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A Statistical-Based Approach to Load Model Parameter Identification

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ABSTRACT In the last few years, a great number of methods for identifying the load model parameters have been proposed. This article discusses the use of statistical approach to estimate the substation equivalent load model parameters for supplying to oil-producing industrial region. The disadvantages of existing statistical approach are the low accuracy obtained for the parameter estimates, especially when using samples size is small. To eliminate this deficiency, the current measurement data archive from SCADA system of electrical parameters for 15 months was collected. For the purpose of verifying the obtained results of statistical processing of SCADA data, a full-scale experiment was carried out in relation to the studied substation. The article describes the statistical method used to process the current SCADA measurement data, the results of archived statistical processing and experimental SCADA data. The electrical load models' parameters received from the experimental studies results are of practical importance.

INDEX TERMS Load modeling, power system, power system study, static load model, ZIP model.

I. INTRODUCTION

In order to effectively manage power grid modes, it is necessary to have adequate models for each element that is included in it. Because of the sheer numbers, diversity and fickle nature of electrical loads, their modelling is the greatest challenge. This task has attracted and continues to attract a great deal of attention from researchers and engineers around the world. Traditionally, there are two approaches to identifying load models [1]–[4]: component-based approach. Here, we consider in detail the measurement-based approach. Hereby consider the second of them in more detail. Its idea is to identify the load model and evaluate its parameters using the measured voltage and power values. The classification of methods for identifying load models from measurement data is given in [5]–[9].

There are staged field tests [10]–[13], laboratory tests [14], [15], disturbances-based [16]–[21] and statistical-based approaches. Each of these approaches has its own field of application, requirements for the organization of the experiment and the quality of measurements. Staged field tests require the organization of experiments with interventions in the power supply by consumers. The advantage of this approach is its high accuracy; the disadvantage is the impossibility of experimental covering for all existing loads in all their possible states.

Laboratory tests are designed to produce accurate models of individual electrical receivers. In the future, a detailed

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model of their electricity supply scheme and computational experiments are required to obtain a generalized (aggregate) load model.

Disturbance-based methods use load responses to voltage supply indignations. These methods are based on complex mathematical algorithms and allow for the identification of dynamic load models. Their use is limited by high demands on the presence of voltage indignations and the quality of measurements.

Statistical-based approach involves the accumulation of a large number of voltage and power measurements. The accuracy of the resulting models is achieved by the help of mathematical statistics methods. This approach does not require experiments, voltage indignations and is much less dependent on the quality of measurements. In addition, the statistical-based approach allows you to identify the most likely load states and get a model for each of them.

The article describes the statistical method, used for processing current operating mode parameters of collected data from power system to obtain estimates of load model parameters. The method is based on the ideas presented in the works [7], [22], [23]. A fragment of Unified Energy System of Russia with a predominant share of oil industry (about 90 %) was selected for testing. The experiments results related to both the forced change in the voltage on substation tires and statistical processing of archived SCADA data are presented. The conducted survey was organized as follows:

- Selection of power system area for conducting the survey and its coordination with the System operator.
- Data collection of electrical parameters current measurements from all substations in the survey area.
- Improvement of the existing statistical methods for processing measurement data, taking into account the collected measurement data features (voltage quantum up to 0.105 kV; power 0.12 MW Mvar).
- Drawing up a program for conducting a full-scale experiment on forced voltage changes in the survey area. Performing the calculation of electrical modes in order to prevent the emergency situations occurrence during the experiment.
- Processing and analysis of measurement data collected. A detailed description of survey area is provided in section 3. The initial data obtained by observing the load conditions of studied substations are described in section 4. Section 5 contains processing results of current observations data. Section 6 contains the results obtained during the full-scale experiment execution with a forced change in supply voltage.

II. THE STATISTICAL-BASED APPROACH

A. LOAD MODEL

Existing load models are presented in [24], and their recommended parameters are described in [25]. Traditionally, static and dynamic load models are distinguished. In this work, only the static load model is considered, since:

- to identify a dynamic load model, you must have measurements with a high sampling rate of PMU;
- static load model is easier to identify and use in calculation than dynamic one;
- according to the results of the international survey, the static model has the widest practical application (assuming constant + ZIP + exponential models) for steady-state analysis – 100 %, dynamic studies – 70 %;
- paper [26] shows the possibility of using nonlinear static models for transient stability studies;
- according to [27] static model can be easily combined with dynamic models to form composite models.

In this study the static load model in the form of a first (1) and a second (2) degree polynomial was used (constant Z, constant I, constant P or ZIP model):

$$P = P_n \left(b_{P,0} + b_{P,1} \frac{V}{V_n} \right) \tag{1}$$

$$P = P_n \left(b_{P,0} + b_{P,1} \frac{V}{V_n} + b_{P,2} \left(\frac{V}{V_n} \right)^2 \right) \tag{2}$$

where P – active power drawn by the load; P_n – rated active power; V_n – rated voltage; $b_(P, i)$ – load model parameters in per units.

The model represented by a first-degree polynomial will be called the linear model, and the model represented by a second-degree polynomial will be called the ZIP model. Hereinafter, the equations for reactive power are similar.

B. STATISTICAL EQUILIBRIUM LOAD NODE CONDITIONS

The statistical approach is based on the analysis of measurements obtained by passive observation of the object of study [7], [22], [23]. One of the difficulties is clustering of measurements related to different load compositions in use. In this case, we are talking about operation modes of both individual devices and network elements of internal power supply network of consumers. To solve this problem, it is proposed to estimate the load model parameters for some statistical equilibrium condition of the aggregate load.

Such a statistical equilibrium condition is characterized by a quasi-steady operation mode of individual devices forming part of aggregate load. The statistical equilibrium load condition may include measurements related to different time periods. Between these time periods, the load is either in other statistical equilibrium conditions or in a transient mode.

The load model corresponding to a given statistical equilibrium condition remains practically unchanged. Preliminary separation of the entire data on statistical equilibrium conditions allows to solve the problem of ambiguity and variability of the load models in time. Therefore, it is possible to estimate the parameters of the load models for each statistical equilibrium condition. This allows to set your own unique model parameters for each time interval (for example, 30 minutes) during the practical calculations.

An aggregate load is a set of different power consumers, which leads to an increase in the number of statistical equilibrium conditions. The probability of finding an aggregate load in a statistical equilibrium condition primarily depends on the cyclic processes of human activity and technological cycles of industrial equipment. There is no point in considering all possible statistical equilibrium load conditions, it suffices to limit the most probable of them for a given time interval. This allows to simplify the task of aggregate load model identification.

C. MEASUREMENT CLUSTERING

To separate the measurement data arrays by statistically equilibrium states, we used the idea of applying cluster analysis to the measurement data described in [7]. In contrast to [7], the Bayesian estimation of a Gaussian mixture clustering algorithm from the skikit-learn library was used. Described in more detail in [22], [28].

Let the probability of the emergence of a new point of measurement data be described using a mixture of distributions:

$$\mathbb{P}(\mathfrak{X}) = \sum_{i=1}^{M} \alpha_i \cdot \mathbb{P}_i(\mathfrak{x}_{\mathrm{i}})$$

where $\mathfrak{X}$ – measurement data set; $\mathfrak{x}_{\mathrm{i}}$ – measurement data subset, related to statistical equilibrium condition i; M – amount of statistical equilibrium conditions; $\mathbb{P}_i(\mathfrak{x}_{\mathrm{i}})$ - probability of aggregate load being in condition i; α_i – a fraction of subset $\mathfrak{x}_{\mathrm{i}}$ in set $\mathfrak{X}$.

Let the probability $\mathbb{P}(\mathfrak{X})$ be described using some additive function:

$$f(\mathfrak{X}) = \sum_{i=1}^{M} \alpha_i \cdot f_i(\mathfrak{x}_{\mathrm{i}})$$

Let $\mathbb{P}_i(\mathfrak{x}_{\mathrm{i}})$ obey the Gaussian distribution. Then, to obtain the function parameters, it is necessary to estimate:

- mean of each distribution i;
- dispersion of each measurement data subset $\mathfrak{x}_{\mathrm{i}}$;
- fraction of α_i;
- the amount of mixture components M.

In case of general assumptions, the EM algorithm converges to a local optimum. The quality of such a solution and its degree of convergence, however, are influenced considerably by the initial estimate. The convergence gets worse when there is an attempt to connect a number of components within one group of measurements or to allocate them between these groups [28]. In order to solve this problem, it is proposed to complete a number of calculations (from 20 to 40 simulations) with different initial estimates, and as a result to choose the solution corresponding the greatest likelihood value.

In order to use the cluster data analysis methodology on an automatic basis it is required preliminarily to set a quantity of clusters on which a sample will be divided in. So as to overcome this obstacle a variational estimation of the number of clusters based on the Dirichlet process [29] can be used.

D. PROPOSED ALGORITHM OF STATIC LOAD MODEL IDENTIFICATION USING THE STATISTICAL-BASED APPROACH

The algorithm of static load model identification using continuous field measurements of voltage and active and reactive power is based on the ideas outlined in [7], [23]. The proposed algorithm consists of three steps: data collection and pre-processing, measurement clustering into statistical equilibrium load conditions, and load model identification.

1) STEP 1. DATA COLLECTION AND PRE-PROCESSING

This step includes the collection and separation of data by month of the year and daily intervals, and the subsequent grouping of data according to characteristic load curves.

Data separation by characteristic load curve is necessary for several reasons. Firstly, it allows to reduce the number of statistical equilibrium conditions in one sample and leads to simpler algorithmic solutions at the stage of cluster data analysis. Secondly, to solve the problem of predicting the load model, it is necessary to have information about which daily time intervals and days of the week the identified load models can be used for.

The need for averaging and the averaging time interval depend on the accuracy of the source data in terms of quantization and aperture errors and the nature of the change in load power and supply voltage.

2) STEP 2. MEASUREMENT CLUSTERING

This step includes the normalization of measurement data and the search for statistical equilibrium load conditions.

Before using the cluster analysis algorithm to search for statistical equilibrium load conditions, it is necessary to perform data normalization [30]. This is necessary to ensure that the measurement units of power and voltage do not affect the results of clustering. Data normalization was performed by the Min-max normalization algorithm.

The obtained normalized data is fed to the input of the statistical equilibrium load conditions search algorithm, described in section C. After the estimates of the accessory tags of each measurement to a particular cluster are obtained, one can proceed to the stage of estimating the parameters of the load models from the original non-normalized measurement data set.

3) STEP 3. LOAD MODEL IDENTIFICATION

This step includes:

1) the preparation of a variety of load models;
2) the load model parameter estimation in absolute units;
3) the normalization of obtained load model parameter estimations;
4) the filtering of statistically insignificant models;
5) the averaging of load model parameter estimations for statistical equilibrium load conditions related to the same time interval of one daily characteristic load curve.

One of the difficulties in load modeling is the determination of the type of model, especially in the cycle of automated processing of measurement data. To solve this problem, at the first stage, a number of possible types of load models have been composed into set M.

At the next stage of calculations, the load model parameters are estimated for each model from the set M. Parameter estimation is based on the ordinary least squares technique (OLS) [31].

It should be noted that it is impossible to directly use the OLS technique to estimate model parameters (1) and (2) due to the fact that the values of the rated load power P_n and Q_n for each of the statistical equilibrium load condition are unknown. Therefore, the model parameters were firstly evaluated in absolute units:

$$P = \left(a_{P,0} + a_{P,1} \cdot V\right) \tag{3}$$

$$P = \left(a_{P,0} + a_{P,1} \cdot V + a_{P,2} \cdot V^2\right) \tag{4}$$

where a_i – load model parameters in absolute units. Then the model parameters are found by the method of ordinary least squares in absolute units.

To obtain load model parameter estimates in per unit values, it is necessary to perform normalization. For each statistical equilibrium load condition, load model parameter estimates were obtained in per unit values:

$$b_i = a_i \cdot \frac{1}{P_n} \cdot V_n^i, \quad i \in \overline{0 \ldots N} \tag{5}$$

where N - load model polynomial degree.

The estimation of the rated power value in each statistical equilibrium condition was obtained as follows:

$$P_n = \sum_{i=0}^{N} \left(a_{P,i} \cdot V_n^i\right). \tag{6}$$

The rated voltage V_n of the aggregate load node is predefined and corresponds to the voltage value that the load model reduces to. Usually value V_n is taken equal to the voltage level.

Thus, parameters of each model from the set M are estimated for each statistical equilibrium condition. Statistically insignificant models are rejected based on an assessment of statistical significance (F-test).

Taking into account the errors of measuring systems and small load fluctuations, the dispersion of load model parameter estimates can be quite large. In other words, the error in estimating the load model parameters for a single statistical equilibrium condition is significant and the obtained parameter estimates are not applicable in the power system models. The accuracy of model parameters estimates can be improved in the case of a large number of statistical equilibrium conditions with a close load structure. In this case, instead of individual estimates, their expected values should be used.

The resulting estimates of the parameters of all load models are calculated by averaging all the remaining parameter estimates corresponding to the same time interval of one characteristic daily load curve:

$$\mathbb{E}(b_i) = \frac{1}{L} \sum_{j=1}^{L} b_j, \tag{7}$$

where $\mathbb{E}(b_i)$ – resulting estimate of load model parameter i, $i \in \overline{0 \ldots N}$; L – number of statistical equilibrium conditions.

It is important to emphasize that only load model parameter estimates for statistical equilibrium conditions belonging to the same time interval of one characteristic daily load curve can be averaged.

III. OBJECT UNDER STUDY

As the object of study, the load of the nodal substations 110 kV Substation 1 and Substation 2 were chosen. A 110-500 kV electrical circuit of the study subsystem is shown in Fig. 1. The 500 kV power network is highlighted in red, 110 kV in blue, 35 kV in brown, and 6 kV in green. This part of the electrical network has a connection with the Unified Energy System of Russia on the 500 kV and 110 kV lines, and also has two power plants: one with an installed capacity of 1 830 MW (6 × 305 MW), and the second with an installed capacity of 8 MW.

There are two step-down transformers (with capacity of 25 MVA each) supplying 35 and 10 kV loads at Substation 1 and Substation 2. The main share of the transformers' load is made up of pumps of oil producing installations, there is also a small share of residential load (about 3 %). The total maximum load level of Substation 1 and Substation 2 is about 40 MW.

The task of applying the statistical-based approach is to obtain static load models of an aggregate load, which is powered by 110 kV buses of substations 1 and 2 via step-down transformers T1 and T2.

The peculiarity of the 6-35 kV electric network is the radial structure of the network. This leads to the fact that each step-down transformer connected to the 110 kV network has its own load. The load of each transformer has its own unique properties. Consequently, the task of load model identification must be solved for each transformer separately.

The measurements were carried out on the high voltage side of the transformers T1 and T2, the measurement points are shown in Fig. 1.

The approximate active power consumption curve over time for one oil producing installation is shown in Fig. 2. It is clearly seen that most of the time, this device is in the active power consumption mode, which is variable in time, and a small part of the time in the mode of active power generation. The shape and period of the curve shown in Fig. 2 depend on the depth at which oil is pumped, and the setting of the pump mechanical system. In the studied part of the power system, oil pumps are driven by asynchronous motors without automatic control systems. It is necessary to note that the pumping unit generates active power due to the partial recuperation of the pumping jack motion kinetic energy.

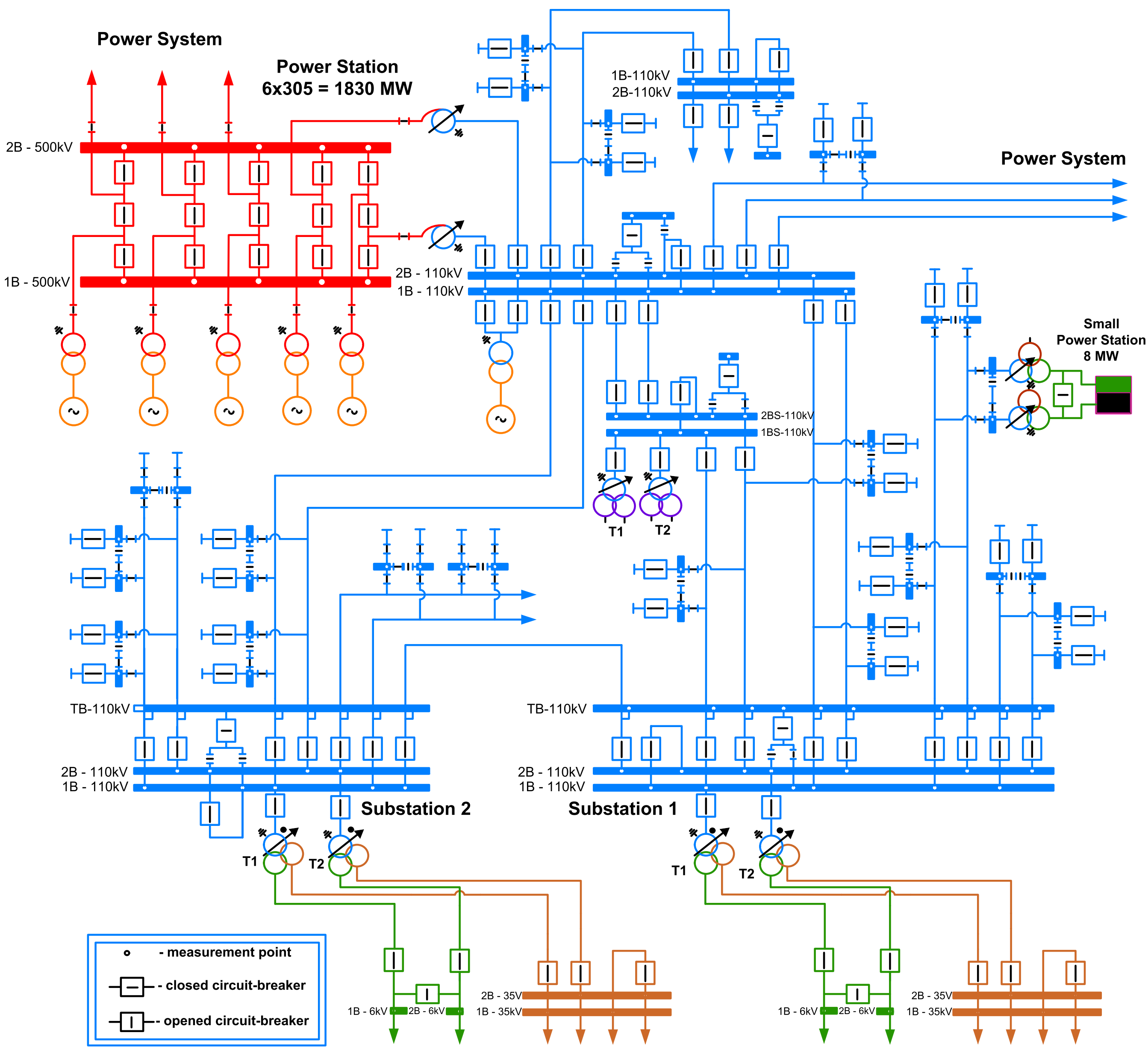

FIGURE 1. Part of the Power System of Russia used in experimental investigations.

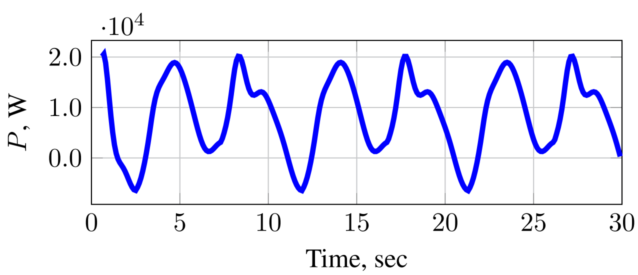

FIGURE 2. Approximate active power curve for a single consumer within the oil industry.

If we take this single individual device as the object of study, then the task of identifying a static load model has no practical meaning. This is due to the fact that power consumption changes over time, and consequently the model parameters will constantly change. For each separate extraction unit, it would be more appropriate to use a dynamic load model.

However, hundreds of such extraction units are connected to the buses of the considered 110 kV Substation 1 and Substation 2. Random power fluctuations of individual devices are not correlated; therefore, their dynamic characteristics are neglected in total. This fact allows to make the assumption that there is a quasi-steady state of the node with aggregate load. In this case, the presence of active power generation periods by extraction units is also neglected. This is due to the fact that all the energy is redistributed in the electric network (35; 10; 6 and 0.4 kV) and generated energy does not flow into the 110 kV supply network.

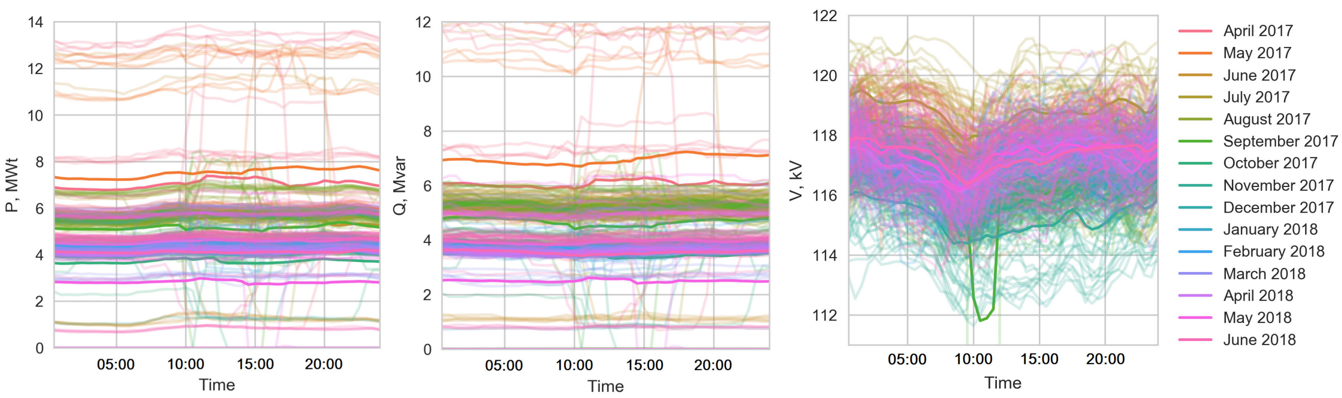

FIGURE 3. Daily voltage, active and reactive power curves, Substation 2, T2 110 kV.

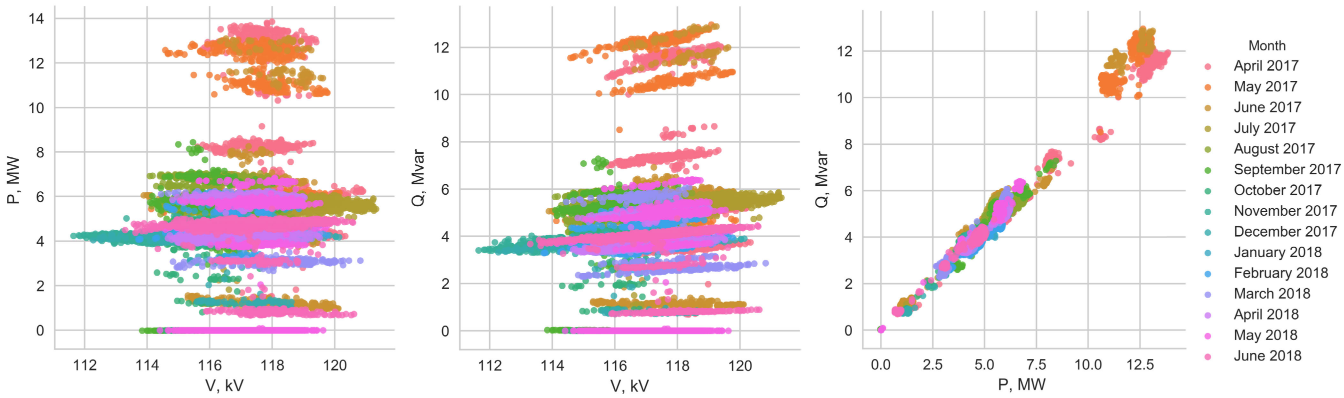

FIGURE 4. Average half-hour voltage, active and reactive power values, Substation 2, T2 110 kV.

IV. FIELD MEASUREMENT

To estimate load model parameters, arrays of telemetry data consisting of voltage and active and reactive power that were received through the SCADA system to the dispatching center of the System operator throughout 15 months were used. Telemetry data on the 110 kV side of the step-down transformers of Substation 1 and Substation 2 was used. Telemetry data consists the values of voltage, active and reactive power, averaged over a time interval of one second. The sampling depth was 15 months, which amounted to approx $39.4 \cdot 10^6$ data points for each telemetry data channel. The voltage quantum value is 0.105 kV, the power quantum value is 0.12 MW and 0.12 Mvar. The maximum error in estimating the timestamp of each second measurement is up to 200 ms, and the average is about 100 ms. The total amount of data was about 120 GB for all substations of the power subsystem under study.

The composition in use and operation mode of the studied group of devices may not change for extended period of time (up to several days). This is clearly seen in the active and reactive power consumption daily curves shown in Fig. 3. Pale lines indicate daily curves, and bright lines highlight the average daily curve for the month. Small fluctuations of the residential load of these substations are within one quantum of power and voltage, therefore, the measured values of voltage, active and reactive power may not change over long periods of time (minutes). The rise and fall of power consumption in Fig. 3 is mainly caused by the 6 and 35 kV network maintenance diagrams. Significant power deviations mainly occur when the network elements are undergoing maintenance outage, when the load is switched between 110 kV bus sections of substation or when the load is transferred over a 6 and 35 kV network to adjacent 110 kV substations.

Any change in the adjacent 110 kV network (operation mode and composition in use of devices, composition in use of network elements, etc.) will cause a change in the magnitude of the supply voltage on the buses of the substations under study. The presence of long-time intervals of the quasi-steady-state operation mode of the load under study allow to use all (even insignificant) changes in the external electrical network to obtain the information necessary to identify load models.

Points in Fig. 4 indicate voltage, active and reactive power measured values of the transformer T2 averaged over the half-hour interval. Points corresponding to different months are depicted in different colors.

V. STATIC LOAD MODEL IDENTIFICATION

A. STEP 1 - DATA COLLECTION AND PRE-PROCESSING

Measurement data was not divided into typical daily load curves due to the fact that the share of residential loads is

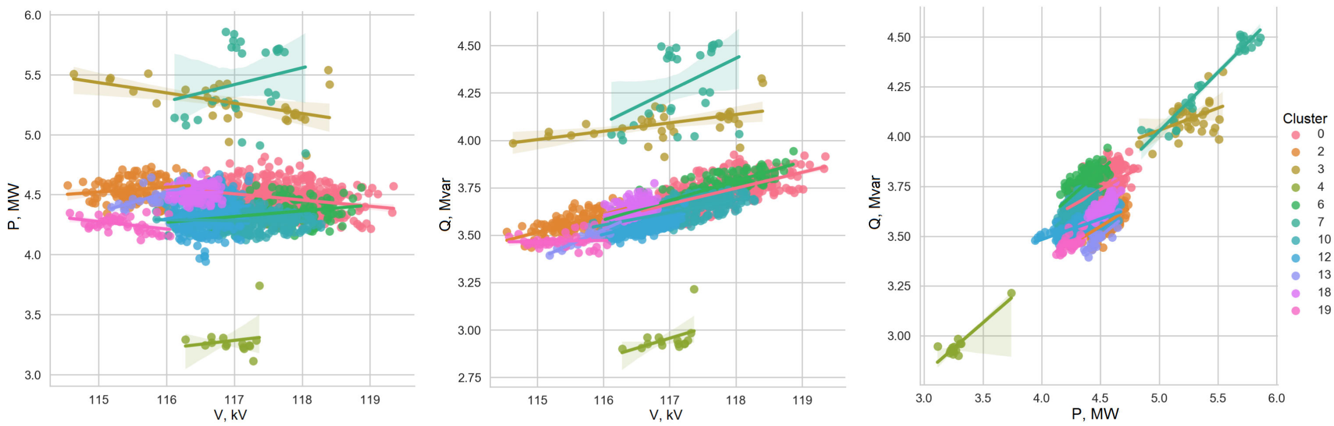

FIGURE 5. Results of measurement data clusterization for T2 on Substation 2, january 2017.

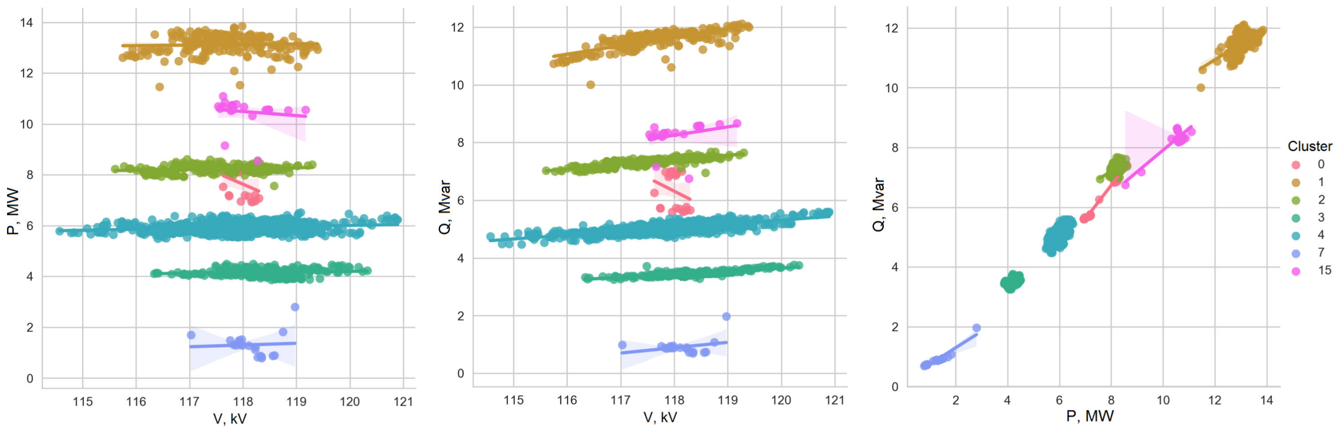

FIGURE 6. Results of measurement data clusterization for T2 on Substation 2, april 2017.

insignificant, and the total load of extraction units has a uniform load curve. Also, seasonal changes in power consumption were not taken into account due to their insignificance.

Measurement data was divided into monthly intervals. This is necessary to reduce the number of clustering errors during the search for statistical equilibrium load conditions. Measurement data clustering error reduction means that the individual statistical equilibrium load conditions become more distinct and it is easier to draw boundaries between them using monthly slices. This effect can be seen comparing the entire 15-month sample presented in Fig. 4 for the load of transformer T2 of Substation 2, and the results of clustering according to January 2017 Fig. 5 for the transformer T2 of the same substation.

In this example, the averaged half-hour values presented in Fig. 4 are selected for further calculations. For practicability, averaging and averaging time interval are chosen assuming that a significant number of small parameters changes are present within one quantum, and the same measured parameter value can be repeated many times in a second data set. It is necessary to reduce the temporal discreteness and the value of the quantum of measurements, in the case of reducing of time intervals of the aggregate load node presence in a statistical equilibrium condition.

B. STEP 2 - MEASUREMENT CLUSTERING

Each month interval of active and reactive power measurements was normalized using the Min-max normalization algorithm. After that, the normalized month arrays were input to the statistical equilibrium load conditions search algorithm.

An example of cluster analysis results for the transformer T2 of Substation 2 is shown in Fig. 5 and 6. The lines show the results of a point estimate of the linear load model for each of statistical equilibrium load conditions that were found. Presented sets of clusters have gaps in the numbers. This is a consequence of the operation of the variational cluster determination algorithm. The software implementation of the algorithm in the library Scikit-learn that was used starts with the maximum possible number of clusters (set manually) and gradually reduces their number by combining several clusters. The Fig. 6 shows that cluster 0 is erroneous, since it does not represent a statistical equilibrium load condition, but is formed by parts of two statistical equilibrium conditions and data points showing the transition from one state to another. Most of these clusters will be filtered in the next step by a F-test or simply using a threshold filter with the minimum required number of points in the cluster.

Practical calculations for processing the results of clustering showed that the F-test at the next stage of calculations

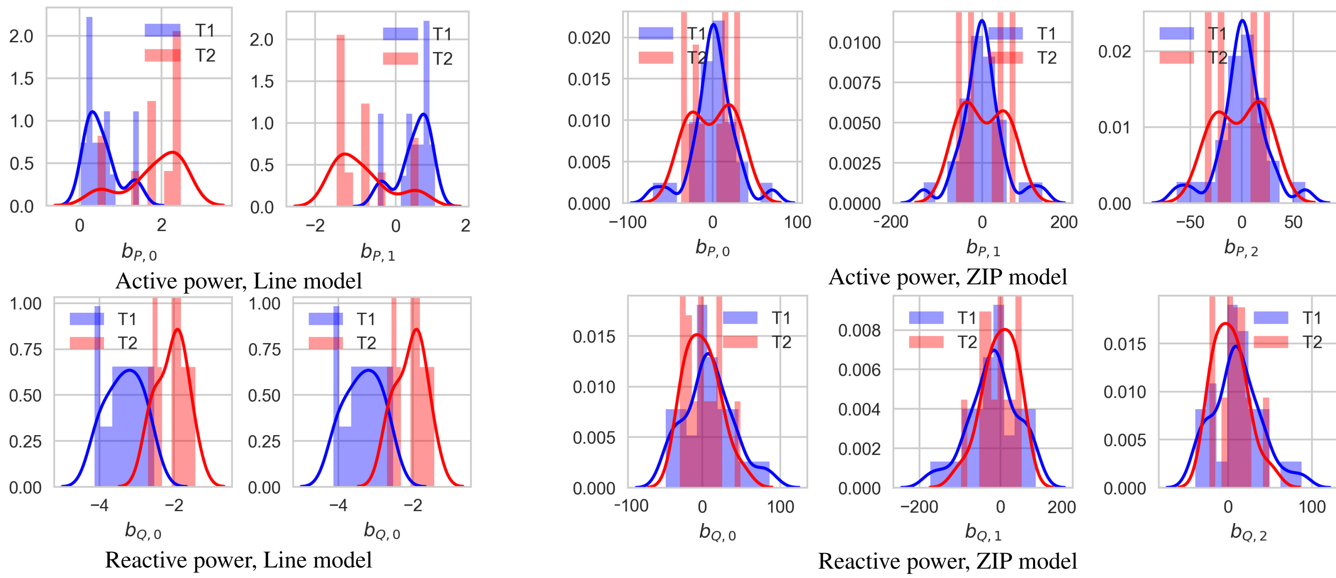

FIGURE 7. **Distribution histogram of load model parametrs in statistical-based approach for Substation 2.**

does not always allow to reject erroneous clusters, especially in cases when there are a small number of points in them. To solve this problem after data clustering, a threshold filter was used, which neglects all clusters containing less than 50 points. The minimum number of points was determined experimentally based on a series of calculations. Given that each point corresponds to a half-hour interval, the load must be in equilibrium for more than a day. However, due to the fact that the sampling depth is rather large and the power consumption curve is close to uniform, this filter can be used. By the criterion of the minimum required number of points, clusters 7 and 15 were also neglected (Fig. 6).

During practical testing of the proposed approach to the processing of measurements, it was revealed that a large number of statistically equilibrium states found have a voltage swing of only 2-3 kV, which is only about 2.3 % of the rated voltage.

C. STEP 3 – LOAD MODEL IDENTIFICATION

An estimation of the load model parameters from the set M was made for each cluster remaining after the threshold filter. Due to the fact that the data normalization algorithm did not use the nominal values P_n, Q_n and V_n, but the maximum ones over the one-month interval, the original arrays in absolute units were used to estimate the load model parameters, taking into account the resulting cluster markers. Then, all obtained model parameter estimates in absolute units were converted to per units.

The share of residential load is insignificant and all found statistical equilibrium load conditions correspond to one general uniform characteristic load curve. Therefore, all parameter estimates of the load models M can be combined into one set. The frequency distribution histograms of the model parameter estimates are shown in Fig. 7. Then the resulting model parameter estimate will correspond to the expectation of the entire set of parameter estimates for each model.

The estimate of the confidence interval for each resultant coefficient is based on the analysis of the parameter distribution histogram. Let the confidence level be 95 %, then the estimate of the confidence interval is reduced to the calculation of percentiles: 2.5 % and 97.5 %.

The estimates and confidence intervals of the load models parameters in per units, obtained using the statistical-based approach, are presented in tables 1, 2, 3 and 4.

VI. VALIDATION BY STAGED FIELD TEST

The verification of the results obtained using the statistical-based approach was carried out on the basis of a staged field test specially conducted on the power subsystem under study. It was held in September 2018, in the second half of a weekday. The duration of the experiment was slightly less than two hours. Voltage regulation in the power subsystem was carried out by sequential voltage changes on 110 kV buses of Power Station by adjusting the reactive power (excitation) of synchronous generators. The generators participating in the tests worked according to the active power dispatch load curve. All operations associated with the sequential change in the reactive power of the generators were performed in accordance with a previously developed experiment program.

During the test, the transformer T2 was put into repair at Substation 2, with a large share of the load transferred to the transformer T1 and a small share of the load to adjacent 110 kV substations. Therefore, in the field test at Substation 2, only the model parameters of the load supplied from T1 were estimated. The parameters of the load model supplied from T2 were not estimated.

The range of voltage variation in the power subsystem under study is limited by the highest allowable operating voltage, the adjusting range of generator excitation systems, and the voltage stability. in this case, it was 116–124 kV (rated voltage level is 110 kV). The change of the voltage and power during the field test is shown in Fig. 8 and 9.

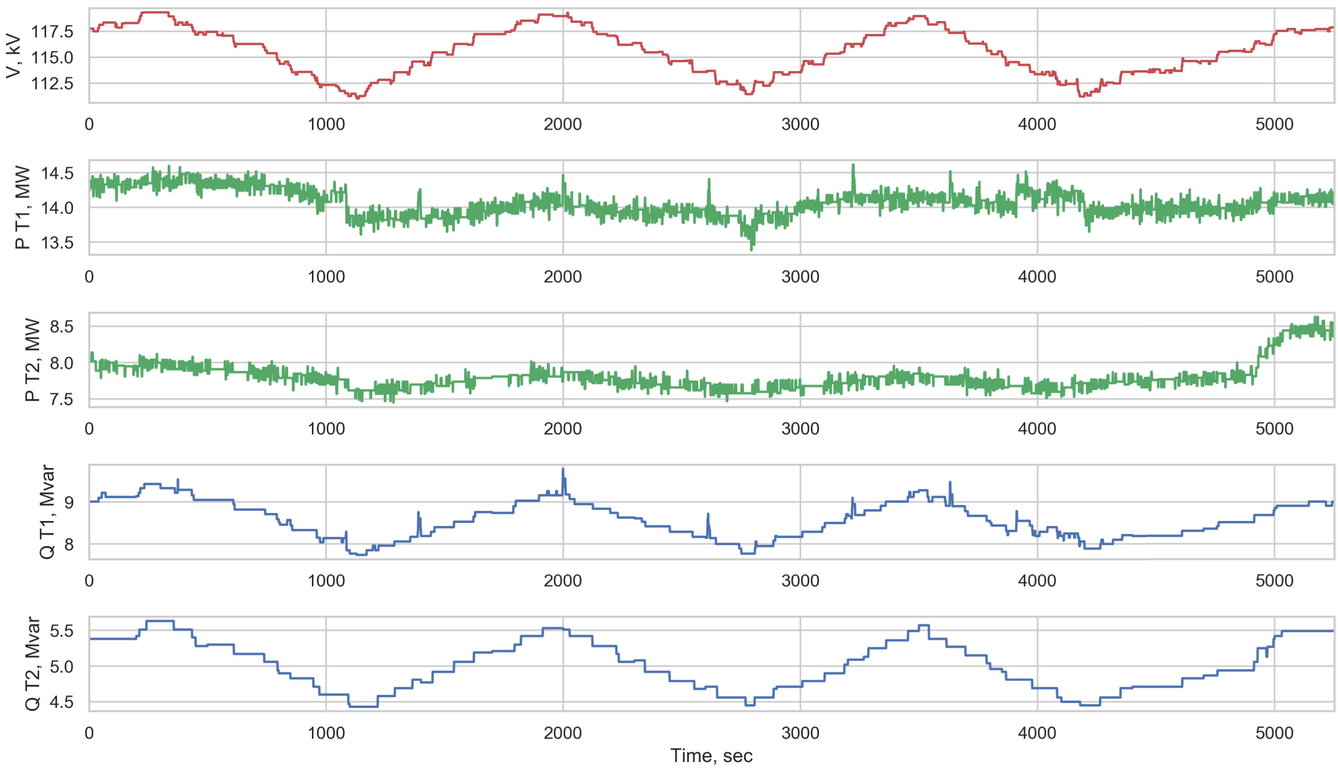

FIGURE 8. The change of the voltage and power during the field test, Substation 1.

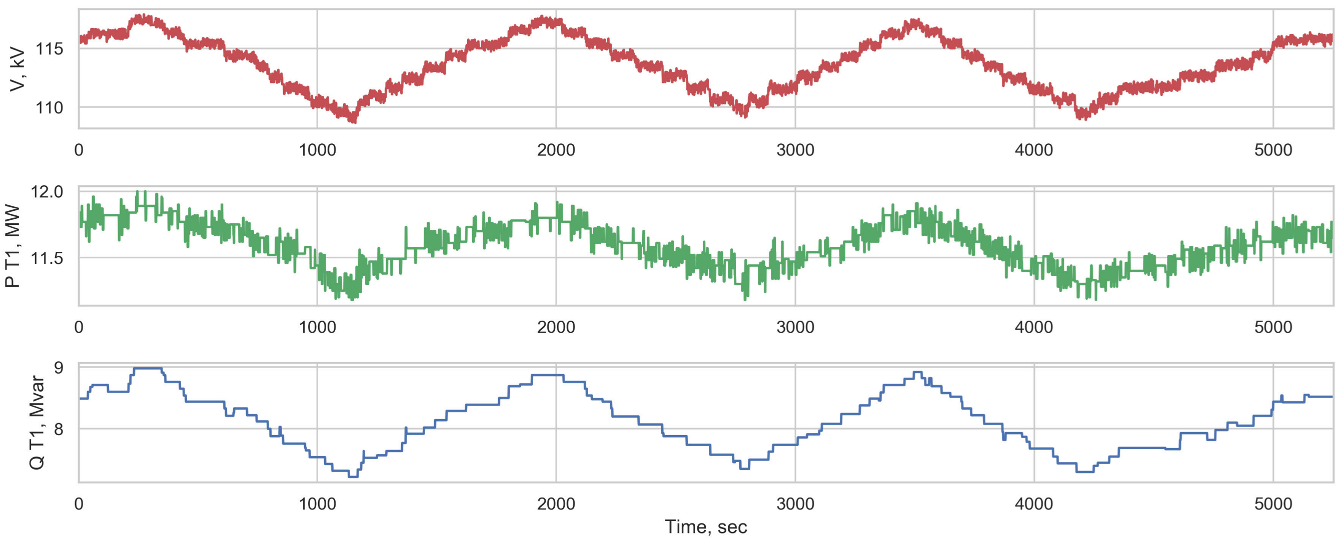

FIGURE 9. The change of the voltage and power during the field test, Substation 2.

The figures clearly show that changes in the active and reactive power of the load correlate well with supply voltage fluctuations. This conclusion is confirmed by the scatter plots presented in Fig. 10 and 11. The results of field test data processing are presented in tables 1, 2, 3 and 4. The confidence intervals of the load model parameters were estimated on the basis of T-criterion with confidence level 95 %. in per units for Substation 1 and Substation 2 is shown in Fig. 12.

Dotty assessment of static load characteristics obtained during the Field Test are located within the confidence interval of assessments based on SCADA data. At the same time, dotty assessments on the results of field tests and statistical approaches are close.

VII. RESULTS AND DISCUSSION

A comparison of the results obtained using the statistical approach with the results obtained using staged field test shows the following:

- In all cases, the confidence intervals of the load model parameters in field test are less than in the statistical-based approach.

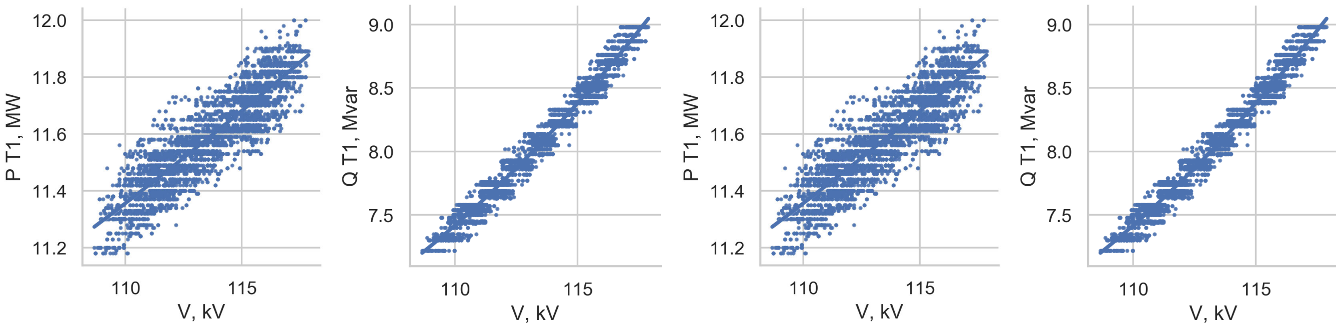

FIGURE 10. Dependencies of active and reactive power on voltage during the field test, Substation 1.

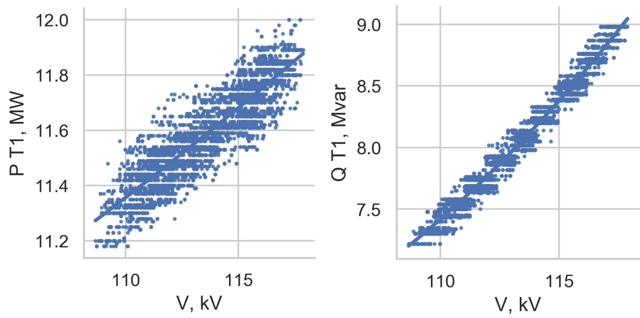

FIGURE 11. Dependencies of active and reative power on voltage during the field test, Substation 2.

TABLE 1. Line load model parametrs for active power.

Active power, Substation 1

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{P,0}$	0.59	$(+0.40$ to $+0.73)$
T1	Stat.	$b_{P,1}$	0.42	$(+0.27$ to $+0.60)$
T1	Test.	$b_{P,0}$	0.70	$(+0.68$ to $+0.72)$
T1	Test.	$b_{P,1}$	0.30	$(+0.29$ to $+0.32)$
T2	Stat.	$b_{P,0}$	0.69	$(+0.50$ to $+1.19)$
T2	Stat.	$b_{P,1}$	0.31	$(-0.19$ to $+0.50)$
T2	Test.	$b_{P,0}$	0.49	$(+0.47$ to $+0.50)$
T2	Test.	$b_{P,1}$	0.51	$(+0.50$ to $+0.53)$

Active power, Substation 2

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{P,0}$	0.55	$(+0.09$ to $+1.39)$
T1	Stat.	$b_{P,1}$	0.46	$(-0.39$ to $+0.91)$
T1	Test.	$b_{P,0}$	0.36	$(+0.35$ to $+0.37)$
T1	Test.	$b_{P,1}$	0.64	$(+0.63$ to $+0.65)$
T2	Stat.	$b_{P,0}$	1.82	$(+0.47$ to $+2.46)$
T2	Stat.	$b_{P,1}$	-0.82	$(-1.46$ to $+0.53)$

Notes: Stat. – statistical-based approach; Test. – staged field test

TABLE 2. Line load model parametrs for reactive power.

Reactive power, Substation 1

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{Q,0}$	-3.09	$(-3.93$ to $-2.28)$
T1	Stat.	$b_{Q,1}$	4.09	$(+3.28$ to $+4.93)$
T1	Test.	$b_{Q,0}$	-1.65	$(-1.67$ to $-1.63)$
T1	Test.	$b_{Q,1}$	2.65	$(+2.63$ to $+2.67)$
T2	Stat.	$b_{Q,0}$	-3.13	$(-3.83$ to $-2.62)$
T2	Stat.	$b_{Q,1}$	4.13	$(+3.62$ to $+4.83)$
T2	Test.	$b_{Q,0}$	-2.86	$(-2.88$ to $-2.84)$
T2	Test.	$b_{Q,1}$	3.86	$(+3.84$ to $+3.88)$

Reactive power, Substation 2

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{Q,0}$	-3.34	$(-4.10$ to $-2.60)$
T1	Stat.	$b_{Q,1}$	4.34	$(+3.60$ to $+5.10)$
T1	Test.	$b_{Q,0}$	-2.02	$(-2.03$ to $-2.00)$
T1	Test.	$b_{Q,1}$	3.02	$(+3.00$ to $+3.03)$
T2	Stat.	$b_{Q,0}$	-2.06	$(-2.66$ to $-1.48)$
T2	Stat.	$b_{Q,1}$	3.06	$(+2.48$ to $+3.66)$

- In most cases, the field test parameter estimates are in the confidence intervals of the statistical-based approach.
- The expected values of model parameter estimates, obtained with the statistical-based approach, are quite close to the parameter estimates obtained using field test. In the case of Substation 2, where during the field test most of the load was transferred to the transformer T1, its coefficients during field test are close to the arithmetic mean values of the coefficients for T1 and T2 in the statistical-based approach.
- With the statistical-based approach, the linear model confidence intervals are significantly shorter than the ZIP model confidence intervals.
- According to different transformers of different substations, the model parameters are quite close to each other, but not exactly equal. This may be due to both small differences in the load structure, and the error of model parameter estimates.
- For the transformer T2 of the Substation 2, the active power load model has a negative slope, which is due to the large length of the 6-35 kV distribution network and a small load value. This leads to the fact that in the total load of the transformer T2 a large share is occupied by the heat losses of wires and cables. Therefore, when the voltage drops, losses in the 6-35 kV network grow faster than the load decreases.

This allows to draw the following conclusions:

- the staged field test with all its shortcomings allows to obtain the most reliable model of the load for a given period of time and composition of the load, which is

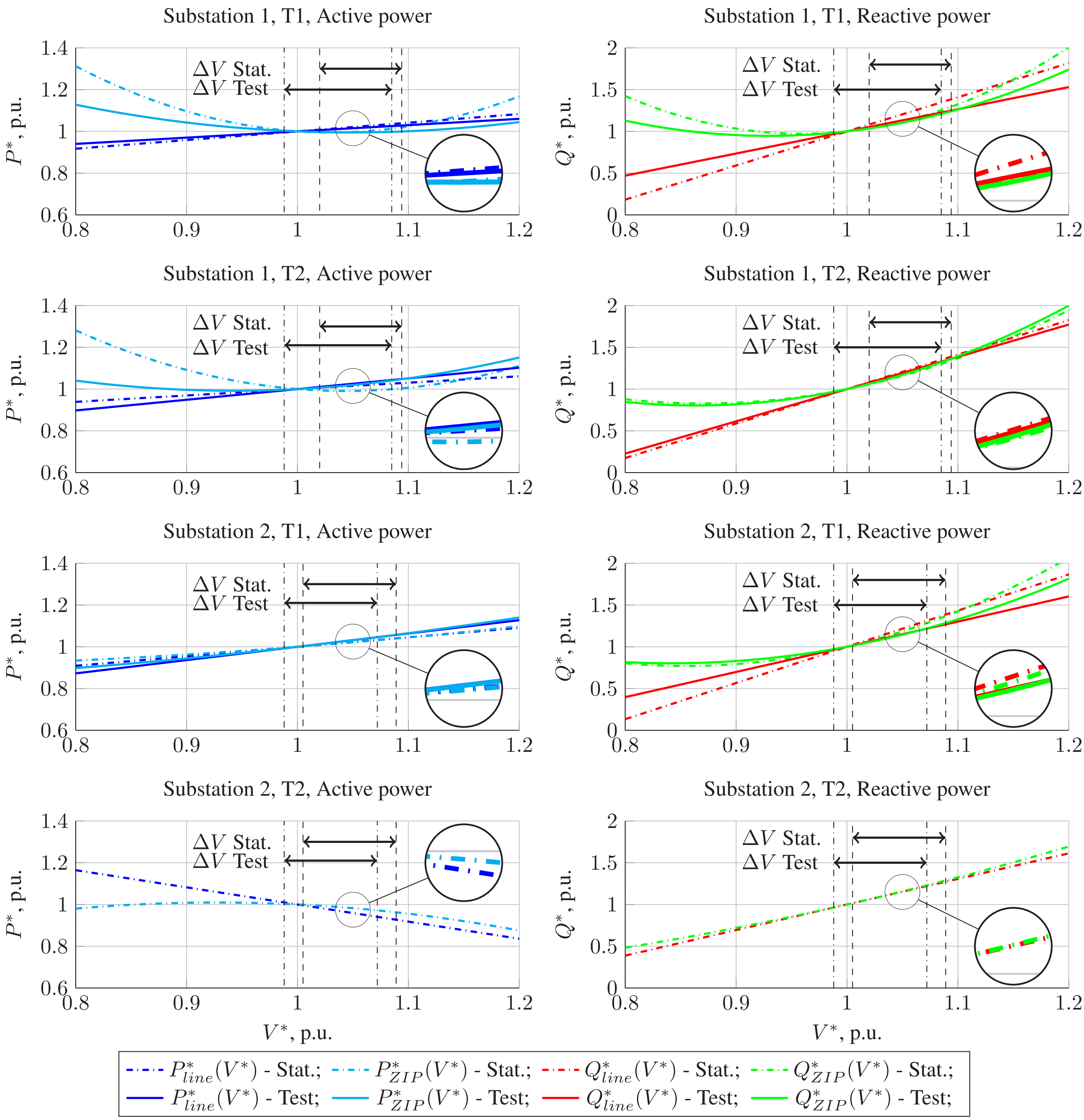

FIGURE 12. Comparison of collected load models in p.u. (Stat. – statistical-based approach; Test – staged field test).

achieved by increasing the range in which the voltage changes;

- the statistical-based approach, having obviously less accuracy, nevertheless, allows to make an estimate of load model parameters and to make their confidence intervals estimation;
- for similar but not identical in composition loads, the parameters of the models in the absolute units may differ significantly, however, after converting to per units, these differences are usually not significant.

If the dependence of load power on voltage is rather flat, then parameter higher than the first-degree polynomials may not be statistically significant. This fact is clearly seen when comparing the obtained confidence intervals of linear and ZIP models for active power in tables 1 and 3. At the same time, the staged field test gives the estimates of ZIP load model parameters $\mathbb{E}(b_i)$, which are close to the results of the statistical-based approach. This allows to use ZIP load model parameters obtained using statistical-based approach in power flow analysis.

TABLE 3. ZIP load model parametrs for active power.

Active power, Substation 1

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{P,0}$	7.36	(−7.55 to +26.06)
T1	Stat.	$b_{P,1}$	−12.35	(−47.68 to +15.67)
T1	Stat.	$b_{P,2}$	6.00	(−7.13 to +22.62)
T1	Test.	$b_{P,0}$	3.06	(+2.14 to +3.99)
T1	Test.	$b_{P,1}$	−4.51	(−5.98 to −2.45)
T1	Test.	$b_{P,2}$	2.15	(+1.31 to +2.99)
T2	Stat.	$b_{P,0}$	6.33	(−28.39 to +32.19)
T2	Stat.	$b_{P,1}$	−10.23	(−58.97 to +55.57)
T2	Stat.	$b_{P,2}$	4.90	(−26.18 to +27.78)
T2	Test.	$b_{P,0}$	3.12	(+2.21 to +4.03)
T2	Test.	$b_{P,1}$	−4.51	(−6.26 to −2.76)
T2	Test.	$b_{P,2}$	2.40	(+1.56 to +3.23)

Active power, Substation 2

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{P,0}$	0.99	(−58.54 to +45.70)
T1	Stat.	$b_{P,1}$	−0.39	(−85.30 to +112.90)
T1	Stat.	$b_{P,2}$	0.40	(−53.36 to +40.74)
T1	Test.	$b_{P,0}$	0.87	(+0.39 to +1.35)
T1	Test.	$b_{P,1}$	−0.34	(−1.27 to +0.59)
T1	Test.	$b_{P,2}$	0.47	(+0.02 to +0.92)
T2	Stat.	$b_{P,0}$	−0.54	(−35.55 to +32.30)
T2	Stat.	$b_{P,1}$	3.35	(−58.21 to +70.65)
T2	Stat.	$b_{P,2}$	−1.81	(−34.11 to +27.41)

TABLE 4. ZIP load model parametrs for reactive power.

Reactive power, Substation 1

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{Q,0}$	17.39	(−7.81 to +42.65)
T1	Stat.	$b_{Q,1}$	−34.23	(−81.22 to +12.81)
T1	Stat.	$b_{Q,2}$	17.84	(−4.00 to +39.57)
T1	Test.	$b_{Q,0}$	10.33	(+9.20 to +11.46)
T1	Test.	$b_{Q,1}$	−20.19	(−22.34 to −18.04)
T1	Test.	$b_{Q,2}$	10.86	(+9.83 to +11.88)
T2	Stat.	$b_{Q,0}$	8.60	(−37.19 to +41.58)
T2	Stat.	$b_{Q,1}$	−17.87	(−81.46 to +70.45)
T2	Stat.	$b_{Q,2}$	10.27	(−32.26 to +40.88)
T2	Test.	$b_{Q,0}$	8.68	(+7.49 to +9.87)
T2	Test.	$b_{Q,1}$	−18.23	(−20.52 to −15.95)
T2	Test.	$b_{Q,2}$	10.56	(+9.46 to +11.65)

Reactive power, Substation 2

Trans	Exp.	Koef	$\mathbb{E}(b_i)$	95% CI
T1	Stat.	$b_{Q,0}$	7.38	(−43.98 to +76.35)
T1	Stat.	$b_{Q,1}$	−18.47	(−147.70 to +81.21)
T1	Stat.	$b_{Q,2}$	10.81	(−36.24 to +72.35)
T1	Test.	$b_{Q,0}$	6.40	(+5.59 to +7.20)
T1	Test.	$b_{Q,1}$	−13.29	(−14.84 to −11.73)
T1	Test.	$b_{Q,2}$	7.89	(+7.14 to +8.65)
T2	Stat.	$b_{Q,0}$	0.18	(−26.93 to +40.76)
T2	Stat.	$b_{Q,1}$	−1.38	(−79.75 to +48.99)
T2	Stat.	$b_{Q,2}$	2.20	(−21.06 to +39.99)

Each aggregate load is characterized by its own unique load model. This fact is confirmed by the results of processing experimental data for two substations with a similar load structure, but different configurations and the length of the 6–35 kV power supply network.

It is necessary to have as wide voltage range as possible to obtain statistically significant load model parameter estimates. In this case, the wider the voltage range, the smaller the confidence intervals of the load model parameters will be and the higher the probability of identifying more complex relationships between power and voltage.

Concluding the discussion of the results, we would like to highlight the scope of the proposed approach. The statistical-based approach works quite well on the aggregate load nodes, in which the load is in one statistical equilibrium condition for enough time periods. But, for example, an attempt in the same way to process continuous measurements data of the substation that feeds an automobile plant assembly line was unsuccessful. This is due to the fact that the sharply variable nature of the load allows to obtain the power system reaction, but does not give any information about the load model. It is possible that the use of more complex data processing algorithms for each statistical equilibrium condition of the load, in comparison with OLS, will solve this problem.

VIII. CONCLUSION

The experiments results showed that static load characteristics determination is fundamentally possible on the basis of voltage current measurements, active and reactive power. The use of the statistical method makes it possible to analyse the available data of SCADA systems using modern methods and Data Science software packages.

The area of the electric grid selected for experimental studies contains about 90 % of the load in the oil industry. A characteristic feature of this load is a uniform load curve. This allows us to sufficiently accumulate large amounts of current measurement data for the close composition of individual electrical receivers in the network under study. This makes it possible to accumulate large arrays of measurement data for close switched-on composition and operational mode of individual electric receivers in the distribution network of 0.4 . . . 6 kV. At the same time, the question of the possibility of using a statistical method for an electric load, which include the composition and mode of operation of which changes during the day (for example, utility load), remained unexplored.

In this investigation:

- The possibility of using a statistical approach to solve the problem of estimating the load models parameters based on archived SCADA data is shown.
- The load models parameters obtained from statistical processing results of archived SCADA data (tables 1, 2, 3 and 4) are presented.
- The shortcomings of the statistical approach for processing archived SCADA data are revealed; i.e., the inability to predict the load actual behavior at large voltage deviations, and the significant difficulties in collecting

statistical information for the load with sharp variable behavior.

When processing the archived data, the most reliable results were obtained only for the case of linear load model. This is due to the small-supply voltage on substation tires under survey during the day.

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