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List of Abbreviations

LA	Lab Access
UP	User Project

Executive Summary

As electricity grid operators encounter new challenges in grid operation due to profound changes in the electric energy system, such as decentralization of generation, also new methods to cope with these challenges are sought after. Therefore, an investigation of a concept for remote detection of malfunctioning grid-supporting devices is under development within the project. The operation of future electricity grids depends on the behavior of these devices and their support functions such as reactive power dispatch, used for example for voltage control. Using operational data of medium voltage transformers at first, as well as topological data and smart meter data at the low voltage level, the functionality developed is to enable better surveillance of grid-connected devices. This is to be achieved by combining machine learning algorithms for anomaly detection, classification, and load disaggregation. These are applied to the transformer data as well as to the device data to identify and classify unwanted behaviour. The aim is that the framework should be a future tool for grid operators and for cooperation with them to help them implement a central novel surveillance of low voltage grids regarding the connected devices. This framework will also be tested with some selected use cases in order to prove its usability. The data used will both be generated synthetic data from grid simulations as well as recorded data that can be gained in laboratory setups. The data collected in laboratory scenarios can then on the one hand be used to further enhance the quality of the synthesized data by comparing and filtering out possible influence factors that might have been neglected in the simulations.

On the other hand, the data can be used as a validation set to validate the performance of the used machine learning methods. These are trained and tested on the synthetic data, making such a validation set very valuable to assess the robustness of the approach and also be able to further improve the same. Multiple scenarios and setups were implemented to capture various use cases under different circumstances. The outcomes of the work are therefore the collection of such a validation set of operational data of grid participants and substations in scenarios that involve misconfigurations of grid connected devices such as inverters, battery energy storages or controllable loads. This dataset as a main outcome will then be used to robustify and further develop the monitoring approach.

1 Lab-Access User Project Information

1.1 Overview

The title of the project conducted is Data-Driven Detection of Malfunctioning Devices in Power Distribution Systems Validation, and the corresponding acronym is DeMaDsVal. The access period was split up into two stays: the first from the 15h to the 26th of November 2021, the second from the 19th of April to the 2nd of May 2022. The project was conducted at the PNDC of Strathclyde University. The user group member present was David Fellner.

1.2 Research Motivation, Objectives, and Scope

The new requirements regarding the sustainability of energy lead to new forms of generation but also new consumers. These new grid participants or grid-connected devices are often installed decentrally in the power distribution system. Due to the historical development of the power system, this part of the power grid is designed to merely distribute electrical energy in a very static manner. Due to this decentralization of generation and the introduction of new devices in general, the operation of the grid is becoming increasingly complex. To counter these new challenges, grid-connected devices have to provide grid-supporting functionalities. However, for the same legacy reasons, the distribution grid is ill-equipped with sensors. This makes the monitoring of the execution of these support functionalities difficult. To ensure the grid is operated in a safe and reliable manner, DSOs need new solutions to tackle this problem.

The main result to be achieved is collecting data for a framework that actually allows monitoring of grid-supporting devices. Therefore, the goal of this work is the validation of a method allowing central and remote surveillance of the expected function and behavior of grid-connected devices, such as generation units and their inverters, via detection of changes in their behaviour. If anomalies in the profiles are being detected a classification should help to categorize the unwanted behavior and help refer to a cause. This should be possible on the medium voltage level using operational data at a transformer, as well as on the low voltage level using the disaggregated transformer load profile. The overall aim is that the framework should be a future tool for grid operators and for cooperation with them to help them implement a central surveillance of low voltage grids. An important restriction is to only use relevant and necessary data for the purposes explained above in order to limit data traffic and avoid legal issues. Part of this aim is also to test the framework with some selected use cases in order to prove its usability.

The topological setup of such a scenario for data collection and testing of detection of misconfigurations is in a symbolic manner depicted in Figure 4: in the modelling approach, as the figure shows, all loads and PVs are connected to a terminal, which is in turn connected to a feeder via a line. Each household load and PV follow real consumption or generation profiles, respectively. Figure 1 also shows the malfunction assumed in this scenario: a single PV inverter altering its settings for unknown reasons such as a glitch during a firmware update. This inverts the control curve parameterized. In this case, this function is a re-active power dispatch curve controlled by the active power, which influences the voltage at the terminal the PV is connected to: the PV units are parameterized to follow the same control curve regarding reac-tive power dispatch. Therefore, one or more grids or parts of them were set up in a laboratory, where grid participants can be parameterized and malfunctions can be enacted at a given time, allowing for the creation of a labelled validation dataset. Numerous forms of malfunctions of various devices can be employed in the scenarios, which were then run for a certain amount of time capturing the behavior. This simulation was conducted in a reasonable amount of time since the time resolution of the data recorded is 15 minutes and no real-time simulation was necessary.

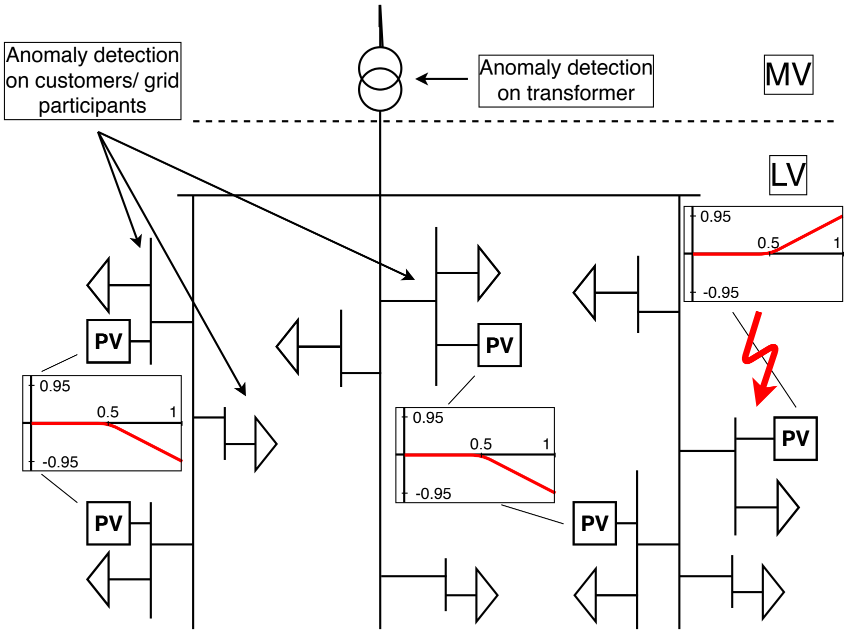

Figure 1: Selected test setup (Fellner et al., 2022)

To conduct such experiments and recordings infrastructure like controllable loads, generators and inverters, lines as well as measurement devices, such as Smart Meters, were necessary. These were then set up in a typical way for grids to be exhibiting the sought-after malfunctions, for example in a radial topology for rural grids. Loads and generation are parametrized to follow certain consumption or generation profiles, as well as certain control schemes regarding their consumption, dispatch or charge and discharge behavior in the case of storages. The operational data such as voltages and currents were then recorded at the grid participants as to mimic Smart Meter data as well as their power flows as to be able to validate the scenario. In this manner, one datapoint would be gained by a quick measurement at a certain setting of generation and load profiles. As already pointed out the generation and load profiles as well as dispatch and charging control patterns were controlled, whereas operational data was measured. Selected scenarios and time frames were picked out for the testing of methods. This was iteratively done after a first round of assessment of the data collected in order to decide which setup might yield valuable insights for further robustification of the approaches against real-world influences.

1.3 Structure of the Document

This document is organised as follows: Section 2 briefly outlines the state-of-the-art/state-of-technology that provides the basis of the realised Lab Access (LA) User Project (UP). Section 3 briefly outlines the performed experiments whereas Section 4 summarises the results and conclusions. Potential open issues and suggestions for improvements are discussed in Section 5.

2 State-of-the-Art/State-of-Technology

2.1 Current condition of the electric energy system

Electricity grid operators nowadays face many challenges connected to the fundamental changes the en-ergy system is undergoing. However, this transformation is essential in the shift to a new green and sus-tainable energy system. Many of these challenges arise due to the decentralization of power generation (Béné & Neiland, 2006), leading from regulatory barriers to environmental questions and ending at technological issues, such as energy storage and transmission. Especially a high density of photovoltaic (PV) power generation has grave impact on a grid, as pointed out in (Von Appen, Braun, Stetz, Diwold, & Geibel, 2013): PV generation exceeding local energy demand leads to re-verse power flows from lower voltage levels to the transmission system, as well as voltage rises. Locally violations of the admissible voltage magnitude, the so-called voltage band, are often the consequence, whereas the system frequency can be affected globally. To avoid such unfavourable effects, but limit re-newable energy generation as little as possible, control strategies are needed. As a result, the grid be-comes more difficult to operate due to decentralization of power generation, and as explained above, this leads in many cases to voltage band violations. Due to this circumstance, voltage regulation is regard-ed as the most important aspect in the integration of distributed generation in distribution networks (Mahmud & Zahedi, 2016). This is implemented through grid supporting functionalities provided by the generation units. Generation units are required to be able to perform certain control.

2.2 Behaviour monitored

Generation units need grid supporting functionalities which range amongst others from curtailing the ac-tive power dispatched, to controlling the reactive power injection of generation units with inverters, most commonly via a local droop control (Barrios, Burstein, & Nguyen, 2019). Generation units are required to be able to perform certain control mechanisms as defined in the TOR ("Technische und Organisatorische Regeln für Betreiber und Benutzer von Netzen" / "Technical and organizational rules for grid operators and users") (*Technische und organisatorische Regeln für Betreiber und Benutzer von Netzen*, 2019). Even the generation units with the least rated power listed have to implement a reactive power control depending on the local voltage, as well as actually dispatch the proper amount of reactive power.

2.3 Anomality detection

To be able to guarantee the intended behaviour of the units, methods are needed to ensure the correct behavioural patterns are actually being executed. Nevertheless, no framework covering the entirety of this task can be found in literature. Yet, many approaches exist presenting solutions to parts of the chal-lenges raised: (Sharma, Singh, Lin, & Foruzan, 2017) applies and compares several different algorithms, such as k-means, fuzzy c-means, to cluster consumption patterns of medium voltage transformers at main substations. Then the local outlier factor (LOF) is used to identify unusual consumptions in hourly load data. Unusual consumptions are characterized by certain traits such as irregular peak unusual consumption, broadest peak demand, sud-den large gain and nearly zero demand unusual consumption. Even though the results seem promising, it is to be seen if the characteristics exploited for identification are applicable to a broader spectrum of problems. In (Cui & Wang, 2017) a hybrid model combining polynomial regression and gaussian distribution to model electricity consumption data of different schools in order to detect anomalies therein. Therefore, the ap-proach presented is suited for anomaly detection on a household or grid connected device level. Still the models used in the paper are not fitted automatically for each application, which will most certainly be necessary. The work in (Shahsavari, Farajollahi, Stewart, Cortez, & Mohsenian-Rad, 2019) presents an approach combining an anomaly detection, based on an estimator that can run residue test on the median of micro phasor measurement units (micro-PMU) data, with a classifica-tion by a multi-class support vector machine (SVM). Also (Seyedi, Karimi, & Grijalva, 2018) uses micro-PMU data trying to detect irregu-lar energy generation of decentralized energy resources. This shows the potential benefit additional sources of data could have.

2.4 Classification

Techniques for clustering and thereby analysing load profiles for distribution stations are being treated in (Bobric, Cartina, & Grigoras, 2009). This is used to classify load patterns into different categories such as seasons or weekend versus weekday. The data used is the electricity demand at a 15 minutes interval. Here the method is intended for use in optimal planning and operation of distribution networks, classification of extraordinary opera-tional patterns is omitted though. Ref. (Capozzoli, Piscitelli, & Brandi, 2017) treats the extraction of typical load profiles of buildings. Build-ings are a-priori divided into classes depending on different traits such as type, physical features or weather conditions. Then typical load profiles are extracted for the classes. Furthermore, the paper men-tions possible applications of this method in fault detection and diagnosis (FDD). How exactly, for exam-ple by extracting load profiles of fault cases, this could be done the authors don't elaborate.

2.5 Disaggregation

In (Ledva, Balzano, & Mathieu, 2018) online disaggregation of a distribution feeders demand is presented. The paper shows how net measurements of a feeders can be separated into its components in real time with the help of domain knowledge of load and generation. The problem is referred to as feeder-level energy disaggregation. The online learning algorithm applied is called dynamic fixed share (DFS) and uses the real-time distribution feeder measurements in combination with models gained from historical building and device-level data. The method is compared to an approach using a set of Kalman Filters, delivering similar or even better re-sults. However, the feeder load is disaggregated in just two contributions: the demand of a population of air conditioners and the remaining load. For real world applications though, disaggregation in several dif-ferent components is likely to be crucial. Summarizing, there are the following open issues in monitoring of device behaviour:

3 Executed Tests and Experiments

3.1 Test Plan, Standards, Procedures, and Methodology

To conduct the experiments and recordings infrastructure like controllable loads, substations, and inverters, lines as well as measurement devices, such as smart meters, were necessary. These were then set up in a typical way for grids to be exhibiting sought-after malfunctions, for example, in a radial topology for rural grids. Loads and generation were parameterized to follow certain consumption or generation profiles, as well as certain control schemes regarding their energy consumption or dispatch behavior. The profiles were created following the profiles used by the SIMBENCH (Meinecke & et al., 2020) project, which provides grids that are specifically designed for simulation purposes. Profiles of consecutive days were chosen to mimic the data collected during grid operation in the course of about 2 weeks.

Given that at a 15 minutes resolution there are 96 datapoints per day, 35040 tests would be necessary to collect data of one year. Since the single test do not need any reconfiguration of the setup the conduction of tests ought to be automatable and quick. Only if another grid setup is to be introduced, manual intervention becomes necessary. Due to this the proposed sequence of tests here is to collect data from one grid automatically by setting up all profiles and configurations, updating them automatically and hereby collecting data of the behavior of the grid over a year in a time-warped way. After that another grid can be implemented to collect data in the same manner. As already pointed out the generation and load profiles as well as dispatch and charging control patterns are to be controlled, whereas operational data is to be measured. This measurement would ideally be done both by Smart Meter devices as well as, if possible, more accurate measurement devices in order to be able to model the Smart Meter data and its noise better.

In the first phase, two grid setups were implemented. In both setups 15 scenarios each reflecting the behavior during one day were implemented. These scenarios were played through for both grid setups: in the first one, two setups of reactive power control at the inverter were implemented, and in the second three different controls were implemented. This yielded 30 test runs for the first setup and 45 test runs for the second test setup. In the second phase, also two grid setups were implemented. Due to a technical failure, not as many test runs were possible as in the first phase. Therefore, only 30 test runs were conducted for both setups. These setups varied a load control at a load, leaving the inverter at the same control setting in this case. In total, 135 test runs that yielded valuable data were conducted.

3.2 Test Set-ups

Figure 2 shows the lab setup for phase 1.

The data collected here concern the PV inverter reactive control curve in the case of intended configuration as well as in two relevant misconfiguration cases. These data are very useful for the development of detection approaches at the transformer level. Only operational data was collected and is used in the following as explained and justified above.

The operational data such as voltages and currents were then recorded by the grid participants to mimic smart meter data and their power flows to be able to validate the scenario settings. Additionally, readings were recorded at the substation connecting the grid to the medium voltage level. In this manner, one data point would be gained by a quick measurement at a certain setting of generation and load profiles. Given that at a 15 min resolution there are 96 data

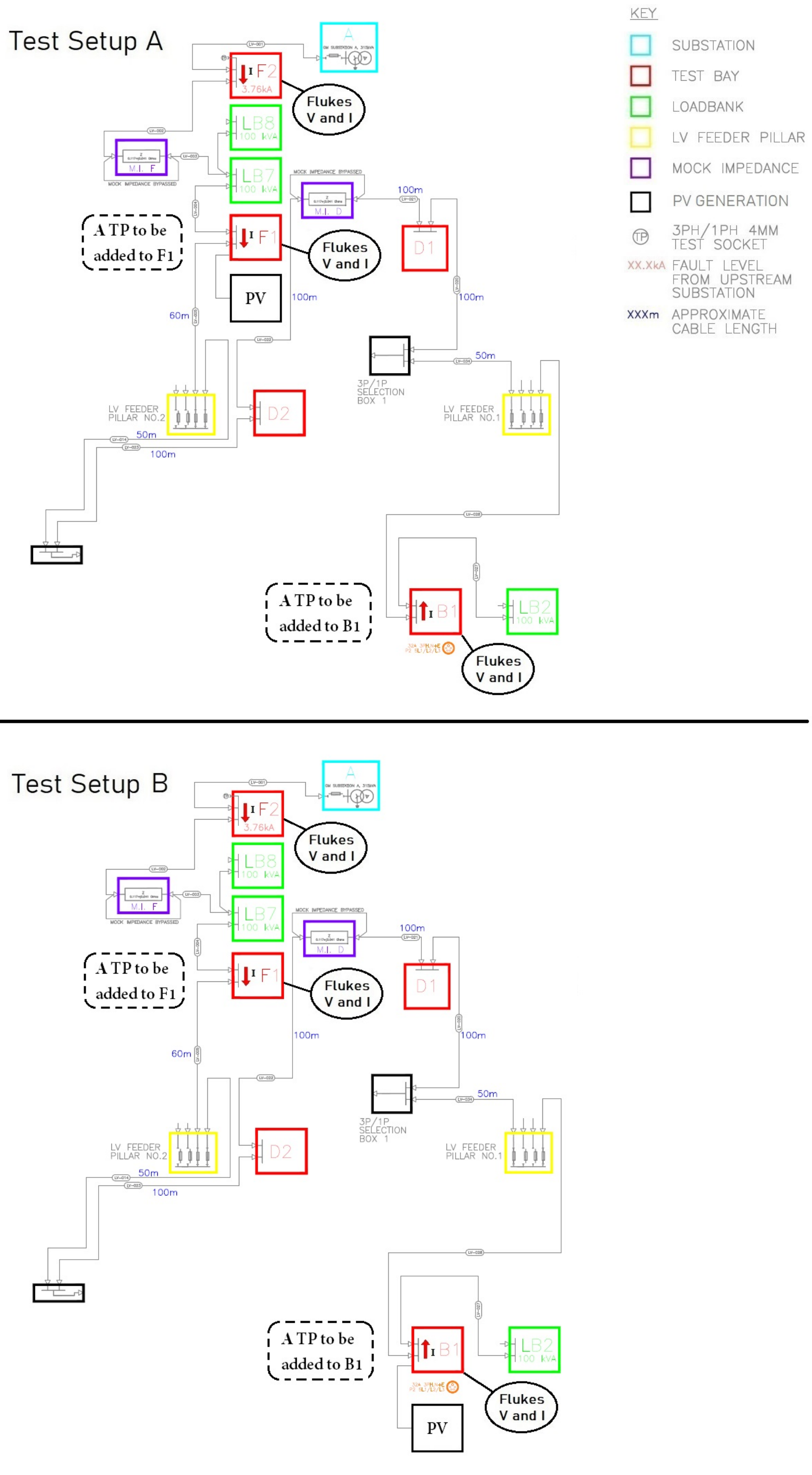

Figure 2: Test setup phase 1

points per day, 96 tests would be necessary to collect data for one day. As already pointed out, the generation and load profiles, as well as dispatch and charging control patterns, were to be controlled, whereas operational data was measured. This measurement was made using Fluke measurement devices, which delivered 398 different variables per time step, which is 0.25 seconds. In a first selection step, this was manually reduced to 84 relevant variables for further use. As the setup was as close as possible to a real-world power distribution grid, the experiments yielded as realistic results as possible, which should guarantee the highest robustness for the detection methods and monitoring mechanisms developed using this data.

In the experiments conducted, 15 sets of time series that each match a day from 9 am to 3 pm were collected. This time span was chosen to save on valuable laboratory access time and still have as much data with meaningful PV contribution, since the night hours are not expected to contain much valuable information. 15 scenarios, each one consisting of a set of load and generation patterns, were applied to two grid setups depicted in Figure 3; both setups consist of a substation in Dyn configuration with an apparent power of 315 kVA, two individually configurable load banks and a PV inverter, as well as cables of up to 100 meters length each connecting them. Measurements are taken at 3 points; at the substation (corresponding to measurement point F2), as well as at both connection points of the loads (measurement points F1 and B1) and the inverter (situated at, and therefore corresponding either to measurement point F1 or B1, depending on the setup). The positions and connections of the measurement points are indicated in the figure.

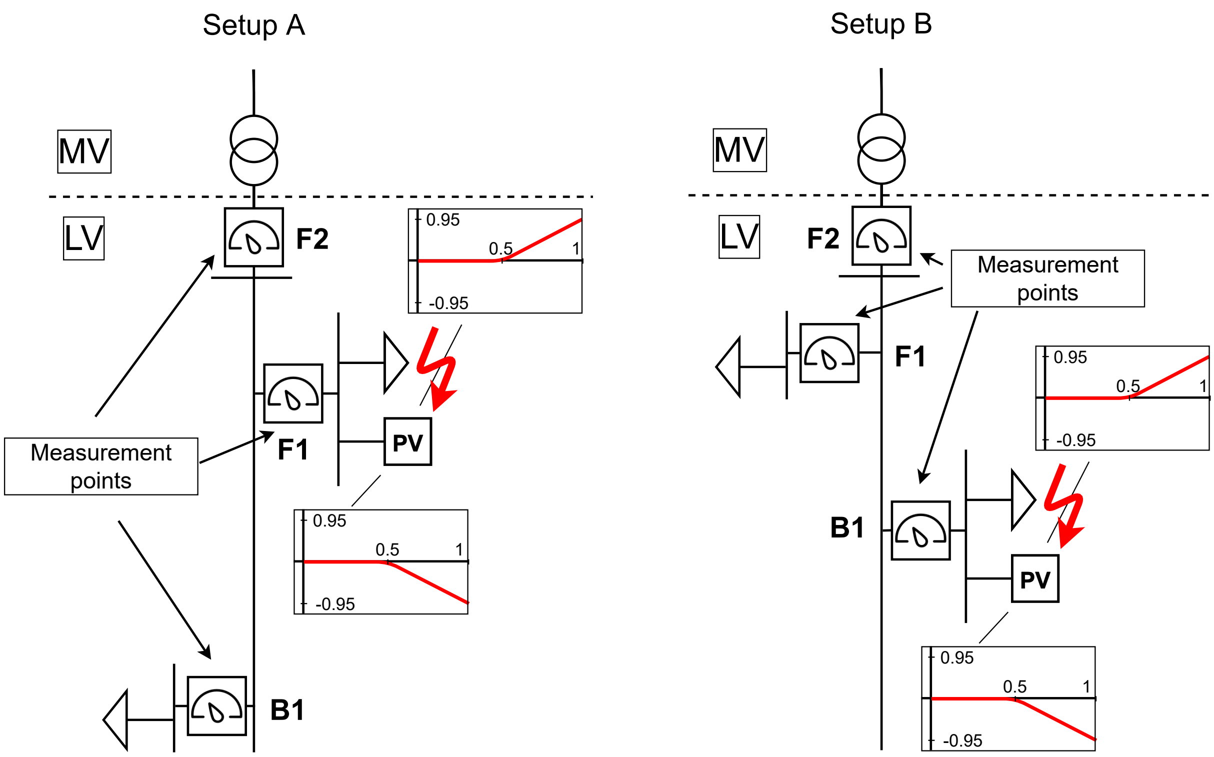

Figure 3: Setup A (left) and Setup B (right)

For the first setup, Setup A, the reactive power control curve was either parameterized correctly or just set to a flat curve, which is called 'wrong' in the following. A flat control curve setting does not provide reactive power at all. Running the 15 scenarios for both control configurations yielded 30 sets of time series for this setup. For the second setup, Setup B, the control curve was, in addition to the correct and wrong options, inversed, yielding 45 sets of time series. An inversed curve setting provides the same amount of reactive power as the correct one, however, with a wrong sign. In total, 75 sets of time series were obtained.

In Setup A, the inverter is closer to the substation, whereas it is further away from it in Setup B. This is done to be able to later assess the impact of grid strength on the detectability of the misconfiguration in the data. In both setups, the misconfiguration is applied to the inverter, as the different exemplary control curves in Figure 3 indicate; one is correct, the other is inversed. Because of laboratory access time limitations, only two control configurations were implemented for Setup A, as Setup B is deemed the more interesting case.

In phase 2, also two grid setups were used. These are depicted in Figure 4. Here three load banks were used. Also, one PV was installed, which varied its location depending on the grid setup. The case investigated here concerned a demand-side management algorithm for one of the load banks. The algorithm shifted the load at one load bank in a way so that it would coincide better with the adjoined PV production in order to maximize local consumption. In the case where this worked the load was therefore shifted to the middle of the day. In the malfunctioning scenario, the load was not shifted and behaved like a regular load following the standard load profile. Here, 15 test runs were conducted per case, meaning 30 per grid setup. This yielded 60 test runs in general for this phase.

3.3 Data Management and Processing

The data was collected at the above-indicated measurement bays using Fluke measurement devices. These devices contained SD cards on which the data was stored. These SD cards were used to transfer the collected data to PCs on which the Fluke Dataviewer software was available. Using this software, the data collected during every single test run had to be exported manually to text files. Using a script in python this data was extracted and saved to comma-separated value files for universal and easy use.

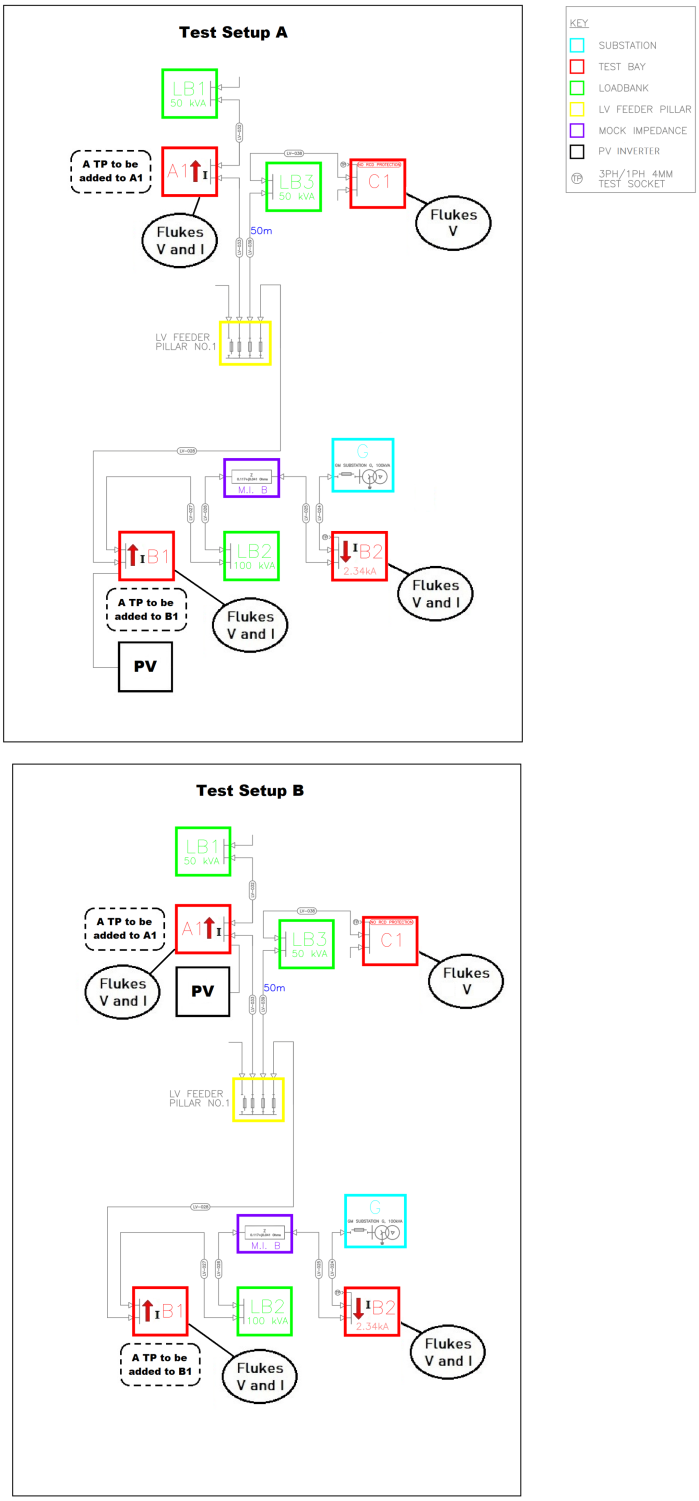

Figure 4: Test setup phase 2

4 Results and Conclusions

4.1 Discussion of Results

Data collection in a laboratory setting complements data collection conducted through simulations in an important way. Laboratory data is as close to real-world data as one can hope for, since real-world field data is practically impossible to obtain during the regular operation of a distribution power grid. This is because the occurrence of misconfigurations is not noted in time by the system operators, and therefore, the data collected can not be labelled. When using this data, one would not know whether it stems from regular or erroneous behaviour of a grid connected device.

In summary, the experiments were conducted using 15 sets of load and generation profiles in both phases. In each phase, 2 grid setups were used, once under up to 3 different inverter settings and once applying demand side management. A regular working control curve, a flat control curve ('wrong control'), and an inversed control curve were used in phase one. A demand-side management approach was applied or not in the second phase. An example of the first phase of the voltage data collected per measurement point in one of these scenarios can be seen in Figure 5; as one can see, the voltage is mostly higher in cases where the control curve is wrong or inversed, as is to be expected. For the Setup A, the difference is not as grave since the inverter has, as was expected, as well, a lower impact at a closer position to the substation where the grid is stronger.

Figure 6 shows data, again from the lab from phase one, for the individual cases of control configuration.

To visualize all scenarios as well as the relationships between each other, clustering was employed, namely, hierarchical ward clustering; first a similarity matrix is computed using the Pearson correlation coefficient. Then a dendrogram is built linking similar time series using the ward linkage method, which is a variance minimization algorithm. The results comparing the data in case of a correct or wrong control curve are shown in Figure 7. It becomes obvious that rather the data of the same scenario, in terms of loads and generation, than of the same control setting, such as correct or wrong, are similar. This makes the detection task built using the data at hand a nontrivial one.

4.2 Conclusions

The collection and assessment of the data presented as well as the detection methods to be explored using it serve as a building block for the envisioned decision support tool for electric power grid operators, facilitating the monitoring of low voltage distribution grids centrally. In such a solution, as data is collected at the transformer level, it is checked for signs of misconfigurations. After passing this check by the detection methods, simulations of misconfigured cases would be conducted to form the kind of dataset used in this assessment. An incoming abnormal data sample would most likely be recognized by a detection method trained on such a dataset, as the real world samples showed a greater impact on the control curve compared to the simulated samples. The simulations would require the load and generation profiles of grid participants, which could be obtained through disaggregation of the transformer load profile into its components. An approach to this disaggregation is the most important task concerning further work. It could be developed in combination with the load and PV measurements that were at this point only used for validation of the transformer measurements. Therefore, low

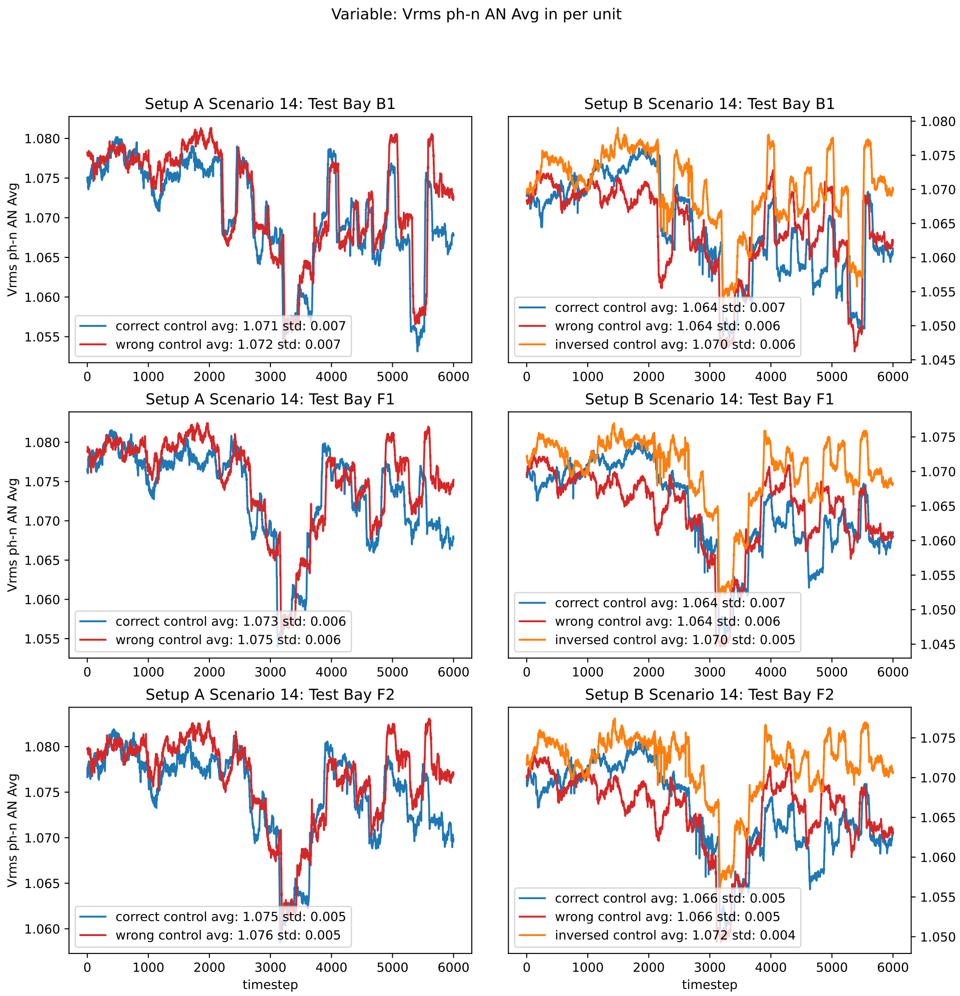

Figure 5: Laboratory data by measurement point

voltage distribution grids, or representative parts of these, were imitated in a laboratory, where grid participants were parameterized and malfunctions were enacted at a given time, allowing for the creation of a labelled validation dataset.

The combination of these methods would then allow for the creation of the already mentioned decision support tool, which would only require a few days of calibration along with regular grid operation before being operational. Such a solution would increase DSOs monitoring capacities in a substantial and feasible manner.

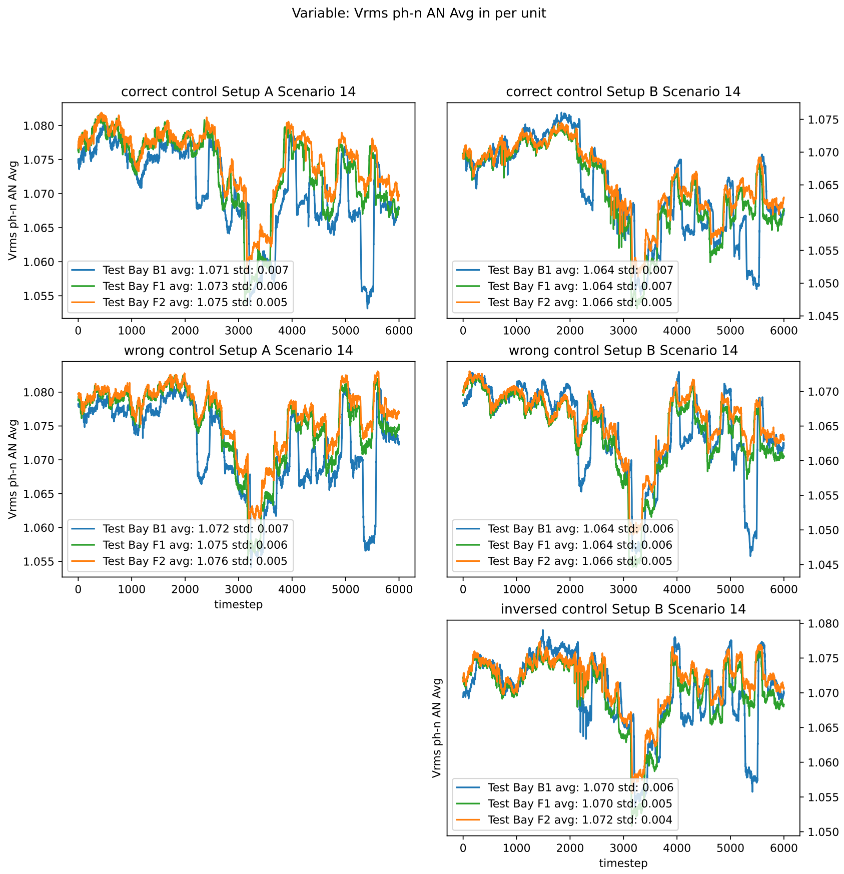

Figure 6: Laboratory data by control curve

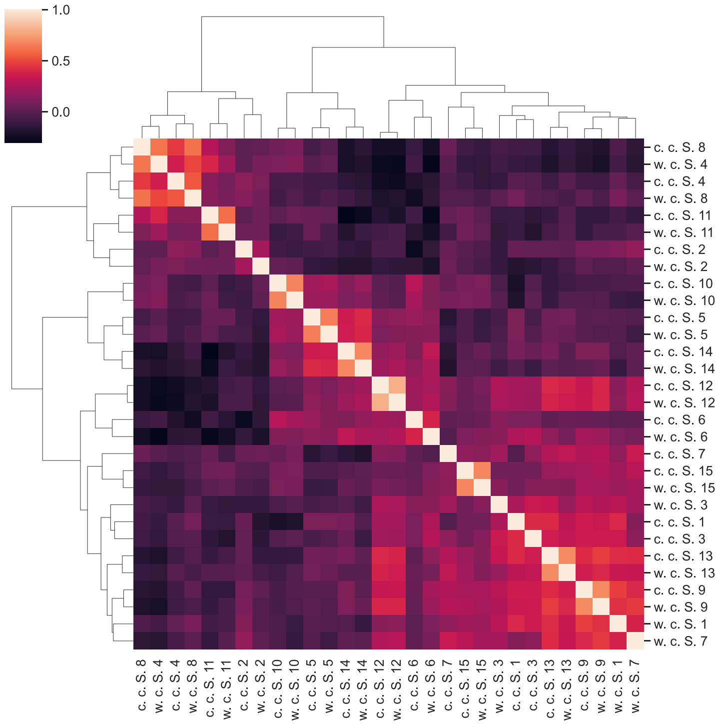

Figure 7: Laboratory data of setup B at measurement point F2 clustered

5 Open Issues and Suggestions for Improvements

The Power Network Demonstration Center (PNDC) lab at the University of Strathclyde in Glasgow, Scotland provides excellent infrastructure overall. One point of improvement could be made on the flexibility of consumers and generators: generators of a bigger variety of sizes could be provided. This is mostly limited by the DC power sources currently available. Furthermore, more freely parameterizable loads such as EVSEs that can be parameterized with control curves could be provided. Also, load banks can currently only be parameterized in 1kV steps, which can be hard to align with small generation capacities.

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