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Data-driven modeling of power system dynamics: Challenges, state of the art, and future work

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ABSTRACT

With the continual deployment of power-electronics-interfaced renewable energy resources, increasing privacy concerns due to deregulation of electricity markets, and the diversification of demand-side activities, traditional knowledge-based power system dynamic modeling methods are faced with unprecedented challenges. Data-driven modeling has been increasingly studied in recent years because of its lesser need for prior knowledge, higher capability of handling large-scale systems, and better adaptability to variations of system operating conditions. This paper discusses about the motivations and the generalized process of data-driven modeling, and provides a comprehensive overview of various state-of-the-art techniques and applications. It also comparatively presents the advantages and disadvantages of these methods and provides insight into outstanding challenges and possible research directions for the future.

KEYWORDS

Data-driven modeling, machine learning, model construction, parameter identification, power system dynamics, system identification.

Accurate modeling is an essential prerequisite for simulation, analysis, control, and protection of power systems[1, 2]. The time scale of power system phenomena vary widely from microseconds to days. Among them, electromagnetic transients and electromechanical transients are the relatively fast phenomena of system-level (instead of component-level) interest, and are thus often referred to as power system dynamics. With accurately described dynamic characteristics, system operators can effectively perform a variety of planning and operation tasks towards the goals of reliability, efficiency, resiliency, and sustainability. On the contrary, the absence of proper models may lead to disastrous consequences as has been demonstrated by historical blackout events. For example, after the 1996 Western Electricity Coordinating Council (WECC) blackout, the analysis using the WECC's standard dynamics database failed to produce results consistent with fault dynamics[3], which implies that prior to the blackout, the operator did not have the basis to perform effective security assessment and make proper decisions accordingly. The increasing penetration of renewable energy sources also calls for higher requirements for modeling accuracy. After the 2016 South Australia blackout, the Australian Energy Market Operator (AEMO) discovered that the software settings in some wind farms prevented repeated restarts once frequency or voltage events occurred too often. These wind farms tripped unexpectedly during the incident, causing a shortage of power supply in the South Australian power grid and ultimately leading to the occurrence of the blackout[4]. However, the scale of modern power systems is so large that accurate modeling of every component at system-level analyses would lead to a computational disaster. A careful trade-off must be made between accuracy and computational efficiency.

A natural way to model the dynamic behavior of power system components is the use of physical laws. From first principles such as circuit laws and motion laws, mathematical relationships between physical variables can be derived. For example, a complete mathematical model of a cable segment can be derived based on physical information such as material, geometry, and length[5]. In addition to theoretical derivation by physical laws, dedicated offline experiments can be performed to determine the parameters of a model, for example, the classical locked-rotor test and no-load test can be used to identify the parameters of motors[6]. Modeling approaches described above, where everything from the model structure to the model parameters is derived based on the physical laws or obtained through dedicated experiments before the object put into service, can be referred to as knowledge-based modeling (KBM) approaches, as they exclusively rely on knowledge acquired prior to the operation of the component or system. KBM approaches have been widely used in power systems. Another example is transmission grid equivalence methods such as coherence[7] and synchrony[8]. However, with the continual evolution of power systems, especially the rapid growth of the power electronics for renewable energy integration, the dynamics of power systems have changed dramatically and traditional KBM approaches are faced with two major challenges. First, it has become increasingly difficult to construct appropriate models that exhaustively reflects the physics of power system components, as much of the required prior knowledge is difficult to obtain. The dynamics of Inverter Based Resources (IBRs) are complex due to their low inertia and high dependence on their control algorithms[9, 10]. Different manufacturers of IBRs adopt different control strategies and are reluctant to disclose their control models. Second, as renewable energy generation is widely distributed, the number of parameters of KBM models regarding individual components becomes astronomical.

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Meanwhile, the impact of these parameters becomes less significant as the sizes of the generation devices becomes smaller. It is intractable to attain and utilize such a high-dimensional exhaustive KBM model to describe and simulate system behaviors.

To tackle these challenges, data-driven modeling (DDM) has become a sensible option. DDM refers to approaches relying on the measurement data generated from the actual operation of power systems after the object to be modeled is put into service. The advantages of DMM are three folds. (1) Unlike KBM, DDM does not require complete prior knowledge about the object to be modeled, which makes it highly applicable to both gray-box and black-box components or subsystems. (2) DDM approaches allow the optimal determination of model structures via data, which has the potential of reducing model complexity without losing dominating characteristics. (3) DDM approaches allow the determination of model parameters without offline experiments, hence potentially saving human effort, reducing equipment downtimes, and allowing online adjustment as system operating conditions change. Despite the major advantages described above, successful DDM typically requires a large amount of dynamic data, which is highly challenging in traditional power systems. In recent years, with the proliferation of advanced measurement devices such as phasor measurement units (PMUs), merging units (MUs), digital disturbance recorders (DDRs), and smart inverters (SIs), the obstacle of data availability is being cleared for the development and implementation of DDM. The applications of DDM has been witnessed in various fields such as wind farm modeling[11], photovoltaic (PV) plant modeling[12], transmission grid equivalence[13], distribution grid equivalence[14], load modeling[15], etc.

To discuss the objectives of DDM, power system dynamics can be characterized by the following set of equations:

$$\begin{cases} \dfrac{\mathrm{d}(\boldsymbol{x})}{\mathrm{d}t} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}) + \boldsymbol{w}, \\ \boldsymbol{y} = \boldsymbol{h}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}) + \boldsymbol{v}, \end{cases} \tag{1}$$

where $\boldsymbol{x}$ denotes the states; $\boldsymbol{u}$ denotes the inputs; $\boldsymbol{y}$ denotes the outputs; $\boldsymbol{\theta}$ denotes system parameters; $\boldsymbol{f}$ denotes the state transfer function; $\boldsymbol{h}$ denotes the output function; $\boldsymbol{w}$ and $\boldsymbol{v}$ denote the process noise and output noise, respectively. The objectives of DDM of power systems is to determine model structures $\boldsymbol{f}$ and $\boldsymbol{h}$ and to obtain their parameters $\boldsymbol{\theta}$, such that the output of the model is as close as possible to the output $\boldsymbol{y}$ measured from the actual system with the same input $\boldsymbol{u}$. Therefore, model construction and parameter identification are the essential steps for dynamic model equivalence. At the same time, as DDM many use massive and corrupted measurement data, data pre-processing may also be performed to assist model construction and parameter identification.

As discussed in the previous section, the area of power system modeling has been constantly evolving. There are already some literature surveys on the modeling of various components, such as wind farm modeling[11], load modeling[16], or the modeling of an entire power grid[17]. There are also review articles that discuss the modeling within long time scales, such as load forecasting[18], which are not within the scope of power system dynamics. In all these surveys, DDM is mentioned as one of the modeling approaches without in-depth coverage. Furthermore, as these papers only review DDM approaches for specific types of components, they provide limited insight into the generic methodologies that apply to various types of components. A general overview of DDM with a systematic summary and comparison across different components and methodologies is still missing. Considering the continual growth of renewable energy, the increasing complexity of power system dynamics, and the recent advancement of data analytics and machine learning, DDM is bound to play an increasingly important role in the near future. Therefore, a comprehensive survey of DDM of power systems is considered imperative to portray the state of the art of this research area and to provide insight into the challenges to be further addressed. This is exactly the objective of this paper. The attention of this paper will be paid to the three main steps of DDM, data-preprocessing, model construction, and parameter identification. It should be noted that for parameter identification, this paper only reviews the techniques that are part of holistic modeling approaches; pure online parameter identification techniques without model construction effort, especially those for electric machines, will not be reviewed in this paper. This is due to the fact that the online parameter identification of electric machines has been a relatively mature area[19–21]; online parameter identification of electric machines is closer to KBM methods with an add-on parameter identification function, as the model structures of electric machines are rigorously derived from and supported by physical laws.

The rest of the paper is organized as follows. Section 1 briefly introduces data pre-processing techniques for DDM. Section 2 presents various model structure methods according to the objects to be modeled and the essence of the methods, and also describes the conceptual relations between different methods. Section 3 describes various parameter identification methods following the determination of model structures, including the problem formulations, solution techniques, and several special issues to be addressed. Section 4 concludes the paper with discussions on the limitations of the existing approaches and exploration of possible future research directions.

1 Data pre-processing

DDM uses the measurements generated during system operation for model construction and parameter identification. The measurements are likely to contain noise and bad data arising from sensor imperfection and failures, communication delays and packet losses, etc. The direct use of raw data may reduce the accuracy of DMM[21, 22]. In addition, the massive volume and high dimensionality of raw data may present difficulty for direct information extraction[23]. Therefore, data pre-processing is sometimes performed for denoising, bad data removal, and dimensionality reduction, producing refined datasets that can be directly used for model construction and parameter identification.

In recent years, data preprocessing for DDM has received more attention than ever before. One reason is that earlier research is more limited to theoretical developments and typically uses simulated data for validation of the methods, ignoring the data quality problems that exist in the real world. Another reason is that some parameter identification methods themselves have certain denoising effects. However, as DDM continues to evolve from theoretical research to practical applications, data pre-processing is bound to receive more attention. This trend is confirmed by increasing adoption of a data pre-processing stage in recent DDM methods.

1.1 Denoising and bad data detection

Denoising techniques and bad data processing are not exclusive to DDM. Some widely used filters can also be adopted for data pre-processing. However, for the case of DMM, it is important to note that the dynamic processes that require attention cannot be filtered out as noise during the filtering process. Ref. [21] compares the advantages and disadvantages of three filters, the moving average (MA) filter, the Savitzky–Gorey (SG) filter, and the butterworth (BW) filter, in the presence of different noises, and also constructs three metrics to measure the performance of the filters, namely efficiency in noise removal, preservation of the dynamic features of the original signal, and the quality at the terminal points (start and end of the disturbance). The SG filter is ranked first in terms of dynamic feature preservation and the quality at terminal points, and is ranked second after the MA filter in the efficiency in noise removal, and thus it is overall recommended to use the SG filter for data pre-processing.

In addition to the aforementioned techniques, Ref. [22] uses a Hampel filter (HF) in addition to the SG filter for noise reduction to improve the accuracy of parameter identification. Ref. [24] uses Hampel filter for bad data detection, including missing data detection and outlier location detection, while for denoising, wavelet denoising technique is used. In addition to the above filters, Ref. [25] adopts a prior automatic filtering by means of Gaussian processes modeling.

As denoising and bad data processing are not unique to DDM, it is expected that more types of filters will be applied to DDM in the future. The three metrics proposed in Ref. [21] provide a good set of criteria for the selection of filtering techniques for DDM.

1.2 Feature extraction and dimensionality reduction

Another purpose of data pre-processing is to extract features and reduce the dimensionality of data to facilitate the following model construction or parameter identification procedures. In this regard, the Prony's method, which combines data pre-processing with model construction, is a widely used approach for feature extraction. For example, Refs. [26] and [27] use Prony's method for dynamic equivalence of distribution networks. The main components of the system dynamics are obtained directly, and the model construction is completed while filtering the harmonics not of interest. Singular value decomposition (SVD) is a popular method for matrix rank reduction too. This technique has been employed in eigensystem realization algorithms (ERA), matrix pencils (MP), and dynamic mode decomposition (DMD). Ref. [28] presents a tutorial of ERA, MP, and the Prony's method. Particularly, the Prony's method was refined with SVD-based rank reduction and achieves better eigenvalue identification capability.

The other category of methods is clustering methods that reduce the dimensionality of data. For example, Refs. [24] and [29] utilize the k-means++ clustering algorithm and fuzzy cluster analysis to cluster data from the distribution network. For each cluster with similar properties, an equivalent model is generated to represent it. This reduces the number of equivalent models and data dimensions without compromising their accuracy. For the equivalent modeling of the transmission network, a coherence analysis method is also used due to the presence of numerous synchronous motors[30, 31]. This method identifies a category of data with similar properties and generates an equivalent model for it. The aforementioned methods can effectively reduce the dimensionality of the data, facilitating the construction of efficient models in subsequent steps.

Since the methods for feature extraction and dimensionality reduction are closely related to the subsequent model construction and parameter identification steps, more details will be introduced in Sections 2 and 3.

2 Model construction

In this section, we will explore one of the two core steps in DDM, i.e., model construction. Since the topic of this paper is DDM, purely KBM without using any data collected after the component of subsystem is put into operation will not be explored. The model construction methods of DDM can be divided into three categories according to the degree of reliance on prior physical knowledge. The first category, called *physics-inspired model construction*, are methods that are not rigorously supported by physics but reflect insights into physical characteristics of certain types of components. A prominent physics-inspired model is the typical ZIP model of loads, which characterize the aggregate effect of loads by three components in parallel: constant impedance load, constant current load, and constant power load[32]. This is clearly inspired by certain known types of loads, such as electric heaters without automatic control (constant impedance), battery chargers (constant current), and electronic devices (constant power). While there is usually no evidence that an actual load block to be modeled only consists of these three ideal types loads, they can fit the behaviors of most aggregated loads relatively well. Note that physics-inspired model construction is different from KBM, as KBM delivers models that are clearly and rigorously supported by physics (e.g., the swing equations of an individual SG following the laws of motion), whereas physics-inspired modeling are essentially "fitting functions" with structures inspired by physical phenomena (e.g., aggregated load characteristics heuristically broken down to constant impedance, constant current, and constant power components). Another category of approaches, which does not require any prior knowledge at all, is referred to as *purely data-driven model construction*. A prominent example is the neural-network-based model construction approach[33]. This approach requires almost no prior knowledge of the modeled objects and uses a unified architecture to model different objects. The last category of methods, which combine the characteristics of physics-inspired model construction methods and purely data-driven model construction methods, can be referred to as *data-assisted physics-inspired model construction* or *hybrid model construction*, which integrates some prior knowledge of the object with certain purely data-driven methods via multiple stages or parallel blocks[24].

The rest of the section is organized as follows. We classify the common objects to be modeled into four categories, load, renewable energy, transmission grid, and distribution grid, as shown in Figure 1. The model construction approaches for each category of objects are described in one subsection. For each category of objects (in each subsection), the existing model construction approaches are then presented separately based on the categorization introduced above (physics-inspired, purely-data-driven, and data-assisted physics-inspired, i.e., hybrid). The relationships between the categories of methods, and between the categories of objects that each category of methods can be used to model, are shown in Figure 2.

2.1 Load modeling

Load is an essential component of any power system. There are many well-established load modeling approaches. For example, the two commonly used static load models, ZIP model[32] and exponential load (EL) model[34], have simple structures with few parameters to be identified, and have been widely used and tested in practice. Ref. [32] uses ZIP model to characterize real-world household loads in New York. The EL model considers that the active and reactive power consumption are exponentially related to the voltage. Ref. [34] uses the EL model to equivalence different

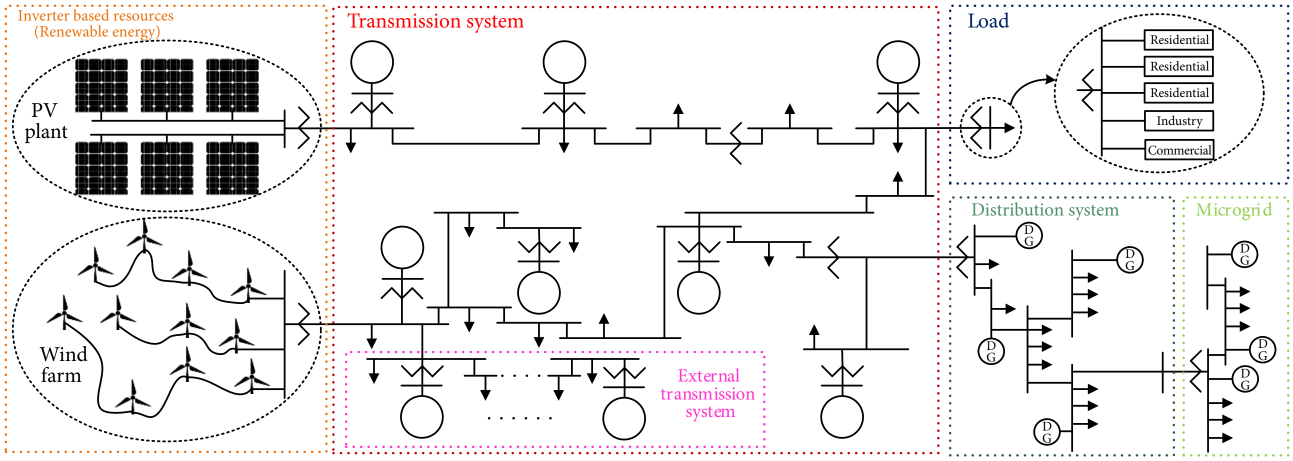

Fig. 1 Composition of power systems and objects to be modeled.

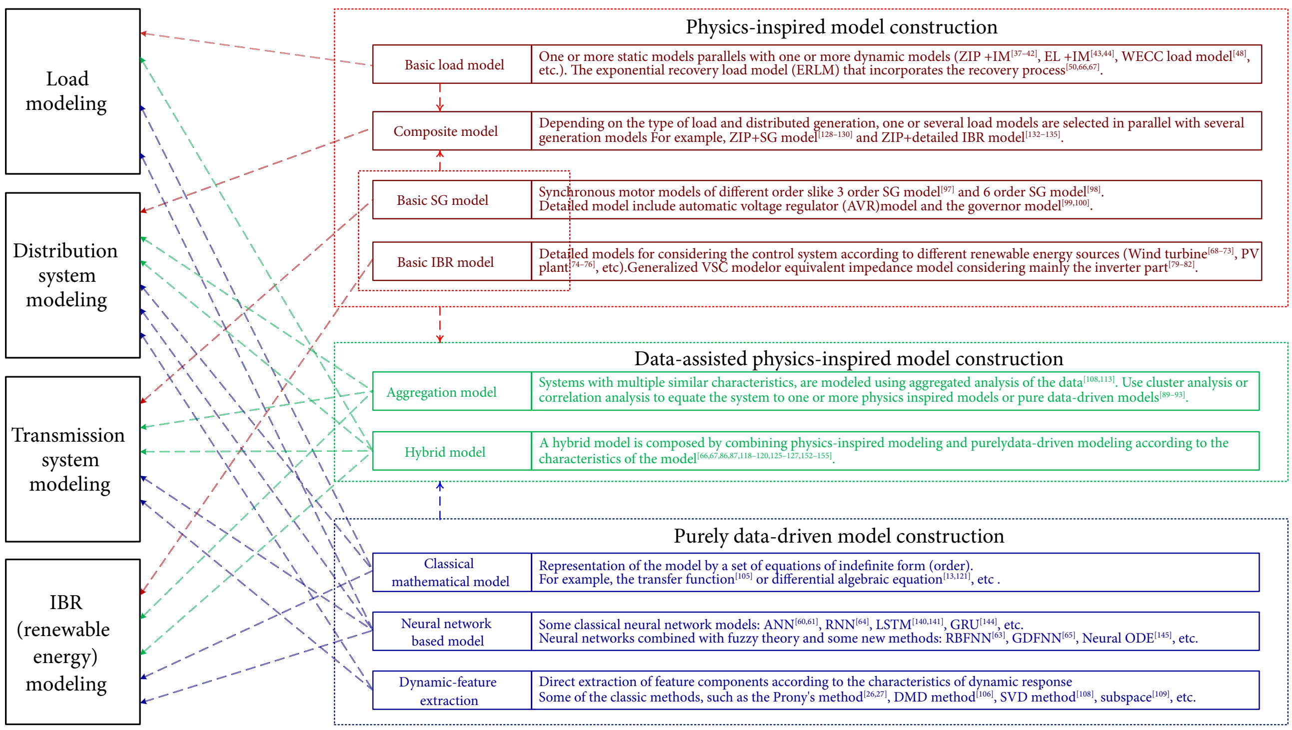

Fig. 2 Model construction: objects and approaches.

loads under substations and finds that the model obtained good performance for commercial loads, industrial loads, and residential loads. Ref. [35] treats the parameters of the ZIP model and EL model as time-varying parameters and fits the load by online parameter identification.

However, with the deepening of electrification, the diversity of loads is also growing. Static load models cannot accurately describe the dynamic processes associated with loads, hence dynamic load models should be constructed.

2.1.1 Physics-inspired model construction

A summary of commonly used dynamic load models is presented in Figure 3. Traditionally, it is considered that the dynamics of loads mainly occur from motor-type loads. Therefore, a common load model structure is a traditional ZIP or EL model in parallel with an IM (induction motor) model, as illustrated in Figures 3(a) and 3(b). The model better integrates residential loads with industrial loads and is therefore used in many applications. Ref. [36] uses the ZIP + IM modeling approach to equivalence loads, but its parameters are calculated using a component-based approach based on offline data, which is refined later with online data. Refs. [37–42] use ZIP + IM model and measurement data for parameter identification. Refs. [43] utilizes the EL + IM model and explore an improved parameter identification method, which not only maintains accuracy but also enhances the convergence speed of the algorithm. Ref. [29] uses the ZIP + IM model for equivalence and fuzzy cluster analysis to find the best substation data that characterizes the load information. The adaptability of the model is enhanced by considering the rotor impedance in the IM model as a time-varying parameter. Ref. [44] compares the ZIP + IM model, EL + IM model, and Z + IM model and finds that the ZIP + IM model has the optimal adaptation capability in most cases. Ref. [45] uses the static component model, random component model and EL model to characterize loads under a substation and finds that different models are suitable for different types of users. For example, the static model is more suitable for shopping

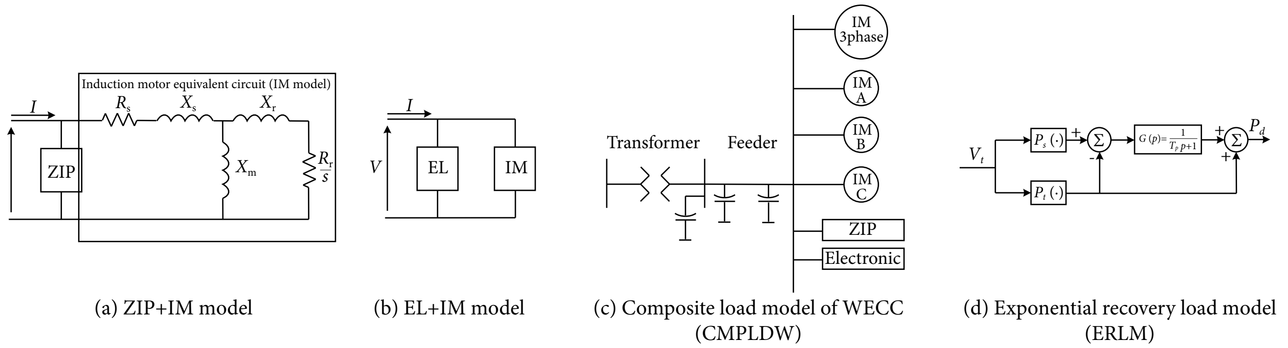

Fig. 3 Basic load models.

malls. WECC[46] and North American Electric Reliability Corporation (NERC)[47] models the increasing number of power electronics devices by a piecewise function related to bus voltage, which is referred to as the electronic model. On this basis, Ref. [22] modeled the loads using the ZIP + electronic model.

A more comprehensive composite model than the ZIP/EL + IM model is the standard dynamic load model proposed by WECC[48]. Ref. [48] presents the composite load model of WECC (CMPLDW), and the authors discuss the reason for choosing this model as well as its effectiveness. CMPLDW contains a substation transformer model, a feeder model, and six parallel equivalent loads shown in Figure 3(c). The six equivalent loads are a three-phase IM, three single-phase IMs connected to the three phases respectively, a ZIP load, and an electronic load. The increased complexity of the model brings about greater expressiveness but requires a large number of parameters to be fitted. Ref. [49] discusses the parameter identification technique when using CMPLDW for load equivalence.

In contrast to the idea of obtaining an equivalent model by connecting different types of load components in parallel, it has been found that there is a recovery process for the load when the voltage surge is over, so an exponential recovery load model (ERLM) or the general load model shown in Figure 3(d) is proposed based on this characteristic[50]. The expression of ERLM is shown in Eq. (2).

$$\begin{cases} P_{\mathrm{s}} = P_0\left(\dfrac{V_{\mathrm{t}}}{V_{\mathrm{t0}}}\right)^{\eta_{\mathrm{s}}}, P_{\mathrm{t}} = P_0\left(\dfrac{V_{\mathrm{t}}}{V_{\mathrm{t0}}}\right)^{\eta_{\mathrm{t}}}, \\ T_{\mathrm{p}}\dfrac{\mathrm{d}P_{\mathrm{r}}}{\mathrm{d}t} + P_{\mathrm{r}} = P_{\mathrm{s}} - P_{\mathrm{t}}, P_{\mathrm{d}} = P_{\mathrm{r}} + P_{\mathrm{t}}. \end{cases} \tag{2}$$

where P_{d} represents the total power response, P_{s} and P_{r}, respectively, denote the static power response and power recovery, P_{t} stands for the transient power response, T_{p} is the load recovery time constant, V_{t0} and V_0 represent the relevant values before voltage changes, and η_{s} and η_{t} represent the static and dynamic load-voltage dependence coefficients.

The ERLM introduces a first-order inertial filter to characterize the load recovery process with greater expressiveness than the EL for more complex nonlinear dynamics[51–56]. Ref. [15] linearizes the ERLM and compares the advantages and disadvantages of the original model with the linearized model. The linearized model is more concise but less accurate than the original model, and the desired model can be selected according to the requirement of accuracy.

The above four models and some variants (e.g., Z+IM model) constitute basic types of physics-inspired load models, which have received a lot of research over the years. The ZIP + IM model and the EL + IM model have simple structures with very few parameters, but at the cost of limited expressiveness. As the loads become more diverse, the dynamics of loads cannot be fully attributed to motors. CMPLDW covers almost all the major dynamic load types and has the potential to characterize complex load dynamics, but its own complex structure makes the parameter identification very challenging. ERLM has a strong expressive power and can be combined with transfer function methods to obtain stronger performance in characterizing dynamics. Overall, the determination of model structures is largely based on user's experience, and there is a need to develop additional data analytics to assist the selection of model structures with a good tradeoff between accuracy and complexity.

2.1.2 Purely data-driven model construction

Load model construction can also be achieved without reliance on prior knowledge of the dynamic properties of loads. This is referred to as purely data-driven methods.

A typical approach is to describe the dynamic properties of the loads through a generally selected mathematical expression. For example, Ref. [57] uses a quadratic equation for load modeling. Refs. [58] and [59] adopt a second-order transfer function to characterize the load characteristics. However, the manually selected fixed model structure limit its capability of equivalence.

Another commonly used class of purely data-driven model construction approach is neural networks. Refs. [60] and [61] use artificial neural network (ANN) to equivalence conventional loads. They take the voltage at the current time as well as the voltage and power at past times as input and the power at the current time as output. Ref. [62] utilizes a similar approach to equivalence third-order motor loads. With the development of neural network technology, Ref. [63] applies radial basis function neural network (RBFNN) and the lookup table (LUT) method to equivalence the electric arc furnace loads. The method used in this paper is not a naive ANN, but is closer to the principle of an autoencoder, where dynamics are characterized by feeding multiple sets of data to obtain a set of many-to-many mapping relations. Ref. [64] uses a recurrent neural network (RNN) to equivalence composite loads including nonlinear dynamic loads such as electronic loads, and is validated using simulated data. Ref. [65] puts forward a generalized dynamic fuzzy neural network (GD-FNN) model to describe dynamic load characteristics.

Neural network models have stronger generalizability and expressiveness than physics-inspired models, but there is no universal method for selecting neural network models, and the selection of network layers and activation functions depends on experience. In addition, the lack of physical insight results in a larger number of parameters to optimize, which in turn requires a larger amount of data for parameter identification.

2.1.3 Data-assisted physics-inspired model construction

As mentioned earlier, the ERLM characterizes the recovery process of loads after a perturbation by means of a first-order low-pass block. By replacing this first-order transfer function with a higher-order transfer function, the ERLM could become even more expressive. Ref. [24] uses this improved ERLM for fitting more complex dynamics by identifying the parameters of the transfer function. Ref. [66] superimposes a damped oscillation component on the existing ERLM. An oscillatory component load (OCL) model is constructed with increased complexity than the ERLM model. These types of methods can be viewed as data-assisted physics-inspired (hybrid) methods, as they still rely on the insight into the load recovery phenomenon, but allows a general formulation of the transfer function that does not have clear physical meanings and has to be identified by measurement data.

Considering the limited capability of transfer functions of a fixed order, the load dynamics can be better expressed by determining the order of the transfer function through measurements. Ref. [67] adjust the order of the transfer function via a vector fitting technique in an improved ERLM. The best order is first obtained by each loop fitting and then the system model is determined. Due to the fact that this method can fit different dynamics by changing the model order, it has strong versatility and has become one of the popular methods in recent years.

As load modeling and distribution grid modeling have overlaps in certain domains, to facilitate the distinction, only load models that do not produce significant bidirectional power flows, i.e., without distributed energy resources (DERs), are described in this section. The model construction approaches that incorporate DERs will be described in Section 2.4.

2.2 Inverter-based resource (IBR) modeling

Renewable energy sources, such as hydro, wind, geothermalenergy, tidal energy, and photovoltaic, have experienced significant growth in recent years due to the increasing demand for carbon emission reduction. At the same time, energy storage technologies such as electrochemical energy storage, pumped storage hydropower, and compressed air energy storage have also made significant advancements in frequency regulation. These energy storage technologies are utilized to compensate for the intermittent nature of renewable energy sources. Among them, the IBRs like wind and solar generation, due to the dynamic differences between power electronic devices and traditional synchronous generators (SG), is rapidly changing the dynamics of power systems.

This section will focus on the model construction approaches for power-electronics-interfaced renewable energy sources from the grid perspective, as is shown in Figure 1. Note that the focus of the section will be on model construction for a single renewable energy source or a large centralized renewable power plant. The aggregated modeling of a mix of numerous distributed generations and loads will be discussed in Section 2.4.

2.2.1 *Physics-inspired model construction*

Similar to the idea of equivalencing loads in aggregate, a renewable power plant with a large number of inverter-based resources (IBRs) can be represented by a single detailed IBR model. Ref. [68] equivalence wind farms with fixed-speed wind turbines (FSWT) to IM models and performs online parameter identification. Ref. [69] equivalences a wind farm with doubly-fed induction generators (DFIG) to an aggregated wind turbine model. Such aggregated model representation has been adopted in Refs. [70] and [71] for type-3 wind farm subsynchronous resonance (SSR) investigation. In addition to the power electronic loads mentioned earlier, WECC has also developed a standard DFIG model including the control system for equivalencing DFIG wind farms in Ref. [72]. Ref. [73] equivalences a permanent magnet synchronous generator (PMSG) wind farm to an aggregated PMSG. After wind farms are equivalenced to a single turbine, it is connected to the grid behind an impedance. A similar approach can be used for solar photovotaic (PV) systems. For example, Ref. [74] equivalences a solar PV farm in a distribution grid to a single-inverter PV system connected to the grid. Refs. [75] and [76] provide further simplified models for type-4 wind farms and solar PVs farms by considering only the grid-connected converter controls while ignoring or simplifying dc-side dynamics. A data-driven approach has been used for dc-side dynamics simplification in Ref. [76] .

Ref. [77] equivalences high-voltage direct current transmission systems (HVDC) and proposes a reinforcement learning method for parameter identification.

Another common type of methods are the impedance or admittance models in the *dq* frame[78]. Impedance models of IBRs are useful for existing analysis tools such as small-signal analysis[79]. Ref. [79] describes two type of stability analysis methods based on *dq* admittance. With the entire system viewed as a network of admittance components, the relationship between the current injection and the nodal voltage may be expressed by the network admittance. Furthermore, the circuit problem may be converted to a feedback system. The first type of stability analysis is based on the loop gain of the open-loop system. Frequency domain analysis based on Bode plots or Nyquist diagrams can lead to stability prediction. The second method is based on the closed-loop system. The eigenvalues of the system can be found and frequency-domain modal analysis may be followed up to identify the influencing components of a certain mode[80].

An excellent feature of impedance or admittance is that they can be obtained through setting up a measurement testbed, conducting experiments (e.g., frequency scan), and postprocessing the data collected, as shown in Ref. [81], or by use of online transient response data[82].

The decentralization and diversity of control modes in IBRs, as well as the privacy of control systems information from manufacturers, increase the difficulty of model construction. They will remain to be outstanding challenges for research in the near future.

2.2.2 *Purely data-driven model construction*

General mathematical modeling approaches that do not require physical insight, such as transfer functions or state transition equations, are also applicable to renewable energy sources. Ref. [83] takes PV inverters compliant with the IEEE 1547-2018 standard[84] as objects to be modeled, and uses the SysId system (integrated in MATLAB) to perform linear fitting and obtain its approximate state transition equations. Ref. [85] uses the trajectory segment linearization method to downscale and equivalence wind farm dynamics under large disturbances.

Neural-network-based model construction for renewable power plants has also been discussed in literature. Ref. [86] uses ANN to model the wake effects of wind farms. Ref. [87] first converts the continuous DFIG model into a discrete model and obtains the traditional linear ARMAX model, then constructs an equivalent dynamic model of DFIG using neuro-fuzzy networks by considering the data uncertainty on the radial basis function-based neural network model. Ref. [25] utilizes ANN to fit the power curve of a wind turbine.

2.2.3 *Data-assisted physics-inspired model construction*

Data-assisted physics-inspired model construction, or hybrid

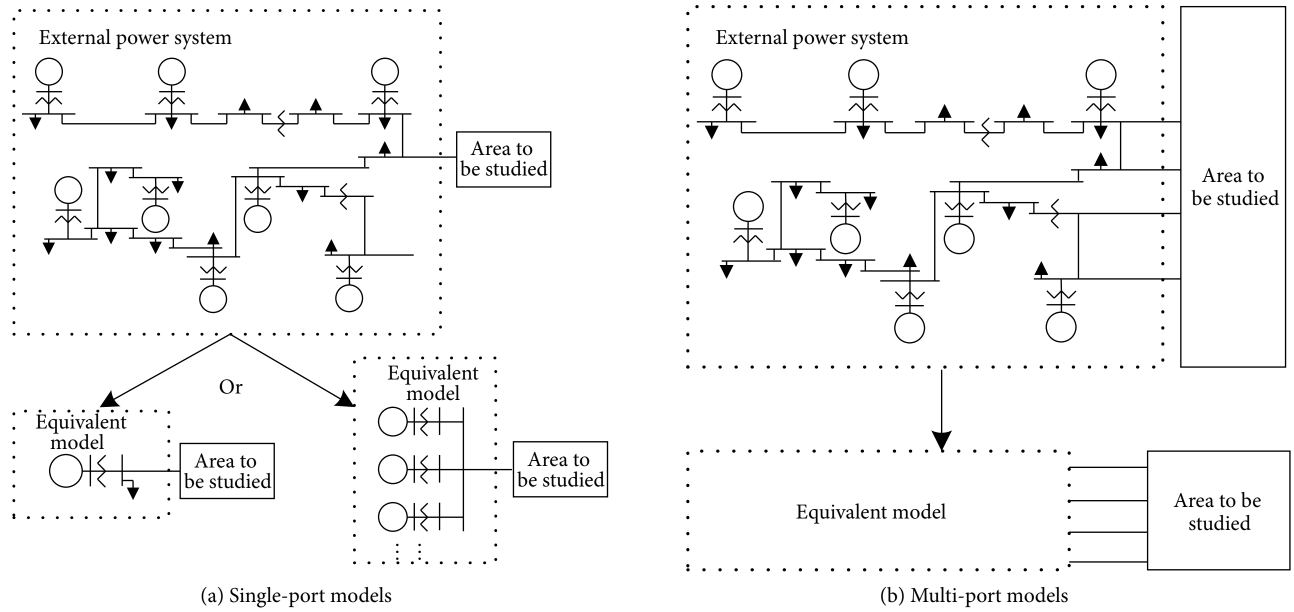

Fig. 4 Two types of transmission grid modeling problems.

model construction, which combines purely data-driven approaches with physics-inspired approaches, either through multiple sequential stages or parallel blocks, have been extensively investigated in order to achieve both accuracy and computational efficiency.

For example, for large clusters of renewable energy generation, such as large wind farms and solar PV plants, the physical-inspired equivalant model of a single IBR may not be accurate enough due to the diverse weather conditions, control logics, and topological locations of different IBRs in the cluster. Therefore, data-driven clustering algorithms are used to develop equivalence with multiple physics-inspired IBR models representing a set of IBRs under different operating conditions. Ref. [88] pilots the use of physics-informed machine learning to enable AI-based electro-magnetic transient simulations, which is capable of capturing fast and slow dynamics in induction machines and is adaptive to various levels of data availability. Ref. [89] first clusters DFIGs using the support vector machine (SVM) clustering method based on wind speed data from the wake effect model, and later obtains equivalent DFIG models. Ref. [90] exploits a similar idea as Ref. [89] to classify DFIGs into groups by a fuzzy C-mean (FCM) clustering algorithm. Ref. [11] first performs a detailed modeling of the DFIG including the specific control systems (grid-side converter control, rotor-side converter control, pitch control, and speed control); after that, the performances of single-turbine equivalence, and multi-turbine equivalence are compared and an SVM is used to classify the turbines for order reduction. Ref. [91] clusters wind turbines using a hierarchical clustering method based on geometric template matching between power output and wind speed. Ref. [92] uses the refined composite multiscale entropy (RCMSE) method with multi-view FCM (V-FCM) to form a new multi-scale V-FCM (SV-FCM) for improving the traditional clustering methods for wind farm equivalencing. Ref. [93] equivalences urban wind farms and clusters coherent wind farms using dynamic time warp (DTW) distances instead of Euclidean distance. Ref. [94] combines neural networks to achieve equivalent impedance identification at different operating points under fixed control modes.

In addition to the combination of clustering analysis with traditional physics-inspired models, clustering analysis can also form another category of hybrid modeling approaches with neural networks. For example, Ref. [12] first clusters PV power plants by k-means clustering algorithm, after which each cluster is equivalenced using deep belief network. Neural networks can also be combined with physics-inspired models to form hybrid model construction approaches. Ref. [95] improves the accuracy of modeling by aggregating VSC clusters into one equivalent VSC and connecting an ANN in parallel to the equivalent VSC, with the ANN correcting errors caused by the aggregation.

Data-assisted physics-inspired model construction makes full use of prior knowledge while enjoying advantages of data-driven modeling approaches, such as compensation for fitting errors that cannot be explained by physics-inspired models as well as the reduction of model dimensionality by the analysis of measurement data.

2.3 Transmission system modeling

The discussion in this section on transmission grid modeling refers to the equivalent modeling of some parts of the transmission grid that do not require detailed analysis from the perspective of a specific part of interest. This is because as the transmission grid becomes increasingly complex, accurate modeling of all its components can result in significant computational costs. Equivalent modeling of the parts that do not require detailed analysis is an efficient solution.

The difference in the number of interfaces between the area(s) to be equivalanced and the areas(s) to be analyzed can lead to different methods. For example, when viewing the transmission grid from the perspective of a distribution grid, there is usually a single port between the two, as shown in Figure 4(a). In another scenario, as shown in Figure 4(b), there are multiple ports between the two, and equivalence accuracy must be ensured at each interface. Single-port models can be considered as a special case of multi-port models[30].

In conventional transmission systems, the dynamics is largely driven by SGs. Therefore, the equivalence of transmission grid to one or more SGs behind impedance has been widely studied[8]. Using the coherence method, the equivalent SG's parameters are calculated directly based on the power angle and power measurement of the generator, etc. This method is shown to work well in conventional SG-based power generation system architectures[7].

The accuracy of conventional model reduction and equivalence approaches is limited by the accuracy of prior knowledge about the transmission grid. With the deployment of precision measurement devices such as PMUs and DFRs, it becomes possible to record the dynamic interactions between two regions of the transmission systems. As such, DDM begins to draw more attention and research effort.

2.3.1 Physics-inspired model construction

Similar to the traditional approach, for some situations where renewable energy has a relatively low penetration rate, the simplest way remains to represent the transmission grid by one or more SGs, while using measurement data for parameter identification. Ref. [96] models the transmission grid containing the field flux decay equation with the IEEE type 4 ST exciter model for a set of swing equations. Ref. [97] uses a 3rd-order synchronous machine model in parallel with a set of constant PQ loads. In Ref. [98], the transmission grid is equivalent to a 6th-order SG with an excitation system. Refs. [99] and [100] add a 2nd-order automatic voltage regulator (AVR) model and a 3rd-order governor model to the 6th-order SG model. For a small hydropower generation cluster, Ref. [101] uses one hydropower generator model in parallel with a set of ZIP load models for system equivalence.

The construction of equivalent models must consider the capability of capturing complex dynamics of a large transmission grid with numerous generators and loads. The more complex the model structure and the higher order, the better the representation of the actual transmission grid dynamics. especially those of excitation systems and turbine-governors. However, with this also comes the increasing computation and data requirements for parameter identification. The advancing computational power and sensor deployment in recent years has opened up the possibility of more complex and accurate modeling.

For large power systems with multiple clusters of SGs, the simple equivalence to one machine may be lead to large errors. Ref. [102] represents each region of the system to be modeled to an SG behind an equivalent impedance. Ref. [103] uses a two-machine system for representing the transmission grid. Ref. [104] reduces the dimensionality of the entire WECC grid by characterizing it with a five-machine system. The multi-machine models may simulate system with multiple SG clusters more accurately, but bring about the same issue of increased complexity for parameter identification.

2.3.2 Purely data-driven model construction

In addition to using the general approach of transfer functions for equivalence[105], it is also possible to obtain the information needed for model construction directly from the dynamic data, i.e., the dynamic feature extraction method.

Ref. [106] explores the optimal choice of time windows for obtaining grid dynamics using the DMD method. The DMD approach is to fit the nonlinear dynamics through a set of linear systems, preserving the main linear part by singular value decomposition (SVD). Based on the DMD method, Ref. [107] uses the Koopman operator to extract the system dynamics. Ref. [108] also uses SVD to extract dynamic features, but then selects the main features to determine the feature generators. The system states are reconstructed by a linear combination of the feature generators to yield nonlinear dynamics. The subspace identification method is also common for dynamic extraction. Ref. [109] adopts this method to equivalence power system dynamics with measurements only. The method mainly leverages the theoretical result that a nonlinear dynamic system can be equivalent to an infinite-dimensional linear system, and thus identifies and reconstructs the main subspace of this infinite-dimensional linear space to fit the nonlinear dynamic system. In Ref. [110] , a neural dynamic equivalence (NeuDyE) approach integrates physics-aware machine learning and neural-ordinary-differential-equations (ODE-Net) to discover a dynamic equivalence of the external power grid while preserving its dynamic behaviors after disturbances with guaranteed closed-loop accuracy.

The purely data-driven methods eliminate the dependency on the prior knowledge of the system with some costs. For example, SVD increases the number of operations, and the state subspace method introduces pseudo-inverse operations with a computational complexity of $O(n^3)$.

Similar to the model construction for other objects, neural networks have been used for modeling transmission system dynamics leveraging their excellent expressive power. Ref. [111] uses two neural networks to equivalence the grid. The first neural network is the bottleneck ANN, which forms a reduced order model. The second one is an RNN that replaces discrete ordinary differential equation (ODE) to make predictions at discrete time steps. Ref. [13] proposes an equivalent method for a set of reduced-order differential-algebraic equations (DAEs) of a transmission grid, with the differential equations in the DAEs partially replaced by ANNs. Ref. [112] adopts an Elman neural network for dynamic modeling. As with any other modeling tasks using neural networks, there are challenges in choosing the number of network layers, activation functions, etc., which have been largely been addressed by trial-and-error approaches in the existing literature.

2.3.3 Data-assisted physics-inspired model construction

In power system operations, prior knowledge of the transmission grid almost always exist to a certain degree. Exploitation of prior knowledge together with data could enhance the efficiency and reliability of the model construction methods.

For example, without high renewable energy penetration, the dynamics of the transmission grid are largely driven by groups of SGs, hence the model construction can first be assisted by clustering analysis or coherence methods using SG characteristics. Ref. [108] exploits MATLAB clustering toolbox before the modeling process. Ref. [113] studies the coherence of the generators in the transmission grid using the measurements of frequencies and power angles of the SGs, and equivalences coherent units to 2nd-order SG models, after which the parameters are identified using measurement data. Ref. [30] takes the power angles for coherence analysis. After each coherent unit is represented by a SG model, and the SG models are connected through an external equivalent impedance. A hybrid dynamic simulation method for sensitivity analysis is developed to determine the key parameters to be identified. Ref. [114] relies on the system topology to directly determine the coherent units as opposed to relying on power angles.

In addition, Ref. [115] adopts an autoregressive with exogenous inputs (ARX) model structure. Ref. [116] discusses model reduction at the electromechanical transient level, using a set of physics-informed PDEs for the Australian grid by converting the tidal equation to an algebraic equation and the swing equation to a differential equation. Ref. [117] constructs a stochastic model for the grid frequency and solves the equivalent parameters one by one based on kramers-moyal, fokker-planck in stochastic theory with the measured data of the system.

For the multi-port network equivalence modeling shown in

Figure 4(b), neural networks have a greater advantage. The complexity of multi-port models, compared to single-port models, lies in the interdependence of properties between different ports determined by the system topology and operating conditions. It is difficult to explicitly use prior knowledge to develop representations of such interdependence. Neural networks, with their rich expressive power, are well-suited for fitting the hidden relationships between data at different ports when combined with prior knowledge such as system topology. Ref. [118] equivalences each port to an SG model with excitation, but this is difficult to represent the relations between different ports. Ref. [31] reduces the order of the complex system by the coherence analysis method, after which a set of ANNs is complemented at each port to fit the difference between the reduced-order network and the actual power, thus achieving highly accurate equivalence. Ref. [119] adds control parameters, switching states and other information to the traditional power and voltage variables as ANN inputs, which leads to better fitting of the grid dynamics. In Ref. [120], a complete black-box equivalence method for large transmission grids is proposed. The voltages and angles of all ports are used as inputs to obtain the active and reactive power of all ports. The equivalence model is an artificial neuro-fuzzy inference system, which contains two parallel networks with different structures to better simulate the system. For faster dynamic simulations under arbitrary contingencies that result in network topology changes, Ref. [121] trains neural network (NN) models that represent the dynamic components in the transmission grid and integrates such NN models with the algebraic equations that represent the physical models of AC power flow. As such, there is no need for re-training the NN models when network topology changes as it only affects the algebraic equations.

The physics informed neural network (PINN) utilizes physical knowledge to provide guidance for the construction of neural networks in the solution to physical problems, which is promising direction of research[122]. In recent years, PINN has garnered comprehensive attention and application in various fields of the power system[123]. The previous section mentioned the Koopman operator analysis method based on DMD, which can be effectively utilized to analyze the dynamics of complex nonlinear systems. However, using the DMD algorithm requires that the spectrum of the Koopman operator is discrete[124]. Correspondingly, the PINN method incorporates physical constraints, treating the neural network as a nonlinear approximator and assigning physical meaning to its inputs and outputs, thus effectively approximating the Koopman operator[124]. Ref. [125] employs an autoencoder to learn the Koopman operator, and experimental results on the IEEE 39-bus 10-machine test system demonstrate that this method exhibits better accuracy in state prediction and transient stability compared to the EDMD algorithm. Ref. [126] introduces a method called deepDMD that utilizes automated dictionary learning to learn the Koopman operator. This method employs deep learning to simultaneously learn the Koopman operator and search for high-dimensional spaces to obtain efficient and sparse dictionaries, which is shown to improve the accuracy of high-dimensional dynamic system prediction by an order of magnitude compared to the EDMD method. Ref. [127] employs a deep input-Koopman learning approach to capture system frequency dynamics, including open-loop swing equations, market behavior, deception mechanisms, and more. This ensures that the controller remains robust even in the presence of price deception.

The hybrid methods reviewed above are based on diverse theories and take good advantage of the prior knowledge of transmission systems, achieving satisfactory results in many applications such as stability analysis[31], system identification[112], etc.

2.4 Distribution system modeling

The transmission system equivalence reviewed above are largely for the modeling of a transmission grid from a regional transmission operator's point of view. The other common challenge to address in transmission system operation is to model the aggregated dynamics of distribution systems. Similarly, as shown in Figure 1, when analyzing a distribution system, it is sometimes necessary to model the aggregated behaviors of parts of system, such as a feeder section or a microgrid. Therefore, the implication of the distribution system modeling discussed in this section is to model the dynamics of a whole or a part of a distribution system when analyzing the system at the higher level. As mentioned before, if the distribution system does not contain distributed generators (DG), most of which are commonly renewable energy sources, then it can be considered as load modeling as reviewed in Section 2.1. Therefore, the influence of DGs, which gives rise to active distribution systems, is the focus of discussion in this section. In addition, this section is different from Section 2.2, in that this section is concerned with aggregated modeling of a distribution system with numerous DGs and loads, whereas Section 2.2 discusses the modeling of a large pure renewable energy plant. As active distribution systems carry the characteristics of all the three systems reviewed above before (load, renewable energy, and power network), it is not surprising that almost all the categories of model construction methods reviewed above can be found here.

2.4.1 Physics-inspired model construction

Based on the fact that a distribution system consists of loads and DGs, one of the simplest equivalents is to select a model from the load model inventory and a model from the generation model inventory, and connect the two in parallel.

Refs. [128] and [129] take the parallel approach by constructing a ZIP + IM model in parallel with an SG model connected to the grid through an inverter. However, the inverter model of Refs. [128] and [129] does not take into account its control characteristics and only equivalence the filter. Ref. [130] uses ZIP + asynchronous machine + SG for equivalence and increases the number of states by introducing a grid connection switch for the equivalent SG.

For those distribution systems where renewable energy constitutes the main type of DGs, the SG model can be replaced with the detailed model of a renewable energy generation system. Ref. [74] constructs a complete PV equivalence model including control and protection, based on which an EL + IM model is developed to represent distribution systems with a high penetration of solar PV[74, 131]. Refs. [132] and [133] replace the PV-based IBR model with the IBR model of wind turbines for the distribution systems with high penetration of wind power. Ref. [134] constructs a distribution system model by means of paralleled wind power IBR model + PV IBR model + ZIP model, and it mainly focuses on the uncertainty caused by geographical distribution. Ref. [135] constructs an equivalent model for a microgrid with a static load + 7th-order SG model + detailed VSC model. The VSC model is constructed based on the classical double closed-loop vector control. Ref. [136] proposes an equivalent model consisting of three components in parallel, two EL models, an IM model with an IBR equivalent model including the inner control loop, which manifests satisfactory performance under large perturbations.

This composite model is simple in structure and fast for parameter identification. The prerequisite for good performance is that accurate prior knowledge of the main types of DGs in the system. In addition, sources of accuracy losses also result from the ignorance of the distribution network properties, especially the impact of the DG locations over the network topology on the dynamic responses.

2.4.2 Purely data-driven model construction

The same methods used for the modeling of other objects also work for the modeling of distribution systems.

Neural networks are one of the widely studied methods for characterizing distribution systems containing complex dynamics. Ref. [137] constructs an ANN for modeling using previous voltage and power data as well as present voltage data as input. Ref. [138] has the same inputs as Ref. [137], but RBFNN for modeling. Ref. [139] establishes a digital twin system for distribution systems through ANN. Ref. [139] verifies the accuracy of ANN-based models under different scenarios and finds them to be more accurate for active power compared with reactive power prediction. Ref. [137] considers the multi-order characteristics of the system, thus incorporating past data as inputs to better simulate multi-order systems. In contrast, RBFNN uses radial basis functions as activation functions[138], enabling faster convergence speed when dealing with nonlinear problems, making it more capable of approximating complex nonlinear relationships, and reducing its sensitivity to noise.

In Ref. [14], distribution system dynamics are modeled using RNN, where the input is a time series of voltage differences and the output is the difference of currents. But it is well known that RNN has the problem of vanishing gradient, which means that it only has short-term memory capability. Therefore, Long short-term memory (LSTM) networks have been promoted in recent years with more complex structures and better performances[140, 141]. Ref. [142] models the distribution grid with LSTM and verifies the equivalence under different faults. Ref. [143] provides a more detailed analysis, first demonstrating that the dynamics of a microgrid can be expressed by a set of DAEs, then further deriving the fact that the DAEs can be expressed by an LSTM model, which is used to model the microgrid. LSTM has the potential to yield better results but also has higher complexity and a larger number of parameters to identify/learn. Gated recurrent units (GRUs) have a simpler structure by eliminating some parameters while maintaining similar performance as LSTM. Ref. [144] splits the dynamics of the microgrid into two components: one characterized by a set of DAEs, and the other representing unknown factors not captured by the DAEs. It fits the latter component by GRU to correct the output of the DAEs, yielding a more accurate result than pure DAE models of microgrids. More recent methods, such as neural ordinary differential equations (neural ODEs), have also been employed to describe distribution system or microgrid dynamics in continuous time[145].

In addition to neural network methods, dynamic feature extraction methods have been applied in the field of distribution grid or microgrid equivalence. Refs. [26] and [27] use the Prony's method for model construction. General system identification approaches are also common, e.g., Ref. [146] constructs the model directly with a general set of DAEs. Ref. [147] uses the state space method for modeling. Ref. [148] compares the Prony's method with the state space method and finds that both have satisfactory equivalence performance in most cases, with the Prony's method being superior in only some special cases.

Overall, in the dynamic modeling of distribution systems, purely data-driven methods receive relatively more interest than other objects to be modeled in power systems, largely due to the complexity of distribution system structures as well as the sheer number and diversity of the components. These methods do not rely on any prior knowledge of the object, but are highly demanding on data. For physics-inspired modeling, even when there is a lack of data for accurate identification of model parameters, the discrepancy of results from the model and the reality is often in a moderate range due to strong generalization capability of model structures with built-in prior knowledge. However, for the purely data-driven approaches, the response of the model may drastically diverge from reality if there is not enough training data or the test scenario is an unforeseen one, as the model may be subject to both overfitting and underfitting simultaneously without sufficient and representative training data.

2.4.3 Data-assisted physics-inspired model construction

Drawing on the idea of modeling IBRs, equivalent impedance can also be used for distribution grid or microgrid equivalence. The difference is that the equivalent impedance method for IBRs requires an prior knowledge about the control loops, while in Ref. [149] for distribution system modeling, the approach of an equivalent impedance model is developed with online equivalent parameters obtained by a machine learning algorithm.

Consistent with load modeling, the improved ER model is used for distribution grid modeling. Ref. [150] modifies the expressions in the parameters of the improved ER model to enabling the capability of representing bidirectional power flow. The order of the transfer function of the improved ER model is determined by fitting in the frequency domain. Ref. [151] obtains similar results by changing the input to the difference of voltages and introducing a symbolic function to the ER model.

Likewise, clustering algorithms can be combined. Ref. [151] first clusters the data using the density-based spatial clustering method, after which the dynamics of each cluster is modeled and finally superimposed to obtain the entire dynamic model.

Ref. [152] devises a neuro-dynamic state estimation method for networked microgrids. This approach establishes an ODE-Net-based dynamic model of the unidentified subsystems, enabling the estimation of dynamic states of the remaining microgrids through Kalman filters. Ref. [153] models microgrids using system identification theory. This method simulates frequency droop control and local secondary load frequency control, while incorporating reactive power and system voltage. It uses instantaneous power theory to treat current as the output of the model. Ref. [154] investigates the problem of equivalence when a microgrid has multiple interfaces with the distribution grid. (similar to the case in Figure 4(b)). It first captures the dynamics of each microgrid using the Prony's method, then performs a clustering analysis to reduce the number of systematic orders. Ref. [155] develops a combination of the ARX method and the state space method for different perturbations to increase the adaptability of the model.

As seen from the review above, there are many possible ways to form a hybrid method based on the chosen physics-inspired and data-driven methods and the mechanism to combine them. Hybrid methods typically integrate prior knowledge and measurement data well and thus gain significant popularity in recent studies.

2.5 Summary of model construction methods

In this section, a categorized introduction is provided for the model construction of loads, renewable energy sources, transmission grid, and distribution grid in power systems.

The dynamic models of these four categories of objects all conform to the form of Eq. (1) (which is a physically general form). However, differences and similarities in the corresponding model architectures, stemming from their respective characteristics, are illustrated in Figure 5. We choose some of these relationships for specific illustration. When comparing transmission and distribution grids, both exhibit complex nonlinear dynamics, making them suitable for methods like DMD. However, the modeling of an external transmission grid might involve multi-port equivalence, unlike the distribution grid which is typically single-port due to its radial structure. Additionally, most transmission grids still primarily feature SGs, allowing for approaches such as synchrony, whereas distribution grids are dominated by IBRs and loads. These differences result in different model construction approaches. For the comparison between the modeling of renewable energy power plants and the modeling of transmission grids, they both need to aggregate multiple dynamic sources, calling for the application of aggregation algorithms. The distinction between them lies in the different dynamic sources: the former is inverter-based, while the latter is primarily SG-based. When comparing IBR (renewable energy source) model construction with load model construction, they both require aggregating equivalent models to a single port, but their emphasis on equivalence differs. The modeling of a renewable energy plant focuses on aggregating the dynamics of the same type of component under different control modes/operating conditions (e.g., the same types of wind turbines with different wind speeds or the same types of solar arrays with different irradiances), while load model construction emphasizes aggregating the dynamics of different types of components (different types of loads). Finally, the dynamics of the distribution grid are mainly provided by loads and IBRs, therefore, the construction of the distribution grid model is influenced by both loads and IBRs.

In terms of the classification of model construction methods, we categorize them into three groups: physics-inspired, data-assisted physics-inspired, and purely data-driven. These three categories vary in their reliance on prior knowledge, ranging from high to low, while their reliance on data follows the opposite trend. The "degree of reliance" here might be difficult to quantify, but the criteria to distinguish between the three categories of methods are distinct. For physics-inspired model construction, the model structure is derived purely from prior knowledge about the object, not from the data. Note that for physics-inspired methods, the parameter identification process may still rely on data (as discussed in Section 3), but data does not play a role in model construction, i.e., determining the structure of the model. Its high reliance on prior knowledge means that if the object is a complete black box, this method cannot be applied since the construction its model structure would be unfeasible. In contrast, purely data-driven methods for model construction only extracts information from data without using any prior knowledge about the physics of power systems. These methods can be used to construct models for black-box systems, but typically have high data requirements and low interpretability. General-purpose transfer functions and neural networks are typical examples of this category of methods. Finally, any methods that leverages information from both knowledge about systems physics and measurement data are classified as data-assisted physics-inspired model construction methods. The criteria above can be used to classify any model construction methods into one and only one of the three categories.

With the comprehensive literature review presented above, it can be observed that the three categories of approaches, i.e., physics-inspired, purely data-driven, and data-assisted physics-inspired, are all evolving towards greater complexity but higher accuracy over time. For physics-inspired model construction, the load modeling, for example, has evolved from the simple ZIP + IM model[36] to the comprehensive CMPLDW model[48], with an increasing number of modeled load types. This provides a stronger capability of characterizing load behaviors; meanwhile, the complexity of the models has also increased, along with the growing number of parameters that need to be identified. This trend is also reflected in other modeling approaches, such as IBR modeling progressing from grid-side models[75] to the models with DC side dynamics[76], and transmission network modeling with an increase in the order of synchronous generator (SG) models[97–99]. For purely data-driven model construction, similar trends are observed. Taking neural network-based methods as an example, the initial ANN methods have simple structures with fewer parameters[137]. They are suitable for fitting relatively straightforward dynamic characteristics. Through improvements in model structure and activation functions, methods like RBFNN[138] achieve better fitting results and convergence speeds. Subsequently, widely used methods like RNN[14], LSTM[140], and GRU[144] employ time series modeling, enabling better fitting of higher-order dynamics.

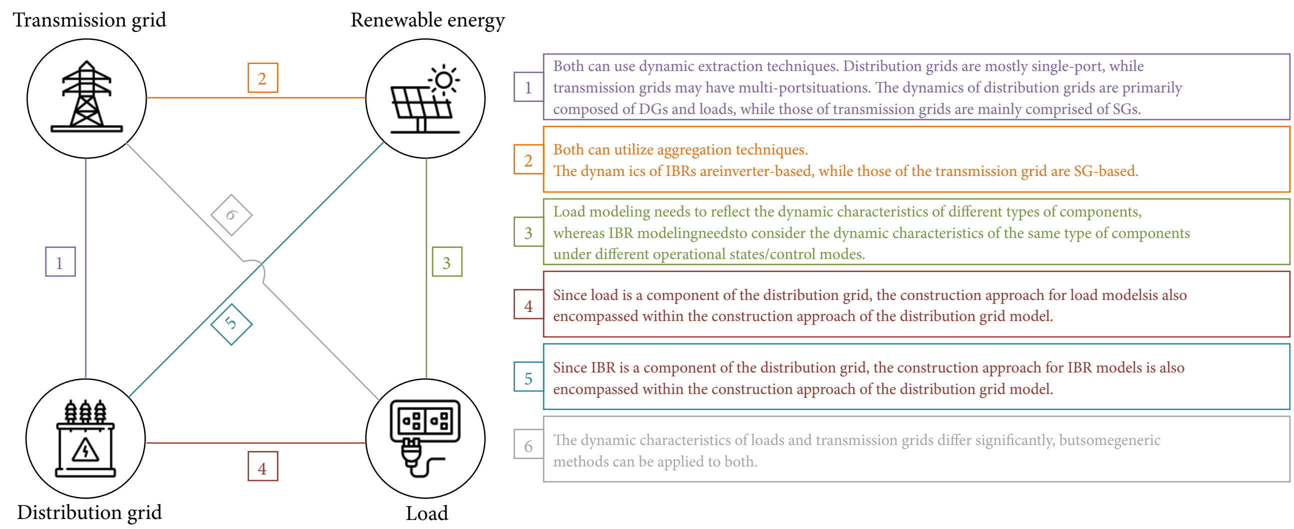

Fig. 5 The relationship between various objects.

The neural-ODE method[145], compared to discrete-time modeling approaches, allows continuous-time modeling. The emergence of deep learning further enhances the fitting capabilities. As has been extensively shown in the literature, as the complexity of models increases, the accuracy of modeling generally improves. However, this also comes at the cost of more intensive computation, larger amount of required training data, higher risks of falling into local optima, and more challenges for interpretability.

These developments and changes have raised higher demands for model parameter identification, which is precisely the main focus of Section 3.

3 Parameter identification

Once the model structure is determined, the next step of DDM is parameter identification, i.e., using measurement data to obtain the parameters of the model, and ultimately completing the entire modeling process. This section will be divided into four subsections to comprehensively introduce the state of the art of DDM parameter identification techniques, including problem formulation, solution algorithms, sensitivity analysis, and online identification methods.

3.1 Problem formulation

For some clustering problems, the parameters may be calculated offline. For example, Refs. [89] and [93] use the clustering algorithm to obtain aggregated turbine parameters directly. But for most other cases, as stated in Eq. (1), once the model structure is determined, that is, $\boldsymbol{f}$ and $\boldsymbol{h}$ are determined, the main objective of parameter identification is to find a set of parameters such that the output of the model can best match the measurement data. This will lead to an optimization problem, and the formulation of the objective function, i.e., the difference between the model outputs and the observed measurements, is an important area of study.

There are many ways to represent the distance between the model outputs and observed measurements, which affect the performance of the identification method. The most common is the Euclidean distance, i.e., L2 norm given by Eq. (3):

$$J = \sum_{i=1}^{N} (\hat{y}_i(\boldsymbol{\theta}) - y_i(\boldsymbol{\theta}))^2 \tag{3}$$

where $\hat{y}_i$ characterizes the output sequence of the model and y_i denotes the actual sequence of measurements. The objective is to find a set of parameters $\boldsymbol{\theta}$ such that J is minimized[50, 52, 53, 59, 66, 68] etc. This problem is known as the least squares problem. The least squares estimator is known to be the unbiased and minimum-variance estimator for linear systems under Gaussian noise. Furthermore, the solution algorithms of least squares problems is computationally efficient and numerically stable, and thus it is the mostly widely implemented objective function for parameter identification. Lease-squares parameter identification have been integrated into various computational software, such as MATLAB[155]. Parameter identification of neural networks, also known as the weight optimization or training process, also tends to consider the least squares as the cost function to minimize[62, 63]. In addition to the classical form of Eq. (3), it can also be averaged or averaged with a square root. Ref. [133] adds some restrictions to it, using the potential barrier function for equivalent identification.

However, the least-squares method also has some drawbacks, such as its ideal Gaussian noise assumption. Actual noise distributions of measurement data may be non-Gaussian and long-tailed, and sometimes may even be colored or time-varying, in which case the performance of least-square estimators may substantially deteriorate. The least squares also treat each individual measurement with equal "trustworthiness", and is unable to account for the different accuracy levels of different information sources. In addition, the least-squares method is very sensitive to outliers, and a gross measurement error can have a high impact on the estimated parameters. Furthermore, the least squares does not take into account the uncertainty of the model structure, which can lead to over- or under-fitting problems. Finally, the least-squares solution is not optimal for nonlinear systems.

To cope with some of the aforementioned problems, other different formulations of objective functions have been studied in DDM in recent years. For example, a classical variant of least squares, is weighted least squares (WLS):

$$J = \sum_{i=1}^{N} W_i (\hat{y}_i(\boldsymbol{\theta}) - y_i(\boldsymbol{\theta}))^2 \tag{4}$$

where W_i indicates the weights of residuals[29, 37, 39, 74, 99, 100]. By assigning different weights to different measurements, WLS can account for different levels of measurement uncertainty. In other words, WLS can incorporate prior knowledge of the data into the identification process, assign high weights to highly reliable data, suppress the adverse effects of outliers, and enhance flexibility and accuracy.

Another typical variant is recursive least squares (RLS)[87, 156]. By recursive, it means to update the estimated parameters after the receipt of each new measurement, which makes it well suited for real-time applications and able to adapt to changing environments and model dynamics. Close to RLS is the application of the Kalman filter framework for parameter identification[51, 73, 157, 158], which also updates the identification results at each data update. The difference is that RLS has a single stage of measurement update while the Kalman filter framework uses a two-stage process, model prediction and measurement update.

To reduce overfitting and improve model interpretability, regularization methods have been applied to least-squares problems, such as least absolute shrinkage and selection operators (LASSO)[107, 159]:

$$J = \frac{1}{N}\sum_{i=1}^{N} (\hat{y}_i(\boldsymbol{\theta}) - y_i(\boldsymbol{\theta}))^2 + \lambda \sum_{l=1}^{n} \left|\theta_l^{\mathrm{ref}} - \theta_l\right| \tag{5}$$

where λ is a scaling factor; n is the dimensionality of parameters and $\boldsymbol{\theta}^{\mathrm{ref}}$ is a reference value for the parameters. Compared with traditional least squares, Lasso adds a penalty term, the most important feature of LASSO is that it also allows feature (parameter) selection by reducing the less important parameters to zero, alleviating the overfitting problem and simplifying the model.

In addition to L2 norm, L1 norm can also be used to describe distances. It leads to the least-absolute-value formulation[57, 119, 160]:

$$J = \frac{1}{N}\sum_{i=1}^{N} |\hat{y}_i(\theta) - y_i(\theta)| \tag{6}$$

The approach takes the absolute value of the residual for minimization. The most prominent property of the least-absolute-value estimator is to reduce the effect of outliers on the model fitting, gaining a much higher robustness than traditional least-squares estimator. The problem can be converted into a linear programming problem. The computation cost is higher than the least-squares, but with the advancement of linear programming solvers and computational power, it has become a less limiting factor than before.

Most recently, Chen et al proposed a new method of data fitting. Instead of fitting the time-series output data, the objective function in Ref. [161] is to fit a data Hankel matrix formed by the output measurements. This data Hankel matrix has a low rank. In turn, a rank-constrained optimization problem is formulated. To solve this problem, rank constraints may be relaxed to a convex optimization problem:

$$J = \left\| H^*_{v,h} - H_{v,h}(\theta) \right\|_F^2 \tag{7}$$

where H is a Markov matrix, v and h represent the number of rows and columns of the matrix, and θ represents the parameters or states to be optimized. Through convex iteration, the optimization problem is solved and the model parameters can be found. This problem formulation and solving strategy has been applied in Ref. [162] to find the parameters of a synchronous generator and a grid-following inverter.

The aforementioned objective functions (loss functions) can be used to estimate parameters in physics-inspired models as well as the training of data-driven models such as the NN. However, PINN goes further by incorporating physical domain knowledge. The general form of the PINN can be expressed as follows:

$$J = L(\hat{y}, y) + \lambda R(\boldsymbol{W}, \boldsymbol{b}) + \gamma R_{\text{phy}}(\boldsymbol{X}, \hat{y}) \tag{8}$$

where L is the conventional loss function; R is the parametric regularization term and R_{phy} is the physical regularization term based on the relationship between equations of physical principles and predict output[123]. This formulation effectively integrates physical knowledge into deep learning.

3.2 Solution algorithms

3.2.1 Solution to LS and NLS problems

With the problem formulation defined, the next step is to devise a suitable solution method. For linear systems, closed-form solutions exist for the least squares problem[50, 59]. Ref. [34] derives its solution under perturbation directly from the exponential model. Ref. [56] identifies the parameters in multiple stages. Some of them are obtained directly by offline experiments, and the remaining ones are identified via measurements. Ref. [85] uses the iterative rational Krylov algorithm to solve the least squares problem with linearization of the trajectory.

However, in reality, power system components are largely nonlinear. For nonlinear least squares (NLS) problems, the solution cannot be obtained directly. Iterative methods are typically required to approach the solution. The traditional quasi-Newton-type method is well established, and the Levenberg-Marquardt method, which is more robust, has gained recent favor[52, 53, 66, 68, 129]. Other algorithms, such as Gauss–Newton[146], Broyden, Fletcher, Goldfarb, and Shanno[163], have also been shown to be reliable. These methods have been integrated into many existing software packages, such as ORIGIN 7.5 and MATLAB’s PSAT toolbox[26, 52, 83, 104, 105, 128, 147]. These iterative methods do not guarantee that the solution found is the global optimal solution. For NLS problems, there are often many local optimums in the solution space. One major limitation of traditional methods is that they are likely to fall into local optimums, which is highly dependent on the initial guesses and search strategies.

3.2.2 Heuristic optimization algorithm

For nonlinear parameter identification problems, in order to tackle local optimums and search for better solutions especially in high-dimensional spaces, intelligent (heuristic) algorithms are often applied.

Refs. [58, 97, 135] use the genetic algorithm inspired by the process of natural selection in biology to identify optimal model parameters. Ref. [57] relies on a population diversity-based genetic algorithm (PDGA) to implement global search, which is faster than traditional GA computation. Refs. [30] and [118] adopt a non-dominated sorting genetic algorithm II (NSGA-II) as a multi-objective optimization algorithm. Ref. [72] improves GA in four aspects: parameter initialization, individual selection, self-adaptive crossover and mutation and iterative identification to improve recognition efficiency. Ref. [29] performs initial search with the GA method, and then applies the simplex search method to quickly obtain the optimal solution. GA can also be used to solve least-absolute-value problems[112].

Particle swarm algorithms (PSO) are also a very common class of methods applied for solving parameter identification problems[164]. Refs. [136] and [153] use the evolutionary particle swarm optimization (EPSO) to solve NLS problems. Ref. [98] uses the novel salp swarm algorithm (SSA), an alternative to PSO designed to handle multi-modal and high-dimensional optimization problems, capable of balancing global and local search.

Compared with the PSO algorithm, the GA algorithm is less sensitive to the initial conditions and more robust, but the convergence speed is typically slower and the computational cost is typically high; the PSO algorithm is simpler with fast convergence, but it is more likely to be stuck in local optimums. Both algorithms have their own advantages and disadvantages, and it may be appropriate to use a combination of the two to achieve better results. For example, Refs. [43] applys crossover operation to the PSO algorithm by borrowing the idea of crossover operation from the genetic algorithm so as to improve the convergence of PSO.

In addition to the above two commonly used heuristics, Refs. [15] use an adaptive simulated annealing (SA) method to identify parameters and the Cramér–Rao Lower Bound to evaluate the estimation accuracy. In Ref. [149], the shuffled frog leaping algorithm is applied to determine the approximate range of parameters, and the GA method is implemented to quickly find the solutions. A new heuristic optimization algorithm called mean-variance mapping optimization (MVMO) is proposed in Ref. [99]. The MVMO method maps random variables to the range of 0 to 1 through a set of mapping functions whose inputs are the mean and variance of the current optimal solution. This method has the feature of being able to search for but not get trapped in local optimal solutions. Ref. [100] improves the MVMO algorithm to include multi-parental crossover for enhanced search capabilities, in addition to a swarm intelligence-based procedure. Ref. [74] prefers the evolutionary algorithm (EA), a meta-heuristic global optimization method, which provides adaptive rules that allow the search to be tailored to specific scenarios. Ref. [101] introduces a self-adaptive control parameters modified differential evolution (SACPMDE) algorithm that adjusts the crossover probability constant based on the current convergence state. This adaptive adjustment improves the convergence properties of the algorithm.

3.2.3 Learning-based algorithms

Neural networks can be used not only for model construction but also for assisting parameter identification. In Ref. [96], measurement data under grid perturbation are leveraged to identify the parameters of equivalent SG model based on a radial-basis function network. Ref. [160] applies ANN as one of its parameter identification methods, which yields better results than the standard multi-start algorithm available in MATLAB Global Optimization

Toolbox. In addition to neural networks, the support vector machine is also shown to be a viable means for assisting the solution of linear regression and its dual model[22], where quadratic programming is formulated to determine the respective parameters of ZIP and electronic load. Finally, Ref. [92] exploits the transfer Q learning to optimize the parameters, demonstrating stronger optimization efficiency.

While learning-based algorithms have shown strong capabilities for obtaining solutions to optimization problems, the parameters of the learning algorithm itself also require to be optimized. For example, for the LSTM model in Ref. [42], a L2 norm with regularization is used as the optimization objective for the parameters of the neural network itself.

3.2.4 Frequency domain identification method

For a frequency-domain model like ERLM, the transfer function parameters can be determined via frequency domain analysis. Ref. [115] uses QR factorization to optimize the ARX model parameters. Refs. [45] and [113] leverage the well-developed curve fitting algorithm integrated in MATLAB. In Ref. [150], the vector fitting (VF) method is applied, which can approximate in frequency-domain the transfer function by means of a two-stage linear least squares problem. Both methods produces the parameters of the function with the best fit and assess the quality of the fit. Ref. [24] uses refined instrumental variable (RIV) approach to estimate the equivalent ERLM parameters. The convolution with a fixed Gaussian kernel is adopted to identify the parameter of the equivalent PDE in Ref. [116].

Other methods such as Prony's method[148], state subspace method[109], etc., have integrated their own frequency domain parameter identification in the modeling phase. These frequency-domain identification methods have been widely used with satisfactory results.

3.3 Time-varying parameter problem

In existing DDM methods, it is most common to collect historical measurement data and obtain a set of parameters that best fit the entire dataset. However, it is possible that system characteristics vary over time due to the changes of system operating points, ambient conditions, external inputs, and/or system properties itself, in which case the optimal model parameters may also vary widely[34]. If the model parameters are not adapted in real time, the accuracy of the model may deteriorate, affecting the performance of model-dependent applications for ensuring power system reliability, efficiency, and resiliency[165]. For example, the accuracy of model parameters is significant factor for effective protection settings[166]. Therefore, various approaches have been proposed to enhance the adaptation of parameter identification in DDM.

3.3.1 Hyperparameters or event-oriented method

One essential idea to tackle the time variance of model parameters is to select different sets of parameters according to systems states or events, such that the selected parameters can best characterize the dynamic behaviors of the components under different scenarios. Hyperparameters can be defined for the selection of model parameters.

Refs. [34] and [52] consider the effect of different seasons on loads, and different sets of parameters are obtained for different seasons. In Ref. [38], optimal parameters under different categories of system perturbations are first obtained, then support vectors are used to determine parameters to be adopted online. Ref. [41] develops an event-oriented time window selection method for parameter identification. When a voltage change event is detected, the original ZIP-based modeling parameters change accordingly; otherwise, the parameters remain the values best describing the steady state. The time window used for parameter identification is adjusted to identify the full range of system parameters to accommodate the various events. Ref. [160] selects the optimal model according to different motor penetration rates, wherein the season, perturbation, or motor penetration rate constitutes a hyperparameter.

In some methods, the relationship between hyperparameters and model parameters also needs to be identified. Ref. [54] first obtains the parameters for different load conditions by the well-established NLS tool and later uses a linear approximation to capture the relationship between load composition, total power variation and parameters, which is referred to the LAGERM method. It is found in Ref. [55] that the optimal parameters obtained by solving for different operating conditions such as dynamic load permeability and voltage disturbance levels are different. Therefore, the optimal parameters for different backgrounds are first solved for, and subsequently, a set of ANNs are used to construct the relationship between the background and the parameters. Ref. [23] first classifies the available data using clustering algorithms. Then, an equivalent model is constructed and parameter identification is performed for each category of data. After completing the above steps, a robust parameter derivation was achieved using an ANN. Ref. [98] proposes a similar approach to those in Refs. [23] and [55], but finally the optimal parameters are selected by a fuzzy-logic selection mechanism. Ref. [21] employs an empirical selection method for the three obtained optimal models to represent the behaviors of loads under different perturbations.

3.3.2 Online parameter identification

Online parameter identification is another way to solve the problem. The main difficulty of online parameter identification is that it needs to be done with time constraints, i.e., the computation time for processing the data received in a time window must be no longer than the length of the time window itself. Many intelligent algorithms are limited by the speed of computation and cannot be executed in an online manner. Therefore, relatively mature NLS or LS solvers or novel fast identification methods are applied to the online parameter identification problems. Ref. [68] performs online parameter identification using the Levenberg-Marquardt method by collecting data from multiple branches. In Ref. [115], system model parameters are identified in real time using the least squares method based on linear expansion of the system operating points. The disadvantage is that the approximation error of linearization. Ref. [156] achieves online parameter identification using a robust recursive least squares method based on the Huber M-estimator, which incorporates a convex cost function and a strategically variable forgetting factor adjustment scheme. In Ref. [39], the parameter identification is expressed as a WLS optimization problem and solved by the Newton-Raphson method. Ref. [167] proposes a manifold boundary approximation method (MBAM), whose basic idea is to approximate a high-dimensional, but thin model manifold by its boundary that only requires the model flow pattern to have a boundary hierarchy without other a priori assumptions.

Once the model structure is determined, online parameter identification is also possible by applying the Kalman filter framework that treats the model parameters as variables. Considering the nonlinearity of the model, extended Kalman filtering (EKF)[158] and unscented Kalman filter (UKF)[51] have been applied. In the case of a large number of parameters, Ref. [73] uses physical knowledge to directly calculate the external impedance of the clustered wind turbine model and identifies the parameters inside the clustered wind turbine in real time based on an adaptive extended Kalman filter (AEKF).

Deep learning and reinforcement learning can also be used for online parameter identification. Ref. [94] uses physics informed neural network (PINN) for online parameter identification of equivalent impedances. A migration learning approach is also used to accelerate the training by applying a large amount of simulation data. An LSTM model for time-varying parameter identification is devised in Ref. [42], and a combined time-varying parameter identification (TVPI) problem of the system-wide load modeling is constructed. Reinforcement learning is more adaptive and convergent than traditional machine learning methods. The capability of reinforcement learning to adapt parameters to changes in the system to be modeled, while being designed to converge to an optimal solution over time, are properties that make it well suited for online parameter identification problems. Ref. [134] adopts an enhanced reinforcement learning algorithm to identify the parameters of the equivalent model in real time. A deep reinforcement learning approach is designed in Ref. [77], which can tackle more complex systems than Kalman filtering and achieve faster speed than intelligent algorithms in the modeling of HVDC systems.

3.4 Sensitivity analysis

Even with some intelligent solution methods, the NLS problem may still suffer the problem of not converging to the global optimal solution. Ref. [168] analyzes the case of locally optimums of the NLS problem and proposes two solutions, the most effective of which is to reduce the number of parameters, in addition to rewriting the equations as a quadratic programming problem with linear constraints. Complex models usually have a large number of parameters; for example, the ZIP model has only three parameters but the CMPLDW model has 121 parameters, which makes it very difficult to find the global optimum in parameter identification even using intelligent methods. The explosive growth of the number of parameters also poses a challenge to the computational efficiency of online parameter identification. At the same time, if the measurement data are not rich enough to fully reflect the effects of all parameters, or the effects of some parameters are not structurally visible, the parameter values may not be reliably estimated, and ill-conditioned parameter estimation problems may arise[44].

The aforementioned challenges give rise to the research topic of parameter sensitivity analysis. With sensitivity analysis, the parameters with a strong influence on the dynamics can be efficiently found[29], so as the pathological parameters[168]. Subsequently, the important parameters are separately identified and the pathological parameters are set to some fixed a priori values, which reduces the dimension of the problem while addressing the ill-conditioning problem as well. With these benefits, sensitivity analysis has received increasing attention in DDM in recent years.

The trajectory sensitivity analysis method is a common class of methods for parameter sensitivity analysis[146]. Ref. [40] uses this method to determine the sensitivity of different parameters of the equivalence model. Therefore, the parameter values recommended by the IEEE standard model are used for some less sensitive parameters to reduce the difficulty of parameter identification and increase the computation speed. Similarly, important model parameters are identified by the improved genetic algorithm and the NSGA-II in Refs. [72] and [30], respectively. The definition of trajectory sensitivity can be shown by Eq. (9):

$$\bar{S}_{y_i/\theta_j[t_1,t_2]} = \frac{1}{N}\sum_{k=0}^{N}\left|\frac{\partial y_i/y_i}{\partial \theta_j/\theta_j}_{\left(t_1+k\frac{t_2-t_1}{N}\right)}\right| \tag{9}$$

where $\bar{S}_{y_i/\theta[t_1,t_2]}$ represents the average sensitivity within the time window from t_1 to t_2, y_i is the ith output, and θ_j is the jth parameter. The implication is that by dividing the output between t_1 and t_2 into N segments, the sensitivity of each segment is calculated and then averaged. Ref. [91] analyzes the parameter sensitivity and model robustness of the wind field aggregation model. As mentioned earlier, one of the main difficulties of online parameter identification is computational efficiency, which is addressed in Ref. [69] by online identification of key parameters and offline identification of the remaining parameters, wherein the key parameters are extracted through sensitivity analysis. Ref. [29] employs the probabilistic collocation method (PCM) to analyze the uncertainty of the parameters and the effects of parameter uncertainties on the dynamics.

Finally, Ref. [49] performs a detailed analysis of all parameters of CMPLDW, combining parameter sensitivity analysis with K-medoids clustering to obtain the sensitivities and dependencies of all parameters, and showing the correlations among all 121 parameters by MDS-Based visualization. On this basis, using the LASSO model, the a priori known parameters are set to reasonable values $\boldsymbol{\theta}^{\mathrm{ref}}$ in Eq. (5).

4 Conclusions

This paper summarizes the recent developments of data-driven modeling techniques for power systems dynamics. The paper generally divides the DDM into three steps and summarizes the recent techniques in each step. In the data pre-processing step, state-of-the-art methods for denoising, bad data detection, feature extraction, and dimensionality reduction are reviewed. In the model construction step, this paper comprehensively discusses the four types of components/subsystems to be modeled: load, renewable energy source, transmission grid, and distribution grid. For each one, model construction methods are introduced according to the degree of reliance on data: physics-inspired (low reliance), purely data-driven (high reliance), and data-assisted physics-inspired (median to high reliance). It is observed that the model construction approaches of different objects share many similar methodologies, such as parallel physical models, differential equations, transfer functions, and neural networks, as well as their combinations. In the parameter identification step, different problem formulations and common solution methods are discussed. The state of the art of the two critical and recently popular topics, online parameter identification and sensitivity analysis, are also summarized in terms of their motivations and existing works. With the continual advancement of data analytics and deployment of high-presision sensors in power systems, it is foreseeable that DDM will gain increasing popularity in the near future. Based on the observations of the literature survey, we identifies several challenges and gaps for future research.

4.1 Experiment design for data generation

Data are the most critical elements for DDM. A proper set of measurement data, collected from normal operation or deliberate experiments, should cover the dynamics to be modeled in terms of time scale, magnitude, and mode. Selection of input and output channels requires an understanding of the original system dynamics. An example of data-driven modeling of phase-locked loop (PLL) is discussed in Ref. [169], where experiments are designed to have the voltage's phase angle as the input while the PLL's angle as the output with the recognition that the main function of PLL is to track phase angles. Speeding up data generation experiment is also desired. For example, it is well known that frequency scan to obtain an admittance model based on real-code black-box models supplied by original equipment manufacturers is very time-consuming. Therefore, many wideband perturbation techniques have been proposed in the literature, such as the recent Gaussian pulse-based perturbation in combination with system identification algorithms[170].

4.2 Selection of model construction methods

The model construction methods for common objects in power systems are mentioned in Section 2. For any given object, there are multiple model construction methods available. The selection of the most suitable model construction method for a specific application is a topic worth exploring in the future. At the same time, as the operating condition or external environment change, the best model construction methods may also change. Therefore, it is worth investigating what information needs to be collected to allow the adaptive selection of model construction methods.

4.3 Integration of prior knowledge and measurement data

As the penetration of renewable energy continues to increase, the dynamics of modeling objects will become increasingly complex and diverse. Reducing the degree of dependence on prior knowledge in various DDM methods will become an increasingly urgent issue. For example, neural network methods do not require any prior knowledge. However, purely-data-driven techniques typically make predictions that lack trustworthiness and interpretability. In addition, the selection of network architecture and hyperparameters still heavily relies on the human experience. The integration of prior knowledge may effectively enhance the trustworthiness and interpretability and guide the selection and generation of model architectures.

In this regard, the PINN method effectively combines prior physical knowledge with deep neural networks, representing a promising endeavor that has found applications in various domains of the power system. In the future, it might be possible to extend the application of PINN, which has proven effective in predicting complex dynamic models in transmission networks, to tasks such as the modeling of IBRs and loads.

4.4 Modeling of dynamics of different time scales

For traditional power systems dominated by SGs, the dynamics are dominated by electromechanical transients with a time scale of hundreds of milliseconds or above. However, with the proliferation of power electronic devices, electromagnetic transients are becoming more important for system-wide analysis. For a single component, such as a synchronous generator or an inverter-based resource, a model can be constructed based on its dynamic characteristics. However, for a distribution system with various equipment, it is critical to investigate how a unified or hierarchical model can be constructed to characterize the dynamics at different time scales.

4.5 Continuous-time modeling

Traditional modeling based on physical knowledge can yield a continuous-time model of the system that allows not only numerical simulation of the dynamics but also analytical studies such as small-disturbance stability analysis. They also allow flexible step sizes in numerical integration. However, most of the state-of-the-art modeling approaches, such as deep neural networks, can only obtain discrete-time models with a predetermined step size. They are not fully compatible with the continuous-time models and the existing analytical and numerical techniques widely applied in power systems. It remains a critical challenge to investigate methods for integrating discrete-time and continuous-time models or devising neural network models in continuous time domain.

4.6 Data imperfection and heterogeneity

In most existing efforts of DDM, it is assumed that data is accurate, complete, and sufficient. However, in reality, data are streamed from various measurement devices such as PMUs, SCADA, and digital fault recorders. Different measurement devices typically have different sampling frequencies. The integration of measurement data obtained at different time scales and sampling frequencies is a challenge that remains largely unaddressed for DDM. Moreover, the data obtained from measurement devices are not perfect. They not only contain noise but may also include bad data due to device and system malfunctions or cyber attacks. Therefore, as discussed in Section 1, data pre-processing techniques and robust modeling techniques will also become essential topics in DDM research.

4.7 Data privacy issues

In addition to the issues of data imperfection and heterogeneity, another potential problem with data is privacy. As indicated in the survey, existing methods almost always assumed that the required dataset is available. However, in reality, due to security concerns, the party that manufactures or operates the component or subsystem to be modeled may not provide all the necessary data for performing DDM. This is particularly common in a deregulated electricity market environment. Federated learning is an effective way to address the risks associated with data exchange between different parties[171]. It achieves privacy by distributing model training to client devices and uploading updated model parameters instead of raw data to a centralized server. As the privacy issue draws attention, methods like federated learning are likely to be explored to achieve a better balance between model accuracy and data privacy.

4.8 Online parameter identification and model construction

The accuracy of dynamic models is critical to the secure operation of power systems. During the operation of the power grid, the characteristics of components and subsystems inevitably change with ambient conditions, such as solar irrandiance and temperature, control modes, such as grid-following and grid-forming controls of IBR, and service statuses, generator and line maintenance. If DDM cannot capture these changes, it cannot accurately reflect the real dynamics of the system. Therefore, in-depth investigation of online parameter identification to enhance the adaptiveness of dynamic models is required in future studies. Besides online parameter identification, online model construction may also be an interesting topic to explore. Almost all the model construction methods discussed in Section 2 have fixed structures once determined offline. However, this may not always be the best strategy. For example, if there are topological changes in the distribution grid, the structure of the equivalent model of the distribution grid may need to be changed in addition to the model parameters. Another example is wind farm modeling — it may be the best strategy to adapt the number the number of equivalent wind turbine models to the operating condition of the wind farm. Therefore, online model construction, sometimes reflected by the online adaptation of model hyperparameters has great potential for investigation.

4.9 Scarcity of data

Compared with the traditional KBM, DDM relies less on prior knowledge and more on data. Therefore, a large amount of real data needs to be collected or generated to enable DDM. However, measurement data recording power system dynamics are always limited. The most obvious example is that system operators cannot actively conduct experiments of fault in a real grid, but have to passively wait for faults to occur. When there is no enough data for training, there are two possible solutions. The first one is to make use of data more effectively. For example, by applying the knowledge of previously trained models on other objects, transfer learning can significantly reduce the need of data of a specific objected to be modeled[172]. The second one is to generate synthetic data to assist training. Generative modeling could be an effective method to populate the data space in DDM training[173].

4.10 Interpretability or explainability of the model

KBM and physics-inspired methods naturally have a high degree of interpretability. This is because each component of the computation graph has its corresponding physical meaning, allowing operators to easily understand the mechanism of the model, thereby comprehending and "trusting" the model. However, in the field of deep learning or, more broadly, in the context of black box problems, the interpretability is becoming increasingly important issue to address. Ref. [174] provides a general definition of interpretability as "the ability to explain or present in understandable terms to a human", and introduces some interpretable machine learning methods applied in smart grids. In the field of deep learning, the complexity of models has reduced their readability. Furthermore, due to their detachment from real-world physical significance, despite achieving considerable success, they still struggle to gain trust from operators. In practice, deep neural networks (DNNs) have been found susceptible to being misled, misclassifying inputs that bear little resemblance to real inputs[175]. Model interpretability is a relatively new topic, and in light of this situation, introducing physical factors into neural networks (such as PINN) is a promising approach to enhance interpretability. Other interpretable machine learning methods can also be considered for application in data-driven modeling of power systems.

4.11 Stability of the power system

Stability analysis in power systems heavily relies on the accuracy of the models. In fact, an important application of DDM is to enhance the accuracy of stability analysis, e.g., the incorporation of DDM into transient stability simulations. However, the design of DDM methods has largely been conducted independently from the context of stability analysis. The impact of DDM errors on power system stability analysis has been largely unstudied, and the design of DDM methods has not been well guided by the needs of stability analysis. One potential approach to these problems is to enhance the interpretability of DDM, allowing operators to have a prior understanding and awareness of the potential errors associated with DDM. Another approach is to modify the problem formulation of DDM by explicitly addressing the needs of stability analysis. For example, modeling errors are critical around the stability boundaries, as small errors can result in completely different stability labels. In DDM, these areas should have more data samples, carry greater weights, or enjoy greater robustness in the DDM training process. This way, the DDM can be better directed towards the enhancement of stability analysis in power system planning and operation applications.

4.12 Summary

DDM is not a category of methods exclusively used in the field of power system dynamics. With the development of computer science, signal processing, and system engineering, new DDM methods and applications are emerging in a variety of science and engineering fields[176]. It is expected that new DDM methods for power systems dynamics will draw on these advancements while tightly incoporating the characteristics and needs of power systems.

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The authors have no competing interests to declare that are relevant to the content of this article.

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