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Classification of measurement-based approaches to load model identification

Abstract. *The paper briefly describes existing methods for processing measuring data of voltage, active and reactive power with a view to identify the mathematical model of substation load for calculating steady-state power system conditions. The authors proposed a classification of methods, described its key features and made a bibliographic list of works for each group.*

Streszczenie. *W artykule przedstawiono przegląd metod przetwarzania danych pomiarowych pomiaru napięcia, mocy czynnej i biernej z uwzględnieniem matematycznego modelu obciążenia podstacji w systemie energetycznym. Autorzy proponują klasyfikację i przedstawiają bibliografię dla każdej z grup.**(Klasyfikacja urządzeń pomiarowych z uwzględnieniem identyfikacji obciążenia)***

Keywords: Load modeling, Power system model, Power system study, Static Model, ZIP Model
Słowa kluczowe: model obciążenia, system energetyczny, dane pomiarowe

Introduction

Modern power systems are complex nonlinear large-scale systems. Managing such systems is a challenging and highly demanding task that is assigned to special organizations called "System operators". System operators rely on the power system design model when making management decisions. It is well known that the correctness of load models has a direct influence on the results of modeling the entire power system [1–4]. There is a huge number (thousands to tens of thousands) of load nodes in every power system. A question arises: what specific load model should the System operator use for each of these nodes? Each power system load node has its own unique technical characteristics, both in terms of the load composition and curve, and in terms of the technical capabilities of obtaining measurement data, the existence of voltage fluctuations and the possibility of conducting experiments [5]. Despite the fact that the scientific field of load modeling has a rich history [6], it still continues to grow rapidly [7]. The growth is mostly connected with the appearance of new load types and modern measurement and data processing systems. At the authors' disposal there is a significant amount of measurement data acquired for load nodes of Ural and Siberian United Power Systems of Russia. Experience in processing these data shows that there are no universal methods for identifying a load model for any given node.

Load modeling difficulties can be divided into three categories:

- the complexity of the object being modeled;
- ways and means of collecting data;
- data processing difficulties.

Power system load can be composed of individual large consumers as well as large-scale electrical subsystems. In the latter case, the load is a large number of individual devices powered by a medium voltage or a low voltage electrical subsystem. Such an electrical subnetwork includes transformer substations and power lines. Obviously, the behavior of such an aggregate load will be determined not only by individual devices, but also by the topology and operating mode of the subnetwork.

The actions of regulating systems and utility staff lead to the fact that the magnitude of the load changes not only according to its natural response, but also by adapting to new power supply conditions. This leads to the fact that the load can behave differently in different time horizons [8]. Dynamic properties of the load lead to the fact that the load response to voltage disturbances will be different depending on the characteristics of a particular perturbation.

Ways and means of collecting data for each power system load node are limited by technical properties of measurement devices. The error in measuring systems is composed of errors of individual measurement devices, non-simultaneity of measurements, quantization errors and aperture errors. Data arrays contain not only information about the response of the research object to changes in the power supply conditions, but also information about the response of the power system to natural changes in the load itself. Accuracy of a measurement-based load model heavily depends on the quality of the data [46].

Processing large amounts of data collected from measurement devices is a challenging task. The algorithms of parameter estimation ought to be resistant to inferior quality data, missing measurements, and modifications in the voltage adjustment scheme [7]. Difficulties in data processing include issues such as selecting usable measurements [9], selecting required window, avoiding spontaneous load changes, identifying load recovery characteristics, and filter design parameters [46]. Separately, it is possible to establish the task of measurement data normalization, since the rated power value is unknown in advance [10, 51].

The difficulties described above could be mitigated or exacerbated in each particular case. Given an adverse combination of factors most methods are not appropriate, and the task of load model identification becomes practically unsolvable.

The authors' aim is to find an approach to identifying load model parameters with low sensitivity to the quality of field measurement data, which can be used when there is a large amount of measurement data. This approach is appropriate for most power system nodes. For this purpose, the following tasks are solved:

- existing load model identification methods are analyzed; their advantages and disadvantages are described;
- methods are organized based on the way of obtaining measurement data;

Classification of measurement-based approaches to load model identification

A detailed overview of methods for identifying load models is given in [2, 6, 7]. Let us briefly review the main approaches to the identification of aggregate load models:

- a component-based approach [4, 11–13];
- a measurement-based approach [2].

The component-based approach is not covered in the article because accurate and comprehensive load composition information is hard to obtain. Legal restrictions in the field of energy do not always permit to collect necessary data in terms of power supply circuits, equipment parameters and target consumer, since these data can be protected by trade secrets. The article focuses on the measurement-based approach. The measurement-based approach in turn is divided into two approaches [2]. Both approaches can be classified depending on the methods and conditions under which the data was obtained:

- An active approach (staged field tests or laboratory tests).
  - staged field tests;
  - laboratory tests.
- A passive approach (continuous field measurements).
  - disturbances-based (high sampling rate);
  - online (real-time data);
  - disturbances-based (low sampling rate);
  - statistical-based approach.

The active approach is based on conducting targeted experiments, whereas the passive approach is based on collecting the measurement data without interfering with the operation of the power grid and without affecting the consumer.

The features of each group of methods are given in the table 1.

Staged field tests

This approach involves conducting targeted experiments for studying load response. To change voltage a transformer on-load tap changer is often used [8, 10, 14–16], whereas generator automatic voltage regulators [17], reactive power compensation units [14, 18] and network topology change are rarely used. In [3] even inducing artificial short circuits in the power system is described. From the authors' point of view, such artificial experiments allow for obtaining the most reliable load models. This is due to the fact that the widest range of voltage variation is achieved in the narrowest time interval. The difficulty of conducting staged field tests, which does not allow covering all the load nodes in the power system without exception, is one of the disadvantages of this approach. In addition, such staged field tests allow the identification of a load model that corresponds only to a specific period and load condition [52, 54] in a certain voltage range. How the load will behave under other operating conditions is not known [7].

Laboratory tests

This category combines studies in which the results of laboratory experiments are used as data. The first part of them is devoted to load model parameter estimation of individual devices [19, 20] for later use in the component-based approach. The second part includes methods for load models' parameters estimation such as the improved particle swarm optimization method [21], the generic modeling procedure [22], the vector fitting technique [23], and others [24] that have been tested only on laboratory data. The question of how effective the proposed approaches will be for identifying aggregate loads in a large-scale power system from real-life data is the subject of further research.

Disturbances-based (high sampling rate)

This category combines methods in which measurements taken during voltage disturbances with a high sampling rate — from several measurements per second and higher — are used as data. The field measurement is done with phasor measurement units (PMU). For estimating parameters of dynamic load models the autoderivation method [25], the multicurve identification technique [26], the efficient optimization based on parameter sensitivity [27], the genetic algorithms [28], the variable projection method [29], the global optimization technique [30], the parallel-differential evolutionary algorithm [31], the cross-validation technique [32] and other techniques are used. An advantage of this approach is the ability of dynamic load model parameter estimation. Disadvantages include the requirement for high sampling rate and high sensitivity to noise [9]. This approach requires the presence of PMUs, which are usually installed only at power plants and the most powerful and responsible ultra-high voltage substations. These methods, unfortunately, are not appropriate for power system load nodes that are not equipped with PMUs [49, 52].

Online (real-time data)

The online methods deal with real-time data. These include the adaptive search-based algorithm [33,34], the cross-validation technique [35], the event-oriented method [36], the artificial-intelligence method [37], the automated load modeling tool [38], Bayesian estimation [39], the multistart algorithm [40,41], Taylor series approximation [42], the multi-layer searching method [43] and other methods [44, 45]. The advantage of this approach is the ability to update the parameters of the dynamic load model in real time. Otherwise, these methods are very close to the disturbances-based (high sampling rate) methods discussed above and have the same advantages and disadvantages. For load nodes that are not equipped with PMU devices, they are not suitable.

Disturbances-based (low sampling rate)

Methods that do not require such a high sampling rate are combined in this category. They can be implemented on measurements from Supervisory Control And Data Acquisition (SCADA) systems and smart meters with a sampling frequency of 1 Hz and less. Generally, these methods allow to estimate only the static load model parameters.

Paper [46] describes the stages of load model parameter estimation: a data acquisition system, selection of appropriate measurements, spontaneous power fluctuations, choice of data window size, load recovery, filtering, signal smoothing, and so on. The proposed method allows to estimate the parameters of both static and exponential recovery load model from the data with the registration frequency of one measurement per second.

Paper [50] describes the results of the Customer Load Active System Services (CLASS) Project, implemented at 60 substations in the UK distribution network. The polynomial (ZIP) and exponential (EXP) static load models' parameters are estimated from measurements with a frequency of one measurement per second. The change of parameters depending on the season, day of the week is investigated. The results are compared with literary sources. The methodology described in [50] is only appropriate for substations where the transformer on-load tap-changers are in automatic mode and are switched 2-20 times per day. However, for example, today there are not many such substations under the conditions of the Russian power system, and this method is not appropriate for most nodes.

The recursive least square (RLS) method, [47] is used for the Conversation voltage reduction (CVR) factor estimation based on time with data measurements every minute throughout the full year. A Kalman Filter is used to identify dynamic load model parameter in [48]. The method of assessing the voltage sensitivity factor is presented in [49].

According to the authors, the methods assigned to this

Table 1. Classification of measurement-based approaches to load model identification by the method of obtaining the measurement data

	Approaches	References	Advantages	Disadvantages
Active approaches	A.Staged field tests	[3,8,10,14–18]	• wide voltage range; • load stability due to reduced experiment duration; • high reliability of the resulting model.	• difficulties in organizing of experiments; • models are developed using data measured during certain periods at specific locations, which lacks generalizability.
	B. Laboratory tests	[19–24]	• simplicity and flexibility in organizing of experiments; • possibility of obtaining models for individual devices.	• possibility of application to real power systems' aggregate loads is limited
Passive approaches (continuous field measurements)	C. Disturbances-based (high sampling rate)	[25–32]	• is appropriate for obtaining dynamic models.	• measurements with large disturbances are hard to obtain; • strict requirements for accuracy and sampling rate of measurements; • requires a PMU in the load node; • is not appropriate for SCADA or smart meter data.
	D. Online (real-time data)	[33–45]	• is appropriate for obtaining dynamic models; • real-time load model update.	• strict requirements for accuracy and sampling rate of measurements; • requires a PMU in the load node; • is not appropriate for SCADA or smart meter data.
	E. Disturbances-based (low sampling rate)	[46–50]	• is appropriate for SCADA or smart meter data; • is appropriate for obtaining static models; • allows to evaluate changes in the load model parameters with reference to time and other factors.	• event selection or using increments $(P_{i+1} - P_i)$ and $(V_{i+1} - V_i)$, i – moment of time; • high sensitivity to random load fluctuations; • strict requirements for measurement accuracy in terms of quantization error.
	F. Statistical-based (steady-state measurements)	[51–54]	• is appropriate for SCADA or smart meter data; • allows to evaluate changes in the load model parameters with reference to time and other factors; • reduction in the data requirements in terms of quantization error and sampling rate; • accuracy is achieved by increasing the sample size.	• requires clustering of measurements related to the same load composition and the operating mode of power consuming device; • requires a large amount of data; • is not appropriate for obtaining dynamic models.

category have at least one weak point from the following list:

1. The preprocessing algorithm includes event selection [46, 48–50];
2. Power increments $(P_{i+1}-P_i)$ and/or voltage increments $(V_{i+1} - V_i)$ (i – moment of time) are used during calculation [50];
3. The algorithm is based on an optimization procedure [46, 47].

The first operation imposes the requirement that the data contains voltage disturbances, which in some load nodes may be insignificant or very rare. The second and third operations make the algorithm sensitive to random power load fluctuations. Obtaining accurate load model parameter estimates using described methods is difficult with low-quality data with a high quantization error, a low sampling frequency and a high amount of noise [9].

Statistical-based approach

In contrast to the disturbances-based approach, there is another approach that can be called statistical-based. The basic idea is to abandon considering measurements as voltage disturbances and load responses; do not search for appropriate events; do not use increments and optimization methods. That is, in this case, the array of voltage measurements, active and reactive power is not considered as a sequential time series. Instead, the entire data set is considered as a statistical database of all possible load conditions. To identify measurements corresponding to the same load conditions, cluster analysis methods are used [53]. A similar approach is described in [51, 52].

Paper [51] describes a two-step combined approach. As a first step the parameters of an exponential model are calculated using the disturbances-based approach. The results of this calculation are used as input for the second approach by further filtering the data. Based on this input a more accurate ZIP model is calculated. The second step, described in the article, is very close to the one proposed. However, the EXP model obtained in the first step based on the disturbances-based approach is used for normalization.

In [52] a historical smart meter reading database collected from smart meters installed on the Georgia Tech campus is used for ZIP load model parameter estimation. Data rate is 1 measurement per 15 minutes. All measurements are clustered into three layers: the first layer is the type of the load, the second layer belongs to the time range, and the third layer is determined by the load conditions. In the second layer of clustering, the Kullback-Leibler divergence is used, in the third layer of clustering – the K-subspace method. A ZIP load model is obtained for each load type and each time period.

The approach to identifying the load model considered in [52] is very close to the proposed approach. Key issues that remain unresolved are the following:

- The authors note that more advanced data mining techniques are required to better capture the weak correlation between active power usage and system voltage to improve the P-V model accuracy.
- There is no assessment of the model accuracy and the confidence interval of its parameters.
- The technique was tested only on Georgia Tech campus data, and on individual types of consumers, is it appropriate for identifying aggregate loads in a large-scale power system?
- Data processing issues such as cluster and regression analyses, filtering, normalization, etc. are not described in sufficient detail.

Conclusion

The analysis of existing approaches to load model identification showed that most of them explicitly or implicitly place high demands on the quality of the source data. That includes the accuracy of measurements, the sampling rate, and the presence of voltage disturbances. At the same time, there exist large historical databases of measurements that have been accumulated using SCADA systems and smart meters that do not meet the specified requirements. The advantage of the statistical-based approach is that the reliability of the model is achieved not so much by increasing the quality of the original data, but rather by increasing the amount of data.

The statistical-based approach relies on pre-processing the original data in a way that highlights the characteristic load curves and separates the measurements according to statistical equilibrium load conditions.

The statistical-based approach is the least labour-intensive and is appropriate for the majority of nodes of a power system. There are no costly voltage stage tests, no load component tests, and no public surveys. In addition, the statistical approach allows for identifying an individual load model for each characteristic period of time and updating it periodically with minimal costs.

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