Load Model Identification using Steady-state Measurements for Power System Control

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Abstract. Power system control requires verified models of all its elements: generators, transformers, transmission lines, and power system loads. To identify load model parameters, the measurement data are used. The paper discusses the possibility of using steady-state measurements instead of staged field test data. This requires taking into account an unobvious effect - the network response. The network response is due to the probabilistic nature of the power and voltage changes and the correlation between them. The network response effect is demonstrated using a probabilistic load model and a simple power supply scheme.

1. Introduction

The role of information technologies in the electric power industry in process of development of electric power systems considerably increases. Measurement data processing is one of the key applications of information technology in the electric power industry [1]. To manage the power system and plan its conditions, it is necessary to have exact information about the parameters of the condition. Therefore, strict requirements are imposed on measuring devices and data processing methods. Significant uncertainty in defining the parameters of the condition and in performing calculations is brought in by load. This is due to frequent changes in production technologies and the power of connected devices.

To eliminate uncertainty and improve precision in the analysis of power flow in program complexes, it is customary to model the load using static load model (SLM) in voltage and frequency. Steady-state modes with a constant frequency close to the nominal frequency are considered. Therefore, the load simulation is performed only using SLM in voltage.

Currently, there are component-based approach and measurement-based approach of load model identification, which are discussed in detail in the [2-5]. The component-based approach involves a component-wise analysis of the test load and the selection of an appropriate model determined from statistical data. This approach of determining the load model has a significant error. This is because the models used don't take into account the current composition of the test load. The load composition may differ for different consumers of the same type due to differences in volumes and production technologies. Full accounting of the submitted data is not possible [6]. Often, the load nodes represented in component-based models of power systems are complex and include different types of devices at different voltage levels. This leads to the need for additional conversions in order to find an equivalent characteristic. Such conversions involve additional time-consuming calculations or a more detailed representation in the component-based model. This leads to a decrease in the calculation rate.
of the system-operating condition. For the reasons described above, the component-based approach SLM are currently rarely used.

Measurement-based approach, on the contrary, are highly accurate. This is due to the use of measurements obtained from the test load [6, 7]. In the measurement-based approach of load model identification, it is necessary to use large amounts of data for their processing. This is done to account for all possible load states.

Component-based approach of load model identification are usually divided into staged field test and steady-state measurements [8, 9]. In both cases, it is necessary to register the voltage values in the power supply node of the power system and the corresponding values of the real and reactive power of the load. This allows to define the nature of the dependence of the load power on the voltage. The difference is that in steady-state measurements, external interference in the operation of the power system is not performed. In staged field test realized a forced voltage variation in the load node in as much as possible wide limits.

Based on the presented features, can be identified fundamental differences in the processing of measurement-based data. Not all measurement-based data are suitable for the determination of SLM. The voltage and power of the load are more complex ratios than those reflected by the natural SLM. First, the load power is a random variable. It is constantly changing even at constant voltage [10]. The range and rate of random fluctuations in the load power depend on the type of consumers and can vary significantly. Secondly, the value of the voltage at the load node is also a random variable, correlated with the value of the load power. The voltage can change under the influence of external factors and due to fluctuations in the power of the test load. This implies not functional, but probabilistic dependencies. Precise accounting of these dependencies is very difficult.

In such circumstances, the question arises about the accuracy of the results obtained. Staged field test and steady-state measurements differ in their approach to ensuring accuracy [9]. In the case of staged field test, accuracy is achieved by reducing the duration of the experiment in time and increasing the voltage spread. The brief duration of the experiment allows to choose a period of time with minimal proper changes in the load power. Increasing the voltage spread improves the conditionality of the system of equations obtained by the method of least squares. In detail, the method of identifying SLM by voltage from the results of staged field test is considered in [3, 11-13]. As a model for the identification of SLM by voltage, the authors proposed to use polynomials of the second degree:

\[
P_L(V) = P_{BAS} \left( a_0 + a_1 \frac{V}{V_{BAS}} + a_2 \left( \frac{V}{V_{BAS}} \right)^2 \right),
\]

\[
Q_L(V) = Q_{BAS} \left( b_0 + b_1 \frac{V}{V_{BAS}} + b_2 \left( \frac{V}{V_{BAS}} \right)^2 \right),
\]

\( P_L(V), Q_L(V) \) – the calculated values of real and reactive power of load; \( P_{BAS}, Q_{BAS} \) – real and reactive power values corresponding to the reference voltage \( V_{BAS} \); \( a_0, a_1, a_2, b_0, b_1, b_2 \) – coefficients of SLM voltage polynomials in relative units.

In a general way the problem of determining the SLM from the data of an staged field test does not have a strict solution. This is due to the lack of a priori information about the two components of power. The first is stipulated by response of load to supply voltage change. The second is caused by random fluctuations in the load power [6].

At conducting staged field test the system-operating condition parameters are forcibly changed. This is a disadvantage. Such interference can negatively affect a power system dependability as a whole [12, 14]. In steady-state measurements, the approaches of increasing accuracy are not applicable. Duration of experiment is measured in days, weeks, months, and even years. In this case, the voltage spread is limited by natural fluctuations. The fluctuations don’t exceed 2-3%. It reduces
precision of definition SLM based on the data steady-state measurements. Due to the small voltage spread, it is difficult to precisely identify the SLM voltage by polynomials of the second degree. For this reason, linear SLM are determined according to steady-state measurements [15]:

\[
P_L (V) = P_{BAS} \left[ a_0 + a_1 \frac{V}{V_{BAS}} \right],
\]

\[
Q_L (V) = Q_{BAS} \left[ b_0 + b_1 \frac{V}{V_{BAS}} \right].
\]

Precision in the case of steady-state measurements is ensured by increasing the sample size. In a sufficiently large volume of data, the load is represented in all its possible conditions [16]. The laws of change of random variables manifested more accurately. This makes it possible to use the methods of probability theory and mathematical statistics to determine SLM [17, 18]. The selection of individual states with their partition laws can be carried out using cluster analysis, as shown in works [19-21].

During the steady-state measurements, the load changes are random [8, 10]. The works [10, 22] provide information on the forecasting of power consumption. The authors recognize that for the vast number of consumers random load changes are subject to the normal partition law of probability. In this case, the measurement-based data will be a Gaussian mixture. The Expectation Maximization (EM) algorithm can be used to cluster them [19].

Another significant difference of staged field test and steady-state measurements is the impact of effect, which is called the "network response". The network response is described in detail by Yu. E. Gurevich in his early [23, 24] and later works [8]. The network response is understood as a change voltage of the supply node under the influence of a change load power. This change is due to the presence of resistance that connects the load to the external network.

Further the approach of processing the results of steady-state measurements is considered and the impact of the network response on the results of processing the data of a steady-state measurements is described.

The results of staged field test and steady-state measurements are the vectors of the measured values of voltage \( V \), real \( P \) and reactive \( Q \) of load power. The differences between the results are in the number of measurements. For steady-state measurements, due to the longer duration, the number of measurements is greater.

\( V, P, Q \) are interdependent random variables that form a system \((V, P, Q)\) or two systems of random variables \((V, P)\) and \((V, Q)\). In this paper, we will restrict to consideration of a system of random variables \((V, Q)\). It is described by the following parameters [17]:

- \( m_V, m_Q \) – expected values;
- \( \sigma_V, \sigma_Q \) – standard deviations;
- \( r \) – correlation coefficient;

Consider the case of a unimodal distribution. The system of random variables \((V, Q)\) is completely determined by the expected values \((m_V, m_Q)\) and the covariance matrix (5):

\[
K = \begin{pmatrix}
D_V & K_{VQ} \\
K_{VQ} & D_Q
\end{pmatrix} = \begin{pmatrix}
\sigma_V^2 & r \sigma_V \sigma_Q \\
\sigma_V r \sigma_Q & \sigma_Q^2
\end{pmatrix},
\]

\( D_V \) and \( D_Q \) – the variance of the values \( V \) and \( Q \), respectively, \( K_{VQ} \) – correlation moment.

At graphical displayed on plains in coordinates \((V, Q)\) the system of random variables \((V, Q)\) represents an dispersion ellipse centered at a point \((m_V, m_Q)\) (Figure 1).
Figure 1. Dispersion ellipse

The dispersion ellipse has four characteristic straight lines, that intersect in the dispersion center. These are two symmetry axes of an ellipse that make up the angles with the abscissa axis. They are defined by expression (6):

$$\tan 2\alpha = \frac{2r\sigma_y \sigma_Q}{\sigma_Q^2 - \sigma_y^2}. \quad (6)$$

Equation (6) gives two values of the angles $\alpha$, $\alpha_1$, which differ from each other by 90°. The other two straight lines are the regression lines $Q$ on $V$ and $V$ on $Q$. The angles of inclination of the regression lines to the abscissa axis are accordingly determined by the equations (7), (8):

$$\tan \alpha_Q = \frac{\sigma_Q}{\sigma_y}, \quad (7)$$

$$\tan \alpha_V = \frac{1}{r} \frac{\sigma_Q}{\sigma_V}. \quad (8)$$

The tangent of the slope of the regression line $Q$ on $V$ corresponds to the steepness coefficient of the linear SLM in the named units $B_1$. The coefficients $B_1$ and $b_1$ are related by the equation (9):

$$B_1 = b_1 \frac{Q_{BAS}}{V_{BAS}}. \quad (9)$$

If there is no linkage between $V$ and $Q$, then $r = 0$, the ellipse symmetry axes are parallel axes of the coordinate system. The regression lines coincide with the axes.
2. Network response

Let's illustrate impact of network response on the results of data processing of steady-state measurements. Consider a simple load power supply scheme shown in Figure 2.

![Figure 2. A simple power supply scheme](image)

Let us assume that a purely inductive load $Q$ is powered from infinite buses with a constant voltage $V_{SYS}$ through a purely inductive resistance $jX$. The voltage at the load node $V$ and the value of reactive power consumed $Q$ are related by the equation (10):

$$Q(V) = \frac{V(V_{SYS} - V)}{X}. \tag{10}$$

The graphical dependence $Q(V)$ is an inverted parabola with a vertex at the point $(V_{SYS}/2, V_{SYS}^2/4X)$. It intersects the abscissa axis at points 0 and $V_{SYS}$ (Figure 3).

The operating range of the curve is the range $(V_{SYS}/2, V_{SYS})$. There is no voltage drop on the resistance $X$, therefore at $Q=0$, $V=V_{SYS}$. As the reactive power of the load $Q$ increases from 0 to $V_{SYS}^2/4X$, the voltage $V$ decreases up to the value $V_{SYS}/2$. A further increase of power $Q$ is impossible, because the function transits through its maximum.

![Figure 3. Network response](image)

At the operating point $(m_V, m_Q)$, the network response graph will have a negative slope, determined by the equation (11):

$$\left.\frac{dQ}{dV}\right|_{V=V_c} = \frac{V_{SYS} - 2m_V}{X} = \frac{m_Q}{m_V} = \frac{m_Q}{X}. \tag{11}$$

If the load was connected immediately to infinite power buses with no intermediate resistance, i.e. $X=0$, then $V=V_{SYS}$ for any $Q$ values. In this case, the vertex of the parabola rushes to infinity. The tangent at the point $(m_V, m_Q)$ passes vertically. The value, inverse to value of the derivative, which is calculated by equation 11, corresponds to the network response. Let's denote it by the variable $k$. 
The network response \( k \) distorts a dispersion ellipse. The regression line \( Q \) on \( V \) ceases to coincide with the SLM characteristic [8]. In the staged field test, the voltage changes in a wider range, and the power – on the contrary, less appreciable than in steady-state measurements. Therefore, in staged field test, the effect of the network response is practically not appears.

In the neighborhood of a point \((m_V, m_Q)\) (Figure 3), the impact of the network response \( k \) can be approximately considered the linear functional dependencies (12) - (13), which correspond to the tangent

\[
V(Q) = k(Q - m_V) + m_V, \quad (12)
\]
\[
Q(V) = \frac{V - m_V}{k} + m_Q. \quad (13)
\]

3. Conclusion
Load modeling is an important component of the power system control task. The identification of the load model parameters based on the steady-state measurement data is possible when taking into account the probabilistic nature of the power and voltage changes and the effect of the network response. The effect of the network response is demonstrated by using the simple power supply scheme.

The method for processing steady-state measurements should include two operations:
1. To identify measurements corresponding to the same load conditions, cluster analysis methods should be used.
2. The effect of network response should be considered.

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