Classification of Nonlinear Loads using Current Spectrum

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***Abstract*—One of the most prominent characteristics of nonlinear loads is existence of the higher harmonics in current spectrum. They cause losses and disturbance in power grid; thus, the power factor must be generalized to a total or true power factor where the apparent power, involved in its calculations, includes all harmonic components. Nevertheless, harmonic components of the current spectrum can be regarded as specific "signature" of some nonlinear load, therefore providing the means for identifying classes of nonlinear loads connected to the power grid. In this paper, we will present the method for identifying and classification of nonlinear loads using harmonics' amplitudes as inputs for the artificial neural network.**

***Index Terms*— artificial neural network; harmonics; nonlinear loads.**

I. INTRODUCTION

Transition to the new millennium also marked transition in our use of electric energy. The significant growth in electronic industry had immense impact on world economy and led to significant changes in our lifestyle. The electronic devices and appliances which contain electronics are everywhere. In addition, growing awareness of global warming influenced automotive industry to change from fossil fuel engines to electric motors. As a consequence, electronic devices take a significantly bigger share in overall power consumption.

Electronic devices are nonlinear loads by nature. They are usually very complex circuits, consisting active semiconductor components that require direct current (DC) for polarisation. However, electricity is delivered to end-users using an alternating current (AC), suitable for the transmission of electricity, which cannot be directly applied to electronic circuits. The means of conversion, AC/DC (power) converters, can be analyzed as two-port networks with reactive and nonlinear impedance seen from the power grid. The characterization of the power converter, and hence the electronic device that contains it, can be performed by determining the current spectrum, i.e. calculating current harmonics.

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There are many approaches that are used in identifying and monitoring electronic devices (nonlinear loads) connected to the power grid. They are divided into two categories, depending on the means of collecting data: Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM). ILM methods are implemented with a number of voltage and current probes placed on each monitored device. NILM methods require only one measuring device for the group of devices, for instance entire household. Although ILM methods are more accurate for obvious reasons, NILM methods are commonly used, due to the implementation costs.

In our previous proceedings, we have presented a method for classification of nonlinear loads using artificial neural networks (ANNs), based on active, reactive and distortion power [1,2].

In this paper, we will use amplitudes of current harmonics as inputs for classification of nonlinear loads. The presented method fits into NILM category – we have used one measuring apparatus for various combinations of devices. The method consists of three phases: signal acquisition, current harmonic extraction and device identification/classification using ANNs. The acquisition and harmonic extraction are performed using system for nonlinear load analysis [3,4]. The extracted parameters, i.e. amplitudes of current harmonics are used for ANN training. Finally, the trained ANN is employed for identification of similar nonlinear loads and unknown combinations of loads connected to the power grid.

The paper is organized as follows: in the second section we will present signal acquisition system and algorithms for harmonic analysis, third sections describes ANN topology, training process and obtained results. Fourth section concludes the paper.

II. DATA ACQUISITION AND HARMONIC ANALYSIS

The signal acquisition is performed using acquisition system consisting of acquisition modules for A/D conversion [5], and computer interface. A/D resolution is 16-bit, with 100 kSa/s sampling rate and ±50 A dynamic range. This system is described in great detail in [4]. Although this system is capable for real-time operation, due to the offline nature of ANN training, this capability is not used. However, the authors are aware that when the ANN training is finished, the trained ANN can be integrated into the system, enabling identification of nonlinear loads in real time.

In the presence of nonlinear loads, the circuit no longer operates in sinusoidal condition and use of circuit's fundamental frequency analysis could not be applied any more. Traditional power system quantities such as effective value, power (active, reactive, apparent), and power factor need to be numerically calculated from sampled voltage and current sequences by performing DFT or FFT algorithm.

Having in mind that voltage waveform almost insignificantly deviates from sinusoidal (typically $THD_{\mathrm{V}} < 3\%$), we will focus only on current waveform.

We will review some basic definitions briefly. The RMS value of current is calculated according to the well-known formula:

$$\tilde{I} = \sqrt{\frac{1}{\mathrm{T}} \int_{\mathrm{t}_0}^{\mathrm{t}_0+\mathrm{T}} \left(i(t)\right)^2 dt} \qquad (1)$$

where $i(t)$ represents instantaneous current, T is the period and t_0 is some arbitrary time. We can develop Fourier representation:

$$\begin{aligned} i(t) &= a_0 + \sum_{k=1}^{+\infty} \left(a_k \cdot \cos(k\omega t) + b_k \cdot \sin(k\omega t) \right) \\ i(t) &= i_0 + \sum_{k=1}^{+\infty} i_k \cdot \cos(k\omega t + \psi_k) \end{aligned} \qquad (2)$$

where $i_0 = a_0$ represents DC component, $i_k = \sqrt{a_k^2 + b_k^2}$ amplitude and $\psi_k = \arctan \frac{b_k}{a_k}$ phase of the k^{th} harmonic. $\omega = \frac{2\pi}{\mathrm{T}}$ represents angular frequency.

The Fourier coefficients a_k, b_k can be calculated as:

$$a_0 = \frac{1}{\mathrm{T}} \int_{-\mathrm{T}/2}^{+\mathrm{T}/2} i(t) dt, \quad a_k = \frac{2}{\mathrm{T}} \int_{-\mathrm{T}/2}^{+\mathrm{T}/2} i(t) \cdot \cos\left(\frac{2k\pi t}{\mathrm{T}}\right) dt \qquad (3)$$

and

$$b_k = \frac{2}{T} \int_{-\mathrm{T}/2}^{+\mathrm{T}/2} i(t) \cdot \sin\left(\frac{2k\pi t}{\mathrm{T}}\right) dt. \qquad (4)$$

The RMS value of the k^{th} harmonic, further used for ANN training, as well as for identification, is:

$$\tilde{I}_k = \sqrt{\frac{a_k^2 + b_k^2}{2}}. \qquad (5)$$

As we are dealing with discrete sets of values obtained by sampling, harmonic analysis is achieved by software implementation of some FFT algorithm.

III. ANN TRAINING AND LOAD IDENTIFICATION

For the purpose of this paper, we used current harmonics up to 40^{th} harmonic. Since even harmonics are not present in the spectrum of most electronic devices (as well DC component), only odd harmonics are considered. In this analysis, only amplitudes are taken into consideration.

The measurement is performed on 12 different combinations of various devices, shown in the Table I. We took into account devices that are typical for an office, for example. In fact, we have one PC, one server, one monitor, one kettle, one LED bulb, and an air-condition that can be in two operation modes: cooling and heating. Both the PC and the server operated with idle CPU utilization in all cases, so they can be treated as stationary nonlinear loads with constant power consumptions and current waveforms. The codes are given in the first column of the Table I, and also in the first row of the Table II. First column of the Table II gives the order of the harmonic.

TABLE I
CHARACTERISTIC COMBINATIONS OF THE DEVICES

Code	Device
1	Led Bulb
2	Kettle
3	Server
4	Air-condition heating
5	Air-condition cooling
6	PC + Monitor
7	Server + PC + Monitor
8	Server + PC + Monitor + Kettle
9	Server + PC + Monitor + Led Bulb
10	Server + PC + Monitor + Air-condition heating
11	Server + PC + Monitor + Air-condition cooling
12	Server + PC + Monitor + Air-condition heating + Led Bulb

Artificial neural network needs to be trained for modeling the look-up table. It is a feed-forward neural network with one hidden layer. The measured values from the Table II are inputs to the network, and the Code is network output to be learned. It means that the neural network has twenty input neurons and one output neuron. After training was completed, the number of hidden neurons in the resulting ANN was two, what was found by trial and error after several iterations starting with an estimation based on [6] and [7]. The training error was 3.16916e-017.

This number of hidden neurons in the neural network is very small. This opened a question if twenty input neurons were really needed, or we can train a neural network with smaller set of data. So, we tried to reduce training set to ten inputs. After training was completed, the number of hidden neurons in the resulting ANN was also two, and the error was very small, 2.68838e-019. Next step was to reduce training set to five inputs. We first tried to train an ANN with two hidden neurons, but it was not possible because training error was unacceptable. Then we enlarged the number of hidden neurons to three, and training results were good, the training error was 1.9106e-015. We concluded that we could use five input neurons, but in that case, there were three hidden neurons needed.

So, when we compare the obtained networks, the first one has 20 input and 2 hidden neurons, the second has 10 input and 2 hidden neurons, and the last has 5 input and 3 hidden neurons. The simplest realization would be to realize the third network. It also requires the smallest set of measured data.

TABLE II

VALUES OF HARMONICS' AMPLITUDES ($\tilde{I}_k$ [mA]) FOR THE COMBINATIONS GIVEN IN TABLE II

code → harmonic (k)↓	1	2	3	4	5	6	7	8	9	10	11	12
1	43.24	7450	280.47	3460	3420	235.57	742.57	7990	609.35	3230	2980	3710
3	32.18	22.44	38.09	123.5	215.32	104.12	77.65	27.86	110.79	161.32	211.11	178.84
5	21.22	175.98	33.66	569.31	582.51	51.27	93.59	182.57	44.16	585.62	516.69	553.6
7	20.75	143.29	17.19	266.65	234.98	29.13	34.95	177.49	72	245.08	251.75	231.13
9	20.49	11.72	7.53	39.89	43.92	2.76	8.18	9.86	35.35	35.06	40.04	75.64
11	16.66	6	7.27	28.5	31.05	4.26	8.72	9.69	10.41	15.68	10	35.75
13	14.59	42.15	6.08	25.35	26.21	16.65	28.23	45.23	19.5	25.21	25.75	15.84
15	13.53	6.4	6.23	7.43	8.27	10.28	15.89	10.66	15.74	11.47	12.02	26.5
17	10.71	5.66	5.75	10.03	10.5	2.51	9.66	5.83	13.98	6.88	10.34	5.52
19	8.84	4.86	3.47	2.71	3.1	3.61	1.8	4.41	7.39	8.62	9.95	6.04
21	8.49	7.59	5.19	5.53	3.66	8.39	16.43	11.31	16.39	3.75	7.79	6.47
23	7.18	2.45	2.83	1.7	0.93	3.77	3.96	5.78	5.65	3.09	3.9	7.79
25	6.16	3.14	4.61	1.5	1.22	2.64	6.94	9.15	2.38	5.7	7.31	6.37
27	5.98	3.28	4.38	1.13	0.85	2.3	3.08	11.36	3.43	7.05	8.05	0.94
29	4.98	1.63	2.98	0.8	0.34	2.58	5.74	5.65	8.32	4.91	5.7	10.59
31	4.26	1.13	2.79	0.56	0.4	2.71	8.96	7.06	11.22	8.41	8.32	10.88
33	4.12	0.78	1.38	0.48	0.46	1.13	5.46	5.18	3.56	7.82	7.42	2.19
35	3.45	0.94	0.4	0.31	0.17	1.81	5.33	3.67	6.03	3.73	4.97	7.82
37	3.07	0.49	0.87	0.27	0.37	2.39	3.93	2.16	7.59	4.07	3.36	4.08
39	3.23	0.21	0.77	0.24	0.15	0.73	3.42	1.21	4.19	1.78	2.35	4.05

The structure and the parameters of both obtained ANNs are verified by exciting the ANN with the given inputs. Responses of the ANN show that there were no errors in identifying the codes what is presented in the Table III. Negligible discrepancies may be observed.

TABLE III

ANN OUTPUT CODES

Expected Code	**ANN Output (20 hidden neurons)**	**ANN Output (5 hidden neurons)**
1	1.00002	1.00005
2	2.00003	2.00007
3	3.00002	3.00007
4	4.00003	4.00023
5	5.00003	5.00009
6	6.00002	6.00008
7	7.00001	7.00008
8	8.00002	8.00008
9	9.00001	9.00006
10	10	10.0001
11	11	11.0001
12	12	12.0001

Also, we used one more way to verify this neural network. Namely, we measured all the harmonics when all devices were operating at the same time (Table IV). This in unknown situation for the network, because this data were not used in the training process.

So, this was used as an excitation to the network with 20 inputs. The response of that network was 11,71. This value is closest to 12, giving us information that a combination similar to combination 12 is working. When we check the Table I, we notice that this is correct, while all devices except Kettle are included in combination 12, what is the closest to situation when all devices are operating at the same time. Of course, we cannot have an exact information, but it can be useful in the diagnosis process.

TABLE IV

VALUES OF HARMONICS FOR ALL DEVICES OPERATING AT THE SAME TIME

k	1	3	5	7	9	11	13
$\tilde{I}_k$ [mA]	11400	124.58	692.57	299	65.53	22.38	46.06

k	15	17	19	21	23	25
$\tilde{I}_k$ [mA]	30.16	4.19	11.79	15.75	14.58	14.28

k	27	29	31	33	35	37	39
$\tilde{I}_k$ [mA]	4.81	9.84	10.69	3.04	3.47	4.41	3.68

IV. Conclusion

Most of the known NILM methods for identification devices use artificial neural networks. We have shown one implementation of such method, with current harmonic amplitudes used as ANNs inputs. In our previous work, different definitions of power were used – active, reactive and distortion power. Having in mind that the powers are calculated from voltage and current harmonics, we have concluded that information that characterizes nonlinear loads encoded in those parameters also exists in harmonics.

Although we concluded that we needed only 5 measured harmonics (1^{st}, 3^{rd}, 5^{th}, 7^{th}, 9^{th}), but only for this specific case. This means that in some other situation, when measured values of harmonics have less distinguished values, we would need more input values in order to better distinguish which consumer is on the network.

In this stage of our work, we have deliberately neglected harmonics' phases, which also contains some information of nonlinear load. The development of the method for identification and classification that takes harmonics' phases into account is the next logical step.

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