PV GENERATION MONITORING USING CALCULATED POWER FLOW FROM µPMUS

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Abstract. *The use of PMUs (Phasor Measurement Units) to monitor microgrids has grown over the last years, due to its ability to offer accurate and synchronized voltage, current, and frequency measurements. In many microgrids, the PMUs operate without a current transformer (CT) and measure only voltage phasors values. We propose a power flow (PF) calculation using µPMU (or micro-PMU) voltage measurements, to allow these devices to indirectly monitor photovoltaic (PV) generation or electric loads. We used the µPMU data from a case study at the Centro Politécnico of the Universidade Federal do Paraná - UFPR campus, Brazil. We compared the calculated power flow with the power measured by a conventional power meter. We showed that this "virtual CT" approach with increased time resolution from µPMU can be particularly useful to aid in the detection of events, PV generation monitoring, and non-intrusive load monitoring (NILM) in general.*

Keywords: µPMU, power flow, microgrids, PV generation

1. INTRODUCTION

In energy systems, it is important to understand load behavior for efficient management. Microgrids with renewable energy generation have gained popularity over the last few years. It allows to decrease energy costs for consumers and increase efficient energy utilization. Nowadays, monitoring equipment are used to understand how renewable sources of energy interfere directly in the electrical grid. One such equipment is the phasor measurement unit (PMU), which is a device capable of capturing amplitude and phase angle of electrical voltage and current at higher sampling rates, synchronized with a common time base. This is possible by using the reference clock broadcasted by the global positioning system (GPS) and received by each PMU. An example of microgrid monitoring with PMU is the one installed in the Illinois Institute of Technology in Chicago where load behavior in dozens of buses is studied (Shahidehpour and Clair, 2012). Another example is the microgrid at the Federal University of Parana, with PV generation, power meters and PMUs for continuous monitoring (Oliveira *et al*., 2020). Part of this setup was used as a case of study in this paper.

In recent years, the PMUs have been improved, due to the technological progress. The main improvements were in precision, accuracy and measuring rate, maintaining the similar acquisition process of the former PMUs. This enhanced equipment known as µPMU provides up to 120 phasor measurements per second within microseconds accuracy, which is two times more data than the former PMUs (Lee and Centeno, 2018).

Non-intrusive load monitoring (NILM) was introduced in 1992 by Hart *et al.* (1992). The concept of NILM is to collect power data from a single point in a system and perform individual load studies from calculations for load disaggregation. It was done in the past by using active and reactive power measurements collected at relative low sample rate in the minutes or seconds scale. Today the concept of NILM has expanded and machine learning techniques are utilized to perform load unbundling. Lazzaretti *et al*. (2020) proposed a multi agent combination, for NILM applications. Zoha *et. al.* (2012) presented many NILM methods in use to the date, in a review article. The subject NILM can be addressed in many forms. There are transient and steady state methods (Rathore and Jain, 2018; Chang, 2012; Xingang *et. al.*, 2020).

The use of µPMU opens new possibilities for NILM. The higher acquisition rate (up to 2 amplitudes and phase angles per cycle) can provide more frequent data to the algorithms for load disaggregation. Recent studies used the device as a reliable tool to monitor and disaggregate PV generation data from an aggregate power acquisition in a microgrid. In (Kara *et. al.*, 2018) the power data is collected by the µPMU and further treated to disaggregate photovoltaic (PV) generation values, using four different machine learning methods. Kara *et al*. used data from two µPMUs, one being installed at the substation and the other close to the PVs. Both PMUs measured power using a current transformer (CT). In another study (Jaramillo *et. al.*, 2020), power data is collected using another type of PMU, in a residential sector (one house) to perform PV generation identification and disaggregation. Jaramillo *et. al.* performs PV recognition using machine learning algorithms from statistical NILM methods. In a recent paper (Saeedi *et. al.*, 2021), the µPMU is also used to collect power data, performing behind the meter acquisitions, which represents at some level the NILM approach, collecting the power signatures (V and I) in a single acquisition. Those papers successfully present NILM, PV disaggregation, and the potential of machine learning algorithms for these applications with regards to energy efficiency. The power data in these papers are acquired by the combination of current values, measured by current transformers (CT), and the voltage phasor acquired directly by µPMUs. However, some PMU measurement systems do not use CT, either to lower installation costs or because only voltages phasors are necessary to estimate the system state. In this paper, we propose the use of two µPMU to perform load monitoring without the CT. We implement and evaluate the power flow (PF) calculation between two µPMU to be used as higher rate data for PV power monitoring.

The paper is organized as follows: Section II presents the methodology and overall framework. Section III shows the results for PV monitoring and potential NILM applications using the full capacity of the µPMU. Section IV concludes the paper.

2. METHODOLOGY

The proposed method is based on the power flow calculation between two µPMUs in operation at *Centro Politécnico of the Universidade Federal do Paraná* - UFPR campus, Brazil. The data is stored and analyzed by the Operation and Monitoring Center (OMC), which is located in a laboratory in the Electrical Engineering Department (DELT). The µPMUs used in this paper are fabricated by Powerside. The device records 120 samples per second at 60Hz, 7200 phasors per minute, (Lee and Centeno, 2018).

The proposed methodology is divided in two parts: the first is validation by comparison of the calculated power flow and the power collected by a power meter (Kron Konect). In the second part, graphs are presented to illustrate the full capacity of the PMU sample rate to be used in NILM applications.

In a two-bus system, if one knows the line impedance, the voltage and phase angle at each bus, the active power flow from bus *i* to bus *j* (P_{ij}) can be determined by

$$P_{ij} = \frac{1}{R^2 + X^2}\left(R|V_i|^2 - R|V_i||V_j|\cos(\delta_{ij}) + X|V_i||V_j|sen(\delta_{ij})\right) \tag{1}$$

and reactive power (Q_{ij}) flow is given by

$$Q_{ij} = \frac{1}{R^2 + X^2}\left(X|V_i|^2 - X|V_i||V_j|\cos(\delta_{ij}) - R|V_i||V_j|sen(\delta_{ij})\right) \tag{2}$$

where

- R - Line resistance.
- X - Line reactance.
- V_i - Voltage in bus *i*.
- V_j - Voltage in *j*.
- δ_{ij} - Voltage phase angle difference between buses *i* and *j*.

The Fig. 1 is a diagram of the actual disposition of meters and loads in this case study. We describe the system in 3 sectors: University Substation, Building Panel and Lab, each one with a singular sensor. The first µPMU is installed at the University Substation bus, being the Bus *i* of the method. The second µPMU is installed at the Lab main bus, representing the Bus j. In the Building Panel there is a power meter (Kron) that measures all the power of the Department (Lab + Other Loads). This is not exactly a two-bus system because current to DELT loads do not go all the way to the lab (bus j). But since the DELT loads are small (<3 kW) compared to the main lab power (100 kVA PV inverter) they will introduce small deviations in the comparison. Also, another simplification is to consider only one bus at the Lab, because the two buses are close to each other (<10 m), and power from the last bus is just a small fraction of total power. The first bus had a cable diameter of 95 mm and 45 m of length, the second bus cable had 120 mm diameter and 30 m length. Those values provide the approximation of the impedance used in this paper.

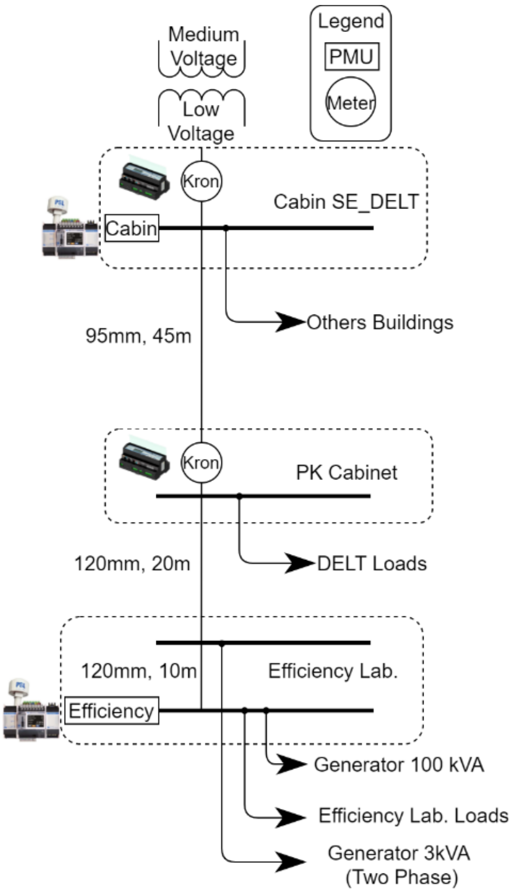

Figure 1- Unifilar diagram of the case study.

The overall load analyzed by this setup are the department loads in the Building Panel plus the Lab Buses loads. The expected power flow based on the sectors shown in Fig. 1 is

$$PF \approx Kron = BPanel + LabBuses \tag{3}$$

where

- *PF:* Power Flow calculated from µPMU measurements (using (1)).
- *Kron*: Power captured by the Kron power meter, in the PK Cabinet.
- *BPanel*: Installed loads in the electrical engineering department (DELT loads).
- *LabBuses*: Generation and load values (Efficiency Lab loads).

Before proceeding to the validation, the data integrity captured by the µPMUs is verified. Fig. 2 and Fig. 3 show examples from gathered data by the µPMU, representing the voltage magnitude and voltage phase angle of buses *i* and *j*. The values shown in Fig. 2 correspond to the variation of PV generation during the day, which occurs between 6 - 19 daily, reaching 20 kVA in a single phase.

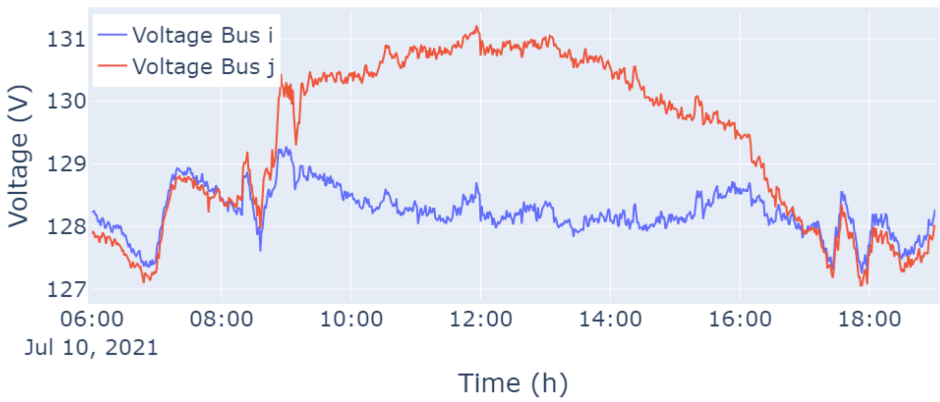

Figure 2 - µPMUs voltage data.

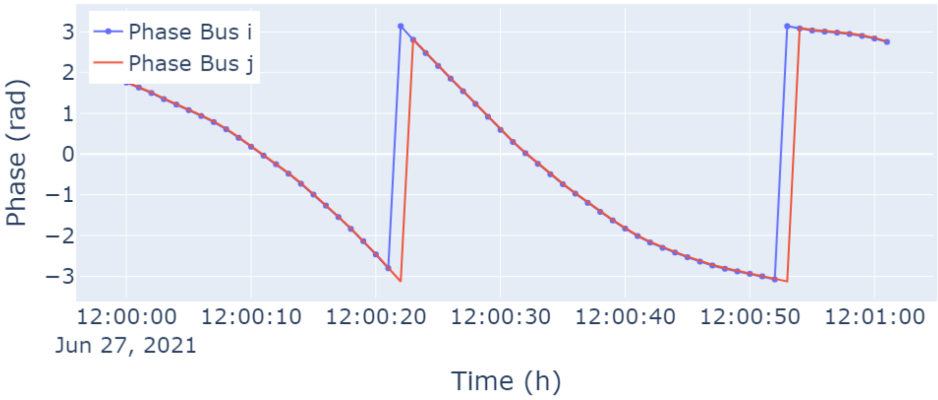

Figure 3 - µPMUs voltage phase data.

Fig. 3 presents the voltage phase angle measured by µPMU in bus *i* and µPMU in bus *j*. The time range was only 60s to show the small difference in the phase angles. Their values varies continuously because they are not synchronized with the measurement time base (GPS time). The plot discontinuities at +π, are only the representation effect of the angle values being limited to [-π, + π] interval. The small lag between the voltage measurement is expected because of the low line reactance (total distance of electric cabling is only 75 m) and the power magnitude (<20 kW). Higher line reactance or higher transmitted power would increase phase lag.

After the data integrity check, the power flow validation is performed. This stage is a side-by-side comparison of the result from the µPMU power flow and the active power data captured by Kron. The objective of this step is to verify if the PF method obtains the lowest value possible of a normalized root mean square error (NRMSE) between those two acquisitions. The normalization is made by using the maximum active power in module from each day and is given by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i}^{N} e_i^2} \tag{4}$$

$$NRMSE = \frac{RMSE}{|Max|} \tag{5}$$

where

- N: Number of samples in the acquisition.
- e_i: Difference between PF_i and $Kron_i$ at the instant *i*.

The data acquisition always starts at 6 a.m. and ends at 19 p.m. on days with full data integrity, when both voltage magnitude and voltage angle have been correctly captured. To implement the power flow, we only use one of the sampled phases, due to similarity between them. For this part, it is important that both data, µPMU and Kron are s configured to show 60 samples per minute, which is the configured acquisition rate of Kron Konect sensor. The approximated values of R and X are compatible with fabricant cable impedance data. The values of reference are:

- Resistance (R) = 23mΩ
- Reactance (X) = 17.5mΩ

The values of R and X remain constants throughout the comparison stage and results stages. We expand the PF validation for other days, to support that the R and X are correct. In the results stage, we continue to implement the method at the Electrical Engineering Department, pushing to the limit the sampling rate from the µPMU. The objective of this step is to show the µPMU as a precise device to monitor PV generation values with the power flow method.

3. RESULTS

The outcome and the implementation of the method are presented to support the use of µPMU without CT as a viable candidate for PV monitoring. Fig. 4 presents the three phases from the µPMU calculations to show that the values are very close, and this can be considered a balanced system. The PV Generation was plotted only for comparison. Total generated power is directly collected from the inverter connected to the PV panels, one third of this value is plotted. The phase 2 was arbitrarily chosen for the overall results. Fig. 5 shows the calculated power flow (PF in blue) from µPMU voltage measurements after the set of R and X described in the Methodology section, together with the measured power (Kron in red) and the power injected by PV generator (green), which is the dominant power source on sunny days. The values are negative by convention, indicating that power is being injected into the grid. The difference between PF and Kron for this acquisition (Fig. 4) was 6.1%, 6.2%, and 6.6%, for each phase, respectively. The overall system is considered fairly balanced, and all analysis will be conducted with only one phase.

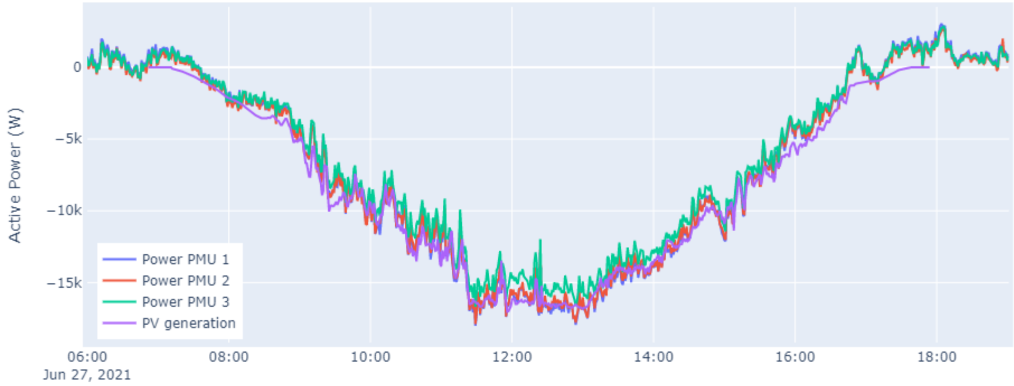

Figure 4 – Three phases of the μPMU, compared with the PV generation.

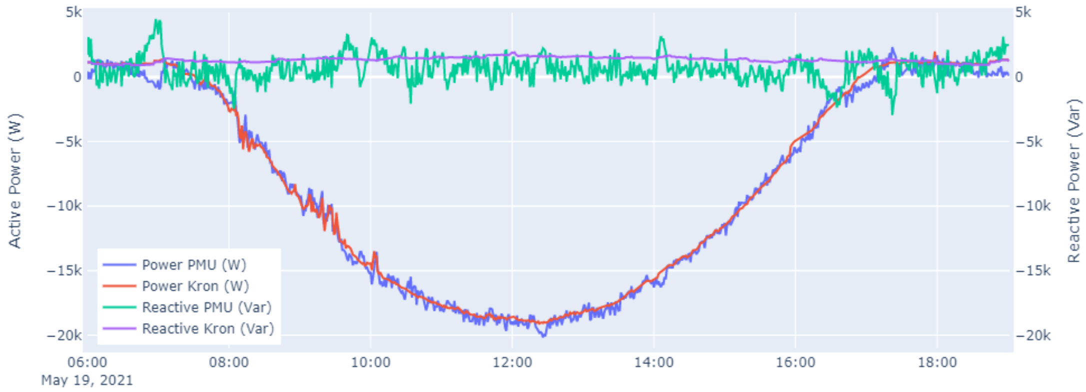

Figure 5.a – Calculated active and reactive power flow (PMU) compared with the measured power (Kron).

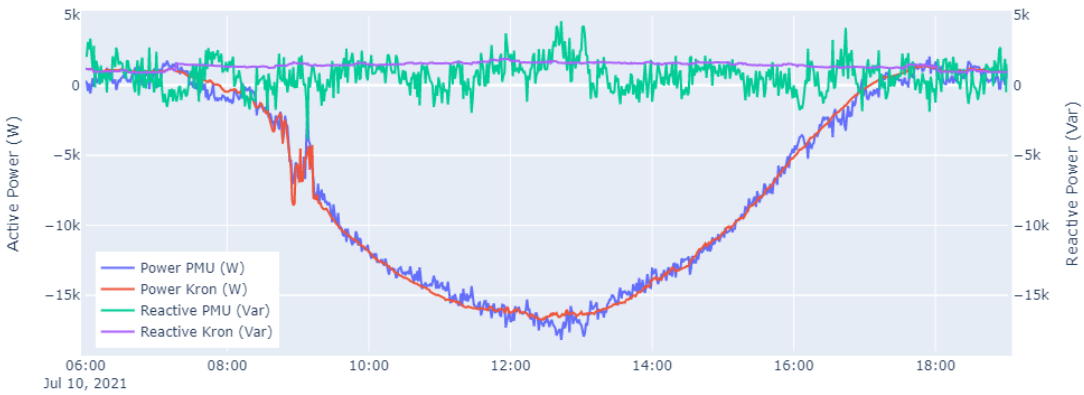

Figure 5.b – Comparison of calculated and measured active and reactive power.

Figure 5.c - Calculated and measured active and reactive power in a cloudy day.

The results of the difference between calculated power flow and the values measured by power meter (Kron) are shown in Fig. 5.a-c. On sunny days, when the amount of generated power is large, the other loads in the building are small and the error is also small (<10 %). On some cloudy days, with less generated power and because the sampling moments are different, the error is greater (10 % < error < 23 %). On June 8th (Fig. 5.c), the PV generation was small and variable. The building loads could not be properly neglected, resulting in higher NRMSE. The power meter measures the power every 60 s, and the power flow calculation is performed with one measurement from the µPMU that operates at 120 phasor per second. The power meter is not synchronized with the µPMUs. Load fluctuation within the 60 s window is not detected in the same way by the two types of measurements. The overall results from May and June presented low NRMSE supporting that the calculated power flow is fairly accurate for PV monitoring applications, and for event and disturbance detection in particular.

The Fig. 6 shows the result of PF calculation with 10 more samples than the Kron meter. This result shows the benefits of high temporal resolution of µPMU measurements which is more appropriate to track fast variation of power.

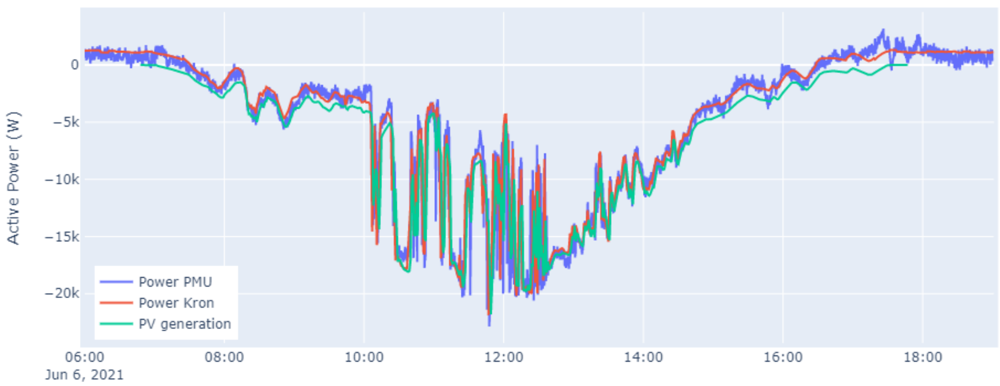

Figure 6 - Generated power on a partially sunny day. Power flow calculated every 6 s.

The next case shows an example on disturbance detection. In Fig. 7 the power flow calculations are performed every second. On this day in particular, we can see the PV generation was automatically turned off around 12:27. If we rely only on data from Kron the conclusion will be that it was a passage of cloud that interferes with the generation. However, when compared with the PF method, a 15kW variation is observed, which possibly represents a full shut-down of the PV generation. This example illustrates how the power flow technique can also be used to capture disturbance events.

In another case, related to an event detection, the day where the PV generation operated in an erratic way, with several automatic shutdowns was analyzed. The on/off events can be seen in Fig. 8, which was the day chosen for this experiment. The power flow was calculated every 16 ms (sampling rate of 60 FPS).

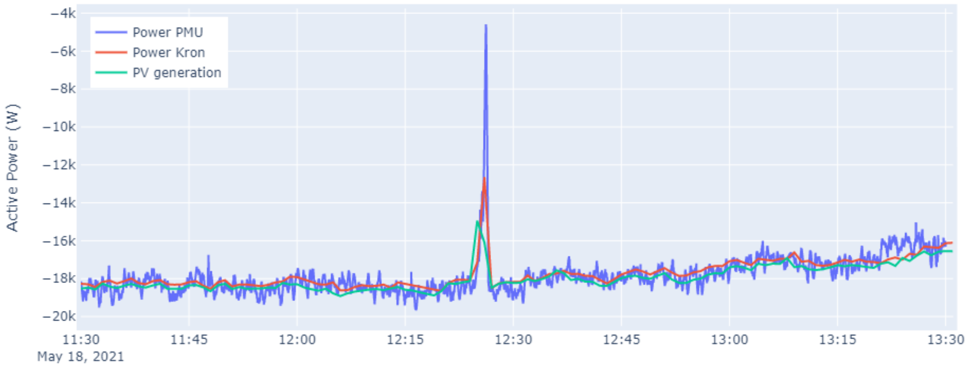

Figure 7 - PV inverter shutdown and power on. Power flow calculated every 1 s.

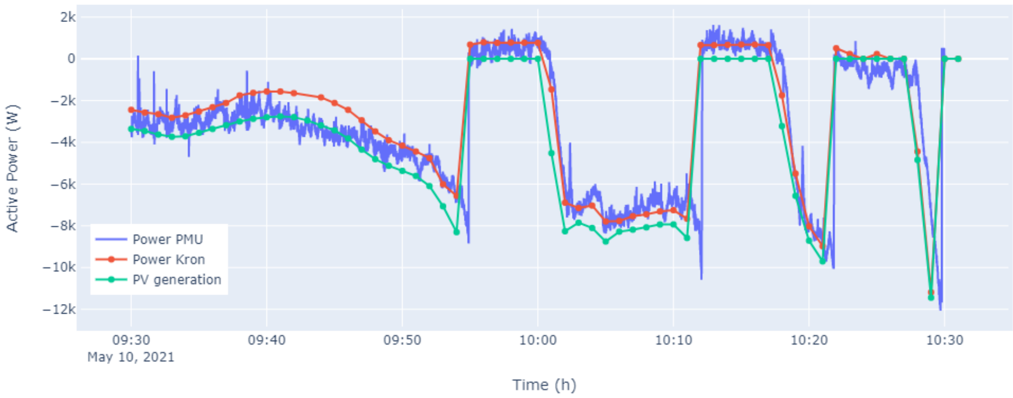

Figure 8 - PV inverter turn off and on. Power flow calculated every 16.6 ms.

Fig. 9 shows a zoom in the shutdown event to see the rising edge of this turn off event. The power flow was calculated using all µPMU samples, which is 1 sample per 8.3 ms (120 FPS). In comparison with Kron, the µPMU power flow method shows with much more time resolution. The exact moment that the turn off event occurred was 9h54m53.858s.

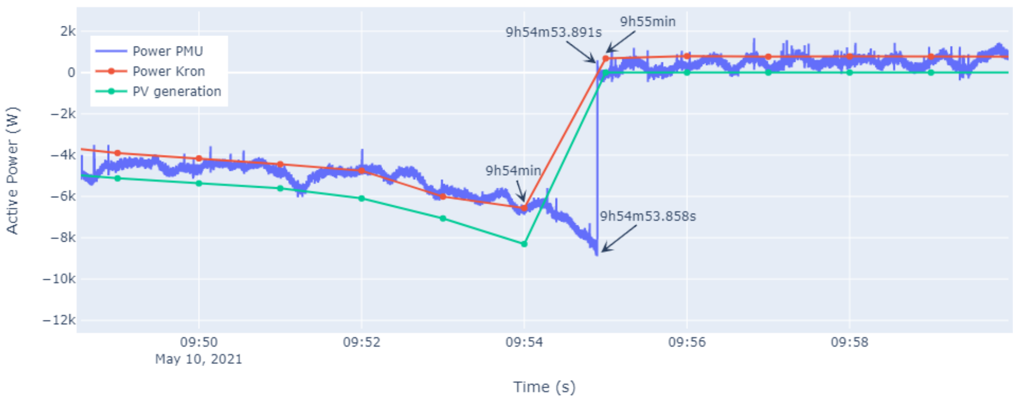

Figure 9 - PV inverter shutdown. Power flow calculated every 8.3 ms.

The PF method presented here also opens possibilities to implement load disaggregation, similar to the one presented by Sossan *et. al*. (2018). In their paper the power flow data is captured from a point of common coupling and further treated to be used in 4 different methods, which perform the PV disaggregation.

4. CONCLUSION

A power flow application using the µPMU data was proposed to allow monitoring of loads and PV generation in microgrids. A case study using µPMUs at the *Universidade Federal do Paraná* - UFPR campus was presented. We compared the calculated power flow from two µPMUs with the power measured by a conventional power meter (Kron). The results confirmed that the calculated power flow based on voltage and phase angle measured by the µPMUs closely follows the expected power measured by conventional power meters. In the enhanced sampling results, the µPMU also works precisely, presenting data that overcomes the power meters monitoring in event and disturbance detection.

The calculated power flow from µPMUs allowed us to obtain consumption profile from loads or PV generation profile with higher temporal resolution at 120 measurements per second, without the need of a CT. This allows one to closely follow events at every 8.3 ms and could benefit many approaches for load analysis in non-intrusive load monitoring (NILM).

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