QUANTIFYING POWER QUALITY IN STAND-ALONE MINIGRIDS USING FUZZY POWER QUALITY INDICES: A CASE OF ILLAUT MINIGRID IN SUB-SAHARAN AFRICA

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Summary

Recently the concept of power quality in stand-alone minigrids is gaining wide recognition. The inherent uncertainties and dynamic operating conditions of the decentralised energy systems have promoted calls for increased research activities in power quality assessment and improvements. This study proposes an innovative approach for quantifying power quality in stand-alone minigrids. The existing conventional power quality indices have limited operational capacity; hence, they require improvement in terms of accuracy, reliability and versatility. The proposed methodology incorporates a hierarchical evaluation index comprising harmonic distortion, frequency fluctuation, voltage variation, dips and interruptions. Results indicate that interruptions got the lowest power index (0), indicating a critical power quality concern. The recorded total fuzzy power quality index for the entire system was below 20%, demonstrating very poor power quality.

Keywords: minigrids, power quality index, voltage variation, fuzzy, power reliability

1. Introduction

The recent campaign by developing countries to increase access to electricity in rural areas has promoted the need for stand-alone renewable energy-based minigrids (MGs) (Come Zebra et al., 2021). Renewable energy systems are very flexible for deployment in regions where there are favourable climatic conditions, such as strong solar irradiance (solar PV) and strong wind intensity (wind energy). However, renewable energy sources are stochastic in nature, and any variation in weather introduces power quality issues into the MG system (Thirunavukkarasu et al., 2022). Furthermore, stand-alone MG optimisation and management, including upholding real-time balance among key grid components, may sometimes be challenging, leading to serious power quality issues. Minigrid power quality has a strong bearing on the system's security, stability and reliability, consequently affecting customers' power service satisfaction (Kumar et al., 2021).

In this regard, establishing the magnitudes of the prevailing power quality concerns and the severity of the perceived damage to the customers is a critical step towards addressing power quality challenges in contemporary MGs (Fathi-Jowzdani et al., 2022). This enables MG owners and all concerned stakeholders to sufficiently respond to all the identified PQ concerns, promoting a stable and reliable power supply. The concept of power quality in stand-alone minigrids continues to attract much attention in the 21st century. Gangopadhyay and Das (2021) applied a fuzzy assessment method to quantify the quality of smart grids with multiple power system variables. They achieved precise results with a high level of consistency. Similarly, Langouranis et al. (2018) applied the fuzzy power quality index to determine the PQ status of an electric network. On the other hand, in a recent study, Nkolokosa et al. (2024) reported power quality issues existing at some of the minigrids in sub-Saharan Africa that require immediate attention. Therefore, this study aims to identify and quantify the critical power quality issues prevalent at the Illaut minigrid in sub-Saharan Africa by applying fuzzy power quality indices. The novelty in this study lies in the combined application of power quality attributes, fuzzy logic and multicriteria decision-making on real field data to derive precise power quality indices.

Tymchuk and Miroshnyk (2015) argue that when the process of measuring PQ is associated with complexity and uncertainty, it is imperative to apply fuzzy logic, a concept that utilises mathematical operations to handle measurement uncertainty. Fuzzy logic is the part of Intelligent Techniques (ITs) that uses algorithms and methods that mimic human experts' behaviour to provide solutions (Langouranis et al., 2018). This approach

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uses reasoning in knowledge-based systems that consequently leads to the formation of rules and conditional statements (Huang & Jiang, 2017; Langouranis et al., 2018). In this respect, the objective probability assessment of the concerned number of measurements and the subjective experts' knowledge are applied. Bajaj et al. (2020) contend that fuzzy representations facilitate quicker decision-making due to their simplicity in object description compared to classical methods of probability theory. Besides, fuzzy logic handles complexity and uncertainties by applying partial truth values between 0 and 1 while upholding mathematical rigour and logical consistency (Shin et al., 2006).

Membership is the core notation of the fuzzy logic. Fuzzy indices are defined by various ways of getting the membership. Index representations are related to the variable of membership function. There are various indices that are used to assess power quality and acceptability. Indices are classified as event-based (SAIDI, SAIFI and SAFRI), magnitude and duration (Kaushal & Basak, 2018). The commonly applied membership categories include membership from magnitude, membership from deviation, membership from duration, membership from counting and membership from others (Bajaj et al., 2020; Gangopadhyay & Das, 2021; Malaisamy et al., 2016). Membership from magnitude represents membership indices that are based on magnitude. This category focuses on the degree of deviation from the nominal rated value as the reference for evaluating PQ status. A Gaussian fuzzy number is applied to ascribe the membership function of the fuzzy set corresponding to a particular quality index. For instance, if U represents voltage, the μ_E is represented as in equation 1.

$$\mu_E(U) = e^{-k(u-u_0)^2} \tag{1}$$

Where u and u_0 are measured and rated voltages, respectively, k is $k > 0$ and k can be determined by the actual conditions.

Membership from deviation represents a category in which a deviation value can sometimes be measured to identify membership, especially for fuzzy representations inside a standard range. Considering the same voltage as shown in equation 1, the change in voltage ΔU is given by equation 2.

$$\mu_1(U) = \begin{cases} 0, & \Delta U \leq -U_S \\ \frac{1}{2} + \sin\frac{\pi}{U_s}\left(\Delta U + \frac{U_s}{2}\right), & -U_s < \Delta U \leq 0 \\ \frac{1}{2} - \sin\frac{\pi}{U_s}\left(\Delta U - \frac{U_s}{2}\right), & 0 < \Delta U < U_s \\ 1, & \Delta U \geq U_s \end{cases} \tag{2}$$

Where U_s can be determined in a similar manner to k in 1. $\Delta U = 0;\ \mu = 1, U_S$ corresponds to $\mu = 0$.

Membership derived from duration takes into account the time aspect of power quality that provides an effective way of generating PQ indices. Consider a duration, $\Delta T \approx 0$ referring to an ideal situation ($\mu = 1$), whereas $\mu = 0$ can be attained when $\Delta T = \infty$ in theory. However, in practice it is difficult to attain $\Delta T \approx 0$, then the duration limit ΔT_s is set for $\mu = 0$. Then the membership function is given by equation 3.

$$\mu_E(\Delta t) = \begin{cases} 1, & \Delta T = 0 \\ e^{-k(\Delta T - \Delta T_s)^2}, & 0 < \Delta T < \Delta T_s \\ 0, & \Delta T \geq \Delta T_s \end{cases} \tag{3}$$

Where $k < 0$, k and ΔT_s are set based on actual requirements.

Membership from counting largely depends on the quality of the detection and monitoring process. Counting is classified into two subcategories, namely duration and event. Duration counting considers membership of a problem that occurred sometime while monitoring quality and is presented as shown in equation 4.

$$\mu_{ed} = 1 - \frac{t_d}{t_f} \tag{4}$$

Where t_d is the duration of quality problem occurrences and t_f is the full monitoring time.

On the other hand, event counting membership considers timing detection on quality for disturbance occurrences that are difficult to precisely capture.

$$\mu_{ce} = 1 - \frac{t_c}{t_t} \tag{5}$$

Where t_c is the quality problem occurrence times and t_t is the total detection times.

Indices obtained from the customers, such as SAIDI, SAIFI and SAFRI are considered as membership from others. For example, fuzzy membership for SAFRI is presented by equation 6.

$$\mu_{SAFRI\,\%V} = 1 - \frac{\sum N_i}{N_T} \tag{6}$$

Where $\%V$ is the threshold of rms voltage, N_i is the total number of customers that experience the event and N_T is the total number of involved customers in the study. SAIDI and SAIFI follow a similar representation to that of SAFRI.

Membership should be selected based on the nature of disturbance occurrence. For instance, voltage and frequency variations are categorised as membership from magnitude, whereas power outages, harmonics and imbalance are classified as membership from duration (Bajaj et al., 2020).

2. Methodology

2.1. Power quality attributes

We logged in a power quality analyser (Fluke 17777) to extract high-resolution one-week data. The extracted power quality metrics included total harmonic distortion (THD), frequency variations (FV), voltage variations (VV), voltage dips (VD) and prolonged interruptions (PI). Data collection and analysis were based on IEEE 519-2022 and EN5060:2010 standards (Nkolokosa et al., 2024). The study also calculated average outage duration (SAIDI) and average outage frequency per customer (SAIFI) as given in equations 7 and 8, respectively, and compared the results with both local and international standards.

$$SAIDI = \frac{Total\ minutes\ (or\ hours)\ of\ interruptions}{number\ of\ customers\ served} \tag{7}$$

$$SAIFI = \frac{Total\ number\ of\ interruptions\ for\ customer}{Number\ of\ all\ customers\ served} \tag{8}$$

2.2. Fuzzy power quality index

Fuzzy logic was utilised to generate the total fuzzy power quality index. The PQ attributes listed in 2.1 were considered input variables. The input variables were then categorised into five fuzzy classes, and each class was assigned a numerical threshold within the 0 (minimum) to 1 (maximum) threshold, as shown in Table 1. Five linguistic rules based on the inference system prescribed by Langouranis et al. (2018) were applied to establish the relationship between the fuzzy variables and the PQ levels. A set of equations in section 2.3 was used to calculate membership function fuzzy values that produced eigenvectors for computing fuzzy indices and reaching a decision.

Tab. 1: Linguistic variables and their corresponding PQ numerical thresholds

Linguistic Variable	Numerical Value	Performance
Very Low (VL)	[0.00:2.00]	Very Poor
Low (L)	[2.00:4.00]	Poor
Medium (M)	[4.00:6.00]	Average
High (H)	[6.00:8.00]	Good
Very High	[8.00:1.00]	Very Good

2.3. Fuzzy system

i. Dips and swells
The fuzzy value for Dips was calculated based on the recommended allowable number (1000) of distortions by international standards and experts as presented by Langouranis et al. (2018)

$$\mu_6(D) = \begin{cases} 0, & D \geq 1000 \\ 1 - \left(\frac{1}{990}\right) \times (D - 10), & 10 \leq D \leq 1000 \\ 1, & D \leq 10 \end{cases} \tag{9}$$

ii. Frequency Variation

The IEEE519-2022 and IEC 61000-3-2 standards that allow frequency fluctuations within 3% of the nominal value for 95% of the time were applied in equation 10:

$$\mu_3(FV) = \begin{cases} 0, & FV \leq 94\% \\ \frac{1}{0.55} \times (FV - 0.94), & 94\% \leq FV \leq 99.5\% \\ 1, & 99.5\% \leq FV \leq 100\% \end{cases} \tag{10}$$

iii. Voltage Variations

EN50160:2010 and IEC 61000-2-2:2002 standards were applied to calculate fuzzy value for voltage variation at a 10% threshold.

$$\mu_7(VV) = \begin{cases} 0, & VV \leq 80\% \\ \frac{1}{0.5} \times (VV - 0.80), & 80\% \leq VV \leq 85\% \\ 1, & 85\% \geq VV \leq 100\% \end{cases} \tag{11}$$

iv. Prolonged Interruption

This was calculated based on IEEE 519-2022 and experts' opinions of an allowable threshold of 10 interruptions per year. A value of 52 interruptions was considered (EPRA, 2017) as the worst performance that a MG can experience.

$$\mu_2(PI) = \begin{cases} 0, & PI \geq 52 \\ 1 - \frac{1}{40} \times (PI - 10), & 10 \leq PI \leq 52 \\ 1, & PI \leq 10 \end{cases} \tag{12}$$

v. Total Harmonic Distortion

The calculation of the fuzzy value of TDH was based on IEC 61000-3-2 and EN50160:2010.

$$\mu_4(THD) = \begin{cases} 0, & THD \leq 95\% \\ \frac{1}{0.04} \times (THD - 0.95), & 95\% \leq THD \leq 99\% \\ 1, & 99\% \leq THD \leq 100\% \end{cases} \tag{13}$$

2.4. Total Fuzzy Power Quality Index

In this study we implemented Saaty's fuzzy variable matrix method under the multicriteria decision-making (MCDM) method to achieve the optimal alternative with the highest level of desirability in accordance with constraints and all criteria, as shown in Table 2.

Tab. 2: Saaty's fuzzy variable

	VD	FV	VV	PI	THD
VD	1.00	0.50	0.50	4.00	3.00
FV	2.00	1.00	1.00	7.00	0.20
VV	0.25	0.14	0.14	1.00	0.33
PI	0.33	0.20	0.20	2.00	1.00
THD	0.33	0.20	0.20	3.00	1.00

We then applied the eigenvector obtained from the fuzzy table given as $w = (w_j)$, where $j = 1,2, \ldots ,5$ for $\sum_i^5 w_i = 5$ as presented in equation 14.

$$w = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \end{bmatrix} = \begin{bmatrix} 1.4727 \\ 2.0328 \\ 0.2933 \\ 0.5438 \\ 0.6039 \end{bmatrix} \tag{14}$$

Total PQ index (TPQI) or power quality monitoring index (PQMI) is calculated by considering the PQ level of a particular site with the lowest number within the weighted membership functions represented in equation 15.

$$TPQI = min[\mu_1(PI)^{w_1}, \mu_2(PF)^{w_2}, \mu_3(THD)^{w_3}, \mu_4(FV)^{w_4}, \mu_5(U)^{w_5}, \mu_6(PI)^{w_6}, \mu_7(PI)^{w_7}, \mu_8(PI)^{w_8}] \tag{15}$$

Finally, on stage 2, the study applied the maximum strategy to the fuzzy sets $\{x_1, \mu_{\tilde{g}j}\}$ to get a decision that has a high value of PQ and set criteria for the lowest PQ value for this alternative.

$$D_{max} = \max_{x_i} \min_{\mu_j} \left(\acute{\mu}_j(x_i)\right) \tag{16}$$

3. Results and discussions

3.1. Frequency variations

A frequency variation of 3.8% was recorded for a 50 Hz nominal frequency system, as illustrated in Fig. 1. A deviation factor of 3.8% exceeds both IEEE 519-2022 and EN50160:2010 thresholds, hence not desirable in MGs. However, this is within range for EPRA 2017 local thresholds.

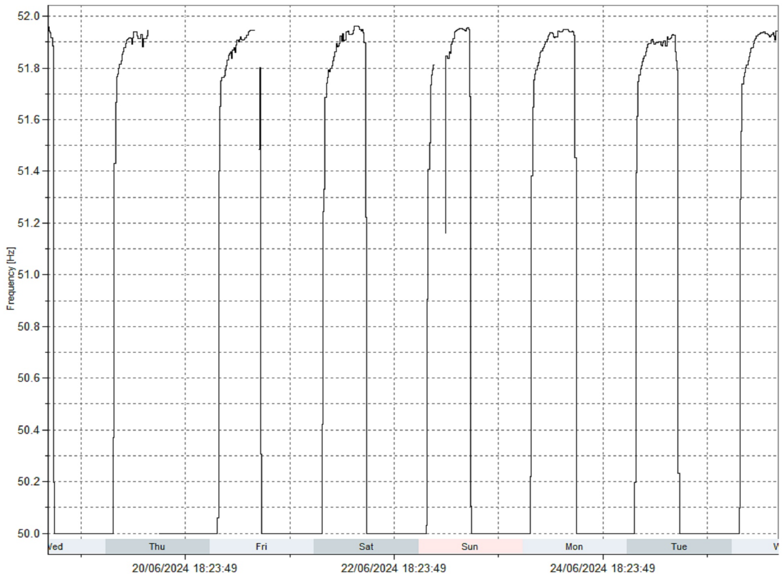

Fig. 1: Frequency profile of Illaut minigrid

3.2. Voltage dips

The study identified substantial voltage dips that were completely outside the acceptable thresholds of more than 70% for t ≤ 200 ms as shown in Fig. 2 (Liu et al., 2022). A total of 14 dips were recorded, with 5 dips less than 40% of the nominal voltage for 200 ms ≤ t ≤ 5s, 5 dips less than 5% for 5s < t ≤ 60s, and 3 dips less than 5% of the nominal voltage at t > 60 s. Such severe dips could have emanated from a dilapidated battery storage system and poor system control. They cause voltage collapse, frequency fluctuations and equipment malfunctions. Severe voltage dips can be mitigated by employing an efficient energy storage system and fixing robust controllers.

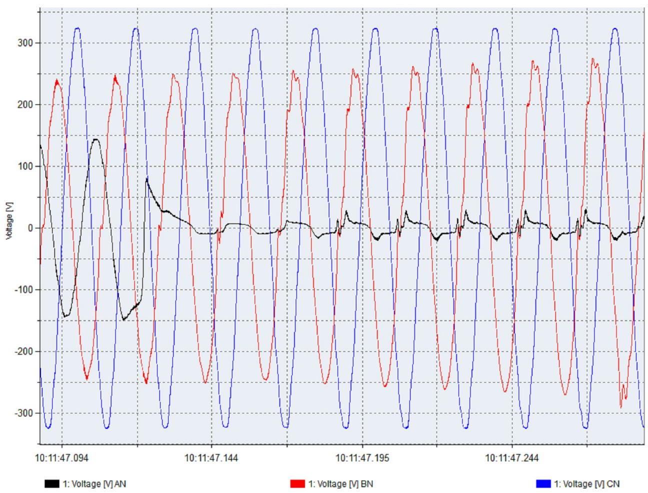

Fig. 2: Voltage dips

4.3 Total harmonic distortion

A 14% average harmonic distortion was observed at the end of the inverter. This is far above the acceptable 8% for both IEEE 519-2022 and EN50160:2010 standards. Fig. 3 shows THD across three-phase lines of the Illaut MG. All three lines recorded average THDs that lie within the acceptable range. Harmonics are usually caused by nonlinear loads and weak control systems and are corrected by applying power filters, converter designing and network reconfiguration.

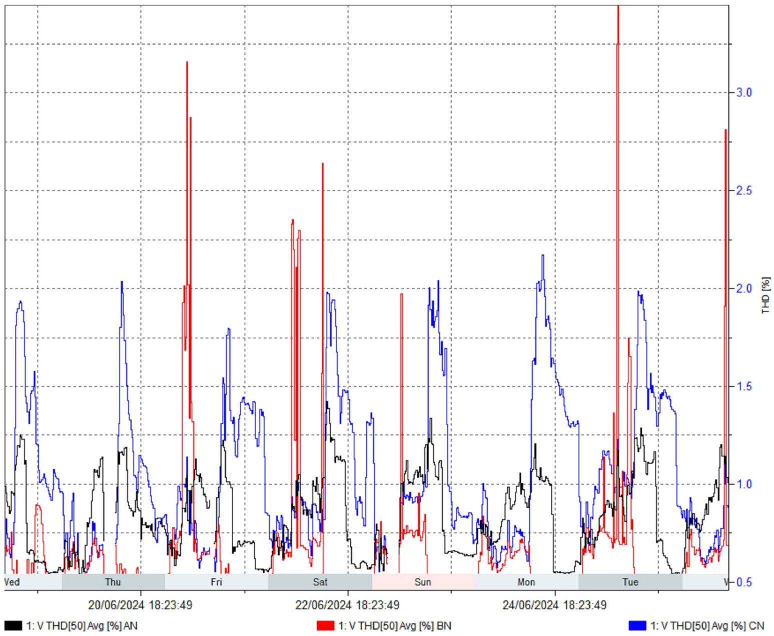

Fig. 3: Total harmonic distortion

4.4 SAIDI and SAIFI values

System average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI) were calculated at 2.59 hrs/week and 3 interruptions/week. These values are quite high compared to internationally accepted thresholds of 10-60 hrs/year (1.15 hrs/week) and 3-15 interruptions/year (~1 interruption/month) for SAIDI and SAIFI respectively (Wu & Sansavini, 2021). The interruptions were largely caused by inefficient system controllers and variability in the sunshine intensity.

4.5 Fuzzy power quality indices (FPQI)

On fuzzy indices for individual power quality attributes, the study observed that prolonged interruptions got the lowest index of zero, placing it within the very poor-performing category, as shown in Fig. 4. On the contrary, voltage variations were identified with a higher index of 1 (very good category). In terms of fuzzy total power quality index, the study recorded a very low power index of zero, indicating a very poor system performance of below 20%.

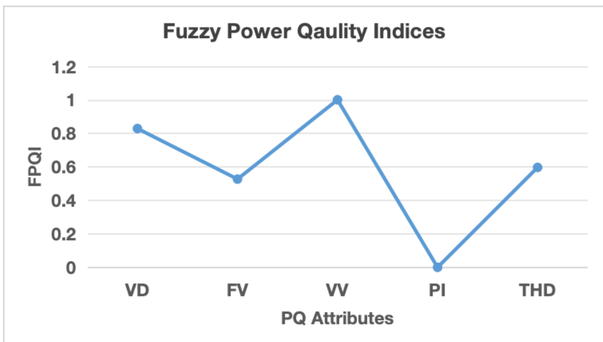

Fig. 4: Fuzzy power quality indices for individual PQ attributes

4. Conclusion

Illaut MG has been identified in the very poor PQ performance category of less than 20%, with prolonged interruptions getting a PQ index below 0.1. The fuzzy PQ assessment method has demonstrated high precision in PQ analysis. More than 90% of the PQ attributes are outside acceptable international standards, while 60% are within acceptable local PQ standards. This reveals significant power quality problems requiring the attention of MG owners. The study has also shown the need for regulatory bodies to enforce adherence to power quality standards in stand-alone MGs.

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