An Appliance Impact Estimation on Power Quality Parameters in Microgrid Environment [†]

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Abstract: Nowadays Off-Grid systems driven by intelligent data analysis, predictive models and real-time optimizations are frequently entitled as Smart Grids. They represent a future step in a sustainable energy supply for applications at various scales, from small household configurations to the systems operating on a scale of larger areas, especially parts of a town or village. One of the key characteristics of such systems is the lower short-circuit power caused by a lower and mostly stochastic nature of their power source, which is represented by a renewable energy source. This phenomenon directly implies the difficulties of sustainable power quality (PQ). Our paper presents an analysis on the lowest possible level, where the impact of household appliances is examined towards a specific kind of response due to PQ parameter variation. The analysis was performed on 120 combinations of appliances. Each combination consisted of three appliances running simultaneously in the microgrid. The measured data were subjected to a statistical analysis. This analysis finds there are several kinds of appliances we need to focus on, in order to express the PQ parameter change of a given parameter. The results show that the microwave, AC heating and drill appliances had a high impact on the total harmonic distortion of voltage (THDV) disturbance. The microwave, AC heating and mower had the highest impact on the total harmonic frequency (FREQ) and the power factor (PF). For the sake of completeness, specific features of the given appliances were examined as for their relevance to the PQ disturbance, which revealed the most relevant features to be taken into account during the development of a predictive model.

Keywords: power quality; off-grid system; t-SNE; clustering; renewable energy sources

1. Introduction

Autonomous energy systems (so called Off-Grid systems) are systems supplied from renewable sources (RESs) and supported by energy storage. Different circumstances need to be considered in

such energy source applications, when compared to the standard distribution and transmission systems. The stochastic and unstable character of RES on the part of a source causes the presence of a low short-circuit power, which decreases the stability of power quality (PQ) parameters in the Off-Grid system [1,2]. The frequency (FREQ), voltage disturbance, total harmonic distortion of voltage (THDV) and current (THDC), and flicker severity belong to the most important PQ parameters [3]. It is necessary to keep these parameters within the requested limits to ensure a reliable and safe operation of appliances.

These different circumstances raised an interest in many researchers to develop optimization tools able to detect and backward optimize the PQPs to meet the requested limits according to the internationally defined standards and norms. Relevant algorithms are mentioned in [4,5]. The dominant approaches are machine learning-based algorithms, such as Support Vector Machines (SVM) [6,7], Artificial Neural Networks (ANN) [8,9], Genetic Algorithms (GA) [10] and their combinations. On the other hand, there are studies suggesting the widely known Wavelet Transformations (WT) [11] or Fuzzy based detection [12] to classify the power quality (PQ) failure from the learned patterns. Most of the studies, as it is concluded in [4,5], concentrate on the on-line detection and moderation of the effects of PQ decrease, but they do not focus on the prediction or avoidance of such events in the first place. While most of the available papers deal with the prediction of the total consumption or production [13], this paper examines the separate executions of several appliance combinations in order to examine their impact.2. Experiment Description

The main goal was to find out which appliances (Table 1) have a negative impact on PQ in the Off-Grid system. To test this, each time, we combined 3 different appliances to create a total of 120 combinations. These were switched on and off at defined intervals. The response of the system, in the view of PQ parameters, was measured and stored for statistical evaluations.

Table 1. Feature values of the applied appliances further used for their relevancy estimation.

Appliance	Load (W)			Power Factor (-)	Characteristic			Power Supply	
	avg	min	max	avg	Inductive	Capacitive	Resistive	Continuous	Switch
Mower	537.6	532.1	549.27	0.52	True	False	False	True	False
Drill	157.1	149.5	167	0.49	True	False	False	True	False
Kettle	619.1	617	628.3	1	False	False	True	True	True
Fridge	207.6	195.5	219.5	0.72	True	False	False	True	False
Switched mode	410	409.7	420.2	0.78	False	True	False	True	True
AC heating	880	852.5	910	0.91	True	False	False	True	False
Microwave	203	76.8	1348.3	0.84	True	False	False	False	True
Boiler	307	305.8	346.5	0.99	False	False	True	True	False
TV	44	42.8	50.5	0.6	False	True	False	False	True
Lights [1]	156	152.5	165.1	0.84	False	True	False	False	True

[1] Mix containing light bulbs, CFL and LED lights.

They revealed the fact that the appliances were responsible for irregular PQ behaviour, and which of their features were the most relevant for this prediction. This study may be used to design deeper feature engineering procedures in the tasks of PQ parameters, forecasting in order to increase their accuracy.

The selected appliances were combined into triplets resulting in 120 combinations. There were three connected appliances at once because single running appliances in a household are rather uncommon. Appliances were turned on for an equal time (12 min) in our Off-Grid platform to measure the system's PQ parameters response. To omit the stochasticity produced by RES but keep the low short-circuit power, the system was supplied by charged batteries. Each combination of appliances resulted in a different State of Charge (SoC). The batteries were re-charged using a hybrid inverter to reach the same defined SoC after each triplet was measured. Re-charge lasted for 18 min.

Figure 1 shows the Off-Grid system where 2 photovoltaic panels produce 2 kWp per each under normal conditions. For the reasons mentioned before, all the energy consumed by appliances was supplied from the batteries.
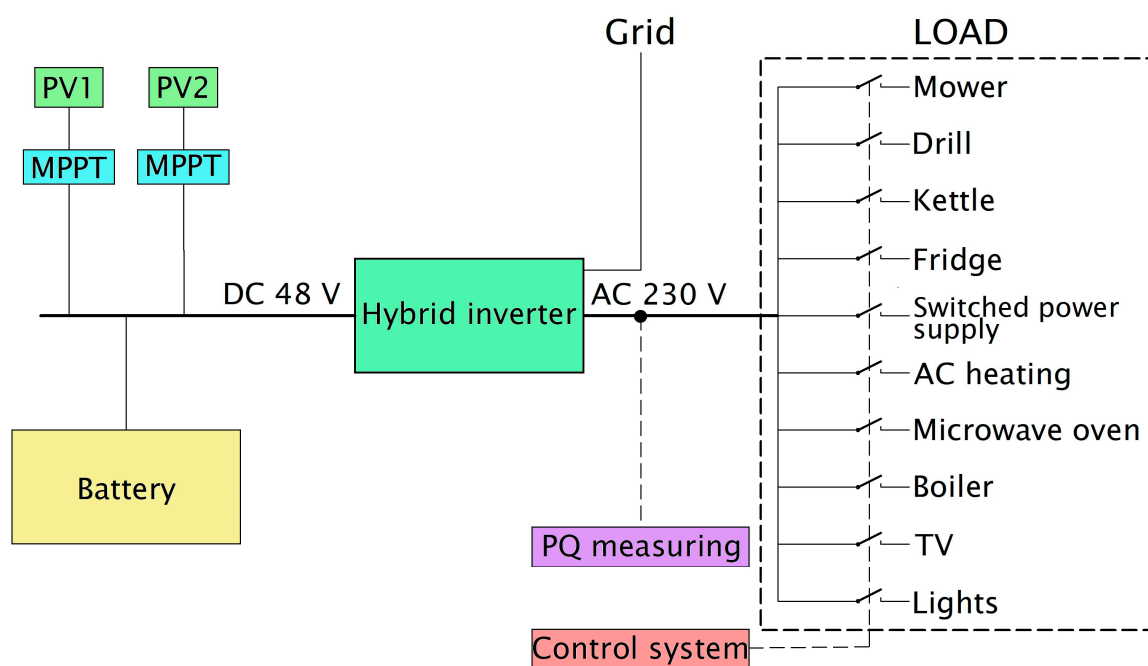
Figure 1. Scheme of an applied testing platform.

3. Results and Conclusions

The results of the experiments provided in this paper clearly distinguish the negative impact of certain appliances on the PQ parameters. The presence of the microwave significantly affected the behaviour of the frequency parameter. This resulted in a separated cluster that was confirmed and visualized by a Gap statistic-driven K-means algorithm.

A similar situation occurred in the case of the THDV parameter, where the appliances with a negative impact were the microwave, AC heating and drill. The last examined parameter was the power factor, the values of which were disturbed mostly by the mower, microwave and AC heating.

Very similar behaviour was observed in both cases, when batteries were fully and half charged. In the second case, the PQ disturbance was more significant, but the nature and source of the response remained the same.

Load value was estimated as the most relevant appliance feature for the PQP response. This has been directly evaluated by Kraskov MI estimation and later confirmed by the probabilities of the most significant appliances having the largest loads or the loads with the highest standard deviation.

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