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RESEARCH ARTICLE

Data-Driven Modeling of Frequency Dynamics Observed in Operating Microgrids: A South African University Campus Case Study

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ABSTRACT South Africa has been experiencing an energy crisis since 2007. Utility loadshedding became the main control for under-frequency events due to a mismatch in generation and consumption. Rolling blackouts are further supported by failing electrical infrastructure and illegal (non-metered) connections to the distribution network. A common remedy to mandatory South African loadshedding, from the perspective of university campuses, is to deploy hybrid photovoltaic-diesel (PV-diesel) microgrids that allow for an uninterrupted power supply for a few hours. Campus microgrids are typically smaller compared to national utilities (less inertia) and require sensitive control schemes to remain stable. In this paper, frequency recordings associated with the operating microgrid of the University of the Free State QwaQwa campus are analysed. A simplistic stochastic mathematical model is presented as a model describing the observed frequency dynamics, describing the transition between the utility grid and the microgrid state, the microgrid frequency controller response, and the influence of the PV generators. Moreover, inter-campus synchronous frequency measurements are showcased and the future implications thereof are discussed. The main contributions of this paper focus on the recording and modelling of the frequency dynamics of fully functioning campus microgrids, and the showcasing of continuous synchronous measurements of frequency at two different campuses.

INDEX TERMS Operational microgrids, frequency dynamics, state classification schemes, synchronous frequency measurements, complex systems, stochastic modeling.

I. INTRODUCTION

South Africa's utility power grid has been degrading over the past 2 decades [1]. The effects of what is now clearly denoted the South African energy crisis have taken root primarily over the past 5 years [2], marked by pervasive loadshedding throughout the country. Industry and the citizens suffer from regulated and sometimes irregular power outages and total blackouts daily [3]. Rolling blackouts permeate the energy landscape, with different regions being deprived of power delivery for 3773 hours during 2022 [4].

Private and public institutions found means of ensuring robust power delivery in order to be able to operate without daily interruptions. The latter converged into strategies commonly known as energy resilience and microgrids naturally form part of the main energy reliability plan.

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Large universities turned to microgrid alternatives with local renewable power generation from photovoltaic (PV) as well as diesel generators to meet their energetic demands [5]. One existing microgrid example, which is explored in detail in this work, is the QwaQwa campus of the University of the Free State (UFS), which accounts for 9.5% of energy consumed across all the campuses. The UFS implemented a combination of PV and diesel generators to provide power at times when no power is delivered by the utility grid (or municipality in this case), constituting a unique University campus microgrid design in South Africa. With setting up and operating a microgrid at the scale of a university campus arise various challenges – and with it multiple opportunities – not discarding the issues involving large volume data management and control policies for the microgrid controllers. A wealth of data is generated pertaining to various crucial variables of a microgrid that directly influence the stability, quality, and optimization of the microgrid. Naturally, on the central variables is the voltage-frequency, which is maintained, as in the utility grid, to operate at 50 Hz. Microgrid controllers mimic the linear response in frequency fluctuations known from inertial systems. Yet the physical and mathematical nature of the observed microgrid frequency is not necessarily identical to that of the frequency from the utility grid, due to different levels of inertia, renewable penetration, network topology, and demand.

The dynamics of frequency changes in an islanded microgrid operation can be described using elementary mathematical models [6]. Herein, dynamical systems – primarily coupled oscillator models – provide one avenue to describe the dynamics of the rotor-angle and frequency (and voltages levels if desired) [7]. These can be augmented with stochastic elements – random noise with adequate characteristics – that help explain the true nature of the data [8]. We explore in this work a set of elementary data-driven processes that explain the recorded frequency excursions [9]. We remark here that this work contains one of the first analyses of *real-world* MG frequency data in a *living* system. This alone constitutes an advance in the understanding of operational MGs in real-world settings. We show that a simple combination of dynamical response and stochastic noise qualitatively mirrors the MG frequency data. The principles underlying elementary mathematical models show that the dynamics of the UFS MG are, in many ways, similar to the dynamics of the frequency of the utility grid. Although not unexpected, as most MG control mechanism seek to reproduce the functioning of conventional inertial synchronous power grids, this work confirms this from an analysis point-of-view of real-world frequency data. This constitutes one of the main contributions of this work. We show that the frequency is negatively impacted by the PV generation at the UFS QwaQwa campus, leading to large frequency responses that resemble Lévy-like noise [10], [11], [12], [13], [14]. Similarly, the actual MG frequency excursions are 'rough' stochastic processes, having a Hurst coefficient $H < 0.5$ [15], [16], [17], [18], [19]. To conclude the frequency modelling and observations, we show, qualitatively, a hysteresis phenomenon induced by the interaction of the controller with various generation units and demand management, pointing to a classical hysteresis behaviour ubiquitous in nonlinear dynamical systems. Secondly, we shortly explore measurements of inter-campus synchronous frequency excursions and showcase the implications of such measurements on the development of synchronicity frameworks. By recording and modelling actual microgrid frequency excursions we exemplify how invaluable these mathematical tools are at qualitatively describing the frequency dynamics of a MG, which in turn also tells us that MGs can safely be described with the same mathematical apparatus used for studying utility grid frequency, dynamical, and stochastic processes of other physical nature, or generally complex systems at large. This paper is structured as follows: Section II provides an overview of the existing UFS QwaQwa Campus Microgrid, Section III outlines the pre-processing associated with recorded frequency excursions, Section IV showcases the modelling of the observed frequency dynamics, Section V highlights some of the recordings of inter-campus synchronous frequency excursions and methodology thereof.

II. OVERVIEW OF UFS QWAQWA CAMPUS MICROGRID

The UFS QwaQwa Campus is located in the Phuthaditjhaba District in the Free State Province of South Africa, near the border to Lesotho. The QwaQwa Campus forms part of three UFS Campuses, the other being the Bloemfontein Campus (320 km apart) and the South Campus, both located in Bloemfontein in the Free State Province of South Africa.

The QwaQwa Campus Microgrid (MG) consists of two electricity-generating elements, namely the PV plant (918 kWp) and the synchronous diesel generators (4×400 kVA), as illustrated in Fig. 1, The MG is grid-tied to the national utility. Both the PV plant and the diesel generators are centralized and connected directly to the 11 kV network, see [5], which highlights the fact that non-centralized generation is linked to grid unavailability, prompting the microgrid layout in a centralised fashion. In addition, initial momentum and load synchronization are needed from the diesel generators to meet the campus load, which is achievable through centralization.

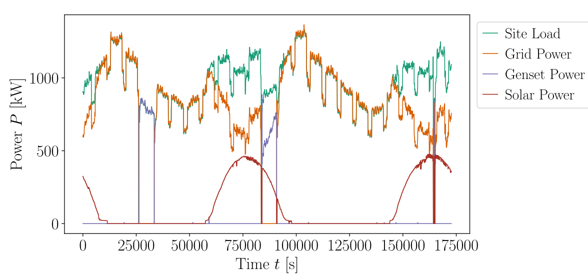

FIGURE 1. Energy mix for the QwaQwa campus MG, illustrating the grid-forming capabilities of the diesel generators in a centralised manner.

Critical to the design of the MG network, the centralised diesel generators allow the campus MG to enter into an islanded state when the national utility grid is unavailable, electrifying the campus network and allowing for PV synchronization. When no power is supplied by the utility grid, i.e., a no-grid condition is detected, the campus network is isolated from the local utility, signaling diesel generation and campus grid formation with subsequent PV synchronization. The MG transition state lasts for several minutes which forces the MG metering into a non-metering state (translating to gaps or repetition in time series data). The MG controller balances generation kVA (diesel and renewable) with demand by signalling generator and inverter controllers to change and alter apparent power output in order to match the demand. Additionally, the MG controller also reacts to the MG's 'health' signals in order to execute the startup procedure of the diesel generators which are locally synchronised before connecting to the 11kV busbar via a step-up transformer. The latter electrification procedure requires the diesel generators to match full demand before PV synchronisation and needs a set of generators with spinning reserves.

III. UNIQUENESS OF THE TRANSITIONS OF HYBRID PV-DIESEL CAMPUS MICROGRIDS

This section discusses the efforts towards transition classification, i.e., identifying whether the microgrid is islanded or connected to the utility based on historical data. The proposed scheme detects the transitions of the system without perturbing or injecting perturbations into the system. The scheme was designed with the aim of processing and reacting to historic frequency data for modelling purposes (see Section IV).

When a rolling blackout (loadshedding) occurs, the MG experiences a transition from one state to another (e.g. transition from the main utility to the PV-diesel powered MG). During such a power supply disruption, there is a time delay (on average 2 $\rightarrow$ 5 minutes) where the diesel generators and network meters start up, thus causing a phenomenon that resembles a Non-Detected Zone (NDZ) or state of transition. During this time the main controllers and meters will store the last frequency value that was recorded prior to the transition. This frequency value is continuously recorded until the generators have reached a stable state around the 50 Hz threshold and the meters have successfully rebooted. The latter repetitive recording phenomenon is unique to each meter type. The continuous repetition of the last recorded frequency creates the transition state.

In order to identify the transition state in historic frequency data, a method of rolling averages is utilised. This method is sufficient due to the continuous and stochastic nature of the frequency excursions. In the above-mentioned detection scheme, firstly the difference between the measured frequency values is calculated so as to simplify the averaging calculations and simplify the Boolean logic required to switch the identified states. A rolling window size of 10 s is used to sweep across the frequency difference data and calculate the average of those 10 corresponding values (since the data has a 1 s resolution, we have 10 values for a rolling window of size 10 s). If 2 consecutive averaged values are precisely equal to 0, then the algorithm classifies this as a transition state and will continue to do so until the average is not exactly equal to 0.

The functionality of the classification algorithm is dependent on the nature of the historic frequency data, where the states before and after a transition can never be the same and the initial state must be pre-classified. The initial state (either utility or MG state) is then used as an input for the algorithm. Boolean values are assigned to the transition, utility and MG states. The first Boolean value is used to keep track of whether the grid is in a transition state or not. The second Boolean value determines whether the next state is microgrid or utility. By identifying the transition state, the algorithm utilises the respective Boolean values to switch between the utility and MG states. The transition finder scheme can be observed to function roughly as a frequency divider, toggling one Boolean variable on the positive edge of another. The resultant state-classified frequency data was used for the statistical analysis as the main modelling result of this paper.

With regards to the classification of islanding states, a typical power grid is set up such that the power consumption is of main importance, and the power supply secondary. However, in the case of the QwaQwa MG, the incoming power supply is the primary focus of the algorithm. This can be seen in the overview section of the algorithm where it uses the profiles of the historic frequency readings to evaluate and label the relevant state, i.e., utility, MG, or transition. Each state has its own unique frequency profile and driving dynamics and thus requires accurate classification.

IV. STATISTICS OF MG FREQUENCY RECORDINGS: MODELLING THE OBSERVED MICROGRID FREQUENCY EXCURSIONS

From the perspective of frequency dynamics, the UFS QwaQwa MG offers a unique mix of signatures, transitions, and control dynamics. As discussed in section II, the ability to record the frequency on the 11 kV common-point-of-coupling allows the operator to retrieve a seamless frequency representation that illustrates all the transitions between grid-connected and MG states, control transients, and different modes of MG states. Fig. 2 illustrates the latter ability with direct seamless comparison between grid/MG frequency and power consumed. It also clearly illustrates high degrees of variability in the power consumption profiles (variable demand and renewable generation) with clear improvements in frequency variances between different states.

Fig. 3 captures a typical transition between the grid-connected state and the MG state. Immediate observed changes in frequency excursions are visible between the states and the MG state which is typically led by a frequency decay over a time span of a few minutes. The stability (observed small variations in frequency) of the MG state is

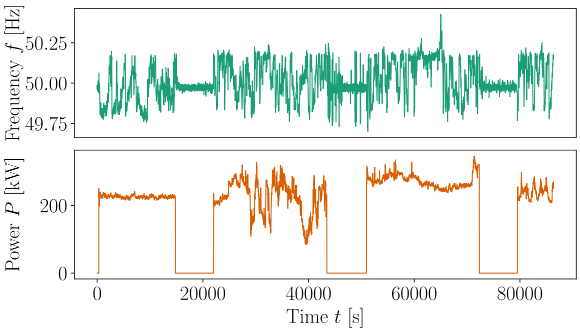

FIGURE 2. Typical MG frequency/power recordings cycling between grid-connected and microgrid state. Note that the gaps in the power consumption correspond to the MG states, hence grid-disconnected states.

influenced by fluctuations in renewable generation, demand, control hysteresis, and failure in diesel generation.

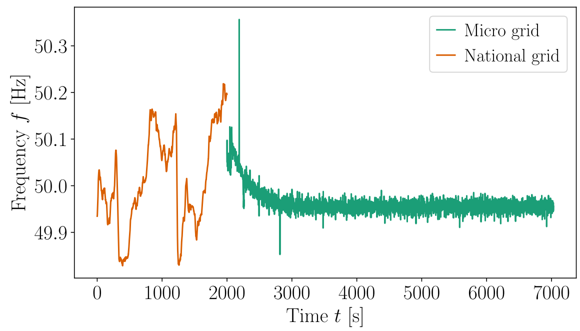

FIGURE 3. Typical transition between grid connected and MG states.

Fig. 6 illustrates the anti-poles in MG states that exist during the day and night. Control dynamics are sensitive to variability in control inputs (loads, renewable generation, and diesel generation) and typically exhibit higher degrees of variability in frequency recordings during the day. During sunny days and low variability, the night/day MG states are indistinguishable upon visual inspection, except for instances of control hysteresis and generation failure of some sort.

A. COMPLEX SYSTEMS MODEL OF THE OBSERVED MG FREQUENCY EXCURSIONS

Having seen a few examples of distinct MG states of the UFS QwaQwa campus, we construct a simplistic stochastic model that qualitatively describes the frequency dynamics. Consider the MG frequency $f(t)$ as a random variable described by [6], [11], [12], [13], and [14]

$$\mathrm{d}f(t) = -\gamma\,(f(t) - \mu(t))\,\mathrm{d}t + \sigma\,\mathrm{d}B^H(t) + L(t), \quad (1)$$

with γ the response strength, $\mu(t)$ a dynamic driver or mean-reverting strength that drives the frequency, $B^H(t)$ a fractional Brownian motion with Hurst coefficient H, and an added noise element $L(t)$ that is induced by exogenous elements. We should immediately note that this representation of the frequency is one of a linear response $-\gamma f(t)$ from the controller. We can now make use of off-the-shelf mathematical tools to show, from a data-driven perspective, that our model is well justified. Let us start with the linear response and dynamic driver.

1) LINEAR RESPONSE AND DYNAMIC DRIVER

In order to show that the frequency controller reacts linearly to frequency changes, we use estimators for the drift, based on a Fokker–Planck description of our model (1) [20]. We employ a non-parametric kernel-density (Nadaraya–Watson) estimator for the drift $D_{m=1}(f)$ and diffusion $D_{m=2}(f)$, given by

$$D_m(f) = \frac{1}{m!}\frac{1}{\Delta t}\frac{1}{N}\sum_{i=1}^{N-1} K(f - f_i)(f_{i+1} - f_i)^m, \quad (2)$$

with an Epanechnikov kernel

$$K(f) = \frac{3}{4}(1 - f^2), \text{ with support } |f| < 1. \quad (3)$$

We note here that f_i is a recorded frequency $f(t)$, which is naturally discrete in increments i of length 1 second, i.e., the sampling rate $\Delta t = 1$ s. We can now employ this estimator for all the MG states separately after a relaxation period of 15 minutes (900 seconds). This is to discard the transitory slow exponential transient evidenced in Fig. 7. In Fig. 4 we can ascertain from the data 1) the controller responds linearly to frequency changes; 2) the operational point lies close to 49.967 Hz; 3) the (negative) slope of $D_1(f)$ results in γ used in Eq. (1).

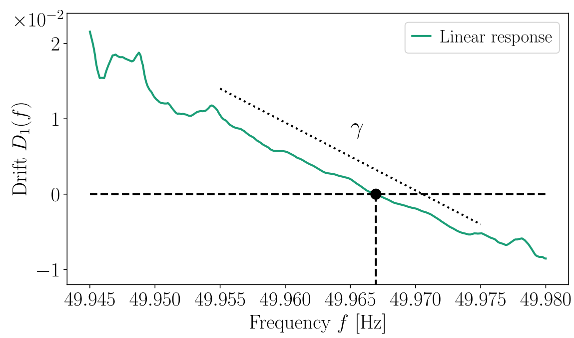

FIGURE 4. Drift estimation following Eq. (2) return the (negative) linear response γ [21].

Here we note a difference between the linear response γ, obtained via the drift $D_1(f)$ and the slow exponential dynamic transient $\mu(t)$, which can easily be captured by considering an exponential function

$$\widehat{\mu}(t) = A\exp(-\lambda t) + c, \quad (4)$$

which can be fitted with a simple least-square method. The response rate λ of the dynamic response is of the order of $\lambda = 4.35 \times 10^{-3} \pm 0.24 \times 10^{-3}\ \mathrm{s}^{-1}$. In principle, one could expect $c = 50$ Hz, i.e., the reference frequency, yet as observed in Figs. 5 and 6 the MG frequency attains equilibrium close to, but not exactly at 50 Hz (cf. Fig. 4).

2) CORRELATED STOCHASTIC NOISE

Just like one observes in utility grid recordings of utility power-grid frequency recordings, the data is *noisy* [6], [8], [22], [23]. The frequency trajectories are not as smooth as one expected for dynamical systems (not in chaotic states). Moreover, these frequency fluctuations are not purely uncorrelated processes like Brownian noise/motion. Employing detrended fluctuation analysis (DFA) [15], [16], [17], [18], [19] we estimate the Hurst coefficient H of the MG frequency trajectories. Hurst coefficient H smaller than $H < 1/2$ are self-anti-correlated processes known as *rough* processes. Purely uncorrelated processes, like conventional Gaussian noise or Brownian motion, have $H = 1/2$. Positively correlated processes have $H > 1/2$ and are *smoother* than all aforementioned noise processes (in the limit $H = 1$ the processes become purely continuous and differentiable and we return to a dynamical systems' setting). Following the well-described procedures to obtain the Hurst coefficient (see [18], [19]) using a first-order polynomial and fitting the fluctuation function between 15 and 300 seconds, we obtain a Hurst coefficient $H = 0.28 \pm 0.14$, i.e., a strong self-anti-correlated process, which educates our choice of fractional Gaussian noise $\mathrm{d}B^H(t)$ in Eq. (1). The amplitude can partially be assessed with the diffusion estimator $D_2(f)$ in Eq. (2) and adjusted to match the magnitude of the fluctuations, educating our choice of σ in Eq. (1).

3) OBSERVED PV-INDUCED SPIKES IN FREQUENCY EXCURSIONS

The elements presented previously, from the dynamic driver describing the exponential transient, the drift $D_1(f)$ from where we retrieved the linear response, the DFA algorithm and the diffusion estimator $D_2(f)$ which elucidate the nature of the noise in the MG, comprise a set of elements that fully describes a stochastic process for MG frequencies. We do note that during active periods of PV power generation, the MG frequency is affected by large spikes/fast frequency deviations. These are sporadic and exogenous to the nature of the stochastic model in Eq. (1). We condense them in a singular element $L(t)$ that is an additive noise term not part of the fundamental dynamics of the frequency. Tangentially following Anvari et al. [24], we utilise a combination of Poisson jumps with Gaussian amplitude (a Lévy-like noise) [25], [26], such that

$$L(t) = \xi J(t), \tag{5}$$

with $J(t)$ a homogeneous Poisson point process in time with an amplitude drawn from a Gaussian distribution ξ with mean zero and variance σ_ξ. We note again that we consider this just as added noise in the model which is not part of the stochastic integral of $\mathrm{d}f(t)$ in Eq. (1).

B. OBSERVED MULTISTABILITY INDUCED BY CONTROLLER-DEMAND MANAGEMENT DISAGREEMENT

Control optimisation for the QwaQwa campus microgrid is continuous in the MG state, especially as demand-side management schemes are operational (as discussed in section II) that reduce the load to a point where the controller cycles between a total of 2, 3, or 4 engaged diesel generators that contribute inertia to the MG. The latter generates interesting periodic frequency signatures, i.e., hysteresis, as seen in Fig. 7. The MG oscillates between two inertia states as generators enter and exit the energy mix, leading so small frequency excursions. The frequency inter-oscillations are led and followed by stable MG frequency states (lower variances).

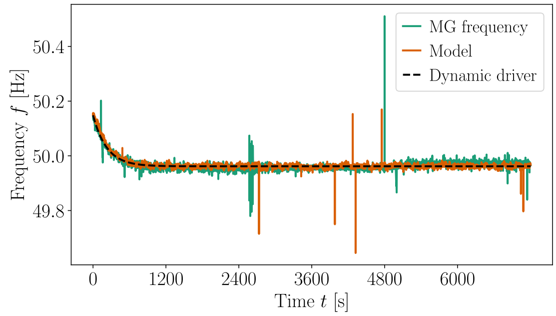

FIGURE 5. Stochastic model of the MG frequency involving a dynamics driver, a rough correlated motion, and an exogenous noise, given in Eq. (1).

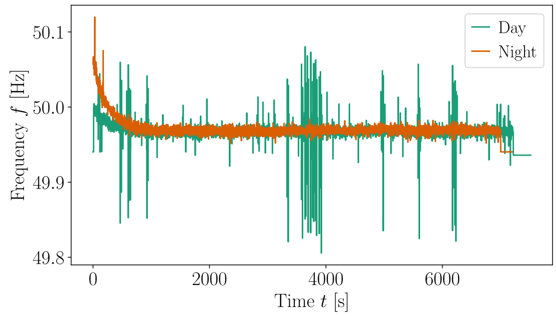

FIGURE 6. Comparison between two different microgrid states, mid-day state (governed by PV production variability) and a night state (governed by diesel generation and low variability).

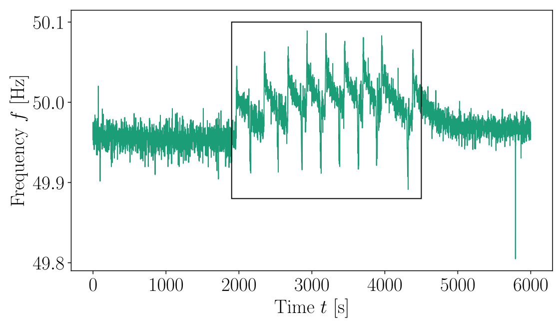

FIGURE 7. Typical control hysteresis induced by demand management reducing the load to a point where the controller experiences difficulty determining the appropriate number of online generators.

Short grid connected states can also occur within MG states, generating transitional states superimposed on the main MG states, see Fig. 8. The latter could be due to network faults, sporadic grid-connected states, or MG failure (in the case of the utility grid being available).

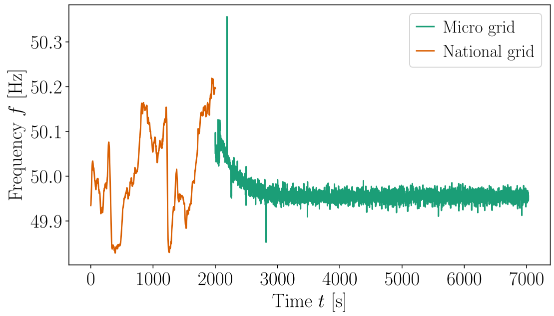

FIGURE 8. Inter MG states super imposed on main MG States.

Unplanned (or transient) MG states also exist due to network faults inducing MG states and could range between minutes, hours, or days.

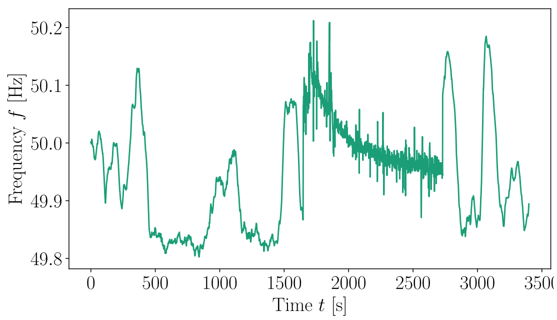

FIGURE 9. Short interim network fault (of a few minutes) inducing a noisy MG state.

The next section explores and showcases the implementation of synchronous frequency measurements at two different campuses 300km apart. The implications of generating seamless recorded frequency excursions, combining utility, and MG states, are discussed.

V. GENERATING RECORDED FREQUENCY EXCURSIONS BY COMBINING UTILITY/MG STATES IN SYNCHRONOUS MANNER

Frequency recordings are similar at different locations when measured at more than 1 minute resolution, but showcase a plethora of dynamical effects (microscopic fluctuations) at 1 and sub-second recording intervals, see [23]. The latter observation can be leveraged for the purposes of generating seamless recorded frequency excursions for MG locations. This particular measurement campaign relies on the ability to measure synchronously, i.e. measurements of the same system at two different locations need to share the same timestamp.

To achieve the most accurate synchronised measurements associated with power system parameters, operators utilise timing servers that offer extreme timestamp accuracy and the opportunity to synchronize many devices within substations or renewable plants, such as meters, controllers and relays. The latter is particularly appropriate when investigating sub-second dynamics and MG responses. The challenge is to synchronise time series data for the purposes of studying dynamics and be sensitive to the timing topology of the network (or networks) under observation. If the aim is to study sub-second MG/utility dynamics and fast controller reactions, the recommendation will be to note inter-campus signal travelling times and propagation times between campuses, especially if meters are remotely polled. If the total propagation time exceeds to desired observation interval, the recommendation will be to re-design the observation campaign.

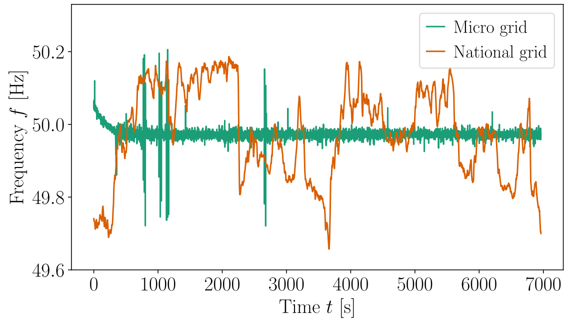

FIGURE 10. Comparison of utility frequency (measured at BFN campus) with QwaQwa campus MG frequency (measured remotely from the BFN campus)

An operator will have two broad timing paradigms to possibly implement: pointing individual meters to a common timing server at each location and transmitting this timestamp to data servers, or pointing individual data servers, further downstream, to shared timing servers. Both paradigms are subjected to delays that can be divided into (ranging from small to large delays) inter-substation delays, substation-to-server delays, and inter-location delays. Any time delays are subjected to varying path lengths between meters, collectors, and data servers. Total time delays are also a function of network topology that could change over time due to failure or transmission loss. In the case of Phasor Measurement Units, onboard clocks or timing servers need to be accurate to nanoseconds to enable synchronous measurements and this is achieved with direct GPS links. Synchronous measurements are also subjected to communication network delays and power outages that are typically flagged during post-processing. In this paper, one-second resolution frequency measurements at both the UFS Bloemfontein (BFN) campus and the QwaQwa campus were recorded. The latter resolution was linked to meter capabilities. Frequency excursions observed at BFN campus were collected from the main meter that is separated by 500 m. Simultaneously with the previously mentioned measurements, QwaQwa frequency data was requested from the BFN campus with a round-trip travel time of 3 ms. In comparison with the desired measurement resolution of 1 s, the longest inter-campus round-trip delay is less, hence the authors neglect the small delays between meters and servers. As mentioned in the preamble of this section, network dynamics are identical at different locations if observed at intervals of 1 s or more, and ultimately, allowed the authors to construct a synchronously observed frequency excursion for the QwaQwa MG that is composed of utility frequency measurements (recorded on BFN campus) and MG frequency measurements (recorded from the BFN campus remotely), see Fig. 10.

VI. CONCLUSION

The main contributions of this work are summarised as

1) Recording real-world, living voltage-frequency of a PV-diesel MG, the in-service QwaQwa campus MG of the University of the Free State
2) proposing a simple physics-inspired model for the observed frequency dynamics of a fully functioning campus MG
3) showcasing synchronous frequency recordings at two different campuses and outlining the technicalities of such data campaigns.

The design of university campus MGs, within the South African setting, will typically be governed by the need for continuous power supply to ensure uninterrupted functioning of university and academic activities. Prioritising continuous power supply above long-term economics and smooth transitions ultimately governs the inherent dynamics of a typical South African MG. The latter-mentioned dynamics are reflected in MG frequency measurements that showcase transitional effects, startup sequences, response times to varying loads, and the effect of volatile renewable generation on the dynamics. The developed simple mathematical machinery is used to describe the observed frequency dynamics, which could also be utilised for larger grids, hence making the QwaQwa microgrid an ideal test bed to explore utility-related control schemes, network stability, reaction to failures, and digital twin-related schemes for MGs. In this work, we showed that renewable generation modulates the frequency response to resemble Lévy-like noise—inherently linked with PV generation—, of which the direct effect could be on schemes that rely on frequency states to control campus loads. We showcased several issues pertaining to hysteresis effects due to conflicting governor actions and transient states in the MG state. This paper also showcased the current status of synchronous frequency recordings at different locations in the power network, by specifically dealing with accurate time stamping and issues arising therein. The latter showcase led to a proposed strategy to generate seamless frequency excursions at various MG locations based on on-site and remote frequency measurements. Future work includes the investigation of load control on the MG stability and the coupling of the social and resource network via demand reduction interventions to reduce diesel usage and reduce control hysteresis.

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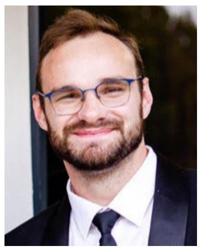

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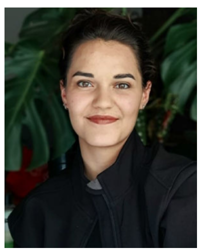

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