Load Modeling – A Review

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***Abstract*— Load modeling has significant impact on power system studies. This paper presents a review on load modeling and identification techniques. Load models can be classified into two broad categories: static and dynamic models, while there are two types of approaches to identify model parameters: measurement-based and component-based. Load modeling has received more attention in recent years because of the renewable integration, demand-side management, and smart metering devices. However, the commonly used load models are outdated, and cannot represent emerging loads. There is a need to systematically review existing load modeling techniques and suggest future research directions to meet the increasing interests from industry and academia. In this paper, we provide a thorough survey on the academic research progress and industry practices, and highlight existing issues and new trends in load modeling.**

***Index Terms*—Load modeling, dynamic models, static models, model identification, distributed generation, demand side management**

I. Introduction

LOAD modeling is essential to power system analysis, planning, and control. For example, studies have shown the importance of accurate load representations in voltage stability assessment [1]. Although the need for accurate load models is recognized by power system researchers and engineers [2], more research is imperative to update existing load models and understand characteristics of modern loads with emerging smart grid technologies such as distributed generators (DGs), electric vehicles (EVs), and demand side management (DSM). The uncertainty and difficulty of load modeling comes from the large number of diverse load components, time-varying and weather-dependent compositions, and the lack of measurements and detailed load information. The goal of load modeling is to develop simple mathematical models to approximate load behaviors.

Load modeling consists of two main steps: 1) selecting a load model structure, and 2) identifying the load model parameters using component or measurement-based approaches. Component-based or physically-based modeling has been extensively investigated in literature [3]-[9]. The method is based on the knowledge of physical behaviors of loads and mathematical relations that describe the functioning of load devices. However, obtaining such information is not always possible, which motivates the research in measurement-based modeling [10]-[19]. Measurement-based modeling collects measurements from data acquisition equipment to derive load characteristics. The main advantage is that this approach directly obtains the data from the actual network, and can be applied to any load. However, a developed model at one network location may not be applicable to other locations. The parameters of load models are estimated by fitting the acquired data to a load model structure using identification and estimation techniques. Other research suggested the use of Artificial Neural Networks (ANN) to model loads by mapping the input data set to the output [25]-[30]. This approach is useful when the model structure is unknown or hard to be mathematically represented. However, data-driven techniques require a large number of datasets and considerable computational effort. Moreover, ANN-based models can only be applied to systems for which they were developed.

A review on load modeling was performed in 1990s [31] [32], which included a bibliography [33] listing papers on load models and typical values of parameters. The International Council on Large Electric Systems (CIGRE) established a new working group to provide guidance with respect to load modeling. The working group C4.605: "Modelling and Aggregation of Loads in Flexible Power Networks" aims to provide an overview of existing load models with a critical analysis on parameter identification methods. Developing new load models and validation techniques are also part of the agenda for CIGRE C4.605. The working group conducted a survey on international industry practice on load modeling in [34]. The paper summarized the key findings from questionnaires collected from power system operators around the world, and identified the prevalent types of load models being used. In [35], CIGRE presented a general overview on load modeling and aggregation. The report included modeling of active distribution networks and a detailed description of the commercial and residential load sectors. In this paper, we present a concise and thorough review on load modeling, including DG models. We review the existing work on load modeling and present the outstanding issues and new research trends. The commonly used load models are summarized and discussed. The ever-increasing integration of demand-side controls and DGs, particularly distributed PVs, further

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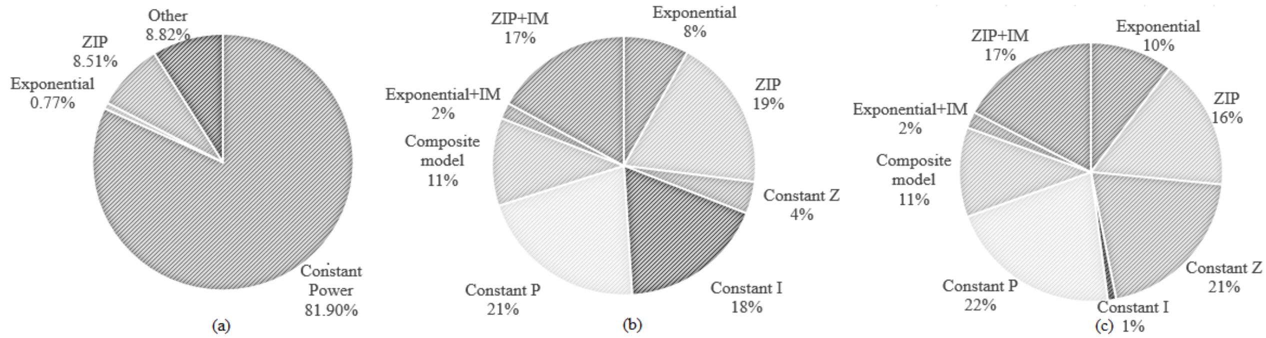

Fig. 1. Load models currently used in the industry for (a) steady-state analysis and dynamic studies (b) active power and (c) reactive power [34]

complicates load characteristics and poses additional challenges to load modeling. In addition, we introduce the latest advancements in developing load models, such as the use of real-time data for online modeling [21], modeling residential loads by considering both electrical characteristics and consumers' behaviors [36], and modeling microgrids (MGs) using a combination of component- and measurement-based methods [37] [38].

The remainder of this paper is organized as follows. Section II reviews various types of load models. Section III introduces DG models. Section IV overviews the existing work on component-based and measurement-based identification methods. Section V concludes this paper and provides suggestions for future work.

II. Types Of Load Models

Load modeling refers to the mathematical representation of the relationship between the power and voltage in a load bus [2]. Load models can be classified into two main categories: static and dynamic models. Fig. 1 shows the currently used load models in industry for static and dynamic studies [34].

A. Static Load Models

Static models express the active and reactive power at any instant of time as functions of bus voltage magnitudes and frequency. These models can be used to represent static loads e.g., resistive loads, and as an approximation for dynamic loads, e.g., induction motors.

1) ZIP Model

ZIP model is commonly used in both steady-state and dynamic studies [2]. This model represents the relationship between the voltage magnitude and power in a polynomial equation that combines constant impedance (Z), current (I), and power (P) components.

2) Exponential Model

The exponential model relates the power and the voltage at a load bus by exponential equations. This model has fewer parameters and is usually used to represent mixed loads [39]. More components with different exponents can be included in these equations. For example, by using three exponential components, the exponential model can be converted to a ZIP model.

3) Frequency Dependent Model

This model is derived by multiplying the exponential or ZIP model by a factor that depends on the bus frequency. The factor can be represented as follows.

$$Factor = [1 + a_f(f - f_0)] \tag{1}$$

where f is the frequency of the bus voltage, f_0 is the nominal frequency, and a_f is the frequency sensitivity parameter. Adding the frequency term to the ZIP model has no physical meaning, since the component related to the constant impedance becomes dependent on the frequency [32].

4) Electric Power Research Institute (EPRI) LOADSYN Model

This model is used in the EPRI LOADSYN computational program and Extended Transient Midterm Stability Program (ETMSP) for dynamic studies [40] [41]. The model combines ZIP, exponential, and frequency-dependent models.

$$P_L = P_0\{P_{a_1}(V/V_0)^{K_{pv1}}(1 + K_{pf_1}\Delta f) + (1 - P_{a_1})(V/V_0)^{K_{pv2}}\} \tag{2}$$

$$Q_L = P_0 Q_{a_1}(V/V_0)^{K_{qv1}}(1 + K_{qf_1}\Delta f) + P_0(Q_0/P_0 - Q_{a_1})(V/V_0)^{K_{qv2}}(1 + K_{qf_2}\Delta f) \tag{3}$$

where P_0 and Q_0 are the power consumed at the rated voltage V_0 of a device, if the model is used to represent a specific device. If it models the aggregate load at a bus, V_0, P_0, and Q_0 are initial operating conditions. The active power is represented by frequency dependent and independent components. The reactive power is composed of two terms. The first represents the reactive power consumption of the load, and the second approximates the effect of the reactive consumption minus compensation, which finds the initial reactive power flow at a bus. P_{a_1} is the frequency-dependent fraction of active power, Q_{a_1} is the reactive load coefficient representing the ratio of uncompensated reactive load to active power, K_{pv1} and K_{pv2} are voltage exponents for frequency dependent and independent active power, respectively. K_{qv1} and K_{qv1} are voltage exponents for the reactive power without and with compensation, respectively. K_{pf1} and K_{qf1} are the frequency sensitivity coefficients for active and uncompensated reactive power load, respectively. K_{qf2} is the frequency sensitivity coefficient for reactive power compensation.

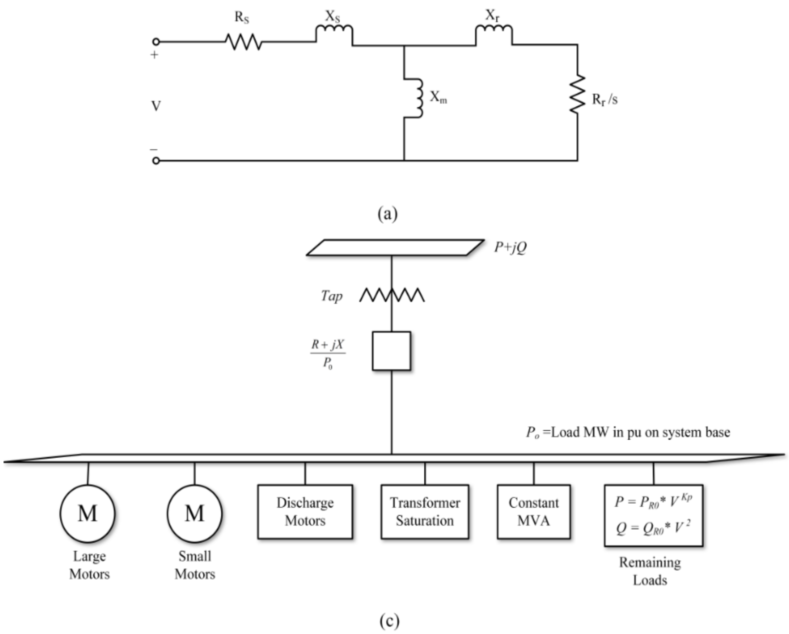

Fig. 2. Schematics of (a) Induction motor, (b) ZIP+IM, (c) CLOD, (d) WECC CLM

B. *Dynamic Load Models*

Studies in voltage stability require the use of dynamic load models for accurate representation [2]. Dynamic models express the active and reactive powers as a function of voltage and time. Examples of the widely used dynamic models are presented as follows.

1) *Induction Motor (IM)*

In dynamic models, the active and reactive power is represented as a function of the past and present voltage magnitude and frequency of the load bus. This type of model is commonly derived from the equivalent circuit of an induction motor [2], shown in Fig. 2 (a). Where R_s and R_r are the static and rotor resistances respectively, X_s, X_r and X_m are the static, rotor and magnetizing reactance, respectively, and s is the rotor slip. The induction motor model is considered as a physically-based model.

2) *Exponential Recovery Load Model (ERL)*

The exponential recovery load model [43] [44] represents active and reactive power responses to step disturbances of the bus voltage. This model is commonly used for representing loads that slowly recover over a time period, which ranges from several seconds to tens of minutes. ERL is also used to model on-load tap changers (OLTCs) which restore the nominal supply voltage after a disturbance. The model is developed as a non-linear first-order equation to represent the load response, as shown in (4-7).

$$T_p \frac{dx_p}{dt} = -x_p + P_0(V/V_0)^{N_{ps}} - P_0(V/V_0)^{N_{pt}} \tag{4}$$

$$P_d = x_p + P_0(V/V_0)^{N_{pt}} \tag{5}$$

$$T_q \frac{dx_q}{dt} = -x_q + Q_0(V/V_0)^{N_{qs}} - Q_0(V/V_0)^{N_{qt}} \tag{6}$$

$$Q_d = x_q + Q_0(V/V_0)^{N_{qt}} \tag{7}$$

where x_p and x_q are state variables related to active and reactive power dynamics, T_p and T_q are time constants of the exponential recovery response, N_{ps} and N_{qs} are exponents related to the steady-state load response, N_{pt} and N_{qt} are exponents related to the transient load response.

The ERL is further extended in [45] as an adaptive dynamic model. The model has the same characteristics as the exponential recovery model, but with the power being a function of the voltage multiplied by the state variable.

$$T_p \frac{dx_p}{dt} = -x_p(V/V_0)^{N_{ps}} + P_0(V/V_0)^{N_{pt}} \tag{8}$$

$$P_d = x_p(V/V_0)^{N_{pt}} \tag{9}$$

$$T_q \frac{dx_q}{dt} = -x_q(V/V_0)^{N_{qs}} + Q_0(V/V_0)^{N_{qt}} \tag{10}$$

$$Q_d = x_q(V/V_0)^{N_{qt}} \tag{11}$$

C. *Composite Load Models (CLM)*

Recent studies focus on combining the dynamic and static load models [11] [13] [21] [46] [47]. References [46] and [47] compared simulation results of different load models with transient disturbances, and concluded that composite models can provide more accurate responses. The widely used composite models are summarized in this subsection.

1) *ZIP+IM*

According to the study in [34], the composite load model consisting of ZIP and an induction motor is the most commonly used model in the US industry for dynamic studies. In [13], several composite load models were considered including ZIP+IM and Exponential+IM. The report concluded that the ZIP+IM structure is able to model loads with various conditions, locations, and compositions. The equivalent circuit of the ZIP+IM model is shown in Fig. 2 (b).

2) Complex Load Model (CLOD)

This model is adopted by the Siemens PTI PSS/E stability program [31]. CLOD is an aggregate dynamic model of large and small motors, non-linear models of discharge lighting, transformer saturation effects, constant MVA, shunt capacitors, and a series impedance and tap ratio to represent the effect of intervening sub-transmission and distribution elements. Fig. 2 (c) shows the schematic of this model.

3) Western Electricity Coordinating Council (WECC) CLM

After the 1996 blackout of the Western Systems Coordinating Council (WSCC) [48], an interim composite load model containing a static part and a dynamic part was implemented by WSCC [49]. The model is assumed to have 80% static loads and 20% dynamic ones. The static part is represented by existing data from WSCC members, and the dynamic part is an induction motor model. The model was designed to capture the effects of dynamic induction motor loads for highly stressed conditions in summer peaks. The interim load model was unable to represent delayed voltage recovery events from transmission faults [5] [50] [51]. WECC improved the interim model [6] by adding the the electrical distance between the transmission system and the electrical end-uses, as well as adding special models for residential air-conditioners. By 2012, the WECC CLM was tested and implemented in major industry-level simulation software including PowerWorld Simulator and Siemens PTI PSSE [6]. Datasets were developed for four seasons in 12 climatic zones across the western region with different load sectors (residential, commercial, mixed and rural) [6]. The model structure is shown in Fig. 2 (d), which includes an electrical representation of a distribution system with a substation transformer, shunt reactance, and a feeder equivalent. At the consumer side, the load model includes a static load model, one power electronics model, and four types of motor models. Although CLM provides a detailed modeling, it is hard to implement as there are 131 parameters to be identified.

D. Artificial Neural Network-Based Modeling

ANN-based load modeling [25]-[30] matches observed system behaviors without using a physical form to obtain the output, i.e., it has no physical meaning and purely relies on measurement data. An ANN is composed by a set of processing units interconnected by weights. The ANNs are trained using a succession of input and output patterns, resulting in the final values of the connection weights that determine the load model. Reference [25] presented two ANN-based load modeling approaches. In [26], an ANN-based composite load model was proposed for stability studies. The authors used a two-step procedure with the first step to develop a recurrent neural network with simulation data and the second step to update it using measurement data. Although ANN is powerful in representing complex nonlinear systems., obtaining enough data over a wide range of operation conditions is challenging. In addition, ANN-based models must be updated periodically when new measurement datasets are available.

E. Low-Voltage (LV) Load Models

LV networks are usually represented by lumped models [52]. However, the integration of renewable DGs and the implementation of demand-side management highlights the need for more detailed modeling of LV loads. Most of existing research focuses on characterizing consumption profiles of LV residential loads [53]-[56]. There are a few studies on developing physical models to represent their electrical characteristics. ZIP and exponential models are most commonly used to represent LV loads [57]-[61]. Table I summarizes ZIP coefficients of typical electrical appliances. The study in [24] used smart meter data and machine learning techniques to obtain aggregated ZIP load models for LV networks.

TABLE I
ZIP LOAD MODEL PARAMETERS OF ELECTRICAL APPLIANCES

Paper	Load	a_1	a_2	a_3	a_4	a_5	a_6
[56]	Air Conditioner	1.6	-2.69	2.09	12.53	-21.1	9.58
	CFL bulb	-0.63	1.66	-0.03	-0.34	1.4	-0.06
	Elevator	2.36	-4.15	2.79	11.7	-19.5	8.81
	Incandescent light	0.54	0.5	-0.04	0.46	0.51	0.03
	LED Light	0.69	0.92	-0.61	1.84	-0.91	0.07
	Microwave	-0.27	1.16	0.11	15.64	-27.7	13.1
	PC	0.18	-0.26	1.08	-0.19	0.96	0.23
	Resistive Heater	0.92	0.1	-0.02	0.15	0.86	-0.01
[57]	Refrigerator	1.19	-0.26	0.07	0.59	0.65	-0.24
	battery charger	3.51	-3.94	1.43	5.8	-7.3	2.46
	advanced washing machine	0.05	0.31	0.63	-0.56	2.2	-0.65
	microwave	-2.78	6.06	-2.28	0	0	0
[58]	Oven	0.99	0	0	0	0	0
	CRT Monitor	0	0	1	0	0	0.15
	LCD Monitor	0	0	1	0	0	0.15

The authors in [62] and [63] applied the equivalent circuit in Fig. 3 to model directly connected motors. Reference [64] developed a component-based modeling approach that divided residential loads into five categories: 1) resistive (e.g. general incandescent lamps, space and water heaters, electrical cookers), 2) power electronics, or switch-mode power supply (e.g. PCs, monitors, laptops, TVs), 3) energy efficient light sources (e.g. CFL and LED loads), 4) directly-connected motors (e.g. fridges, dishwashers, water-pumps, washing machines, tumble dryers and freezers), and 5) drive-controlled motors (e.g. modern air-conditioners). The equivalent circuit shown in Fig. 3 was used to model power electronics, CFL and LED lights, and drive-controlled motors. The circuit consists of an uncontrolled front-end diode bridge rectifier, input impedance R and L, dc link capacitor C_{dc}, and an equivalent resistance r_{eq}. The paper also provided typical parameters for different appliances. The advantage of the proposed component-based approach is that they are able to reproduce the instantaneous current waveform of the aggregated load, thus retaining information of electrical characteristics including harmonic injections. The equivalent model in Fig. 3 was also used to model electric vehicle chargers in [65].

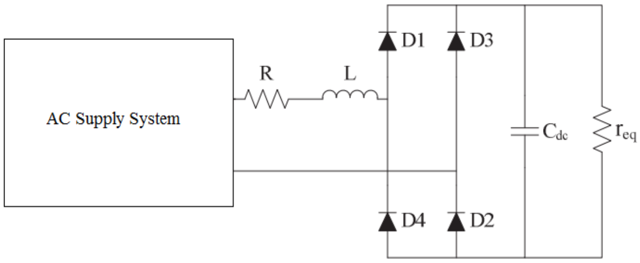

Fig. 3. Generic equivalent circuit for power electronics, CFL and LED lights, and drive-controlled motors

There are studies that develop customer behavior-driven and demand response (DR)-enabled models [36, 66]. The authors in [66] developed price-responsive models considering the optimal scheduling of appliances, thermostatically-controlled loads, and customers' responses to electricity prices. Table II provides examples of this type of loads. Equations (12) represents a thermostatical controller for a cooling/heating unit. The controller has prior knowledge of the peak tariff rate, and maximizes pre-peak period thermal inertia to ensure the maximum ride through, thus lowering in-peak energy consumption. For a cooling unit, the controller alters the thermostatic set-point of the controller, T_{ctrl}, to a lower set-point before the peak, T_{pre}, where t_{start} and t_{store} denote the start time of the peak period and the time before the peak when the thermostatic set point is altered. During the peak period, T_{ctrl} is set to be a higher temperature, T_{peak}, to reduce energy consumption until the end of the peak period, t_{end}. In (13)-(16), an EV receives a signal c_{EV} to change charging behaviors. The EV is rated at P_{EV} and consumes $p_{EV,t}$ at time t. S_{EV} equals 1 if the EV is connected to a charger. The state-of-charge of the battery at time t is SOC_t, and w_{EV} equals 1 if the EV is charging. The initial state SOC_0 depends on the energy used for driving, E_{dr}, and the battery rated capacity, C_{batt}.

TABLE II
DEMAND RESPONSE MODELS

Appliance	Equations
Thermostatic Controlled appliances (cooling) [71]	$T_{ctrl}(t) = \begin{cases} T_{pre}, & t < t_{start} - t_{store} \\ T_{peak,} & t_{start} \leq t < t_{end} \\ T_{set}, & otherwise \end{cases}$ (12)
Electric Vehicle [54]	$p_{EV,t} = P_{EV} \cdot S_{EV_t} \cdot w_{EV,t} \cdot c_{EV,t}$ (13) $w_{EV,i} = \begin{cases} 0, & SOC_i \geq SOC_{max} \\ 1, & SOC_i < SOC_{max} \end{cases}$ (14) $SOC_0 = 1 - \frac{E_{dr}}{C_{batt}}$ (15) $SOC_i = SOC_{i-1} + P_{EV} \cdot \frac{\Delta t}{C_{batt}}$ (16)

In [36], a Markov Chain Monte Carlo (MCMC) modeling approach is used to represent behaviors of individual consumers. The user activity profiles are translated into electrical loads using a database containing information on device usage, operating power range and different operation phases [67-69].

F. Active Distribution Networks (ADNs) and MGs

An ADN is a network with a significant amount of DGs and controllable loads. MG is a small-scale ADN that can operate in either grid-connected or islanded mode. The network can be represented using detailed models of individual components, which is computationally demanding. The lack of details for the DGs and new technologies can further hinder the detailed approach. In recent years, research focuses on providing aggregated models for the entire network using black-box [70]-[72] and grey-box [37], [38], [73] approaches. In the black-box modeling, the mathematical relationship is developed to relate the input to the output without considering a physical structure. Black-box models are applied when little information is available to create a physical model, or if the system is too complex to model. The grey-box model is developed by using physical models and measurements to estimate parameters. The advantage of this method over the black-box one is that it has a clear physical meaning.

In [72], a black-box model was developed for MGs. The developed model focused on representing the dynamic behavior of MGs after a small disturbance. Prony analysis [74] was used to obtain an initial estimate for the parameters, and non-linear least-square optimization was applied to improve the initial parameter estimation. The paper did not filter out harmonics, which should be an important step since Prony analysis behaves poorly when a signal is embedded with noises [75].

Reference [37] presented a seventh order dynamic equivalent model using a grey-box approach. The developed model was composed of a full converter-connected generator (SG) in parallel with the composite load model (ZIP+IM), as shown in Fig. 4. The inputs to the model are the voltage and frequency, and the outputs are active and reactive power. The authors used Levenberg-Marquardt (LM) algorithm to estimate the model parameters. Low-pass filters were used to filter out high-frequency harmonics. In [38], the authors validated the model shown in Fig. 4 by various tests using a multi-generator transmission network, and different types of load models and fault locations.

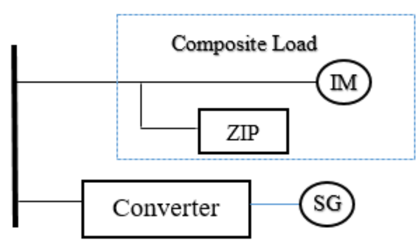

Fig. 4. Equivalent ADN model [37]

Reference [76] presented a grey-box approach to model an ADN considering a large number of PVs embedded with a voltage control scheme. The paper used a ZIP model connected in parallel with a PV model, and a combination of genetic algorithm and sequential quadratic programming to determine the parameters. CIGRE presented a review on ADNs in [77], the review included some of the current research on ADNs, MGs, and aggregated wind power generators. ANN-based black box modeling was presented in [78] to derive a nonlinear dynamic equivalent model for a MV distribution network with a large number of DGs. Another ANN approach was proposed in [79] to develop a dynamic equivalent model for MGs. The study found that the computation is time consuming, and the models are restricted to the test system used to generate the data set. The authors presented an alternative approach in [73] using a grey box modeling approach. The model structure is built based on physical laws, and the parameters are estimated using Evolutionary Particle Swarm Optimization [80]. The modeling of distribution networks becomes more challenging as the integration of distribution energy resources increases.

Table III summarizes the load models introduced in this section.

III. DG Models

For power system analysis, planning and control purposes the models of DGs are typically developed for the aggregated response of multiple DGs as opposed to determine the specific response of an individual DG. There are various types of DGs, which can be divided in to two classes: directly coupled DGs and inverter-coupled DGs. Examples of directly-coupled DGs include back-up/emergency generators, combined heat and power units, and cogeneration units. These applications usually employ directly electrically-coupled rotating machine-based generators. DGs such as PV systems, micro turbine generators and wind generators use a set of power electronic converters to interface with power grids.

A. Static DG Models

The static response of DGs of both directly-coupled and inverter-coupled types is often approximated as a negative real power load assuming the DGs operate at unity power factor. Such model is only valid within reasonable limits of operation. For example, a PV-based DG model, such as the one shown in Fig. 5 [81], is useful to capture the static behavior of a PV system taking into consideration the sizing of the DC PV array and the AC rating of the inverter(s). This model captures the saturation characteristic of the PV system during period of high solar irradiance as well as provides a very simple relationship between the solar irradiance and the modeled PV output power. $E_e[n]$ is the solar irradiance incident on the PV system at time n and $E_{e,sys,sat}$ is the level of incident irradiance that produces the maximum PV system power. $P_{o,sys,STC}$ is the PV system power rating at irradiance/temperature conditions equal to standard

TABLE III
Load Models, Types, Parameters, and Attributes

Type	Model	References	Number of Parameters*	Attributes (+/-)
Static	ZIP	[2], [7], [10], [11], [13], [21], [31]	6	+Clear physical meaning +Simple +Easy to apply + Can be combined with dynamic models easily to form composite models - Fails to represent dynamic loads accurately
	Exponential	[2], [7], [13], [22], [31]	2	
	ZIP w/ frequency	[2], [18], [21], [31]	8	
	Exponential w/ frequency	[2], [31]	4	
	EPRI Loadsyn	[31], [32], [40], [41]	9	
Dynamic	IM	[2], [7], [11], [13], [31]	8 [11]	+ Represent multiple dynamic loads with the same model - The models are based on response to the voltage disturbance which changes under different conditions
	Exponential Recovery	[12], [43], [44]	6	
Composite	ZIP+IM	[7], [11], [13], [14], [15], [17], [18], [20], [21], [23]	14	+ Easy to integrate with existing simulation tools + Simple models with clear physical meaning + Implementation is easier than WECC CLM - less accuracy than WECC CLM
	Exponential+IM	[13], [20]	10	
	ZIP+IM w/frequency	[13], [21]	16	
	CLOD	[7], [31], [33]	8	+ Easy to implement - Inertia constant cannot be modified for large and small motors - Low accuracy
	WECC CLM	[5], [6], [8]	131	+ Detailed modeling + Models up to four motors, which can be single-phase, three-phase, or power electronic loads + Higher accuracy + Can simulate motor load tripping and re-closure - Slow dynamic simulation - Complicated with too many parameters
Machine Learning	ANN-based models	[25], [26], [30]	21, 36, 46 [30]	+ Highly adaptive + Does not require load profiles - Requires a large number of measured data to estimate the model - Does not represent the physical aspect of the load
LV Models	Analytical models	[24], [57]-[61]	Converted to static or dynamic models	+ Captures physical properties of LV loads + Include demand side management - Increased computational burden - Load composition information is needed to aggregated models
	Equivalent circuit models	[36], [62]-[65]	4	
Active Distribution Network (ADN)	Black-box models	[70]-[72]	36 [72]	+ Models the lumped impacts of distribution networks + Considers DGs - Requires a large amount of data for model identification
	Grey-box models	[37], [38], [73]	20 [37]	

* Number of parameters varies with model structures

test conditions (STC). This simple model, and other similar models are typically applied to individual PV systems for distribution-level DG analysis but could also be used for modeling the aggregate PV power expected over a wider, transmission-relevant area.

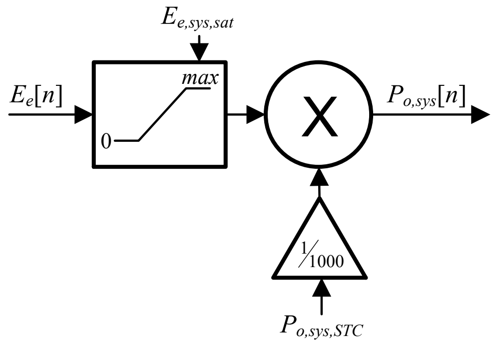

Fig. 5. A simple static model for PV-based DER.

B. Dynamic DG Models

For directly-coupled DGs, conventional rotating machine models are often employed. For example, the study in [82] models DGs using synchronous generators with static exciters. This approach allows the investigation of DG impacts on system dynamics. Modeling inverter-coupled DG requires the consideration of the lack of inherent machine dynamics (e.g. lack of physical inertia characteristics) and the fast control dynamics which can be implemented in the power electronic devices. Generic dynamic models of wind turbines of various technology types are presented in [83]. While these models were developed for transmission-level modeling purposes, typically modeling a single wind generator in regards to distribution connected wind, can be utilized for wind-based DG models. Validation of these models [84] has been completed with reasonable results, particularly for single generator configurations.

Modeling individual components of a wind turbine in power system studies increases the computation complexity. Aggregation techniques to simplify the representation of the renewable resources were proposed. Aggregated models of a wind farm with both constant and variable speed wind turbines were modeled for power system dynamic studies in [85] and [86]. An aggregated model of a grid-connected offshore wind farm was developed for power stability studies in [87]. The authors found that reducing a wind farm to a single-machine equivalent may be insufficient, and suggested the use of a multi-machine equivalent instead. The authors in [88] modeled wind farms by aggregating wind turbines to a single turbine, and by finding an equivalent incoming wind on the wind turbine. The authors proposed equivalent models for wind farms with squirrel-cage induction generators (SCIG) and doubly-fed induction generators (DFIG). The equivalent incoming wind was derived from the wind power curve and the wind incident on each wind turbine in the wind farm. Ali et al. used probabilistic clustering to find an aggregate model of a wind farm in [89]. Support vector clustering is used to cluster wind turbines based on the wind farm layout and incoming wind. Wind turbines in the same cluster and the cables connecting them to the bus bar are aggregated. In [90], the authors developed a dynamic equivalent model for a wind farm by clustering the wind turbines, and developing dynamic equivalent models using the small signal analysis.

There are studies on modeling aggregated PV systems. Tan et al. developed an empirical model based on experimental results for PV systems in [91]. The model was developed using algebraic and difference equations. The authors found that the maximum power point tracking controller, which is used to maximize the efficiency of PV cells, has major impacts on the dynamic response of PV systems. A transfer function model for aggregated PV systems was developed in [92]. The authors derived the transfer function using an aggregated frequency response model, which is obtained via field tests. Reference [93] presented an equivalent model of a PV power plant using a controller that embeds converters with synchronous dynamics. The developed model included the convertor controllers and the DC side dynamics.

The PVD1 model [94], shown in abbreviated form in Fig. 6 was developed by WECC and attempts to capture the dynamic response of aggregated PV systems. PVD1 models aggregated PV as a lumped real and reactive current source. The model includes a mathematical representations of the PV inverters inner current control loop dynamics via first order approximate transfer functions on both the real and reactive current outputs

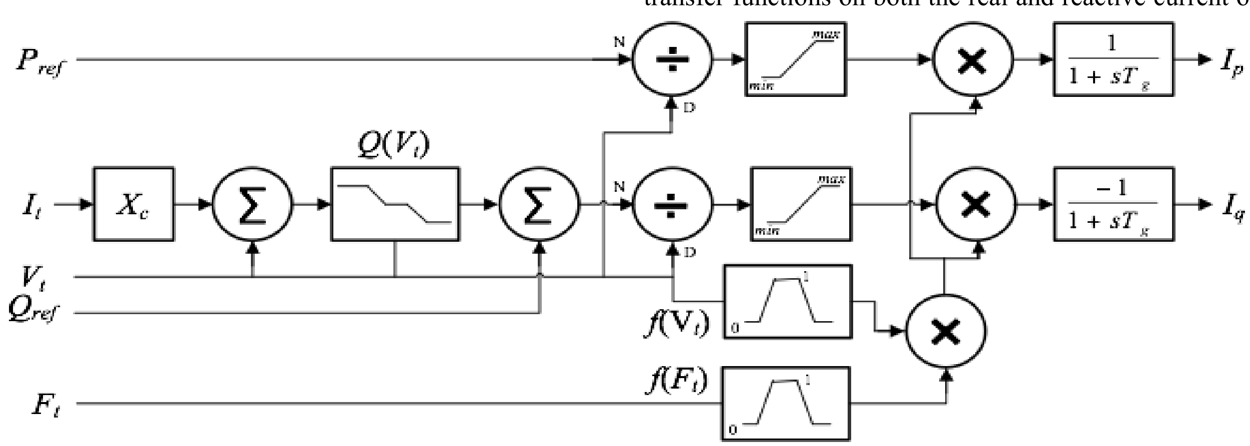

Fig. 6 A simplified block diagram of the WECC PVD1 model.

of the model. Additionally, overall control and functionality of the PV systems is captured via the implementation of particular volt/var functionality and, more generally, the gross behavior of the aggregated PV system response to abnormal voltages and frequencies. For example, the control functionality may include automatic disconnection of a percentage of DGs to capture the aggregate DGs' dynamic responses to low frequency. The PVD1 model can be parameterized so that only a linearly interpolated portion of the modeled aggregate level of DGs are responsive to high and low voltage as well as high and low frequency events – an attempt to model the diversity of individual DG responses across a distribution system. Some difficulty in determining appropriate model parameters for PVD1 has been noted [95,96] and this stems from the fact that the dynamic response of inverter-coupled DG is largely a function of the implemented control logics as opposed to the physical properties of a generator. Thus there is potential for a considerable diversity of inverter-coupled response even among systems of similar rating. Dynamic modeling of DGs at transmission-scale (like the PVD1 model) typically utilize an additional distribution circuit equivalent model. These models are meant to capture the dynamics of the distribution circuit(s) to which the DGs or loads of interest are connected. Fig. 7 shows a simplified model derived from the WECC CLM [95] which is introduced in Section II.C.

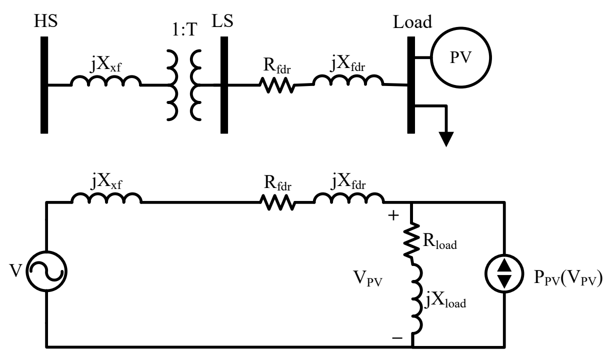

Fig. 7 A simplified equivalent distribution system model that can be used in conjunction with aggregated dynamic DG models.

This equivalent distribution circuit model captures the impacts from the impedance present between DGs and the transmission system. Additionally, the impact from a load tap-changing (LTC) transformer, utilized at the HV to MV substation is captured. The potential for a non 1:1 relationship between HV and MV (in per unit values) is captured but the actual dynamics of the LTC during a dynamic event typically are not considered as LTCs do not typically operate on the time-scales of interest in dynamic simulations.

Several studies have been conducted on modeling other types of DGs. [97] presented a dynamic equivalent circuit for fuel cells and a block diagram for modeling dynamic micro-turbines. A comparison of different dynamic battery energy storage systems (BESS) was presented in [98]. The paper discussed the use of storage systems for frequency regulation studies. WECC developed a model to emulate BESS for the purpose of stability studies in [99]. The model was made specifically for solid state batteries and neglects DC dynamics. EPRI developed a prototype of the WECC model in MATLAB, and validated it using actual field data of a BESS unit operating in the US. A new BESS model that S&C Electric Company developed by configuring the WECC model was presented in [100]. The authors introduced BESS applications on frequency regulation, power reliability and quality, microgrid operations, and other renewable energy applications.

IV. Load Model Parameter Identification

Load model identification methods can be classified into two categories: component-based and measurement-based. The component-based methods aggregate models of individual electrical components to form an aggregated load model. This approach requires knowledge on the load composition, i.e., the percentage of load consumed by each type of load components. Measurement-based approaches leverage data from devices such as PMUs, smart meters, etc. A model structure is selected and its parameters are derived using computation techniques such as statistics, artificial intelligence, and pattern recognition. Component-based methods start from the individual components, while measurement-based ones start from the measurement data as illustrated in Fig. 8. The two methods are summarized in Table IV.

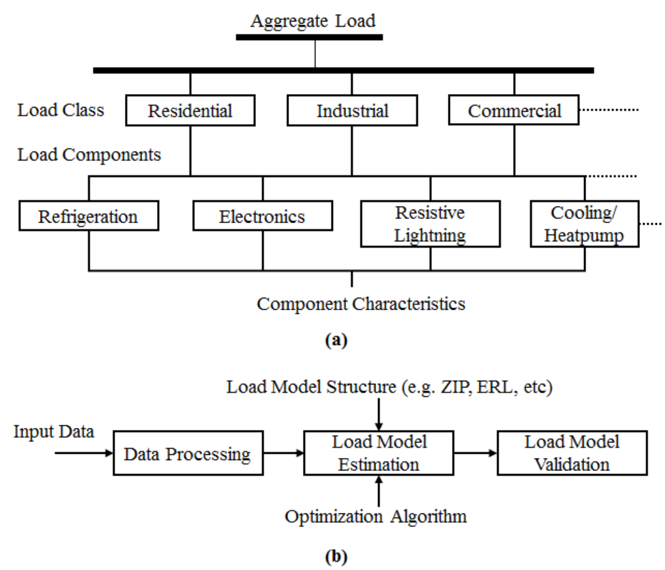

Fig. 8. (a) Component-based modeling approach, (b) Measurements-based method approach

A. Component-Based Approach

The component-based method is a bottom-up approach as illustrated in Fig. 8 (a). Load is commonly divided into industrial, commercial, and residential classes. The approach requires three datasets: 1) models of individual components, 2) component composition, i.e., the percentage of load consumed by each load component, and 3) class composition, i.e., the percentage contribution of each load class to the aggregate load. This approach has been used by WECC to develop their composite load models [6].

The individual load components can be represented using static or dynamic models. Resistive components such as electric cooking appliances and water heaters can be modelled as constant-impedance loads, while other loads such as SMPS are modeled as constant-power loads or the generic model in Fig. 3 [36]. The parameters for individual component models can be obtained through laboratory experiments [57]-[59].

TABLE IV
COMPARISON OF MEASUREMENT AND COMPONENT BASED APPROACHES

	Advantages	Disadvantages
Measurement-based	- Based on data from actual systems - Provide accurate models for measured locations and time - A generic method that can be applied to various models - No need to have deep knowledge of loads	- Unable to account for different operation conditions - Models are developed using data measured in certain periods at specific locations, which lacks generalizability - Measurements with large disturbances are hard to obtain
Component-based	- Field measurement is not required - Physical representation of end-use devices - Can be applied to different operation conditions - Demand side management is considered	- Requires characteristics of individual load components. - Accurate and comprehensive load composition information is hard to obtain - Low adaptability to the integration of new loads

Determining the load composition is the most challenging task as it is impossible to obtain detailed consumption information of all electrical components in a power system. In addition, load composition is affected by geographical locations and weather conditions. For example, Fig. 9 shows consumption profiles of different appliances in residential and commercial sectors during different seasons. Recently, the deployment of smart meters enables the two-way communication between customers and utilities, which provides a new and easy way to obtain accurate load compositions. To determine the load class composition, the metered demand at load buses can be used, which is typically available every 15 minutes.

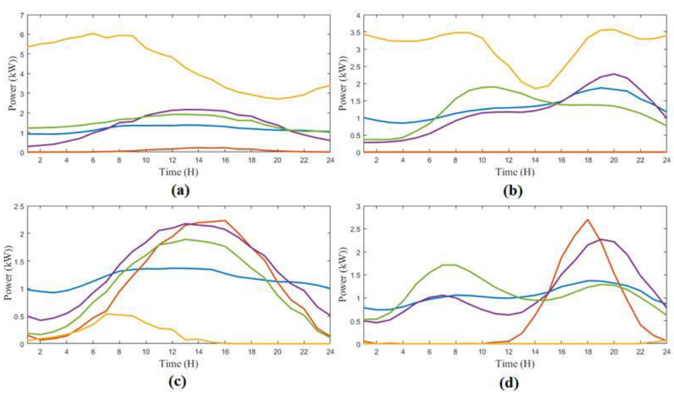

Fig. 9. Typical consumption profiles for (a) winter commercial class, (b) winter residential class, (c) summer commercial class, and (d) summer residential class

A different bottom-up approach was proposed in [101] for industrial facilities. Instead of obtaining the full load model of the system by using composition values of load classes, the paper proposed to create specific models for industrial loads, then obtain the system model using an aggregation algorithm developed in [102].

B. Measurement-Based Approach

Steps of the measurement-based approach are summarized in Fig. 8 (b): 1) obtain measurement data, 2) select a load model structure (e.g. ZIP, exponential, etc), 3) estimate model parameters, and 4) validate the load model. Measurement-based load modeling leverages actual field data to capture load characteristics. The measurements should be obtained under different conditions and disturbances. The model parameters are estimated by minimizing the difference between the response of the load model and the field measurements. The problem can be formulated as a curve fitting problem using the following equation:

$$\min \frac{1}{n} \sum_{i=1}^{n} [(P_i^m - P_i^e)^2 + (Q_i^m - Q_i^e)^2] \tag{17}$$

where P_i^m and Q_i^m are the measured active and reactive power, respectively, and P_i^e and Q_i^e are the modeled active and reactive power, respectively. The parameters are calculated using algorithms such as least-squares, genetic algorithm (GA), support vector machines (SVM), Kalman Filter (KF), Levenberg-Marquardt algorithm, and Simulated Annealing. Table V summarizes existing measurement-based techniques.

TABLE V
EXAMPLES OF MEASUREMENT-BASED TECHNIQUES

Ref.	Algorithms	Load Models	Data Sources
[17]	GA + Simplex search method	ZIP+IM	PMU: NE power grid in China
[20]	GA+LM	ZIP+IM	Simulation + Field measurements
[22]	Improved particle swarm optimization	Exponential + IM	Simulation + Laboratory experiments
[42]	LM	ERL	Simulation + Field measurements
[103]	Least Square	1st order IM model	Simulation
[104]	Gauss-Newton + Trajectory sensitivity	Differential-algebraic equations	Simulation
[105]	Instrumental Variable-based estimation	ZIP and Exponential and dynamic models	Simulation
[106]	Gradient-based parameter estimation	Fifth-order single rotor cage model	Laboratory experiments
[107]	Simulated Annealing	EPRI Loadsyn and IM	Simulation + Field measurements
[108]	Kalman Filter	ZIP	Korea Energy Management System
[109]	SVM	ZIP+IM	Simulation
[110]	Weighted recursive least squares	Exponential and ZIP	CPFL Energia, Brazil
[111]	Recursive least squares	Exponential	Field CVR test data

The measurement-based approach has been extensively studied in the literature. In [11], a multicurve identification technique was used to identify parameters of the ZIP+IM model. Multiple filed measurement datasets were collected and fitted to the model structure using a hybrid GA and simplex search algorithm. [21] presented an event-oriented method for online load modeling based on PMU data from the Illinois Institute of Technology MG. In [22], the authors used the sliding window technique to reflect the real-time dynamic behaviors of loads during disturbances such as voltage sags and interruptions. Least-square methods have been widely applied to identify parameters of various load models including ZIP+IM with frequency. The increasing installation of PMUs makes the online modeling an attractive approach. Reference [112] applied the unscented Kalman filter [113] to perform real-time estimation of the ERL model parameters. The developed approach was tested on both simulated and field measurements with a 6-second resolution. In [111], a time-varying exponential load model was used to represent the load, and a recursive least square algorithm was employed to identify the load model parameters. The paper used the load model to assess conservation voltage reduction (CVR) effects [114]. The authors in [115] used robust least squares approach to estimate time-varying parameters of a ZIP model at the substation level. The proposed method was used to identify the load-to-voltage dependence and analyze CVR.

There are studies using hybrid component- and measurement-based methods. [116] developed load models at high-voltage buses from load compositions of LV buses. SVM was used to classify the loads into various classes based on the load responses to large disturbances. The authors in [117] proposed a variable projection based optimization algorithm to identify the parameters of several different load models. For small disturbances, only the load component composition in each load class was identified, and the remaining parameters remained unchanged. The proposed method was tested on the 246-bus Indian Northern Regional Power Grid system. Reference [118] developed an approach to aggregate various load component models to obtain the system load model. Parameter estimation was used to determine the amount each component contributes to the total power consumption. A Gauss-Newton method based on trajectory sensitivities was used to determine the parameters of each load model structure. Trajectory sensitivities can quantify effects of small parameter changes on a dynamic system's trajectory, which can guide the parameter updates.

The authors in [14] used trajectory sensitivity for model simplification to reduce the number of parameters to be estimated. By applying the trajectory sensitivity analysis to measurement data, load model parameters were classified into two sets based on their sensitivities to the active and reactive power. Parameters with large sensitivities were grouped together and estimated using the measurement-based approach, while less sensitive parameters were set to be their default values. The parameters with low sensitivities are not necessarily unimportant, it means these parameters are hard to be identified from the current data. Reducing the number of parameters makes it possible to include more components in the load model. [23] presented an algorithm for estimating load model parameters based on the analytical similarity of model parameter sensitivities, and demonstrated its computational efficiency and accuracy. The authors in [119] analyzed model parameter sensitivities using eigenvalues of Hessian matrix. The paper used the LM algorithm to solve the optimization problem. The linear dependence between two load model parameters were then identified by examining the condition number of Jacobian matrix. This dependency analysis was used to ensure that low-sensitivity parameters were independent of high-sensitivity ones. Reference [120] presented a computationally efficient technique for estimating the composite load model (ZIP+IM) parameters based on analytical similarity of parameter sensitivity. The paper used the partial derivative of each parameter to identify parameters with similar sensitivities. LM algorithm was used to solve the optimization problem in (17). The presented technique was tested on real measurements collected from Cheongju and Suwon of South Korea. The computation time was reduced by three quarters after reducing the number of parameters from 12 to 9.

V. Conclusion & Future work

This paper reviews the state-of-the-art of load models and parameter identification methods. New approaches for modeling LV networks and ADNs are also discussed. Load modeling is challenging due to the large number of diverse load components, the lack of precise load composition information, and the stochastic, time-varying and weather-dependent load behaviors. Currently, the ZIP+IM composite model is one of the most widely used models in US power industry [34]. WECC and EPRI have been actively investigating load modeling techniques. WECC focused on the component-based approach while EPRI is developing hybrid approaches that integrate component- and measurement-based methods. The WECC composite load model is comprehensive and flexible, however, it is complicated and hard to apply. There are also concerns about the numerical stability and consistency of the WECC model. ZIP+IM is less complicated, but it is unable to capture the full system characteristics. Furthermore, ZIP+IM cannot represent DGs' behaviors. CIGRE provided several overviews and recommendations on load modeling which were combined in [35].

Although load modeling has been extensively studied, more research is imperative to update existing load models and understand characteristics of modern loads with emerging technologies. The future research directions are suggested in terms of modeling and identification technologies:

For load model structure development, more sophisticated models that balance flexibility and complexity are needed. Load consumption is time varying due to human behaviors and weather conditions; thus, different load models may be found in different time periods. Conventional load modeling methods using measurement data in a certain period may not be able to capture time-varying load behaviors, and lack generalizability. More research is needed to develop advanced algorithms to perform online load modeling using the real-time data. After developing new load models, they should be integrated in power system analysis programs. How to model and represent seasonal and geographical variations in load models and load composition is also an ongoing research topic. Capturing the time-varying nature of load behaviors is useful to voltage control, state estimation, and energy management [121]-[123].

The increasing penetration of DGs and the implementation of demand-side management poses additional challenges to load modeling. WECC identified DGs as one of the main priorities in their further efforts to update CLM. DGs and power electronic loads may have complex control systems, which need to be taken into account in the model development. Customer behavior-driven and DR-enabled load models need to be built to facilitate DR studies. Distribution system models were not well studied in the past. There is a need to develop novel models with reduced complexity and computational requirements to represent ADNs and MGs. Modeling and aggregating DGs, controllable loads, and other technologies in ADNs and MGs is a major research topic. New loads such as electric vehicles and storage devices should be modeled to accurately represent the system. Moreover, modeling the interface and control logics of power electronics and testing their impact on stability and dynamic studies is an important research topic.

For parameter identification, measurement-based techniques are prevalent as new devices such as PMUs and smart meters are installed. However, it is still challenging to identify a large number of unknown parameters. Sensitivity analysis has been proposed to reduce the number of parameters and identify the significant ones. Extreme sensitivities could lead to the failure of the load model with small changes in operating conditions. Further research on sensitivity analysis is needed. The deployment of smart measurement devices provides an opportunity to design hybrid approaches that integrate the measurement- and component-based methods. The introduction of new loads and controls will reshape the load composition. The deployment of smart meters provides an opportunity to improve the load composition estimation for component-based load modeling [124]. The amount of data collected from the measurement devices is massive, and processing a large number of data is challenging. Data collection and processing techniques such as data mining and clustering should be improved. Future research on parameter estimation algorithms should be able to process data from existing and emerging measurement devices with different resolutions, such as smart meters, PMUs, and SCADA. Meanwhile, the algorithms should be robust to bad data, missing measurements, changes in the voltage regulation scheme, and noises [125]-[127].

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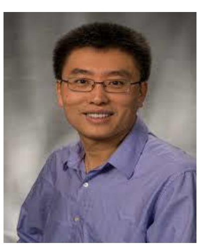

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