Mining Ring Diagnosis using Artificial Neural Networks

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Abstract – **In this paper we will present one aspect of energy consumption caused by equipment for cryptocurrency mining. We will first address problems concerning increscent number of nonlinear loads leading to the fact that the active power no longer represents the main part of total power delivered to customer. We will stress in this paper losses produced by power supply unit in the mining ring, and we will engage an artificial neural network to diagnose how many cards are working at the moment.**

Keywords – **Artificial neural network, Power Meters, Utility Losses, Cryptocurrency Mining.**

I. INTRODUCTION

Our life has become more comfortable during last few decades due to plentiful of smart electronic appliances. Simultaneously, the electronic control systems became inevitable parts of equipment for industrial production. Most of electronic gadgets and apparatus require DC supply. Therefore, AC to DC converters have become the most numerous loads at power grid. Unfortunately, their nonlinear nature generates harmonics in the power network causing numerous unwanted problems [1], [2], [3].

The permanent growth of the number and types of nonlinear loads aggravates the problems caused by harmonics. That enforced almost every country to introduce its own standard that restricts the allowed amount of each harmonic. Two widely known standards in this area are the IEEE 519-1992 and IEC 61000 series [1], [3]. The standard IEC/EN61000-3-2 entered into force in the European Union. It specifies the limits for the allowed nonlinear distortion of the input current up to the fortieth harmonic. The standard is applied to the distortion produced by electronic and electrical appliances in households. This includes loads up to 16A per phase supplied with voltage up to 415V. Both standards regulate limits for the harmonics pollution but do not specify what happens if a customer exceeds them. There are two possibilities: the first suggests that the utility could disconnect that customer but that is stressful and not profitable solution. The better way and the most effective tactic is to charge the harmonics producers a penalty tax if they exceed limits of harmonics pollution. The penalty tax should be proportional to the pollution levels. But this can be possible only in case when we have precise method for identification of the harmonics' producers. The overview of these solutions can be found in [4].

Lately, one of the greatest nonlinear consumers is equipment for cryptocurrency mining. Blockchain technology and its most popular cryptocurrency, Bitcoin, have been called of one of the most intriguing issues of nowadays, having almost equal importance as the internet. There are presumptions and hopes that cryptocurrencies will change the world, for the better, of course. But there is a dark side of this story. According to the Bitcoin energy consumption index, the digital currency already consumes 0.15% of the world's energy, and far exceeds the electricity consumption of Ireland or of most African nations [5]. Or, to get better insight, it costs 29 times as much energy to produce Bitcoins last year as it did to power all the Tesla cars driving today [6].

The reason Bitcoin mining consumes so much energy is because in order to produce each new Bitcoin, solving a complex mathematical puzzle is required, and it takes cryptographic process performed by high-powered computers. The mining computations serve to verify Bitcoin transactions on a digital ledger known as the blockchain, and the greatest advantage is because it ensures security. But, again, this process is extremely energy intensive, and in order to put the energy consumed by the Bitcoin network into perspective we can compare it to another payment system like VISA for example. Considering the numbers [7], we can conclude that Bitcoin is extremely more energy intensive per transaction than VISA, because Bitcoin transaction requires several thousands of times more energy. These problems do not refer only to energy price, it should be about the environment, too.

In this paper we will give one aspect of energy consumption caused by equipment for cryptocurrency mining. Namely, we will refer to power consumption of power supply unit in the mining ring. We will measure quantities of active, reactive and distortion power, and using these values we will diagnose the number of the processing (GPU) cards operating. Artificial neural networks will be used for diagnosis.

II. THE FUNDAMENTAL QUANTITIES

Traditional power system characterization quantities such as RMS values of current and voltage, power (active, reactive, apparent) are defined for ideal sinusoidal conditions. However, in the presence of nonlinear loads, these definitions need correction. The instantaneous values of a quantity rich with harmonics (voltage or current) can be expressed as:

$$x(t)=\sum_{h=1}^{M} X_h \sin\left(\omega_h t+\alpha_h\right) , \tag{1}$$

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where h is the number of the harmonic, M denotes the highest harmonic, while X_h, ω_h and α_h represent amplitude, frequency and phase angle of the h-th harmonic. The RMS value of the signal expressed by (1) is defined as:

$$X_{\mathrm{RMS}} = \sqrt{\sum_{h=1}^{M} X_{\mathrm{RMSh}}^{2}}\,, \tag{2}$$

where X_{RMSh} is the RMS values of the h-th harmonic.

Product of the voltage and current having the same harmonic frequency gives the harmonic power. Total active power is defined as:

$$P = \sum_{h=1}^{M} V_{\mathrm{RMS}_h} I_{\mathrm{RMS}_h} \cos(\theta_h) = P_1 + P_{\mathrm{H}}\,, \tag{3}$$

where θ_h denotes phase angle between voltage and current, P_1 denotes power of the fundamental component ($h = 1$). Therefore, it is known as *fundamental active power* component while P_H comprises sum of all higher components ($h = 2,\ldots,M$) and is referred to as *harmonic active power*.

According to Budeanu [3], [8], [9] reactive power is defined as:

$$Q = \sum_{h=1}^{M} V_{\mathrm{RMS}_h} I_{\mathrm{RMS}_h} \sin(\theta_h) = Q_1 + Q_{\mathrm{H}}\,, \tag{4}$$

where, similarly to (3), Q_1 and Q_H denote *fundamental reactive power* and *harmonic reactive power*, respectively.

Many scientists claim that the Budeanu's definition is not correct and cannot be used for calculating reactive power. According to one of the authors of IEEE1459-2010 standard, professor Emanuel [10], [11], "even today this definition occupies a significant number of pages on *The IEEE Standard Dictionary*". Its past acceptance and popularity among engineers and top scientists is hard to dispute. Modern textbooks written by highly respected researchers are presenting Budeanu's resolution of apparent power as the right canonical expression". More about calculating reactive power can be found in [10].

It is well known that the apparent power is a product of RMS values of voltage and current. In presence of harmonics, the apparent power is calculated as:

$$S = I_{RMS} \cdot V_{RMS} = \sqrt{\sum_{h=1}^{M} V^2_{RMS\,h}} \cdot \sqrt{\sum_{h=1}^{M} I^2_{RMS\,h}} \tag{5}$$

The obtained value for apparent power obtained by using previous equation is greater than the value that can be obtained as $S = \sqrt{P^2 + Q^2}$ .This was noticed for by Budeanu for the first time in 1927. Therefore, he introduced the term *distortion power* and revised the equation for apparent power:

$$S^2 = P^2 + Q^2 + D^2 \tag{6}$$

Consequently, distortion power can be calculated by using next equation:

$$D = \sqrt{S^2 - P^2 - Q^2}\,. \tag{7}$$

III. Measured Results

We obtained measured results that will be used in this paper for a neural network training by using standard power meter produced by EWG [12]. It is based on standard integrated circuit 71M6533 [13]. The power meter completely fulfils IEC 62053-22 standard [14]. The only additional effort was to gather data provided by the meter and to acquire them using a PC to calculate distortion power according to (7).

Figure 1 illustrates the implemented set-up. It consists of the meter, the load and PC. The meter sends the measured data through its optical port. PC receives them on RS232 port. Dedicated software processes data and forwards them to MATLAB script that calculates the distortion power.

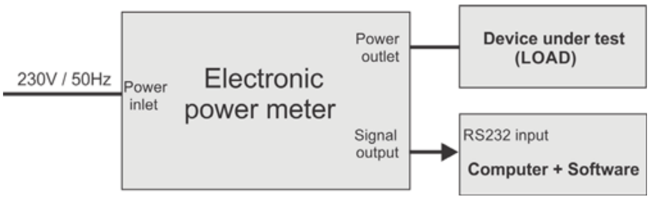

Fig. 1. Set-up circuit for distortion power measurement

The two main components of a mining ring are graphics card with graphic processor (GPU) and power supply unit (PSU). According to mining experts the most profitable GPUs in 2018 are RX580 from AMD and GTX1070 from NVIDIA. The second important thing in mining ring is power supply unit. This unit must be highly efficient because it needs to decrease power consumption, and thus, the costs of mining. So, the most of mining rings have a PSU unit with efficiency more than 80% (bronze, silver, gold, platinum and titan design). The PSUs with the same design have different efficiency when they are loaded differently. For example, 80 PLUS Gold PSU supplied by 230V has 88% efficiency when load rate is 20%, but it has 92% efficiency when load rate is 50% [15].

In this paper we present measured powers' results (active, reactive, distortion and apparent power) for two PSUs.

The mining ring that was used as a device-under-test consists of: PSU Cooler Master 750W bronze design, Sesonic Focus PSU 850W gold design, 6 Gigabyte GTX1070 graphics cards (3 cards are with one single fan, and other 3 are with three fans). The Sesonic Focus PSU supplies graphics cards with three fans, while Cooler Master PSU supplies the other three graphics cards, motherboard and solid-state disc (SSD) [16].

Table I presents obtained measured results for all mining rings. At the beginning of the measurement process, we turned three cards on, one by one. After that we turned off two cards and then started to turn on card by card. In situation when all six cards were working the active power was around 810W, reactive power was around 80VAR, while distortion power was about 125VAR. At the end we turned off 3 cards at the same time, and so only 3 cards continued to work.

We need to stress that each of these values presented in the Table I is averaged out of approximately 50 measurements. For example, value of 225.49W measured for active power when one card was working is obtained as average value of about 50 measurements in the period of 6 hours. Few measurements were not taken into account when averaging, because they were left for testing, what will be given later in the paper.

TABLE I
MEASURED RESULTS GIVEN IN FIG. 2

Meas. No.	No. of cards	P (W)	Q(VAR)	S(VA)	D(VAR)
1	1	225.49	106.85	251.85	34.07
2	2	333.26	120.57	360.75	67.17
3	3	447.19	134.10	476.38	94.38
4	1	217.62	102.03	241.01	16.47
5	2	309.43	113.91	333.50	49.43
6	3	429.93	128.43	456.21	81.63
7	4	556.81	158.62	585.93	89.93
8	5	686.23	172.41	715.87	108.56
9	6	812.45	184.84	842.57	125.09
10	3	434.60	130.37	461.10	82.03

These measurement results are given in the Figure 2, where it is more obvious that values of all the powers are not negligible, what is especially important for the values of distortion power, that is not registered on the network [4].

Also, the values of powers when the same number of cards was working are not always the same. For example, when 3 cards work, we obtain average values of 447.19W, 429.93W and 434.60W for active power. For distortion power, values differ even more (94.38VAR, 81.36VAR, 82.03VAR). This was the reason why we got to an idea to involve a neural network in order to resolve this situation. In fact, we will train an artificial neural network (ANN) that will diagnose how many graphics cards are working at the moment.

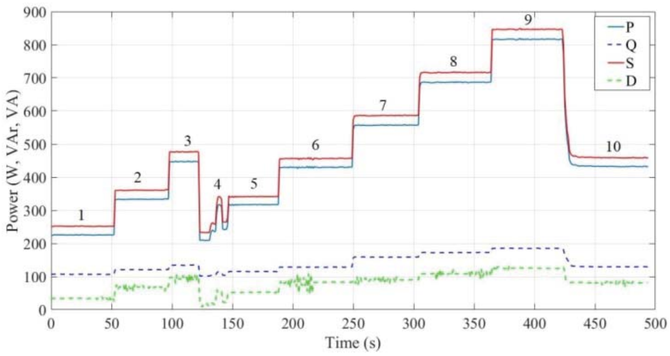

Fig. 2. Measurement results for the whole mining ring

This ANN has four inputs (active power, reactive power, apparent power, distortion power) and one output that should give information about how many cards are operating at the moment. This information is very useful because we can be informed if some card is damaged or it cannot work properly.

After we trained an ANN, we obtained 4 neurons in the hidden layer. The validity of this ANN is first checked when we used excitations that were employed in the training process. Results are given in the Table II, and we can see that we obtained very good results, and expected results match with the ANN response. Error is negligible.

TABLE II
ANN RESPONSE TO EXCITATION GIVEN IN TABLE I

P (W)	Q(VAR)	S(VA)	D(VAR)	Expected response	ANN response
225.49	106.85	251.85	34.07	1	1.0001
333.26	120.57	360.75	67.17	2	1.9997
447.19	134.10	476.38	94.38	3	2.99909
217.62	102.03	241.01	16.47	1	1.00001
309.43	113.91	333.50	49.43	2	1.99977
429.93	128.43	456.21	81.63	3	2.98698
556.81	158.62	585.93	89.93	4	3.99789
686.23	172.41	715.87	108.56	5	5.0011
812.45	184.84	842.57	125.09	6	5.99977
434.60	130.37	461.10	82.03	3	3.01556

The next step in ANN validation is to check if this ANN gives proper response to unknown excitations. So, as unknown excitations we will use some of the measured combinations that were not used in the training process, i.e. they were not used in getting average values presented in the Table I.

TABLE III
ANN RESPONSE TO UNKNOWN EXCITATIONS

P (W)	Q(VAR)	S(VA)	D(VAR)	Expected response	ANN response
226.14	106.76	251.26	24.384	1	1.25892
333.8	121.08	361.97	70.276	2	1.9373
446.84	134.14	475.6	92.39	3	3.01691
236.19	103.1	258.27	16.927	1	1.38708
317.24	114.94	341.14	50.261	2	2.09345
430.19	129.23	456.72	82.64	3	2.96514
558.06	158.95	587.26	90.447	4	4.00486
687.49	172.98	715.95	100.106	5	5.0791
817.11	185.34	847.02	124.224	6	6.05286
432.48	129.49	458.76	81.607	3	3.00226

TABLE IV
ANN ERROR

Expected response	ANN response	Error (%)
1	1.25892	**25.8**
2	1.9373	3.13
3	3.01691	0.56
1	1.38708	**38.7**
2	2.09345	4.67
3	2.96514	2.01
4	4.00486	0.12
5	5.0791	1.58
6	6.05286	0.88
3	3.00226	0.075

Obtained results are shown in the Table III. We chose 10 combinations, each one as a representative of a different group. The ANN response is considered to be correct (i.e. acceptable) when its value was in the range [(m-0.5), (m+0.5)]. So, we can conclude that all the responses are correct, but additionally, we analyzed obtained errors, given in the Table IV.

We can notice from Table IV that significant error occurs when only one card is working. In all other cases, the error is very small. This is expected, when only one graphics card is in operation, the contribution of all other parts of the PC in power consumption is significant, as it accounts for almost half of total power consumption. When we turn on more cards, overall power consumption increase is caused only by the cards, consumption of other components remains approximately the same, so its influence is less important.

IV. Conclusion

From the measured results presented in this paper we can conclude that PSUs used in mining rings are very efficient and generate small number of harmonics. We used these measured quantities as inputs to a neural network whose output diagnoses number of graphics cards operating at the moment. This diagnosis was very successful. We should notice that these quantities are measured for branded PSUs, so in our future work we will focus on PSUs produced by other manufacturers.

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