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Data Driven Transformer Level Misconfiguration Detection in Power Distribution Grids

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***Abstract*—As more novel devices are integrated into the electricity grid due to the changes taking place in the energy system, ways of detecting deviations from the intended settings are needed. If misconfigurations of, for example, reactive power control curves of inverters go unnoticed, the safe and reliable operation of the power grid can no longer be ensured due to possible voltage violations or overloadings. Therefore, methods of detection of misconfigurations of said inverters using operational data at transformers are presented and compared. These methods include preprocessing by dimensionality reduction as well as detection by supervised learning approaches. The data used is of high reliability as it was collected in a lab setting reenacting typical and relevant grid operation situations. Furthermore, this data was recreated by simulation to validate the simulation data, which could also potentially be used for detection applications on a bigger scale. The results for both data sources were compared and conclusions drawn about applicability and usability for grid operators.**

***Index Terms*—Power distribution, detection, device malfunctions, operational data.**

I. Introduction

As the energy system is undergoing massive and quick changes, especially the electric power grid is experiencing a transformation. This leaves power distribution system operators (DSO) facing novel challenges. A major cause of these challenges in the transmission and storage of power is rooted in the decentralization of power generation [1]. One of the biggest effects is caused by the widespread use of photovoltaics (PV) in a grid. Violations of voltage limits as well as bidirectional power flows or overloading of components can be caused by generation exceeding demand in a grid segment [2]. High power infeed from PV can lead to voltage band violations due to elevated voltages. These are to be avoided through controls to allow for an extensive integration of renewable power generation in a decentralized manner. Therefore, the generation units implement some form of voltage regulation [3] that offers grid supporting functions. As the obvious measure of reducing active power dispatch is to be generally avoided to maximize renewable energy output, the voltage is mostly controlled through the variation of the reactive power generation. This is done through variation of the power factor following a droop control curve locally [4].

The behavior of PV inverters and other grid-connected devices has to be monitored to make sure these grid supporting functionalities are performed correctly. Otherwise, a stable and reliable grid operation can not be guaranteed by the DSO. However, limitations in data availability either set by a lack of sensors [5] or data protection regulations [6] have to be taken into account when developing a solution. Therefore, a data driven approach on transformer level to this is advantageous for DSOs as information about components in the grid is frequently lacking [7]. Misconfigurations of grid connected devices are a mismatch between the configuration implemented and the one laid out in the specifications, which is itself defined by grid codes. This mismatch can have two causes; either a different configuration was implemented on purpose or the configuration can change as a result of, for example, malfunctions. The case under scrutiny here is the latter one, meaning the configuration – the control curve – is expected to be initially the correct one. A more extensive discussion on this was already conducted in [8]. This makes obvious that misconfigurations can be detected by a solution using only the operational data collected in the grid, since a misconfiguration leaves a different impact on this data in comparison to a correct configuration of a grid connected device. For this reason, only operational data is used here.

The main contribution of this work is the detailed descrip-

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tion of grid operational data, as well as methods applied on it to detect misconfigurations. Data was collected both in a laboratory environment as well as through simulation, allowing for a validation of the simulation data. Furthermore, data processing methods as well as detection methods were applied on the data so as to assess their performance in the task at hand. Dimensionality reduction methods for processing data as well as supervised learning approaches are employed as their applicability is suggested by previous work [9] as well as literature [10].

This work has the following content: In Section I, a discussion of issues in power distribution grids and monitoring needs is conducted. Section II describes the state-of-the-art related to malfunctions in power systems as well as the relevant usage of artificial intelligence for detecting them. In Section III, the data collected and the means thereof are laid out and in Section IV a description and results of the approaches applied are presented. Finally, Section V provides the conclusions and an outlook about potential further work.

II. Related Work

In [11], energy consumption characterization of buildings of a university campus is presented with the aim of finding anomalies on building level. Features are extracted as well as data reduction methods applied during the characterization. Following, normal patterns for certain times of the day are identified by estimating the most probable one using globally optimal Evolutionary Trees. These, in addition to being more accurate than standard Decision Trees (DT), offer full interpretability of the results. After anomalies are detected on building level, underlying causes are discovered by an unsupervised approach based on Association Rule Mining (ARM). The data used stem from a medium-low voltage transformer, however, in 15 minutes resolution, reducing the applicability of this approach for the higher resolution data at hand.

The work in [12] presents a Deep Learning based anomaly detection method for finding outliers using a Light Gradient Boosting Machine. This machine has the advantage to be less computationally expensive due to the lower number of parameters. Even though the data used in the work has almost the same resolution as the data available here, the approach does not provide extraordinary good results. Moreover, a very big data set is required and therefore also used. This dataset is compiled using only active and reactive power data. This points towards the usage of feature-based approaches that can also handle higher dimensional multivariate data for the problem present.

An approach focusing on phase measurement unit (PMU) data is sketched in [13]; very good results are achieved using Gaussian Mixture Model (GMM) to estimate the probability density function of regular PMU data streams to define the minimum and maximum thresholds for anomalous data streams. Initially Principal Component Analysis (PCA) is used for feature selection as well as k-Means Clustering for clustering of the PMU streaming data. The anomalies under scrutiny here are only faults such as line-to-line or line-to-ground faults. Moreover, the anomalous data is merely simulated, and it is available in a very high resolution, which is not the case for the problem to be treated here. Nevertheless, the approaches to data treatment are relevant. Also [14] indicates that PCA is of use when treating data; it is used here to find the principle components in voltage sags allowing for clustering of them and then assessing the quality of this clustering. The results show that PCA is capable of extrapolating features from voltage data in addition to revealing that the ward linkage method is the best fit for clustering substation power quality data. Both results can be of help in the task presented here.

Methods for anomaly detection on transformer data that are also multivariate are elaborated in [15]. Support vector machines (SVM) as well as k Nearest Neighbors (kNN) and Decision Trees (DT) appear to deliver promising results here. However, the data set is not as high dimensional as the present one and the application described is cybersecurity. Additionally, an ensemble learner of three models is used which makes the approach complex. This makes the utilized supervised machine learning approaches such as SVM, kNN, and DT of interest, leaving nevertheless to be investigated how they perform in the particular case at hand. Another application of SVM and kNN to PMU data can be found in [16]. Here, both show good results when put to the task of detecting voltage magnitude anomalies in feature extracted data. The data used stem both from synthesizing as well as from real world sources and is therefore noised as it has realistic properties in general. However, the detection is only applied to voltage anomalies such as sags, ramps, and steps.

These anomalies do not necessarily have the same properties as the subtle changes in behavior that are to be detected in this work. One more example from the cybersecurity domain can sooth concerns raised by this; in [17], features are also first selected and then the SVM, kNN, and DT algorithms are applied to find anomalies in substation data. Here, these are constituted by, for example, false data injected. These attacks are recognized with a very high probability, showing that these machine learning algorithms are very well capable of detecting all sorts of anomalies in the present work setting.

Summarizing, the work in the electrical grid domain on anomaly detection (see Table I) shows that there are approaches that are either very well suited to certain time resolutions of data, fit for particular dimensionalities of time series data, or require very big amounts of data and computational resources. What becomes clear is that a pre-processing that allows for feature selection appears to be very helpful. Along with classic machine learning algorithms for anomaly detection this approach yields very good results in various applications. However, no solution to the posed problem can be found in the literature, which is why explorations and assessments of approaches to such a solution have to be conducted.

TABLE I: Non-functional requirements (NFR) fulfilled (X) or unfulfilled (–) by approaches in related publications cited.

NFR	**Reference**						
	[11]	[12]	[13]	[14]	[15]	[16]	[17]
Scalability	X	X	X	X	X	X	X
Adaptability	–	X	X	X	–	X	X
Integrability	–	–	X	–	–	X	X
Usability	–	–	–	–	–	X	–
Data Retention	X	–	X	X	X	X	X
Robustness	X	X	–	X	X	–	X
Quality	X	–	X	X	X	X	X

III. Data Collection & Properties

This section is intended to describe the motivation for collecting data in a laboratory setting as well as through simulation and elaborates the respective aims and functionalities it should help develop. The detailed ways of obtaining the lab and simulation data is elaborated along with their properties. Finally, the results produced by it are depicted and analyzed.

A. Laboratory Data

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 labeled. When using this data, one would not know whether it stems from regular or erroneous behavior of a grid connected device.

The data collected here concern the PV inverter reactive control curve addressed in Section I 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.

For this purpose, low 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 labeled validation dataset. Such a facility was found through the H2020 ERIGrid 2.0 project at the Power Network Demonstration Center (PNDC) at the University of Strathclyde in Glasgow, Scotland. 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 [18] 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.

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 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 1; 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.

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

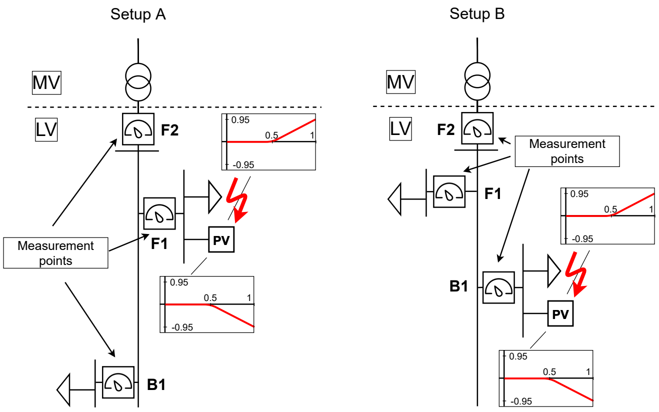

Fig. 1: Setup A (left) and Setup B (right) with the corresponding names (F2, F1, B1) of the measurement points used in the following.

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 1 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.

B. Simulation Data

Data collection through simulations complements data collection conducted in a laboratory setting in an important way. It allows to create more data that can be of guaranteed quality when validated through comparison with laboratory data. As some parameters about the lines of the laboratory were not fully known, assumptions about the line parameters that reflect the most likely properties of the lines were made. Moreover, any modeling of imbalances in the grid was neglected since none were known. These inaccuracies might still have an influence on the simulation quality. The simulations were conducted using the same profiles and setups as in the laboratory setting, recreating the same 75 sets of time series.

In addition to these, simulations with an inversed control curve were also carried out for Setup A, yielding another 15 sets of time series. For the simulation, 30 relevant variables, chosen among the ones available in the software, were selected to be contained in the results. The grid data generation capabilities developed in the course of preceding work [8] were used here.

C. Outcomes

In summarizing, the experiments were conducted using 15 sets of load and generation profiles in both setups under up to 3 different inverter settings; a regular working control curve, a flat control curve (‘wrong control’), and an inversed control curve. An example of the voltage data collected per measurement point in one of these scenarios can be seen in Figure 2; as one can see, the voltage is mostly higher

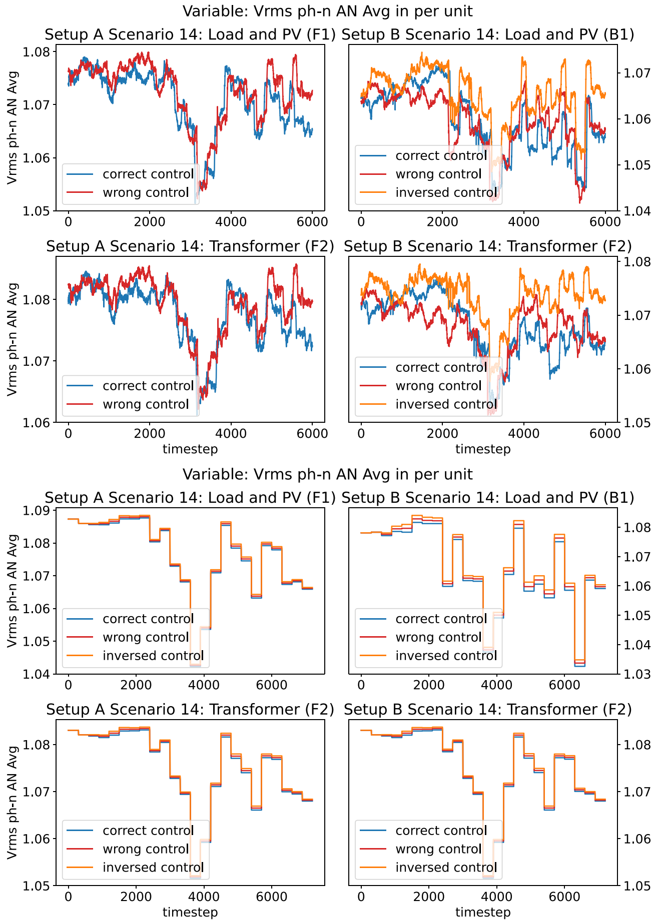

Fig. 2: Laboratory (top) and simulation data (bottom) by measurement point (note that the measurements in Setup A with an inversed control curve are not available due to lab access time limitations).

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. The difference in the simulation data between the two curves is also smaller than in the lab data. This can only be attributed to the inaccurate modeling of imbalances and possible reactive power consumption that results thereof.

Figure 3 shows data, again from the lab and simulation, for the individual cases of control configuration. Again, the impact of the control appears smaller in the simulation data however, it is still noticeable, especially again in Setup B where the PV is farther from the substation and therefore in a weaker point of the grid.

To visualize all scenarios as well as the relationships between each other, clustering was employed, namely, hierarchical ward clustering as described in [19]; 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 4. It becomes

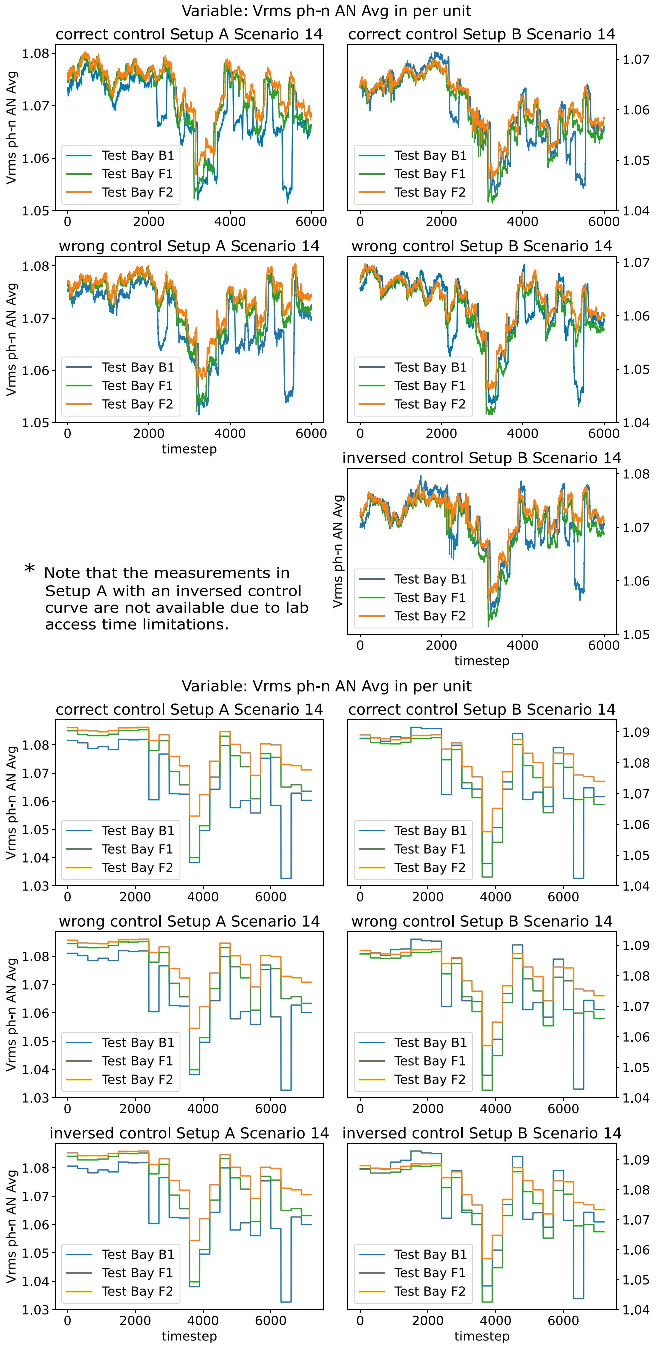

Fig. 3: Laboratory (top) and simulation data (bottom) by control curve.

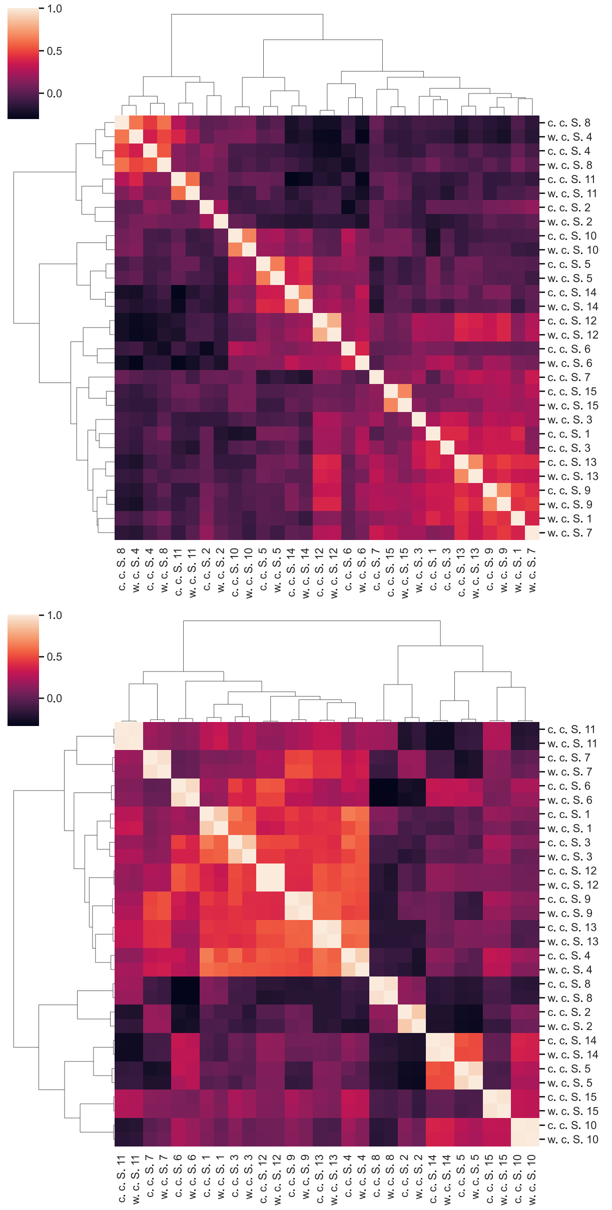

Fig. 4: Laboratory (top) and simulation data (bottom) of setup B at measurement point F2 clustered; 'c. c. S. 1' and 'w. c. S. 1' stand for 'correct control Scenario 1' or 'wrong control Scenario 1' respectively.

obvious that for both lab and simulation data 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. Furthermore, the individual lab data samples seem less similar to each other than the simulation data samples, which are still quite dissimilar. This makes the detection task at hand a nontrivial one.

The simulation model used in a grid simulation software as well as all data and analysis produced using it can be found in the corresponding GitHub repository[1].

IV. Methods & Results

A. Preprocessing

To assemble the dataset, all m multivariate time series data samples, each one representing a scenario with a certain control curve configured in one of the grid setups, which have t rows for t timesteps and n columns for n variables as represented by 1) in Figure 5, are flattened into single rows of a dataframe having $t*n$ columns. Each column, therefore, represents the value of one variable at a certain timestep of

[1] https://github.com/DavidFellner/Malfunctions-in-LV-grid-dataset

a measurement. The resulting dataset is a m x $t * n$ matrix, each of the m rows representing the data of one of the m measurement samples. Only measurements at the substation level (measurement point F2) are used, as a transformer level detection solution is to be developed.

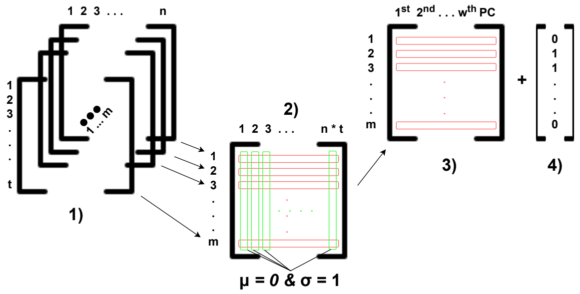

Fig. 5: Preprocessing and dataset creation.

This data is then scaled to have a mean of zero and a standard deviation of 1 along all $t * n$ features, which again are variables at a certain timestep. This is step 2) in Figure 5. The scaled data is then fed into a PCA as described in [14]; PCA is an orthogonal linear transformation, aiming to create a new coordinate system in which the first coordinate, which is the first principal component (1^{st} PC), represents the greatest variance in the data. There can be as many PCs as there are feature vectors in the data however, usually fewer PCs than features are retained to achieve a dimensionality reduction and thereby select important parts of the data, such as the 2^{nd}, 3^{rd}, and so on as higher order PCs retain decreasingly much variance and therefore less information.

As many principal components are kept so as to retain 99% of the variance in the data, which ends up being 17 or 27 components for the simulation, the respective laboratory data of Setup A. Step 3) of Figure 5 depicts this unlabeled dataset.

Lastly, the samples are labeled depending on the state of the control curve applied during the measurement yielding the final dataset, as can be seen in step 4) of Figure 5.

B. Detection

Based on the assessment done in Section II, supervised machine learning algorithms are employed for the misconfiguration detection task at the transformer level. Additionally to the mentioned hyperparameter combinations below, additional sensitivity analyses on hyperparameters were conducted. In cases where little or no impact of variating these could be observed, the respective hyperparameters were set to common values as the default ones defined by the specific library implementation used.

As prompted by [16], SVM and kNN are used. The SVM is capable of binary as well as multiclass classification by finding a hyperplane in an arbitrary dimensional space that guarantees as big as possible separation margins between the classes. This makes the SVM especially suitable for high dimensional applications as the one at hand and therefore attractive. Scitkit-learn's SVM classifier is used here[2], varying the kernels used (linear, polynomial, radial, sigmoid) and their degrees (1 to 6), as preliminary examinations have shown this parameter to have a significant impact on performance. Kernels define how the separation margin is formed, and therefore, how the decision boundary is adjusted to the data. Moreover, another variant, the NuSVM[3], was used. It has the same properties, only that it controls the number of support vectors that are used to find the decision hyperplane to avoid overfitting.

The kNN algorithm[4] uses the Euclidian distance of a data sample to its k-nearest neighbors and decides based on the majority of the neighbor's labels, which class the given sample should be attributed to. This makes kNN a lazy learner, therefore being a very time efficient method. This makes kNN beneficial especially for adding new samples. For this method, the number of neighbors to be taken into account (1 to 4) was varied as well as the weighting of their distances to the data sample. Either the distance of a neighbor would be taken into account, which is called distance weighting, or all neighbors would count equally, called uniform weighting.

Additionally, DTs were applied on the data, as suggested in [11]; a tree is built from the root by recursively partitioning the feature space, until areas, the leaves of the tree, of a certain purity in terms of class labels of the samples in this area are defined. Depending on the splits rule, which in this case the gini impurity, as well as information gain, were used for, the best splits of the feature space are performed. A new sample is then classified following the branches of the tree, which represent the decision rules until it is labeled according to the leaf it ends up with. The DT has a high degree of explainability, which incentivizes its usage in cases where decisions should be justified. Also here the Scitkit-learn implementation[5] varying the splits rule was used.

All experiments were done implementing 7 fold cross-validation with balanced classes in all training and test batches. Using the data in this way is intended to reflect the behavior of a detection system using the operational data of the previous days to decide on whether a misconfiguration is present or not looking at the current data.

C. Results

The code used to produce the datasets and results can also be found in the GitHub repository[1]. The aforementioned datasets were fed to the detection methods, hyperparameters were varied, as well as results cross-validated as mentioned above. The datasets consist of 30 samples for the laboratory data of Setup A labeled as correct or wrong and 45 samples for the lab data of Setup B as well as the simulation data of

[2]https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html\#sklearn.svm.SVC

[3]https://scikit-learn.org/stable/modules/generated/sklearn.svm.NuSVC.html#sklearn.svm.NuSVC

[4]https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html

[5]https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

both setups, which are labeled as correct, wrong, inversed or simply abnormal, meaning of class wrong or inversed.

Table II summarizes the best results found for a certain dataset using the F-score as a result metric. It represents a balanced combination of Recall, how many of the misconfigurations present have been found, and Precision, how many of the found misconfigurations are actually cases of erroneous configuration. As a grid operator using this application would want to balance between finding all occurrences of misconfigurations and false alarms, the F-score is an expressive metric of how useful the approach is to a DSO.

TABLE II: Comparison of best detection results on laboratory and simulation data.

F-Score Result	**Grid Setup and Data Source**			
	Grid Setup A		***Grid Setup B***	
Case	***Lab Data***	***Sim data***	***Lab Data***	***Sim data***
correct vs. wrong	0.93	0.91	1	0.90
correct vs. inversed	*	0.97	1	0.97
correct vs. wrong vs. inversed	*	0.88	0.96	0.90
correct vs. abnormal	*	0.95	1	0.95

* Not available due to lab access time limitations

The methods and their hyperparameter settings leading to the best results for each case are listed in Table III.

TABLE III: Comparison of best approaches on laboratory and simulation data.

Best Approach	**Grid Setup and Data Source**			
	Grid Setup A		***Grid Setup B***	
Case	***Lab Data***	***Sim data***	***Lab Data***	***Sim data***
correct vs. wrong	NuSVM: linear kernel	SVM: linear kernel	SVM: linear kernel	SVM: linear kernel
correct vs. inversed	*	NuSVM linear kernel	SVM: linear kernel	SVM: linear kernel
correct vs. wrong vs. inversed	*	SVM: linear kernel	SVM: linear kernel	SVM: linear kernel
correct vs. abnormal	*	SVM: linear kernel	SVM: linear kernel	SVM: linear kernel

* Not available due to lab access time limitations

V. Conclusions

A. Achievements

Electricity grid operators need to be able to guarantee safe and reliable grid operation, also in the future of widespread decentralized generation of renewable energy. Therefore, better monitoring of the distribution grid becomes necessary. The data collected and described allows for the development of a validated solution for monitoring the behavior of PV systems in such a grid. Furthermore, the methods applied to this data show the applicability of such a solution.

In general, better performance for Setup B can be observed, which is in line with expectations because the PV is installed at a weaker point of the grid here. Therefore, the impact of the control curve is bigger and a misconfiguration of the same easier to detect. The scores reached on the laboratory data are also higher in all cases than on the scenario data. As already discussed above, the simulation data showed only smaller impacts of the different control curves, which also makes detection harder for the simulated data. This also explains only a small difference in performance in the simulation data between Setups A and B. However, this also implies that the results for the simulation data can serve as a lower estimate for the performance on real-world data for Setup A. Nevertheless, the performance is very good, or even perfect, for both setups and all cases. This is likely connected to the rather simple grid topologies and the performance might deteriorate in more complex settings.

In all cases, the method delivering the best results was found to be a form of SVM with a linear kernel, which can be explained by the high suitability of this algorithm for high dimensional data and for datasets with a high feature to sample ratio. This property also allows for the usage of only very recent data, meaning data of the previous days, for detection properties.

The work presented shows that a classical supervised machine learning approach, the SVM, applied to transformer level data can yield very good misconfiguration detection results. As this is the case for both laboratory and simulation data, wide applicability of the method is implied. The even better results on the laboratory data underline the robustness of such a solution.

B. Outlook

The collection and assessment of the data presented as well as the detection methods explored 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. Other additional tasks are the assessment of additional use cases, such as monitoring of demand side management.

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.

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