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Original research paper

Non-Technical Losses Detection in Power System

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Abstract: The digitization of distribution networks enables the collection of big data from which it is necessary to draw conclusions and detect anomalies among electricity consumers. This paper explains methodologies to detect non-technical losses, commercial losses, and electricity theft. Based on monthly electricity consumption measurements, possible and prevalent cases of anomalies and theft among consumers are identified. Indicators that can detect anomalies have been proposed for such types of load diagrams. The sensitivity of the indicators to different types of consumers was analyzed. The applicability of this methodology was examined for a set of real measurements, and its advantages were pointed out. This concept represents a good recommendation, as it is possible to observe and detect irregularities in electricity consumption.

Keywords: non-technical losses (NTL), smart meter, energy theft detection, power system.

INTRODUCTION

The goal of every energy system is the safe transmission and distribution of energy with minimal losses. Losses in the distribution electricity network can be divided into technical and non-technical losses. Technical losses are calculated using well-known methods, while non-technical losses can't be easily and clearly detected and evaluated. Non-technical or commercial losses are the result of measurement inaccuracy, incomplete readings of metering devices, non-simultaneous readings, improper control of metering points, irregular meter calibration, untimely detection of unauthorized consumption, insufficient technical equipment of teams to work on customer control, insufficient training of readers and controllers of metering devices, insufficient support and assistance (of the law) after the detection of unauthorized consumption, unauthorized use of electricity on various grounds of unregistered consumption (electricity theft from existing customers and "wild" connections of new customers), error in the operation of measuring devices (delay in balancing customers' meters, malfunctions of meters and measuring transformers), and error in the reading and calculation of electricity. [1]

The review papers [2–5] presented the possibilities of applying a large number of measurements at Distribution System Operators (DSO) and smart grid in order to detect non-technical losses, commercial losses, and electricity theft. Reference [6] presents an intelligent energy meter that provides solution for maintaining power quality, provides superior metering and billing system, and also controls power theft. The research paper

[7] presents prevention of power theft in distribution system using smart hardware device. Three latest gradient boosting classifiers are used for smart grid energy theft identification in the paper [8]. A data analytic approach with false data injection is present in paper [9]. An IoT solution for electricity theft prevention is presented in [10]. Two methodologies based on artificial intelligence present stacked sparse denoising autoencoder [11] and support vector machine [12] for electricity theft detection.

The detection of non-technical losses, commercial losses, and electricity theft is not defined by international standards or internal standards and recommendations of the DSO. In all DSOs within the framework of Industry 4.0, mass digitization is launched, and as many data as possible is collected. In research papers, possible methods of detection and examples of detection of energy losses and electricity theft are presented. However, a comprehensive method and a clear algorithm for detection have not been defined.

This paper provides explanations related to the measurement of electricity consumption. The main load diagrams, energy consumption, as well as main parameters are explained, and multi-day load charts are analyzed. Based on that, the parameters that are important for the detection of anomalies in electricity consumption were observed: coefficient of variation, ratio between peak and valley load, load rate, valley coefficient, daily load variance, and equivalent time. The mentioned parameters are calculated for a normal energy consumption state and states with different types of anomalies: peak random anomaly, on-off anomaly, time random anomaly, and anomaly of decreasing peak. For these types of anomalies, the parameter bounding values are calculated. The algorithm is proposed to detect anomalies based on the analysis of the given parameters.

The paper is organized as follows. Section 2 presents the concept of smart grid and smart meters. In section 3, a load diagram is presented and an overview of the most significant parameters is given. Section 4 shows the results of electricity measurement for consumers where there are no anomalies and for specific consumers where there are special cases of anomalies. Section 5 provides the algorithm for detection and threshold values for parameters with results. Conclusions of the research are derived in Section 6.

SMART GRID AND SMART METERS

A smart grid is a power grid that uses analog and digital information and communication technologies in order to increase the reliability of electricity supply. One of the main components of the smart grid is definitely the communication network and accompanying sensors and measuring devices. Two-way communication between a utility and its consumers is a prerequisite for the smart grid. This communication enables advanced metering and control options, and it is known as the Advanced Metering Infrastructure (AMI). In addition to AMI, data management is very important. Namely, when big data is collected, it has to be properly stored and utilized. Data can be used for many purposes, and detection of electricity theft (non-technical losses) is one of them. Currently, AMI provides physical and wireless connections, bidirectional metering and billing, data storage and management, detection and diagnostics of system faults, and end-to-end communication.

Some of the most important goals of AMI implementation are:

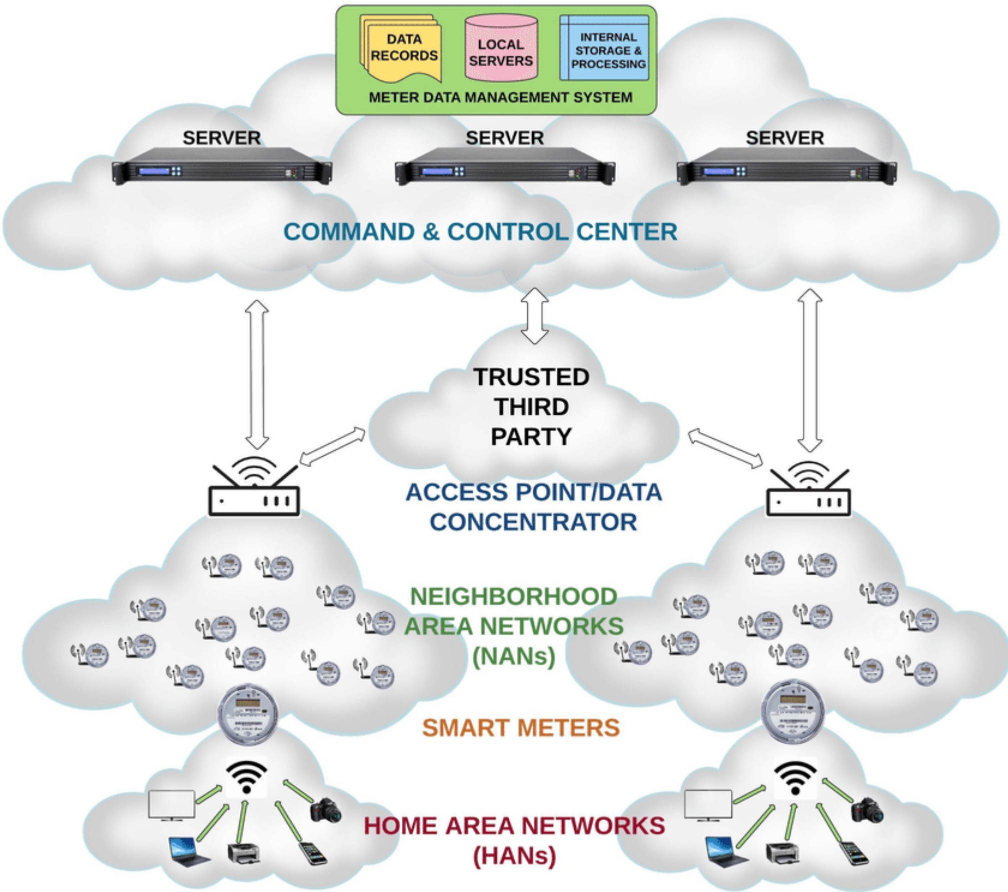


Figure 1. *Architecture of AMI.*

- Reduction of meter reading expenses;
- Increasing the accuracy of measurements;
- Expediting billing;
- Enabling centralized control of customers;
- Reducing non-technical losses; and
- Increasing network reliability.

The main parts of AMI are smart meters, data concentrators, and data management centers. Figure 1 shows the simple architecture of the AMI system.

POWER LOAD DIAGRAM AND INDICATORS

The daily load diagram presents dependence between power and time. Talking about time, load diagrams appear as daily, weekly, monthly, and yearly charts. The basis of all these diagrams is the daily load diagram, whose shape depends on several factors: the nature of the consumer area, the share of individual consumers in a certain consumer group area, the season (summer, winter), and other factors [1]. The daily load diagram can be estimated as the average measured value within 15, 30, or 60 minutes. It is characterized by three basic indicators: maximum daily load (*Pmax* [kW]), minimum daily load (*Pmin* [kW]), and total daily consumed energy (W [kWh]). Other characteristic indicators are defined from the basic indicators:

$$P_{mean} = \frac{W}{24} \tag{1}$$

$$m = \frac{W}{24P_{max}} \tag{2}$$

$$T = \frac{W}{P_{max}} \tag{3}$$

$$n = \frac{P_{min}}{P_{max}} \tag{4}$$

where P_{mean} is the daily mean load, m is the daily load factor , T is the maximum power utilization time, and n is the ratio of daily minimum and maximum.

Measurement data was taken from more than a thousand smart meters in a part of a distribution network that comprises mostly households. According to the collected data, seven-day hourly diagrams are given in Fig. 2.

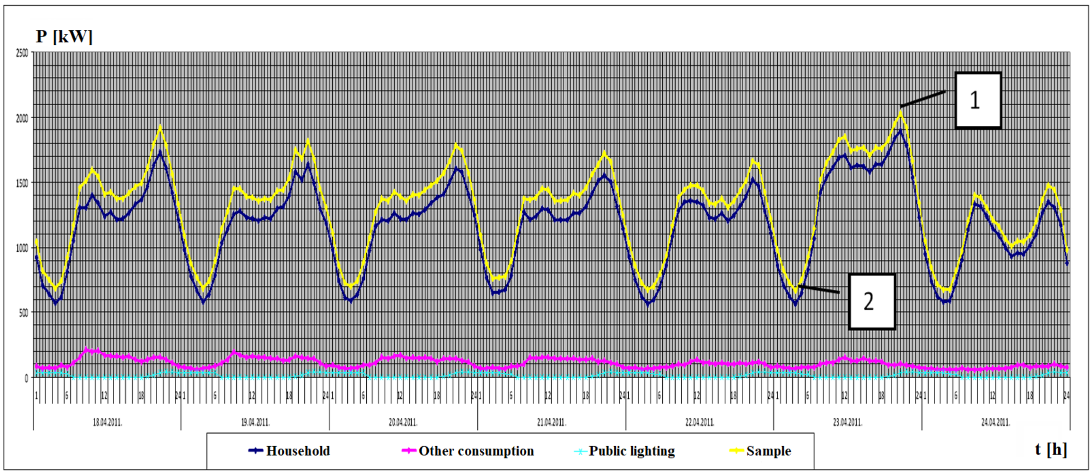


Figure 2. *Weakly load diagrams.*

For the sampled data, the highest daily maximum load for consumption at the sample level is 2027.64 kW (point 1), and the lowest daily maximum is 1474.89 kW, with a relative ratio of 0.73. The mean power value at the sample level is 1295.75 kW, while the relative ratio of minimum and maximum power is 0.33.

The problem with DSO is that the digitization of the network is not complete, and a large number of consumers do not have smart meters. Because of that, data is available only with monthly consumption readings. It is necessary to detect anomalies in the data collected in this way, and this is a specific problem. Figure 3 shows the monthly energy consumption over a period of seven years. In that case, it is necessary to observe the annual load diagram shown in Fig. 4. Such an annual load diagram can be compared with previous annual diagrams and diagrams of neighboring consumers in the same category. The diagram in Fig. 4 refers to three arbitrary users, and it is concluded that the diagram must be normalized with the maximum energy or mean energy over the observed time interval. Data processing was performed in Matlab [13].

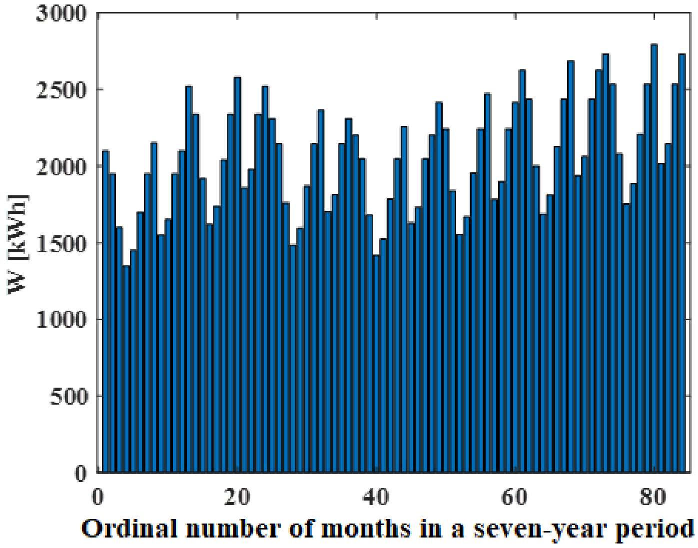


Figure 3. *Monthly load diagrams.*

In Fig. 4 (the normalized diagram), different load failures and different user behaviors can be observed. For these reasons, quantifiers were calculated for a set of 237 users. In order to observe the monthly consumption of different consumers, new quantifiers, shown in Table 1, will be introduced. The behaviors and values of the quantifiers depend on the load diagram. Excessive quantifier deviation for some users from other users will indicate the existence of an anomaly. This analysis is present in Section 5.

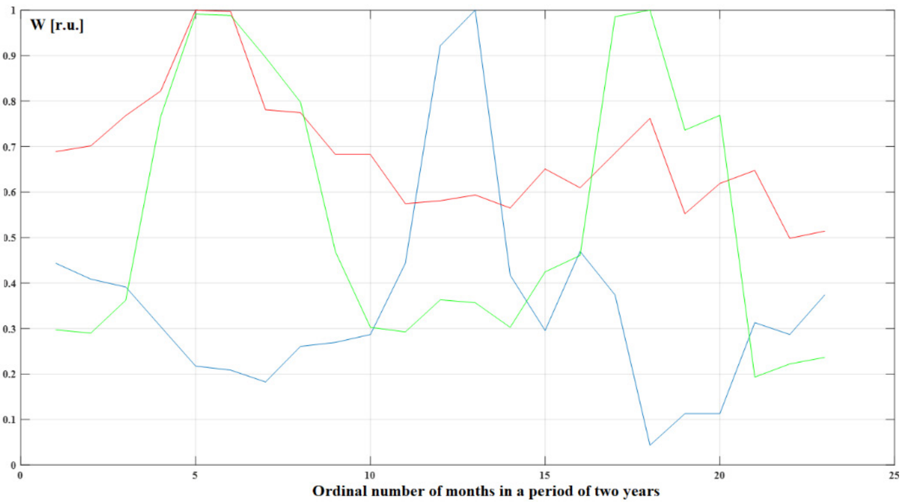


Figure 4. *Normalized monthly load diagrams for different users in the same part of the distribution network.*

Table 1. *Statistical indicators for anomaly detection.*

Indicator	Description code
Coefficient of variation	a1=Pmax./(Pmin+eps)
Ratio between peak and valley load	a2=Pmin./Pmax
Ratio between peak and average load	a3=Pmax./Psr
Valley coefficient	a4=max(P(i+1)-P(i))
Load variance	a5=sum(ΔP(i))
Time of maximum power utilization	T= sum(P').Pmax

TYPES OF POWER CONSUMPTION ANOMALIES

Non-technical losses, commercial losses, and electricity theft detection can be done by processing the collected measurement data. The easiest way is to compare the characteristic indicators of load diagrams. If there are load diagrams of customers with and without electricity theft, it is possible to create indicative critical values for indicators. If there are no measurements from consumers with regard to theft, then there is the possibility of creating different diagrams with certain anomalies. The types of electrical energy theft occurring in DSO can be presented as follows:

1. Multiplying all samples by the same randomly chosen value (lower than one)
2. "On-off" attack in which the consumption is reported as zero during some intervals
3. Multiplying consumption by a random value that varies over time
4. The combination of the second and the third type
5. Multiplying only the peak loads by the same randomly selected value (lower than one).

Computer simulation is used to form all five anomalies from a set of real measurement data. The obtained annual diagrams are given in Fig. 5.

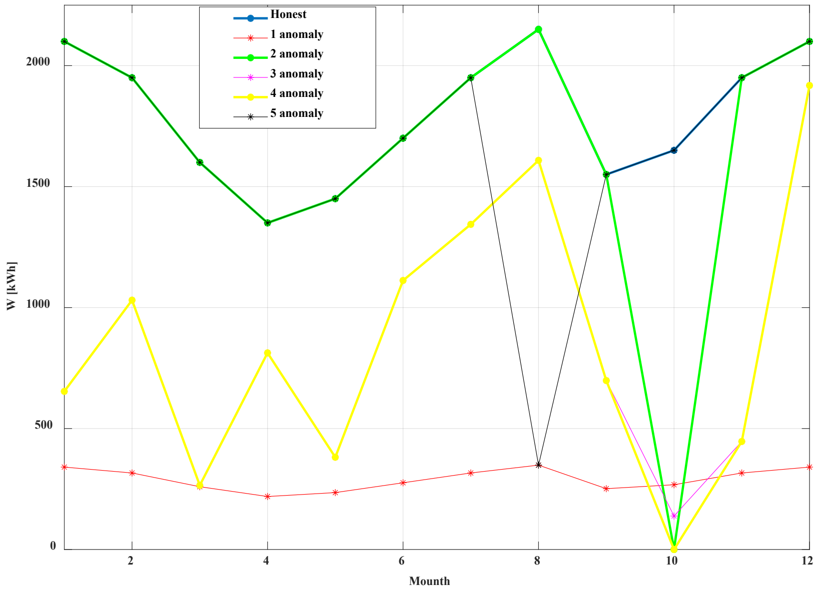


Figure 5. *Comparing the diagrams of the honest consumer and the created anomalies.*

For all six cases from Fig. 5, the indicators from Table 1 are calculated. Fig. 6 presents the values of these parameters.

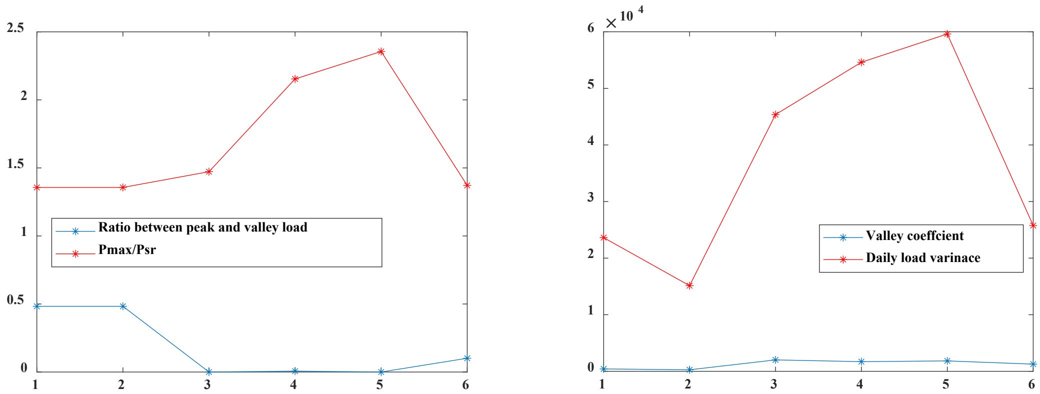


Figure 6. *Comparing the indicators a_2, a_3 (left) and a_4, a_5 (right) in six cases.*

In order to analyze the sensitivity for two different consumers, for two different consumption diagrams (7 a) and b)) the parameters were calculated and plotted. By looking at Fig 7 c), d), e) and f), the behavior of the parameters is very similar for different types of anomalies. Based on that, it can be concluded that it is necessary to further determine their limit values, which would represent triggers for finding anomalies. Table 2 presents exact values, while the bold numbers indicate the limit values of the operating parameters.

Table 2. *Exact vales for statistical indicators for anomaly detection.*

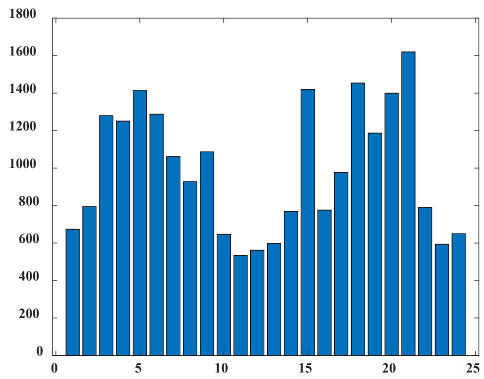
Indicators	Base case	1. anomal.	2. anomal.	3. anomal.	4. anomal.	5. anomal.
a_1	1.2723	1.2723	4.50E+15	22.8547	4.21E+15	**16.5368**
a_2	0.7859	0.7859	0	0.0437	0	**0.0604**
a_3	1.1038	1.1038	1.2034	2.1825	2.3660	**1.1637**
a_4	0.2140	**0.1525**	0.9584	**0.6903**	0.7815	0.8404
a_5	1.5846	**1.1293**	5.0990	7.3465	7.1403	**3.2666**
T	21.7411	21.7412	19.9424	10.9962	10.1435	**20.6222**

RESULTS FOR REAL DATASET

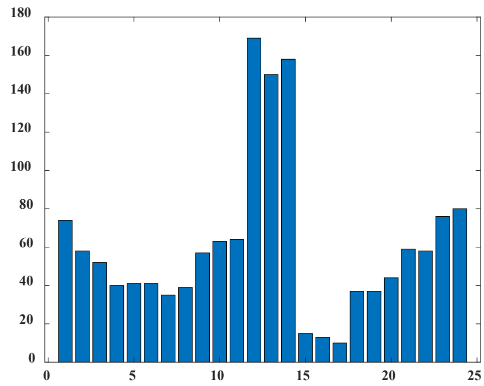
One way to create the limit values for indicator is shown in the previous section. This method involves creating artificial anomalies and monitoring whether consumers will fall into these behaviors and deviate from their daily electricity consumption habits. The second way is to analyze each real load diagram for each consumer from one part of smart grid. This method requires the existence of measurements from all smart meters and data storage. For each consumer and his diagram, the indicators from Table 1 are calculated. Then, for each of the 237 consumers that were considered, the values of those coefficients are observed, and deviations are detected. For that deviation, the limit values are specified and shown in Fig. 8. Table 3 presents the number of users that meet the conditions for each indicator. The cross section of all conditions picks out 5 consumers whose load diagram satisfies all 6 conditions in terms of indicators. So, those five consumers definitely have an anomaly and need to be checked by DSO inspection.

Table 3. *Number of customers with detected anomalies.*

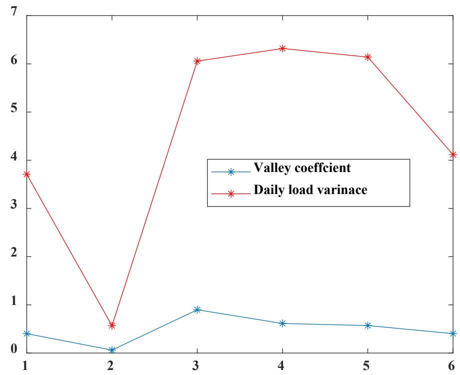
Condition	$a_1 > 20$	$a_2<0.1$	$a_3>2$	$a_4>0.6$	$a_5>4$	$a_6<10$	Cross
Detected customers	15	24	31	20	19	21	**5**



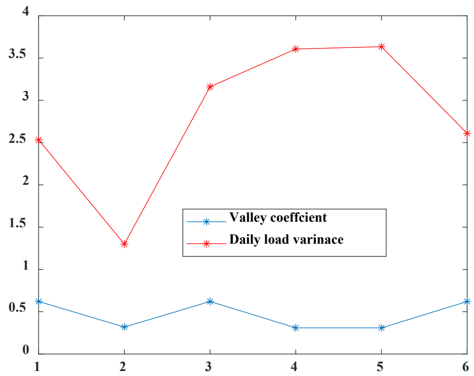
(a)



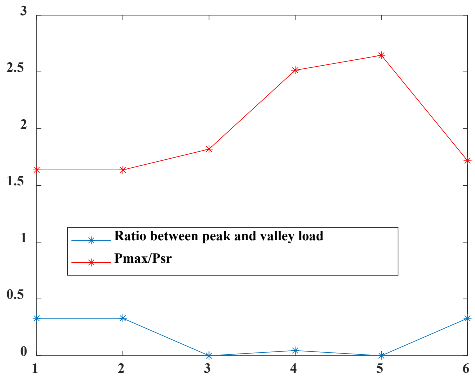
(b)



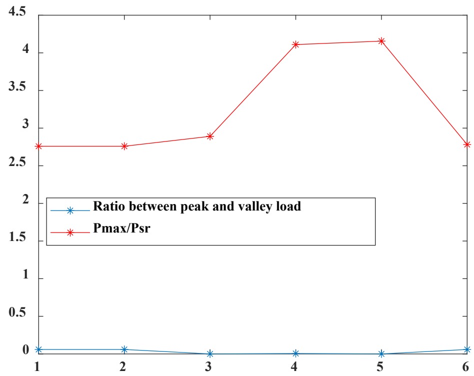
(c)



(d)



(e)



(f)

Figure 7. Statistical indicators calculated based on Table 1: (a) Load diagram for user 1; (b) Load diagram for user 2 (c) a_2 and a_3 for user 1; (d) a_2 and a_3 for user 2 (e) a_4 and a_5 for user 1 (f) a_4 and a_5 for user 2.

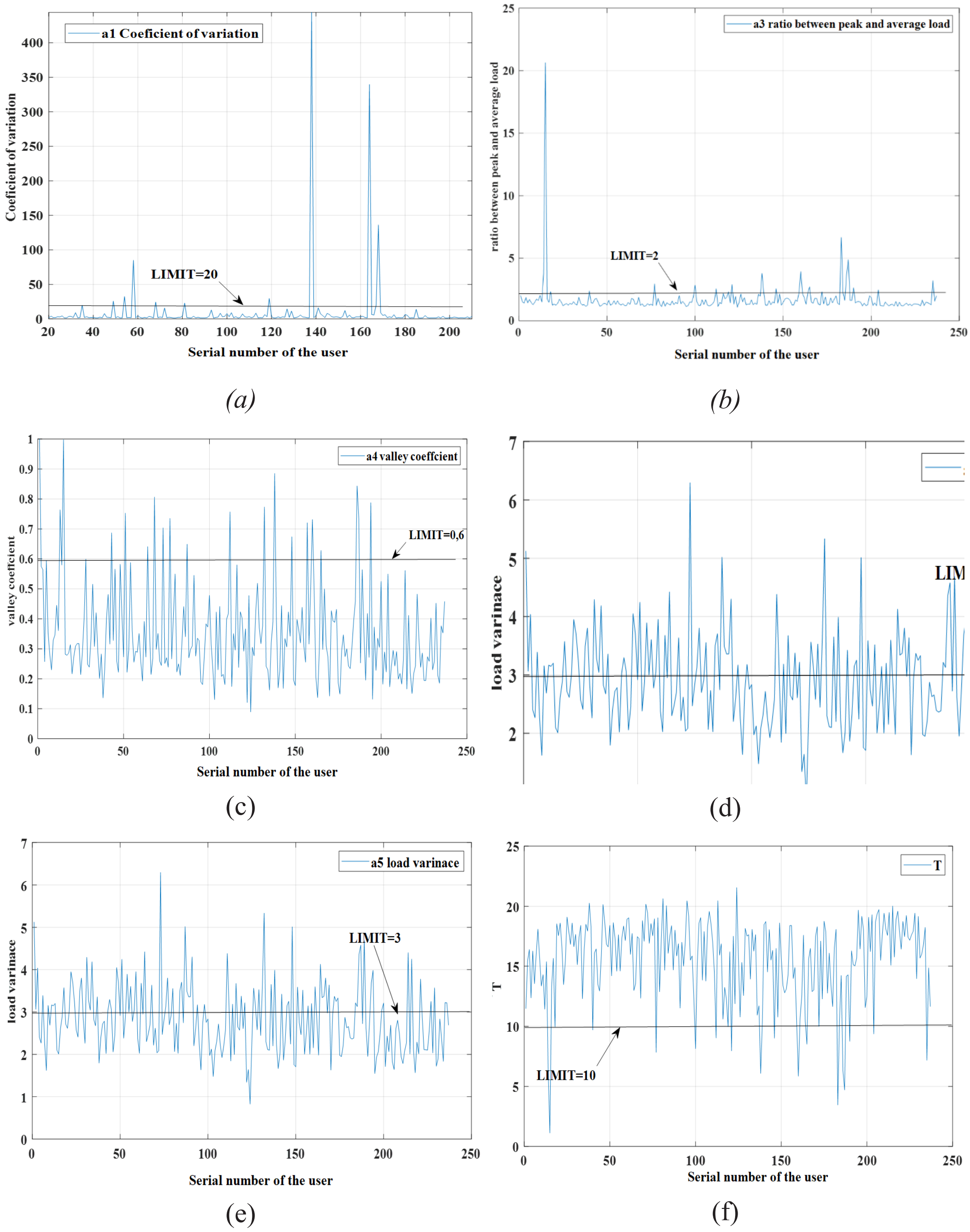


Figure 8. *Statistical indicators with specified limits for 237 consumers: (a) a_1; (b) a_3 (c) a_4; (d) a_2 (e) a_5 (f) T.*

CONCLUSION

This paper presents a method of detecting non-technical losses based on indicators for anomaly detection in load diagrams. Based on the collected measurements, the paper explains the possible methodologies for observing and detecting anomalies at the measurement points to detect non-technical losses, commercial losses, and electricity theft. The paper points to the possibility of simulating the creation of anomalies based on a realistically recorded load diagram. Also, the paper indicates the possibility of comparing all recorded load diagrams from the same part of the smart grid. In both cases, indicators are calculated to detect the existence of an anomaly using their limit values. Future work will be focused on using artificial intelligence and big data from the smart grid to create an algorithm for the same purpose.

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INFORMED CONSENT STATEMENT:

Not applicable.

CONFLICTS OF INTEREST:

The authors declare no conflict of interest.

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