramírez-Moreno, M.A.; Ramírez-Mendoza, R.A.; de J. Lozoya-Santos, J. Digital Twin Technology Challenges and Applications: A Comprehensive Review. *Remote Sens.* **2022**, *14*, 1335. [CrossRef]
10. Bhatti, G.; Mohan, H.; Raja Singh, R. Towards the Future of Smart Electric Vehicles: Digital Twin Technology. *Renew. Sustain. Energy Rev.* **2021**, *141*, 110801. [CrossRef]
11. Jayasinghe, H.; Gunawardane, K. Unlocking Untapped Solar PV Energy in DC Microgrids Through Hydrogen Energy Storage Solutions. In Proceedings of the 2023 IEEE Fifth International Conference on DC Microgrids (ICDCM), Auckland, New Zealand, 15–17 November 2023; pp. 1–6.
12. Digital Twins and Their Use in Future Power Systems | Digital Twin. Available online: https://digitaltwin1.org/articles/1-4 (accessed on 22 February 2024).
13. Cioara, T.; Anghel, I.; Antal, M.; Salomie, I.; Antal, C.; Ioan, A.G. An Overview of Digital Twins Application Domains in Smart Energy Grid. *arXiv* **2021**, arXiv:2104.07904.
14. Moreno Jaramillo, A.F.; Laverty, D.M.; Morrow, D.J.; Martinez del Rincon, J.; Foley, A.M. Load Modelling and Non-Intrusive Load Monitoring to Integrate Distributed Energy Resources in Low and Medium Voltage Networks. *Renew. Energy* **2021**, *179*, 445–466. [CrossRef]
15. Arif, A.; Wang, Z.; Wang, J.; Mather, B.; Bashualdo, H.; Zhao, D. Load Modeling—A Review. *IEEE Trans. Smart Grid* **2018**, *9*, 5986–5999. [CrossRef]
16. Zhou, K.; Yang, S.; Shen, C. A Review of Electric Load Classification in Smart Grid Environment. *Renew. Sustain. Energy Rev.* **2013**, *24*, 103–110. [CrossRef]
17. Proedrou, E. A Comprehensive Review of Residential Electricity Load Profile Models. *IEEE Access* **2021**, *9*, 12114–12133. [CrossRef]
18. Pasiopoulou, I.D.; Kontis, E.O.; Papadopoulos, T.A.; Papagiannis, G.K. Effect of Load Modeling on Power System Stability Studies. *Electr. Power Syst. Res.* **2022**, *207*, 107846. [CrossRef]
19. Mohammed, M.; Abdulkarim, A.; Abubakar, A.S.; Kunya, A.B.; Jibril, Y. Load Modeling Techniques in Distribution Networks: A Review. *J. Appl. Mater. Technol.* **2020**, *1*, 63–70. [CrossRef]
20. Huaman-Rivera, A.; Calloquispe-Huallpa, R.; Luna Hernandez, A.C.; Irizarry-Rivera, A. An Overview of Electric Vehicle Load Modeling Strategies for Grid Integration Studies. *Electronics* **2024**, *13*, 2259. [CrossRef]
21. AlMuhaini, M.; Yahaya, A.; AlAhmed, A. Distributed Generation and Load Modeling in Microgrids. *Sustainability* **2023**, *15*, 4831. [CrossRef]
22. Htita, I.; Abdalla, O.H.; El Korfolly, M.I.; Elmasry, S. Nonlinear Loads Modelling and Harmonics Analysis: A Review. *Former. Recent Pat. Electr. Electron. Eng.* **2024**, *17*, 429–443. [CrossRef]
23. Hill, D.J. Nonlinear Dynamic Load Models with Recovery for Voltage Stability Studies. *IEEE Trans. Power Syst.* **1993**, *8*, 166–176. [CrossRef]
24. Wohlin, C.; Mendes, E.; Felizardo, K.R.; Kalinowski, M. Guidelines for the Search Strategy to Update Systematic Literature Reviews in Software Engineering. *Inf. Softw. Technol.* **2020**, *127*, 106366. [CrossRef]
25. Singh, B.; Kumar, R. A Comprehensive Survey on Enhancement of System Performances by Using Different Types of FACTS Controllers in Power Systems with Static and Realistic Load Models. *Energy Rep.* **2020**, *6*, 55–79. [CrossRef]
26. Milanovic, J.V.; Yamashita, K.; Martínez Villanueva, S.; Djokic, S.Ž.; Korunović, L.M. International Industry Practice on Power System Load Modeling. *IEEE Trans. Power Syst.* **2013**, *28*, 3038–3046. [CrossRef]
27. Höger, M.; Širanec, M.; Altus, J. Power Flow Analysis of Networks with Loads of Constant Current—Constant Power Factor Type. In Proceedings of the 2019 20th International Scientific Conference on Electric Power Engineering (EPE), Kouty nad Desnou, Czech Republic, 15–17 May 2019; pp. 1–4.

28. Ghanbari, N.; Bhattacharya, S. Constant Power Load Analysis in Droop Controlled Microgrids for More Electric Aircraft Application. In Proceedings of the 2020 IEEE Transportation Electrification Conference & Expo (ITEC), Chicago, IL, USA, 24–26 June 2020; pp. 814–819.
29. Shahsavari, A.; Farajollahi, M.; Mohsenian-Rad, H. Individual Load Model Parameter Estimation in Distribution Systems Using Load Switching Events. *IEEE Trans. Power Syst.* **2019**, *34*, 4652–4664. [CrossRef]
30. Cucuzzella, M.; Kosaraju, K.C.; Scherpen, J.M.A. Voltage Control of DC Microgrids: Robustness for Unknown ZIP-Loads. *IEEE Control Syst. Lett.* **2023**, *7*, 139–144. [CrossRef]
31. Oh, H. Analytic Solution to Swing Equations in Power Grids with ZIP Load Models. *PLoS ONE* **2023**, *18*, e0286600. [CrossRef] [PubMed]
32. Fan, B.; Peng, J.; Yang, Q.; Liu, W. Distributed Control of DC Microgrids with Improved ZIP Load Adaptability. *IEEE Trans. Syst. Man Cybern. Syst.* **2022**, *52*, 4623–4633. [CrossRef]
33. Leinakse, M.; Andreesen, G.; Tani, P.; Kilter, J. Estimation of Exponential and ZIP Load Model of Aggregated Load with Distributed Generation. In Proceedings of the 2021 IEEE 62nd International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga, Latvia, 15–17 November 2021; pp. 1–6.
34. Wang, Z.; Wang, J.; Chen, B.; Begovic, M.M.; He, Y. MPC-Based Voltage/Var Optimization for Distribution Circuits with Distributed Generators and Exponential Load Models. *IEEE Trans. Smart Grid* **2014**, *5*, 2412–2420. [CrossRef]
35. Abul'Wafa, A.R. A Network-Topology-Based Load Flow for Radial Distribution Networks with Composite and Exponential Load. *Electr. Power Syst. Res.* **2012**, *91*, 37–43. [CrossRef]
36. Price, W.W.; Taylor, C.W.; Rogers, G.J. Standard Load Models for Power Flow and Dynamic Performance Simulation. *IEEE Trans. Power Syst.* **1995**, *10*, 1302–1313.
37. Load Model Data Processing and Parameter Derivation (LMDPPD) Version 2.1. Available online: https://www.epri.com/research/products/000000000001017802 (accessed on 22 February 2024).
38. Zuo, Y.; Paolone, M.; Sossan, F. Effect of Voltage Source Converters with Electrochemical Storage Systems on Dynamics of Reduced-Inertia Bulk Power Grids. *Electr. Power Syst. Res.* **2020**, *189*, 106766. [CrossRef]
39. Grigsby, L.L. (Ed.) *Power System Stability and Control*; CRC Press: Boca Raton, FL, USA, 2007; ISBN 978-0-429-12972-8.
40. Saxena, N.K.; Sharma, A.K. Estimation of Composite Load Model with Aggregate Induction Motor Dynamic Load for an Isolated Hybrid Power System. *Front. Energy* **2015**, *9*, 472–485. [CrossRef]
41. Pereira, L.; Kosterev, D.; Mackin, P.; Davies, D.; Undrill, J.; Zhu, W. An Interim Dynamic Induction Motor Model for Stability Studies in the WSCC. *IEEE Trans. Power Syst.* **2002**, *17*, 1108–1115. [CrossRef]
42. Xu, W.; Mansour, Y. Voltage Stability Analysis Using Generic Dynamic Load Models. *IEEE Trans. Power Syst.* **1994**, *9*, 479–493. [CrossRef]
43. Kao, W.-S. The Effect of Load Models on Unstable Low-Frequency Oscillation Damping in Taipower System Experience w/Wo Power System Stabilizers. *IEEE Trans. Power Syst.* **2001**, *16*, 463–472. [CrossRef]
44. Ma, J.; Han, D.; He, R.-M.; Dong, Z.-Y.; Hill, D.J. Reducing Identified Parameters of Measurement-Based Composite Load Model. *IEEE Trans. Power Syst.* **2008**, *23*, 76–83. [CrossRef]
45. Aoun, R.M.; de Souza, A.C.Z.; Passaro, M.C. The Role of Load and Distributed Energy Resources Modeling in Voltage Recovery Studies. *Sustain. Energy Grids Netw.* **2024**, *39*, 101428. [CrossRef]
46. Tofighi-Milani, M.; Fattaheian-Dehkordi, S.; Lehtonen, M. Investigating the Impact of Electrical Load Types on the Frequency Response of Low Inertia Power Systems. *IEEE Access* **2024**, *12*, 59771–59781. [CrossRef]
47. Rios Penaloza, J.D.; Adu, J.A.; Borghetti, A.; Napolitano, F.; Tossani, F.; Nucci, C.A. Influence of Load Dynamic Response on the Stability of Microgrids during Islanding Transition. *Electr. Power Syst. Res.* **2021**, *190*, 106607. [CrossRef]
48. Wang, F.; Ke, D.; Yu, X.; Huang, D. Enhanced Predictive Model Based Deadbeat Control for PMSM Drives Using Exponential Extended State Observer. *IEEE Trans. Ind. Electron.* **2022**, *69*, 2357–2369. [CrossRef]
49. Xu, X.; Yousefian, R.; Tang, J.; Choi, B.; Huang, L.; Mao, Y. Sensitivity Studies on Composite Load Models in PJM System Stability Assessment. In Proceedings of the 2023 IEEE Power & Energy Society General Meeting (PESGM), Orlando, FL, USA, 16–20 July 2023; pp. 1–5.
50. Albatran, S.; Alzubi, I.; Smadi, I.A.; Harasis, S. Comprehensive Dynamic Mathematical Representation and Parameter Evaluation for the Complex Load Model (Clod). 2024; *preprint*. [CrossRef]
51. Gaikwad, A.; Markham, P.; Pourbeik, P. Implementation of the WECC Composite Load Model for Utilities Using the Component-Based Modeling Approach. In Proceedings of the 2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Dallas, TX, USA, 3–5 May 2016; pp. 1–5.
52. Zhang, H.; Diltz, N.; Roychowdhury, R.; Wu, X. Time Series Power Flow and Contingency Analysis with Weather Adjusted Line Ratings: A Synthetic WECC Case Study. In Proceedings of the 2024 IEEE Power & Energy Society General Meeting (PESGM), Seattle, WA, USA, 21–25 July 2024; pp. 1–5.

53. Khazeiynasab, S.R.; Zhao, J.; Duan, N. WECC Composite Load Model Parameter Identification Using Deep Learning Approach. In Proceedings of the 2022 IEEE Power & Energy Society General Meeting (PESGM), Denver, CO, USA, 17–21 July 2022; pp. 1–5.
54. Chen, D.; Mohler, R.R. Neural-Network-Based Load Modeling and Its Use in Voltage Stability Analysis. *IEEE Trans. Control Syst. Technol.* **2003**, *11*, 460–470. [CrossRef]
55. Behm, C.; Nolting, L.; Praktiknjo, A. How to Model European Electricity Load Profiles Using Artificial Neural Networks. *Appl. Energy* **2020**, *277*, 115564. [CrossRef]
56. Buyukyildiz, M.; Kumcu, S.Y. An Estimation of the Suspended Sediment Load Using Adaptive Network Based Fuzzy Inference System, Support Vector Machine and Artificial Neural Network Models. *Water Resour. Manag.* **2017**, *31*, 1343–1359. [CrossRef]
57. Wang, L.; Lee, E.W.M.; Yuen, R.K.K. Novel Dynamic Forecasting Model for Building Cooling Loads Combining an Artificial Neural Network and an Ensemble Approach. *Appl. Energy* **2018**, *228*, 1740–1753. [CrossRef]
58. Chowdhury, M.M.-U.-T.; Biswas, B.D.; Kamalasadan, S. Second-Order Cone Programming (SOCP) Model for Three Phase Optimal Power Flow (OPF) in Active Distribution Networks. *IEEE Trans. Smart Grid* **2023**, *14*, 3732–3743. [CrossRef]
59. Chen, L.; Wang, J.; Wu, Z.; Li, G.; Zhou, M.; Li, P.; Zhang, Y. Communication Reliability-Restricted Energy Sharing Strategy in Active Distribution Networks. *Appl. Energy* **2021**, *282*, 116238. [CrossRef]
60. Shahcheraghian, A.; Madani, H.; Ilinca, A. From White to Black-Box Models: A Review of Simulation Tools for Building Energy Management and Their Application in Consulting Practices. *Energies* **2024**, *17*, 376. [CrossRef]
61. Rouhani, S.H.; Su, C.-L.; Mobayen, S.; Razmjooy, N.; Elsisi, M. Cyber Resilience in Renewable Microgrids: A Review of Standards, Challenges, and Solutions. *Energy* **2024**, *309*, 133081. [CrossRef]
62. Papadopoulos, P.N.; Papadopoulos, T.A.; Crolla, P.; Roscoe, A.J.; Papagiannis, G.K.; Burt, G.M. Black-Box Dynamic Equivalent Model for Microgrids Using Measurement Data. *IET Gener. Transm. Distrib.* **2014**, *8*, 851–861. [CrossRef]
63. Shi, Y.; Xu, D.; Su, J.; Liu, N.; Yu, H.; Xu, H. Black-Box Behavioral Modeling of Voltage and Frequency Response Characteristic for Islanded Microgrid. *Energies* **2019**, *12*, 2049. [CrossRef]
64. Li, Y.; Wang, Z.; Yang, J.; Wang, X.; Feng, J. Dynamic Equivalence Modeling for Microgrid Cluster by Using Physical-Data-Driven Method. *IEEE Trans. Appl. Supercond.* **2021**, *31*, 5401004. [CrossRef]
65. Frances, A.; Ramirez, D.; Uceda, J. Blackbox Small-Signal Modeling of Grid-Connected Inverters in Asymmetrical Power Grids. *IEEE Trans. Power Electron.* **2023**, *38*, 13064–13073. [CrossRef]
66. Espín-Sarzosa, D.; Palma-Behnke, R.; Cañizares, C.A.; Annakkage, U.; Elizondo, M.; Espina, E.; Du, W.; Kabalan, M.; Meegahapola, L.; Mendoza-Araya, P.A.; et al. Microgrid Modeling for Stability Analysis. *IEEE Trans. Smart Grid* **2024**, *15*, 2459–2479. [CrossRef]
67. Samadi, A.; Söder, L.; Shayesteh, E.; Eriksson, R. Static Equivalent of Distribution Grids with High Penetration of PV Systems. *IEEE Trans. Smart Grid* **2015**, *6*, 1763–1774. [CrossRef]
68. Shah, A.A.; Ahmed, K.; Han, X.; Saleem, A. A Novel Prediction Error-Based Power Forecasting Scheme for Real PV System Using PVUSA Model: A Grey Box-Based Neural Network Approach. *IEEE Access* **2021**, *9*, 87196–87206. [CrossRef]
69. Shao, S.; Pipattanasomporn, M.; Rahman, S. Development of Physical-Based Demand Response-Enabled Residential Load Models. *IEEE Trans. Power Syst.* **2013**, *28*, 607–614. [CrossRef]
70. McKenna, K.; Keane, A. Residential Load Modeling of Price-Based Demand Response for Network Impact Studies. *IEEE Trans. Smart Grid* **2016**, *7*, 2285–2294. [CrossRef]
71. Bianco, G.; Bracco, S.; Delfino, F.; Gambelli, L.; Robba, M.; Rossi, M. A Building Energy Management System Based on an Equivalent Electric Circuit Model. *Energies* **2020**, *13*, 1689. [CrossRef]
72. Kang, L.; Liu, L.; An, Q.; Yang, J.; Zhao, J.; Jia, H.; Wang, D. The Equivalent Thermal Parameter Model and Simulation of Air Conditioner System in Demand Response Programs. *Energy Procedia* **2014**, *61*, 2004–2007. [CrossRef]
73. Agostinelli, S.; Cumo, F.; Guidi, G.; Tomazzoli, C. Cyber-Physical Systems Improving Building Energy Management: Digital Twin and Artificial Intelligence. *Energies* **2021**, *14*, 2338. [CrossRef]
74. Ejaz, W.; Naeem, M.; Shahid, A.; Anpalagan, A.; Jo, M. Efficient Energy Management for the Internet of Things in Smart Cities. *IEEE Commun. Mag.* **2017**, *55*, 84–91. [CrossRef]
75. Cai, H.; Zhu, J.; Zhang, W. Quality Deviation Control for Aircraft Using Digital Twin. *J. Comput. Inf. Sci. Eng.* **2021**, *21*, 031008. [CrossRef]
76. Espín-Sarzosa, D.; Palma-Behnke, R.; Valencia-Arroyave, F. Towards Digital Twins of Small Productive Processes in Microgrids. *Energies* **2023**, *16*, 4324. [CrossRef]
77. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of Digital Twin about Concepts, Technologies, and Industrial Applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
78. Liu, T.; Yu, H.; Yin, H.; Zhang, Z.; Sui, Z.; Zhu, D.; Gao, L.; Li, Z. Research and Application of Digital Twin Technology in Power Grid Development Business. In Proceedings of the 2021 6th Asia Conference on Power and Electrical Engineering (ACPEE), Chongqing, China, 8–11 April 2021; pp. 383–387.
79. Padmawansa, N.; Gunawardane, K.; Madanian, S.; Than Oo, A.M. Battery Energy Storage Capacity Estimation for Microgrids Using Digital Twin Concept. *Energies* **2023**, *16*, 4540. [CrossRef]

80. Abo-Khalil, A.G. Digital Twin Real-Time Hybrid Simulation Platform for Power System Stability. *Case Stud. Therm. Eng.* **2023**, *49*, 103237. [CrossRef]
81. Sharma, P.; Bora, B.J.; Deepanraj, B.; Jarin, T. Overview of Digital Twins in Renewable Energy. In Proceedings of the 2024 1st International Conference on Trends in Engineering Systems and Technologies (ICTEST), Kochi, India, 11–13 April 2024; pp. 1–6.
82. Huang, J.; Koroteev, D.D.; Rynkovskaya, M. Machine Learning-Based Demand Response in PV-Based Smart Home Considering Energy Management in Digital Twin. *Sol. Energy* **2023**, *252*, 8–19. [CrossRef]
83. Brosinsky, C.; Krebs, R.; Westermann, D. Embedded Digital Twins in Future Energy Management Systems: Paving the Way for Automated Grid Control. *at-Automatisierungstechnik* **2020**, *68*, 750–764. [CrossRef]
84. Sharma, A.; Kosasih, E.; Zhang, J.; Brintrup, A.; Calinescu, A. Digital Twins: State of the Art Theory and Practice, Challenges, and Open Research Questions. *J. Ind. Inf. Integr.* **2022**, *30*, 100383. [CrossRef]
85. Mihai, S.; Yaqoob, M.; Hung, D.V.; Davis, W.; Towakel, P.; Raza, M.; Karamanoglu, M.; Barn, B.; Shetve, D.; Prasad, R.V.; et al. Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 2255–2291. [CrossRef]
86. Feng, H.; Qiao, L.; Lv, Z. Innovative Soft Computing-Enabled Cloud Optimization for next-Generation IoT in Digital Twins. *Appl. Soft Comput.* **2023**, *136*, 110082. [CrossRef]
87. Chen, H.; Zhang, Z.; Karamanakos, P.; Rodriguez, J. Digital Twin Techniques for Power Electronics-Based Energy Conversion Systems: A Survey of Concepts, Application Scenarios, Future Challenges, and Trends. *IEEE Ind. Electron. Mag.* **2023**, *17*, 20–36. [CrossRef]
88. Aghazadeh Ardebili, A.; Zappatore, M.; Ramadan, A.I.H.A.; Longo, A.; Ficarella, A. Digital Twins of Smart Energy Systems: A Systematic Literature Review on Enablers, Design, Management and Computational Challenges. *Energy Inform.* **2024**, *7*, 94. [CrossRef]
89. Brosinsky, C.; Westermann, D.; Krebs, R. Recent and Prospective Developments in Power System Control Centers: Adapting the Digital Twin Technology for Application in Power System Control Centers. In Proceedings of the 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, 3–7 June 2018; pp. 1–6.
90. Lak, P.Y.; Key, S.; Yoon, S.-M.; Nam, S.-R. Digital Twin Application for the Evaluation of Protection Performance in IEC-61850-Based Digital Substations. In Proceedings of the 2023 IEEE International Conference on Advanced Power System Automation and Protection (APAP), Xuchang, China, 8–12 October 2023; pp. 68–72.
91. Wang, L.X.; Zheng, J.H.; Li, M.S.; Lin, X.; Jing, Z.X.; Wu, P.Z.; Wu, Q.H.; Zhou, X.X. Multi-Time Scale Dynamic Analysis of Integrated Energy Systems: An Individual-Based Model. *Appl. Energy* **2019**, *237*, 848–861. [CrossRef]
92. Omoyele, O.; Hoffmann, M.; Koivisto, M.; Larrañeta, M.; Weinand, J.M.; Linßen, J.; Stolten, D. Increasing the Resolution of Solar and Wind Time Series for Energy System Modeling: A Review. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113792. [CrossRef]
93. De Kooning, J.D.M.; Stockman, K.; De Maeyer, J.; Jarquin-Laguna, A.; Vandevelde, L. Digital Twins for Wind Energy Conversion Systems: A Literature Review of Potential Modelling Techniques Focused on Model Fidelity and Computational Load. *Processes* **2021**, *9*, 2224. [CrossRef]
94. You, M.; Wang, Q.; Sun, H.; Castro, I.; Jiang, J. Digital Twins Based Day-Ahead Integrated Energy System Scheduling under Load and Renewable Energy Uncertainties. *Appl. Energy* **2022**, *305*, 117899. [CrossRef]
95. Urquizo, J.; Ramirez, N.; Sanchez, D.; Plazarte, J. Off-Line Measuring Sampling Data Identification Parameters for Digital Twins Mirroring Load Modelling and Stability Analysis. *Sci. Rep.* **2023**, *13*, 4653. [CrossRef] [PubMed]
96. Nguyen-Huu, T.-A.; Tran, T.T.; Tran, M.-Q.; Nguyen, P.H.; Slootweg, J. Operation Orchestration of Local Energy Communities through Digital Twin: A Review on Suitable Modeling and Simulation Approaches. In Proceedings of the 2022 IEEE 7th International Energy Conference (ENERGYCON), Riga, Latvia, 9–12 May 2022; pp. 1–6.
97. Huxoll, N.; Aldebs, M.; Baboli, P.T.; Lehnhoff, S.; Babazadeh, D. Model Identification and Parameter Tuning of Dynamic Loads in Power Distribution Grid: Digital Twin Approach. In Proceedings of the 2021 International Conference on Smart Energy Systems and Technologies (SEST), Vaasa, Finland, 6–8 September 2021; pp. 1–6.
98. Baboli, P.T.; Babazadeh, D.; Kumara Bowatte, D.R. Measurement-Based Modeling of Smart Grid Dynamics: A Digital Twin Approach. In Proceedings of the 2020 10th Smart Grid Conference (SGC), Kashan, Iran, 16–17 December 2020; pp. 1–6.
99. Söderäng, E.; Hautala, S.; Mikulski, M.; Storm, X.; Niemi, S. Development of a Digital Twin for Real-Time Simulation of a Combustion Engine-Based Power Plant with Battery Storage and Grid Coupling. *Energy Convers. Manag.* **2022**, *266*, 115793. [CrossRef]
100. Amadou Adamou, A.; Alaoui, C. Energy Efficiency Model-Based Digital Shadow for Induction Motors: Towards the Implementation of a Digital Twin. *Eng. Sci. Technol. Int. J.* **2023**, *44*, 101469. [CrossRef]
101. *IEC 60034-2-1*; Rotating Electrical Machines-Part 2-1: Standard Methods for Determining Losses and Efficiency from Tests (Excluding Machines for Traction Vehicles). International Electrotechnical Commission: Geneva, Switzerland, 2014.
102. Luo, Y.; Wang, L.; Sidorov, D.; Dreglea, A.; Chistyakova, E. An Approach to Estimate the Temperature of an Induction Motor under Nonlinear Parameter Perturbations Using a Data-Driven Digital Twin Technique. *Energies* **2024**, *17*, 4996. [CrossRef]

103. Arraño-Vargas, F.; Konstantinou, G. Modular Design and Real-Time Simulators Toward Power System Digital Twins Implementation. *IEEE Trans. Ind. Inform.* **2023**, *19*, 52–61. [CrossRef]
104. Yang, Y.; Li, H.; Aichhorn, A.; Zheng, J.; Greenleaf, M. Sizing Strategy of Distributed Battery Storage System with High Penetration of Photovoltaic for Voltage Regulation and Peak Load Shaving. *IEEE Trans. Smart Grid* **2014**, *5*, 982–991. [CrossRef]
105. Hua, W.; Stephen, B.; Wallom, D.C.H. Digital Twin Based Reinforcement Learning for Extracting Network Structures and Load Patterns in Planning and Operation of Distribution Systems. *Appl. Energy* **2023**, *342*, 121128. [CrossRef]
106. Tomin, N.; Kurbatsky, V.; Borisov, V.; Musalev, S. Development of Digital Twin for Load Center on the Example of Distribution Network of an Urban District. *E3S Web Conf.* **2020**, *209*, 02029. [CrossRef]
107. Schmidt, H.; Prokop, G. Experimental Analysis of Powertrain Test Bed Dynamometers for Black Box-Based Digital Twin Generation. In Proceedings of the 2023 IEEE Transportation Electrification Conference & Expo (ITEC), Detroit, MI, USA, 21–23 June 2023; pp. 1–6.
108. Morkunaite, L.; Kardoka, J.; Pupeikis, D.; Fokaides, P.; Angelakis, V. Digital Twin for Grey Box Modeling of Multistory Residential Building Thermal Dynamics. *arXiv* **2024**, arXiv:2402.02909.
109. Hong, Y.-Y.; Apolinario, G.F.D. Ancillary Services and Risk Assessment of Networked Microgrids Using Digital Twin. *IEEE Trans. Power Syst.* **2023**, *38*, 4542–4558. [CrossRef]
110. Zhao, X.; Zhang, Y. Integrated Management of Urban Resources toward Net-Zero Smart Cities Considering Renewable Energies Uncertainty and Modeling in Digital Twin. *Sustain. Energy Technol. Assess.* **2024**, *64*, 103656. [CrossRef]
111. Wileman, A.J.; Aslam, S.; Perinpanayagam, S. A Component Level Digital Twin Model for Power Converter Health Monitoring. *IEEE Access* **2023**, *11*, 54143–54164. [CrossRef]
112. Srinivasan, R.S.; Manohar, B.; Issa, R.R.A. Urban Building Energy CPS (UBE-CPS): Real-Time Demand Response Using Digital Twin. In *Cyber-Physical Systems in the Built Environment*; Anumba, C.J., Roofigari-Esfahan, N., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 309–322. ISBN 978-3-030-41560-0.
113. Das, O.; Zafar, M.H.; Sanfilippo, F.; Rudra, S.; Kolhe, M.L. Advancements in Digital Twin Technology and Machine Learning for Energy Systems: A Comprehensive Review of Applications in Smart Grids, Renewable Energy, and Electric Vehicle Optimisation. *Energy Convers. Manag. X* **2024**, *24*, 100715. [CrossRef]
114. Kummerow, A.; Nicolai, S.; Brosinsky, C.; Westermann, D.; Naumann, A.; Richter, M. Digital-Twin Based Services for Advanced Monitoring and Control of Future Power Systems. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020; pp. 1–5.
115. Sifat, M.M.H.; Choudhury, S.M.; Das, S.K.; Ahamed, M.H.; Muyeen, S.M.; Hasan, M.M.; Ali, M.F.; Tasneem, Z.; Islam, M.M.; Islam, M.R.; et al. Towards Electric Digital Twin Grid: Technology and Framework Review. *Energy AI* **2023**, *11*, 100213. [CrossRef]
116. Jafari, M.; Kavousi-Fard, A.; Chen, T.; Karimi, M. A Review on Digital Twin Technology in Smart Grid, Transportation System and Smart City: Challenges and Future. *IEEE Access* **2023**, *11*, 17471–17484. [CrossRef]
117. Renold, A.P.; Kathayat, N.S. Comprehensive Review of Machine Learning, Deep Learning, and Digital Twin Data-Driven Approaches in Battery Health Prediction of Electric Vehicles. *IEEE Access* **2024**, *12*, 43984–43999. [CrossRef]
118. Shezan, S.A.; Kamwa, I.; Ishraque, M.F.; Muyeen, S.M.; Hasan, K.N.; Saidur, R.; Rizvi, S.M.; Shafiullah, M.; Al-Sulaiman, F.A. Evaluation of Different Optimization Techniques and Control Strategies of Hybrid Microgrid: A Review. *Energies* **2023**, *16*, 1792. [CrossRef]
119. Saad, A.; Faddel, S.; Mohammed, O. IoT-Based Digital Twin for Energy Cyber-Physical Systems: Design and Implementation. *Energies* **2020**, *13*, 4762. [CrossRef]
120. Kabir, M.R.; Halder, D.; Ray, S. Digital Twins for IoT-Driven Energy Systems: A Survey. *IEEE Access* **2024**, *12*, 177123–177143. [CrossRef]
121. Yapa, C.; de Alwis, C.; Liyanage, M.; Ekanayake, J. Survey on Blockchain for Future Smart Grids: Technical Aspects, Applications, Integration Challenges and Future Research. *Energy Rep.* **2021**, *7*, 6530–6564. [CrossRef]