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RESEARCH ARTICLE

Data-Driven Misconfiguration Detection in Power Systems With Transformer Profile Disaggregation

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ABSTRACT Rapid and necessary changes in the energy sector are leading to the rise of new, decentralized devices for generation and consumption in the electrical distribution grid. Such devices are inverter-connected photovoltaic (PV) generators, heat pumps (HP), or electric vehicle supply equipment (EVSE). These new components make the power grid operation more difficult as they display volatile behavior and therefore also need to provide grid-supporting functionalities. Distribution System Operators (DSOs) need to make sure these grid-supporting functionalities are performed correctly, in order to guarantee a safe and reliable operation of the grid. However, especially the low voltage distribution grid is still ill-equipped with sensors and therefore difficult to monitor. This contribution, therefore, presents a data-driven application for detection of misconfigurations using the data available at metering points of substations and selected voltage measurement points in combination with a transformer load profile disaggregation approach. The assembled application outlined is both functional, scalable, and easy to integrate into current monitoring schemes. Such a monitoring application has not been designed yet and is therefore novel. The data used were collected in a life-like laboratory setup and recreated using simulations in order to be able to test and validate both the detection as well as the disaggregation method. Two monitoring use cases of control functions are considered; the first one is a reactive power control of PV inverters, and the other one is a Demand Side Management (DSM) control of loads. The results presented offer insights into both the quality and performance of the application assembled. The best achieved performance is a F-score of 0.83, which also serves as a future benchmark as there are no comparable results to be found in literature. Furthermore, the influences of the individual methods of the approach are explored as well. The conclusions drawn show that a functional monitoring solution of reasonable reliability can be implemented using the methods presented and tested here. The application can serve as a decision support tool for DSOs requiring only minimal adjustments to the sensing infrastructure.

INDEX TERMS Data-driven monitoring, detection, machine Learning, device malfunctions, transformer profile disaggregation, load estimation, low voltage grids, misconfigurations, operational data, power distribution.

I. INTRODUCTION

Both ecological and economic pressures force major paradigm shifts onto the electric power system. One of these is the introduction of decentralized renewable energy generation on a grand scale [1]. Another one is the increased electrification of loads, spanning from heating systems to electric vehicles [2]. These are located decentrally as well, making their impacts on the electric power grid just as troublesome: for historic reasons, the power grid is designed

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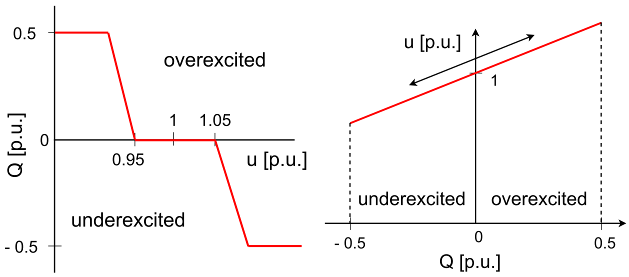

FIGURE 1. **Q(U) control (left) used for voltage control (right).**

to transmit electric energy as well as distribute this energy to customers whose consumption is relatively static and easy to anticipate. However, on one hand, the availability of this energy is getting more volatile as it is linked to, for example, solar and wind yields. On the other hand, it is generated decentrally which may lead to production overtaking local demand [3]. This in turn can cause reverse power flows from the low voltage level of the grid to higher voltage levels, which was unconsidered before. It can also lead to local voltage and current problems, as the grid is not laid out to cater to the decentral infeed of this energy. Furthermore, the aforementioned electric loads are being installed in the low-voltage distribution grid. This means for example more electric vehicles are charged in grid locations that may also not be designed for such high additional loads [4]. This can also lead to voltage or current problems.

A. PROBLEM STATEMENT

To cope with these problems, for example, of over-voltage in the case of distributed generation, as well as under-voltage in the case of additional loads, the devices installed need to provide grid-supporting functionalities. These functionalities include power factor control curves depending on the active power infeed ($cos\phi(P)$) or reactive power control curves depending on the voltage (Q(U)) for distributed generation units [5]. An example of the latter is shown in Figure 1; the left side of the figure depicts a reactive power infeed control depending on the local voltage. If the voltage is either too high or too low, reactive power of the according sign is fed in. On the right side of the figure, the impact of this reactive power is depicted. Capacitive reactive power, which is dispatched in what is called underexcited operation, helps to dampen overvoltages by lowering the voltage. The opposite is true for inductive reactive power, dispatched in overexcited operation, which bolsters the voltage and helps control undervoltages by lifting the voltage.

Both the $cos\phi(P)$ and the Q(U) control alter the reactive power dispatched by the inverter of a PV generation unit. The reactive power infeed can be used to control, or lower in this case, the local voltage and thus support the grid during operation to operate within the acceptable limits [6]. Similarly, loads can be equipped with control functions aiding the grid; EVSEs can follow a charging power control curve limiting the active power drawn in case the voltage drop is too low [7]. Also, household loads can follow patterns in order to shift their consumption to more favorable times of the day as far as the grid or possible self-consumption is concerned. The latter is relevant in case a rooftop PV system is installed that can be used to cover at least parts of the load's consumption. This is commonly referred to as DSM [8].

However, all of these generators and loads are usually installed decentrally in the low voltage distribution grid, which has, as already mentioned, not been designed for such use. This also manifests in the lack of sensor capabilities which are usually limited to substation measurements on the transformer or Smart Meter (SM) measurements [9]. The use of the latter is often restricted by data protection regulations, which leave the state of the distribution grid as a blind spot to the Distribution System Operator (DSO) [10]. Nevertheless, the DSO has to ensure the grid is working safely and is within acceptable limits of loading and voltages. To ensure this, the DSO needs to be able to monitor the correct execution of the discussed grid-supporting functionalities, as configurations might change in an undesired manner due to faults, software updates, or user interference [11]. This would then lead to misconfigurations. At the moment, this is only possible through manual check-ups conducted by maintenance crews which are costly and unfeasible. As the rollout of the novel decentral generation and consumption devices proceeds, the need for an automated solution arises. This solution should be both easy to install and robust during use. Furthermore, it should require as little adaption to changes in the grid as possible, which can be used by the sole use of operational data, as discussed in previous work [12]. The need for insights into how such a solution could be designed and how well it could perform motivated the study conducted.

B. CONTRIBUTIONS AND OBJECTIVES

As there is no solution to this monitoring need, a new approach is needed. All of the requirements mentioned above lead to the question formulated: "Given the scarce availability and usability of data in low voltage distribution grids, what approach is the best fit to detect grid-supporting devices' misconfiguration in such grids?"

A number of objectives has to be fulfilled to answer this question:

- Detect unusual transformer profiles given only aggregated medium-low-voltage transformer data.
- Distinguish abnormal transformer operational data depending on the underlying cause.
- Based on the same aggregated transformer data, gain information on the behavior of decentral devices.
- Determine the data and its quality needed to offer a useful accuracy of detection.

These requirements and the goals that stem thereof led to the main contributions of the present work: a detection method using traditional Machine Learning (ML) methods on the transformer level is introduced and elaborated using a novel DSM use case. Furthermore, a disaggregation approach using load estimation is laid out that helps gaining information on the low voltage level given the transformer operational data. To conclude, the detection method and the disaggregation method are combined to form a detection application that is suited to be installed in DSOs' control rooms as a decision support tool. The quality and influences of the individual parts are assessed in the course of the work, helping to reach the objectives set.

C. ORGANISATION

The remaining work's structure can be listed in the following manner: In Section II, the state-of-the-art related to configuration monitoring in power systems and the usage of data-driven methods for the same are treated. Section III details on implementation and functionality of the detection and disaggregation method and lines out the assembled detection application. In Section IV, the use cases and deployed grid setups for assessing them are described. Section V presents the results achieved for each application and stage. Finally, in Section VI the discussion, conclusions, and an outlook about potential further work are given.

II. RELATED WORK

In the literature, no solution for the stated problem exists. However, approaches to solving parts of it can be found, even if they might not be straightforwardly applicable. In the following, these related contributions are assessed in this regard.

A. BACKGROUND AND DATA PREPROCESSING

As the review conducted in [13] outlines there are various disciplines when it comes to monitoring power systems. The first applicable one is fault detection, which treats the detection of the occurrence of deviations from regular operating conditions. Another one is fault classification, which encompasses the fault type to be identified. Lastly, fault location is mentioned, which obviously means localizing the fault which is constituted by singling out the part of the grid covered by the substation. Therefore, the problem at hand falls into the category of fault diagnosis, as this discipline combines all the aforementioned challenges. However, the publication mentions explicitly the lack of automatic fault location methods implemented by DSOs. The same applies to fault classification, whereas there is even only a small number of publications in this field. What also remains to be said is that the review mentions only line fault location and classification scenarios. Also the review conducted in [14] does not address misconfigurations but only power quality disturbances and lists causes for numerous ones. It only provides methods on how to detect these. Another current related review article [15] only addresses power system frequency and control as an application of Deep Learning. It does not mention misconfiguration detection in the way it is regarded here. The last related review article to be found is [16], which treats condition monitoring of wind power systems. This is also somewhat related to the problem defined, however, this is a very general monitoring task. The specifics of it do not necessarily apply to the problem at hand. For the misconfiguration detection case treated in the work presented here, no reviews or related works apart from previous work by the authors could be found.

Treating data in the principal component subspace in order to reduce dimensions and filter for relevant features using Principal component Analysis (PCA) is a promising strategy. PCA assesses which components, meaning which features of a sample, have the highest impact on the feature vector. This is done by evaluating which projection of the data onto a vector retains the most variance in the data. This vector is the first primary component. If one wishes to keep a certain percentage of the variance of the data, an according number of primary components can be used to represent the entire data. This means the data can be projected onto these components and then use said components instead of the original data. In [17] this approach is employed, also using measurements at the substation bus where a data-driven operation model is assembled. However, once more this solution is used to detect line faults and not misconfigurations.

B. MONITORING APPROACHES

In [18], fault diagnosis of single-phase to ground and three-phase faults are conducted using gradient boosting trees. Even though the application is once again not congruent with the one at hand, Decision Trees (DT) are of interest for the detection and classification of misconfigurations. This method works by using a training set of data in order to divide the feature space along linear decision boundaries. This is done iteratively until, ideally, only samples of the same class remain in the so-called leaves of the formed branches of the decision tree. To avoid overfitting, the depth of the tree can be limited, leading to impure leaves but a better ability of the trained model to generalize. These decision boundaries can then be used to classify new, unseen samples. Even though this appears to be applicable, the method presented makes extended use of feeder data measurements, which is to be avoided here. Also, [19] uses Random Forest Decision Trees to localize faults. Here, they are used as regressors to estimate the distance on a feeder to a fault, but also to identify the faulted branch. Therefore, DTs are considered a detection method to be assessed.

Deep Learning (DL) is another approach for fault detection and location proposed in [20]. The properties of feeders are learned by a deep neural network such that it is able to generalize on fault location and occurrence. The main advantage of DL is that it is able to condense its own features from the data, making complex preprocessing of the input data unnecessary. The method is, as the authors elaborate, able to do this even if only measurements at the beginning and end of a feeder are available. For this reason, the method could be of interest. Nevertheless, the training of such a network is conducted with hundreds of thousands of time series covering every imaginable operation scenario. These data stem from simulation and basically constitute a look-up table that is engraved in the deep neural network. Reference [21] applies a DL Attention Mechanism to voltage sag type and location detection. Attention Mechanisms offer weighting inputs according to their importance to the output, thus improving the learning of the relation between the two. The work presents good results, yet the problem of proper data sourcing remains. For the present work, an approach is to be found that is easy to integrate and scale without major adaptions for new grid setups or changes within the grid. This renders the DL approach impractical for the task at hand.

The work in [22] mentions k-Nearest Neighbour (kNN) as an instance-based learning method that can be used for fault detection and classification. The kNN algorithm classifies samples according to the labels of their neighbors: depending on the number of neighbors and, optionally, the distance to these neighbors, a vote is taken by all training samples on the class assigned to the unseen sample. This means no classifier has to be built per se, making kNN a non-parametric method. The only parameter is said number of nearest neighbors considered and whether their vote should be weighted according to their individual distance to the sample to be classified. A large number of data samples, however, lets the computational cost of kNN explode, as all of them have to be evaluated when making a prediction. Also, [23] uses kNN for fault detection, but also to classify events like PV outages. However, data at high resolutions from phaser measurement units (PMU) positioned in the grid measure voltage magnitudes and also angles. Additionally, [24] finds kNN a fit solution for detecting voltage sags in distribution grids, which also shows that the method is not necessarily limited to line faults. Even though kNN seems to be an approach worth being explored, it remains unclear if it can also perform well under the present circumstances.

The authors of [25] use a Support Vector Machine (SVM) classifier for fault location. The SVM is suited for small datasets with data of high dimensionality and building the classifier has a low computational cost. Furthermore, the SVM can be used using various kernels, allowing for non-linear decision boundaries. In general, decision boundaries are found by the large margin principle: the decision boundaries are calculated in a way to maximize the margin of the samples to the decision boundaries. They also use dimension-decreased data for their solution. The results are promising, however, the solution works using micro-PMU data which is not available in that form for the problem at hand. Reference [26] also uses the SVM for fault detection and location, but uses an online data bank of simulated fault locations to build the classifier. It is to be evaluated if this poses an interesting approach to solving the problem of data availability. Additionally also [27] uses the SVM approach, in this case, to classify power quality disturbances such as well, harmonics, flicker, or interruptions. This shows the wide range of applications the SVM can cope with, making the approach of particular interest to the problems stated initially.

C. DISAGGREGATION APPROACHES

The problem of disaggregating a load profile into its contributing profiles without using and installing sensors that track them directly is generally known as Non-Intrusive Load Monitoring (NILM) [28]. In general, only disaggregation of household profiles into individual appliance profiles is found in literature [29]. NILM is only partly congruent with the approach to transformer load profile disaggregation needed here, as the origin and availability of the input data differ as well as the sought output profiles as these usually fall into application categories. Of particular interest here is energy estimation as elaborated in [30]: this estimation is further dissected into event-based and eventless-based NILM. It is to be said that, even though an arbitrary number of appliances can make up the profile to be disaggregated, the appliances are usually identified beforehand. Identification also means extracting a particular typical profile for each appliance, which can be time-consuming and requires a lot of adaptations. This might be cumbersome or not possible in a grid setup as loads appear very different depending on their position in the grid and the resulting influence of lines on these loads' consumption. This is especially a problem for the application at hand if not many adjustments are to be done for individual grids.

Approaches for disaggregation regarding entire transformer profiles in a distribution system using substation data only treat estimating PV or other distributed generation [31]. Here again, historic load data is used which corresponds to the appliance identification mentioned earlier. This can pose a problem again as not many manual adaptions to certain grids are to be conducted for the solution envisioned. Similar approaches that can be found only treat system-level disaggregation, meaning disaggregating even more aggregated power profiles such as national consumption. In [32], the authors disaggregate national consumption into substation-level contributions, which is still of too big granularity for use cases related to our work.

In [33], the NILM problem is reframed as a source separation problem, meaning that the source of an aggregated profile is to be determined. Mostly Neural Network (NN) architectures are proposed for the task. Here. only high-frequency signals are being treated, for example, 16 Hertz signals. If the method works on data with lower frequencies is still to be evaluated. The authors of [34] address the problem as feeder-level disaggregation, which means disaggregation of substation profiles into components. They use NNs for this task, however, to make quantile predictions and not point predictions, as would be more suited to the problems stated above. Lastly, [35] mentions a wide range of NN architectures to be fit for the task of disaggregation, even though the use case under scrutiny is not a feeder-level disaggregation but the disaggregation of a household profile into its devices' contributions.

Different regressors for disaggregation are compared in [36]. The results of this work show more or less equal performances for different regressors such as NN, SVR, or Random Forest with each of them having an edge over the others depending on the dataset they are applied on. Therefore, no solution seems to be outstandingly favorable over the others. Also, the work in [37] uses very simple regression methods for disaggregation: even Linear Regression (LR) seems to offer a good option. For that reason, also well-known and simple solutions such as LR should be considered for the problem at hand.

D. SUMMARY AND OPEN ISSUES

Summarisingly, the work on monitoring with regard to misconfigurations as well as the works on disaggregation (see Table 1) in the electrical grid domain shows quite some gaps to be filled. Either the approaches don't treat the same problem as the one at hand as is the case for monitoring which covers only line faults and not misconfigurations. Here, some methods appear worth exploring, mostly traditional Machine Learning (ML) approaches such as kNN or SVM. Deep Learning seems not applicable as the data set size and availability of data, in general, is a problem. Regarding disaggregation mostly the household level NILM is the focus of the works found in the literature. A wide range of methods, traditional regressors but also NNs seem to be valid solutions. It remains to be seen if they can also be applied in the same manner on the feeder-level disaggregation problem present here, as the constraints are quite different from the ones usually found with NILM problems. The main contributions of the work here are to apply detection approaches in the misconfiguration use case, but also combine them with methods applied to the feeder-level disaggregation task in order to yield an integrated and deployable misconfiguration monitoring solution.

III. METHODS AND ALGORITHMS

The approach presented in this work integrates a transformer profile disaggregation method in the form of a load estimation with a detection method for specific misconfigurations. First, this detection method is explained in detail. Then, the disaggregation method is elaborated. Ultimately, the complete detection application and its functionality are illustrated. How these individual parts are linked is also depicted in the overview flowchart of Figure 2. The entirety of the code used to develop, test, and assess all of the methods presented can be found in the corresponding repository.[1]

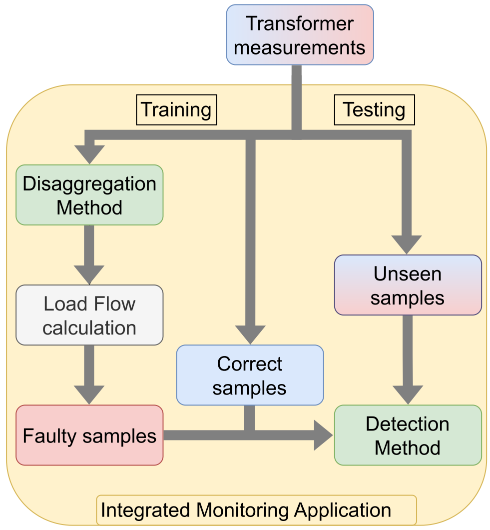

FIGURE 2. Flowchart linking the methods of the monitoring application.

A. DETECTION METHOD

The detection method used has been presented in detail in previous work [38]: here the applicability of the method was shown using laboratory data as well as their respective recreations using simulation of substation data. The misconfiguration to be detected was a PV reactive power control misconfiguration. Such misconfigurations can be, for example, a flat $cos\phi(P)$ curve which leads to a lack of voltage control. The method works on substation transformer measurement data. It constructs a classifier using samples of regular grid operations as well as of the corresponding operation circumstances when a misconfiguration is present. The classifier is then used to assess new, unseen samples making a statement on whether a misconfiguration is present or not. The assessment yielded good results, both on the recorded laboratory data as well as on the simulation data. The misconfiguration could be detected in all, or almost all cases, depending on the specific misconfiguration, its position in the grid, and the data source. This paved the way for further usage of this method and its transformation into other use cases as well as its integration into the final detection application.

The approach for detection can be briefly summarised as follows: the highly dimensional substation measurement data, which consists of voltages and currents but also active and reactive power flows are used. These data were recorded at a 4 Hertz rate and also recreated at the same frequency. The data of one entire day are regarded as a single data sample. This is made possible by flattening the data into a single row, whose columns are marked as certain variables at a specific time step, such as the voltage at phase A at 10 am. This yields a number of columns equivalent to the product of the number of rows times the number of channels recorded. 15 days' worth of data were recorded in all configurations, totaling 15 data samples for the assumption of regular operation as well as for cases where a certain misconfiguration is present. Taking a simple example, 15 sets of load and generation profiles were applied and the substation recorded both for the PV reactive power control to be on or off. The resulting data set has 30 samples in total, 15 correct ones, and 15 samples of malfunctioning cases. PCA was then applied to this data set in order to filter for the most important features. The PCA was specified to retain 99% of the variance in the data, which still reduced the dimensionality of the individual samples significantly. After this step, the final data set is

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

TABLE 1. Non-functional requirements (NFR) fulfilled (X) or unfulfilled (–) by approaches in related publications cited.

	Reference								
NFR	[17]	[18], [19]	[20], [21]	[22] - [24]	[25] - [27]	[28] - [30]	[31], [32]	[33] - [35]	[36], [37]
Scalability	–	–	–	X	X	–	–	X	X
Adaptability	X	X	–	X	X	X	X	X	X
Integrability	X	–	–	–	–	–	–	–	X
Usability	–	X	–	X	X	–	–	–	X
Data Retention	X	–	X	X	X	X	–	X	X
Robustness	–	X	–	–	X	X	X	X	X
Quality	X	X	X	X	X	X	X	X	X

assembled. This data set is then fed to classification methods, namely the aforementioned kNN, DT, and SVM. The latter two build a classifier using the training set and then use the found decision boundary to classify unseen examples as either stemming from regular operation or a misconfigured operational state. kNN, as elaborated before, performs the classification by looking at each testing sample's neighbors and classifying it in accordance with the majority of them. For the PV use case under scrutiny in [38], the best-fitting solution was the SVM.

B. DISAGGREGATION METHOD

Usually, only cases of correct operation are recorded or assumed as such as grid operators are unaware of the occurrence of a misconfiguration. A real application would need to know what the faulty samples look like to be able to build the classifier. As only substation data is to be used for the detection method, and some form of recreation of misconfiguration cases is necessary, also some form of data mining to gain information about loads' consumption in the underlying grid is needed.

The approach chosen is a load estimation approach. In order to be able to conduct this estimation, the properties of the grid the loads are situated in have to be captured. In order to achieve this, a training set of generic load flow results is generated using grid simulations. This is done by running 10,000 load flows where loads and generation units are assigned profiles with uniformly distributed values. The results are saved as a data set. The only properties necessary to know here are the minimum and maximum power values of the loads and generation, which should both be available to grid operators since they are either needed for billing or installment of devices. The load flow results, in addition to power flows, then also contain the voltage values for each combination of load and generation settings.

This training set is in turn used to train a NN or build the regressor used for LR as a benchmark. The training set obviously contains the same inputs as used later for the estimation, which is depicted in Figure 3: voltages at the substation and at neuralgic points in the grid, as well as active and reactive power, flows at the substation are measured. Furthermore, the production of generation units is assumed as known through external estimation. This estimation is, for example, straightforward for PVs, as radiation models

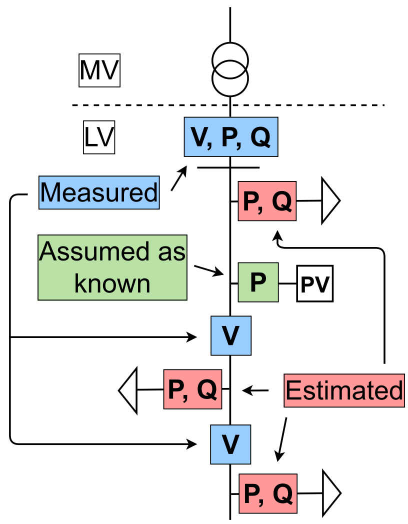

FIGURE 3. Requirements for the disaggregation method.

in combination with the installed rated power yield very accurate estimations of production. In the case presented, the estimation is done in hindsight, meaning that the historic radiation data is easy to obtain. The outputs in the training set, the labels, are the active and reactive power consumption of the loads, marked as estimated.

The NN trained is a very simple one, made up of only 1 hidden layer with ReLU as an activation function and Adam as an optimizer. ReLU, in contrast to the Sigmoid activation function, avoids the vanishing gradient problem, which was encountered during developing the solution. Adam optimizer has the advantage of computing individual adaptive learning rates for different parameters which speeds up learning compared to using classic gradient descent for the optimizer. The learning rate was set to 10^{-3} and the batch size to 32. The voltage input data were scaled using a standard scaler which scales the data around the mean divided by the standard deviation. The standard scaler is used here since the voltage values are expected to be clustered around a nominal value, like 230V. The load inputs and outputs were scaled using a minimum-maximum scaler, scaling the data between 0 and 1. For the loads, the minimum-maximum scaler was chosen as these values are easy to determine for grid operators from historic billing data, and therefore a minimum and maximum

TABLE 2. Requirements and output of disaggregation method by device.

Device	known	estimated
Transformer	V, P, Q	–
PV	P	–
Voltage sensor	V	–
Load	–	P, Q

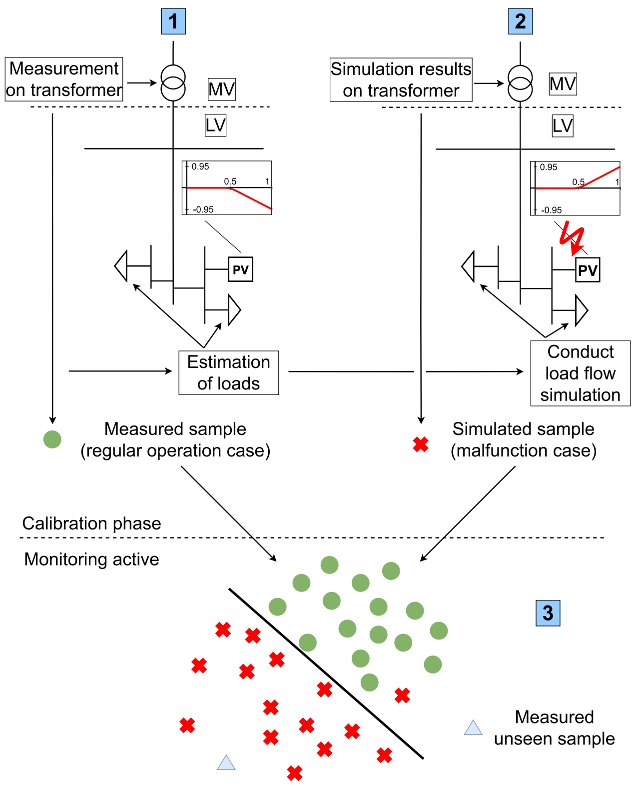

FIGURE 4. Scheme of the integrated monitoring application.

value can be defined for the uniformly distributed inputs. Scaling in these two forms allows for consistent inputs for the NN without any outliers that might inhibit the learning of the model.

Table 2 summarises the requirements and the outputs of the disaggregation method by device class. As mentioned before, the voltages and power flows at the substation, voltages at points between loads, and the infeed of generation devices are needed. The estimation then yields active and reactive power values of the loads in the grid.

C. INTEGRATED MONITORING APPLICATION

In order to merge the aforementioned detection method and disaggregation method into a monitoring application, the two have to be integrated. The functionality of the application is sketched in Figure 4 as well as described in the following.

The substation data are used for detection as elaborated above. In order to build a classifier employed for monitoring, a certain calibration period is necessary. During this calibration period, new unseen samples of transformer level data, the data of one day constitute a sample, are assumed to have been collected during regular operation without any misconfiguration present, as in part 1 of Figure 4. In order to obtain the corresponding faulty sample consisting of data collected under misconfigured circumstances, grid simulations are employed. These simulations recreate the grid operation of the previous day by setting the load and generation values to the corresponding historic values. During the simulation, the control curve to be monitored is set to a misconfigured setting. Multiple simulations are conducted to cover an arbitrary number of misconfigurations in this way by producing grid operational data under such circumstances. To attain a complete data set, the measured 'correct' samples and the simulated 'faulty' ones are combined. To be able to simulate the 'faulty' samples though, the values of the individual loads in the underlying grid need to be determined. For this task, the already described disaggregation of the measured transformer power profile is used. The simulation is done using the load and generation profiles, the latter are assumed to be known from external sources, and simply changing the configuration under scrutiny to the misconfigured setting. The load flow simulation then yields the transformer data for this respective case, as shown in part 2 of Figure 4. This can be repeated for an arbitrary number of misconfigurations without high computational cost and only requires modeling the misconfiguration once.

After the calibration was conducted, which in the presented case was done for 14 days, the monitoring application is ready for use. New, unseen data are then treated, as lined out in the description of the detection method: a day's data is flattened into a single row and treated by PCA to form one sample. This sample is then classified as either stemming from regular operation or not, which is depicted in part 3 of Figure 4. Therefore, the monitoring application delivers a diagnosis of device's configuration status once a day. The classifier can then also be updated each day, in case the sample collected is deemed to be of regular operation. This leaves the application with a rolling window of historical data making up the classifier which also accounts for possible drifts in the grid operational data.

IV. MONITORING EXAMPLES

Here the two applications the monitoring approach was tested on, as well as the grid setups the data for these were collected and the corresponding data properties are presented. Both applications are highly relevant to the integration of renewable energy sources into the power system. The PV use case aims at the monitoring of the direct mitigation of the impact of decentral integration through a reactive power control. Such controls are widely configured at PV inverters. The DSM monitoring use case tends to the detection of incorrect load shifting looking to maximize PV self-consumption, which is a more indirect grid-supporting functionality since it also mitigates stress on the grid.

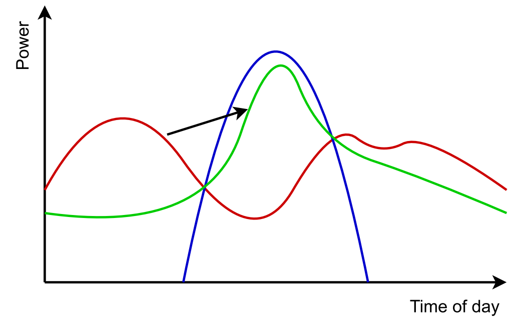

FIGURE 5. DSM working principle; red: original load; green: load after DSM; blue: PV generation.

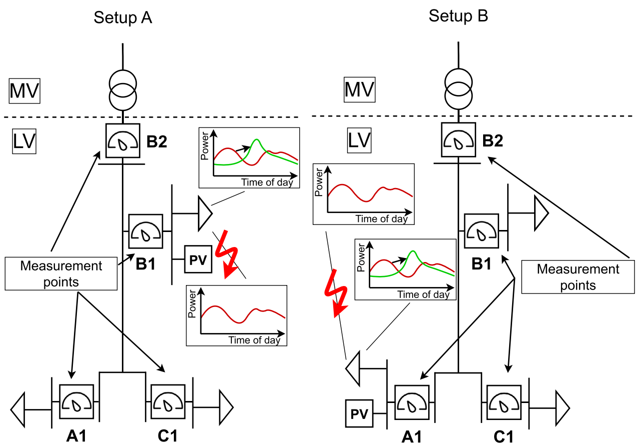

FIGURE 6. Test setups used for data collection.

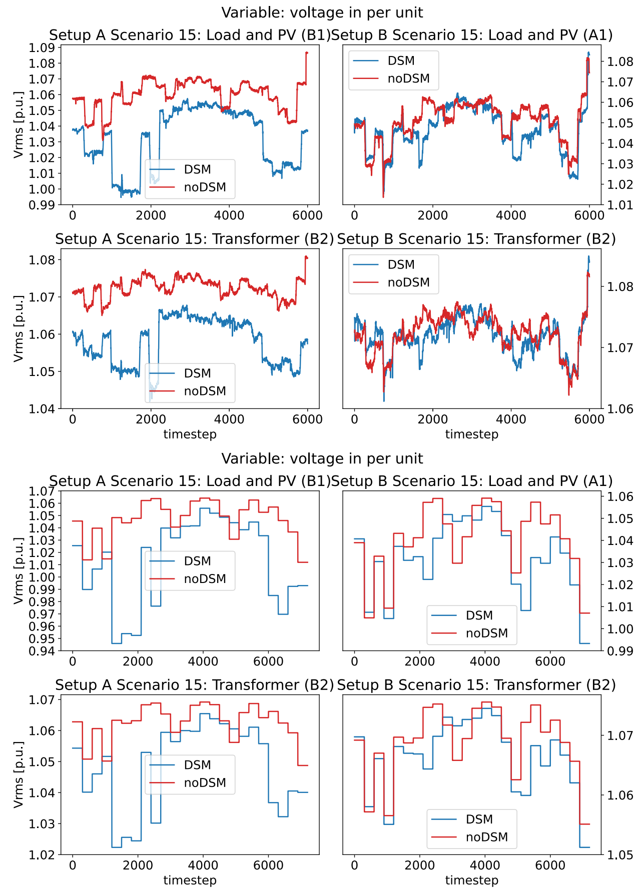

FIGURE 7. Laboratory (top) and simulation data (bottom) by measurement point.

A. DSM USE CASE

The first application is the monitoring of a DSM functionality of loads. The DSM in question aims to shift the load in a way, as to maximize PV generation self-consumption as depicted in Figure 5: the load profile assigned to a household load (the red profile) which has a PV generator attached is shifted (the green profile) so that the biggest consumption peak coincides with PV production (the blue profile). Therefore, it is shifted to sometime during the day, lowering energy demand from the grid. The overall energy consumed throughout the day remains unchanged, though.

This is considered a correctly configured load that implements DSM control. In case the load is not shifted in the way described, the load is considered to have no DSM control. Data were collected in a laboratory environment using two grid setups shown in Figure 6: both setups contain a transformer, 3 loads, and one PV unit. In setup A, the PV is located at a load close to the substation and therefore close to the start of the feeder. In setup B, the PV can be found at the end of the feeder. Data were measured at the connection points of the loads as well as at the substation. The data was collected at a 4 Hertz rate, measuring a multitude of signals such as voltages, currents as well as active and reactive power flows.

Using these grid setups, data corresponding to 15 days of grid operation were collected by assigning load and generation profiles and measuring the grid data. Each of the profile combinations is referred to as a scenario in the following. This was done twice as the data were collected once with the DSM control in place, and once with no DSM control. This yielded 30 samples, 15 of which were 'correct' and 15 were 'faulty'. Figure 7 allows a glimpse at the data collected: the top part of the figure depicts the voltage measured in the lab environment at the load with attached PV as well as at the transformer. The DSM control helps curtail over-voltages by raising the self-consumption of otherwise excessive PV generation. This effect is more pronounced in the setup where the PV is closer to the substation. The lower part of the figure shows the recreation of these measurements by simulation: the basic behavior is the same, however, the effects of the DSM are less pronounced than in the real-life data.

In order to get a full picture of all scenarios with both DSM control and no control, a cluster map can be created. The clustering was conducted using ward clustering [39] which creates a similarity matrix using Pearson correlation and then builds a hierarchical dendrogram linking together the most similar time series. This is done by the ward linkage

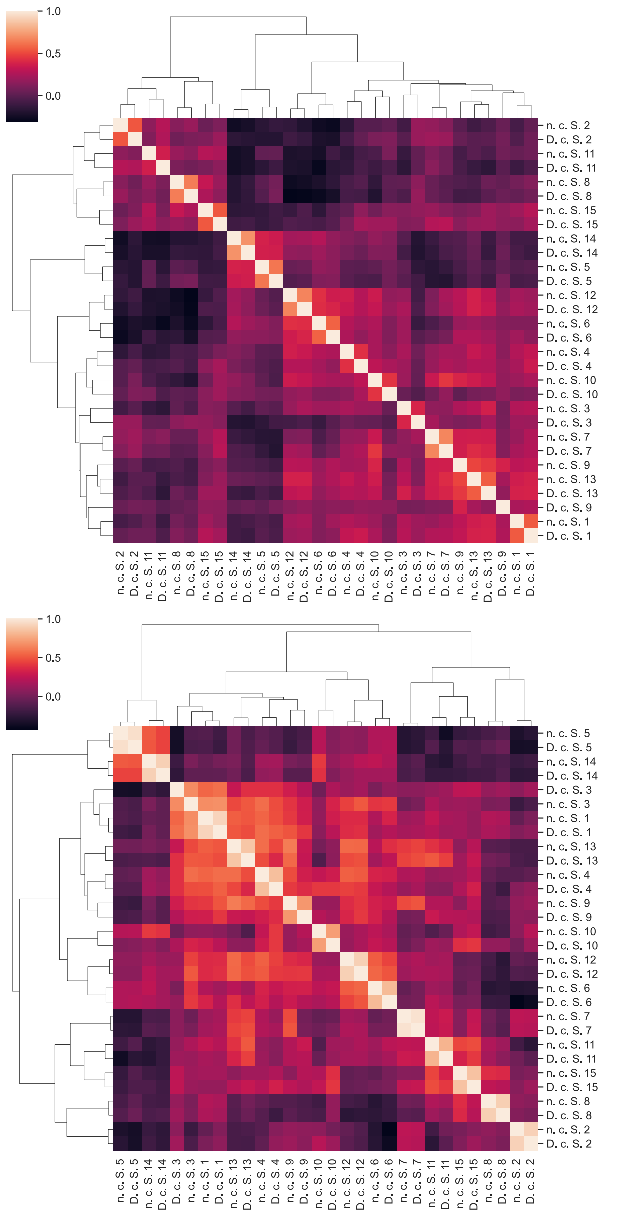

FIGURE 8. Laboratory (top) and simulation data (bottom) of setup B at measurement point B2 clustered; 'D. c. S. 1' and 'n. c. S. 1' stands for 'DSM control Scenario 1' or 'no control Scenario 1' respectively.

method, an algorithm minimizing the variance. The clustering was done for the laboratory data, which can be seen in the top part of Figure 8, as well as for the simulation data, which is depicted in the bottom part of the figure. Two aspects can be derived from these cluster maps: first that the data from the same scenario are more similar to each other than the data collected with the same control setting. This means that data samples from the DSM and Pv use case are not trivial to separate. Secondly, the laboratory data are in general less similar to each other than the simulated data, which is in accordance with the observation made earlier that the impact of the control is less pronounced in the simulated case. This could have implications for the

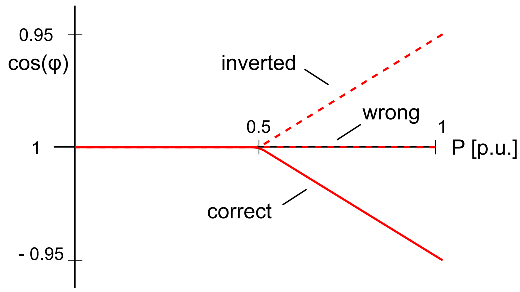

FIGURE 9. cosϕ(P) control curve and its abnormal configurations.

performance of the monitoring application, as it combines real-world measurement data with simulated data. However, a sample from the real world shows more pronounced effects of the control, meaning it should be easier to detect in case of a misconfiguration than its simulated peers used to build the classifier, as elaborated above.

B. PV USE CASE

The second application is the monitoring of a PV inverter and its reactive power control curve. The curve under scrutiny is a cosϕ(P) control curve. The misconfigurations, sketched in Figure 9, are either a flat control curve, called 'wrong' in the following, which means no reactive power infeed, or an inversed curve leading to an infeed of the opposite sign. As mentioned above, this power factor control is used to dispatch reactive power in order to avoid or mitigate overvoltages at high PV active power infeed. The same data as described above was collected for this use case, also using two grid setups. Both consisted of a transformer, two loads, and a PV generation unit. In one setup, this PV is located closer to the substation, in the other one, at the end of the feeder. A detailed description of these setups, the control curve as well as its misconfigurations, the data collected, and the results of the detection method achieved on this data can be found in previous work [38]. Also here, the number of samples collected for each case of configuration is 15, meaning 15 days' worth of data were collected.

V. RESULTS AND DISCUSSION

The results achieved by the individual parts of the monitoring application, but also by the entire application are shown here.

A. DSM DETECTION METHOD

First, the performance of the detection method is evaluated. This is done for the DSM use case, as the results for the PV use case can be found in previous work [38]. Table 3 shows these results: the first row shows the F-score achieved in both grid setups and when using data collected in the laboratory as well as through simulation. The results were achieved by conducting a 7-fold cross-validation. The F-score is calculated using Recall, how many of themisconfigurations present were also found, and Precision, how many of the found misconfigurations are actually misconfigurations. The

TABLE 3. Comparison of best detection results on laboratory and simulation data of the DSM use case.

Metric	Grid Setup A		Grid Setup B	
	Lab Data	Sim Data	Lab Data	Sim Data
F-Score	0.91	0.70	0.85	0.68
Best method	NuSVM: RBF kernel	SVM: sigmoid kernel	SVM: linear kernel	NuSVM: sigmoid kernel

F-score, therefore, balances the two. The second row lists the classifier yielding the best result.

The results clearly show a good performance on the data collected in the laboratory setting, whereas the misconfigurations appear harder to detect in the simulation data. This ca be explained when considering the aforementioned higher similarity between samples in the simulated cases compared with the samples collected in the lab environment. In general, the results in setup A have an edge over the results in setup B. In setup A, the DSM-controlled load is closer to the substation and therefore has a higher impact on the transformer data, as discussed already. This makes the misconfiguration easier to detect. However, in both cases the detection is feasible. Furthermore, either the SVM or NuSVM, which constrains the number of support vectors making up the decision boundary depending on the so-called nu parameter ranging between 0 and 1, is found to be the best-performing algorithm for detection. This was to be expected, both considering the results of previous work as well as the properties of the SVM which shows good performance on small, highly dimensional datasets.

B. DISAGGREGATION METHOD

The performance of the disaggregation method and its load estimation as the next building block of the monitoring application is assessed here. This was done for both use cases, so for four grid setups in total. Figure 10 shows examples for the estimation of a load's active and reactive power consumption for grids used for the PV use case. The active power value is depicted on the left, and the reactive power value is on the right. The estimation is done using both a NN as well as LR. The active power estimation follows the actual value quite accurately, whereas the reactive power seems to be underestimated generally with some peaks in the NN estimation that are off.

The estimation of the consumption of a load, which has the same active and reactive power profile as the one shown before but in a grid used for the DSM use case can be found in Figure 11: here the active load estimation seems to be too high in a few instants, whereas the reactive power appears to be more accurately estimated with the LR estimation being

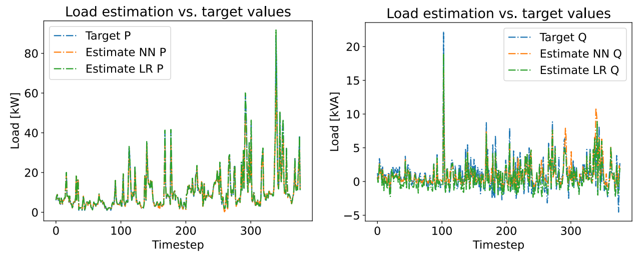

FIGURE 10. PV use case: estimation of load profile.

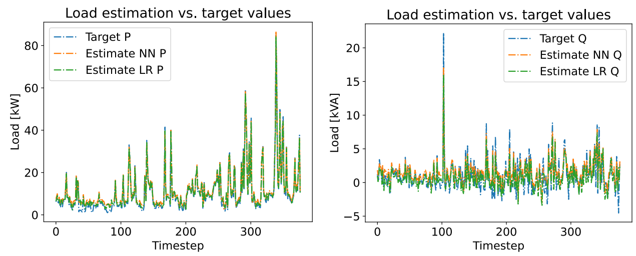

FIGURE 11. DSM use case: estimation of load profile.

farther away from the actual value when it comes to peaks. This allows for the conclusion that the estimation is generally better for the active power values than for the reactive power consumption, which might have to do with the properties of the grid and the varying reactive power consumption of the lines therein.

The complete results on all grid setups are listed in Table 4. The metric used is the mean squared error, which in this case is based on the scaled values ranging from 0 to 1. The results for the first two grid setups used for the PV use case are much worse than the results for the second two used for the DSM use case. The grids used for the DSM use case have more loads than the ones used for the PV use case, having 3 instead of 2 voltage measurements and fewer lines without any measurements in general. This is likely to be the cause of the better performance on the 'denser' grids used for the DSM use case. The performance of the NN and LR are almost the same here, with the NN having a slight edge over the LR performance. For the less 'dense' grids employed in the PV use case, the LR shows better performance, pointing to the LR being the more robust option. Whether this has an impact on the overall performance of the monitoring application remains to be determined in the following.

C. INTEGRATED MONITORING APPLICATION

Finally, the detection method and the disaggregation approach were combined and the resulting monitoring application was put to test. The performance results for the PV and the DSM use case are both evaluated using the aforementioned F-score as well as by pointing out the best scoring algorithm for detection. Furthermore, the impact of the disaggregation approach is evaluated. this is done by comparing the performance of the monitoring application

TABLE 4. Comparison of disaggregation error results for both the PV and DSM use cases.

Mean squared error (MSE)	PV Use Case		DSM Use Case	
	Setup A	Setup B	Setup A	Setup B
Neural Network	$23 * 10^{-3}$	$20 * 10^{-3}$	$0.8 * 10^{-3}$	$0.85 * 10^{-3}$
Linear Regression	$17 * 10^{-3}$	$16 * 10^{-3}$	$0.9 * 10^{-3}$	$0.87 * 10^{-3}$

using the actual load data as inputs for the simulation of the misconfigured samples to the performance using estimated load data as inputs. Both the NN as well as the LR estimation are considered inputs. As there are 15 samples available for each of the use cases and grid setups, 15 combinations of training and test sets were formed. In each of them, all but one sample of regular operation as well as one of grid operation with a misconfiguration present are used for training. The two test samples originate from the transformer measurements. In this way, the real operation of the monitoring application is emulated.

Table 5 shows the results for the PV use case. The results consider the detection of the flat reactive power control curve, called 'wrong', as well as the detection of an inversed curve, or simply an abnormal curve which means either a flat or inverted curve. The top part of the table shows the results for grid setup A where the PV is closer to the substation, and the bottom half lists the results for grid setup B which contains a PV at the end of the feeder. The detection of the 'wrong' control curve works equally well in both setups, also with regard to the origin of the load data for the simulation. The best-performing detection method here is a form of SVM with a non-linear kernel. The inversed control curve can be better detected in grid setup A when the actual load data are used for simulations, even though the best detection approach is a kNN considering two neighbors indiscriminate of their distance in both cases. There is no difference in performance between the grid setups when the estimated load data are used, however, an SVM with a sigmoid kernel is the best-performing method then. The best performance is achieved when detecting both misconfigurations at once. The performance is the same for both grid setups, with the best performing algorithm being kNN with two neighbors weighted for their distance in the case of the actual load data being used and again SVM with a sigmoid kernel when either the NN or LR estimated load data are used for simulation. In this use case, the detection results are generally significantly worse in case the estimated load data are used. However, it does not seem to matter whether they stem from the NN or LR estimation even though the LR estimation was more accurate as already discussed. This general drop in performance can be attributed to the poor estimation quality for the grid setups used here. In general, the results are acceptable for individual misconfigurations or even good when trying to detect any misconfiguration of the PV reactive power control curve.

TABLE 5. Comparison of best detection methods using the original or the estimated input data of the PV use case.

PV use case: Grid Setup A				
Best score / method		**Data Source**		
Case	Metric	Original	NN Estimated	LR Estimated
correct vs. wrong	F-score	0.71	0.62	0.62
	Best method	NuSVM: polynomial 4^{th} degree kernel	SVM: sigmoid kernel	SVM: sigmoid kernel
correct vs. inversed	F-score	0.80	0.67	0.67
	Best method	kNN: 2 neighbors uniform weights	SVM: sigmoid kernel	SVM: sigmoid kernel
correct vs. abnormal	F-score	0.83	0.80	0.80
	Best method	kNN: 2 neighbors euclidian weights	SVM: sigmoid kernel	SVM: sigmoid kernel
PV use case: Grid Setup B				
Best score / method		**Data Source**		
Case	Metric	Original	NN Estimated	LR Estimated
correct vs. wrong	F-score	0.71	0.62	0.62
	Best method	NuSVM: polynomial 4^{th} degree kernel	SVM: sigmoid kernel	SVM: sigmoid kernel
correct vs. inversed	F-score	0.76	0.67	0.67
	Best method	kNN: 2 neighbors uniform weights	SVM: sigmoid kernel	SVM: sigmoid kernel
correct vs. abnormal	F-score	0.83	0.80	0.80
	Best method	kNN: 2 neighbors euclidian weights	SVM: sigmoid kernel	SVM: sigmoid kernel

TABLE 6. Comparison of best detection methods using the original or the estimated input data of the DSM use case.

DSM use case				
Best score / method		**Data Source**		
Case	Metric	Original	NN Estimated	LR Estimated
Setup A:	F-score	0.67	0.67	0.67
DSM vs. no DSM	Best method	NuSVM: polynomial 4^{th} degree kernel	NuSVM: polynomial 4^{th} degree kernel	NuSVM: polynomial 4^{th} degree kernel
Setup B:	F-score	0.69	0.69	0.69
DSM vs. no DSM	Best method	SVM: RBF kernel	SVM: RBF kernel	SVM: RBF kernel

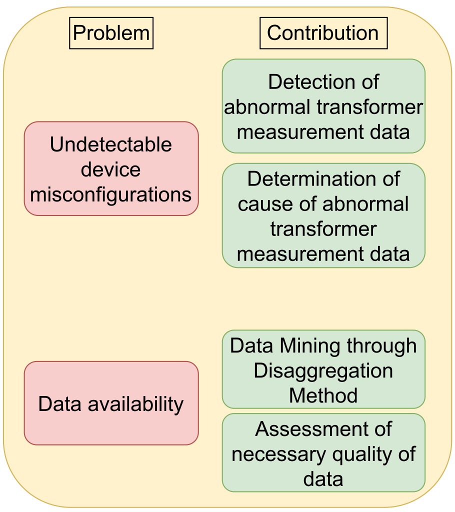

FIGURE 12. Problems stated and corresponding contribution by the work presented.

The results of the monitoring application on the DSM use case can be found in Table 6: The results for both grid setups are quite similar with the only difference being the best method found. In grid setup A, this is a NuSVM with a polynomial kernel of the 4^{th} degree, whereas in grid setup B, it is an SVM with a Radial Basis Function (RBF) kernel. What is of particular interest here is that the performance is the same when using the actual load data as input for the simulation as when using the estimated load data, regardless of whether NN or LR is employed. This can be traced to the much better estimation accuracy in the grids under scrutiny here. This allows defining the MSE as sufficiently small at about 10^{-3} for the estimation not to have an impact on the performance of the detection. The overall results are decent, with them matching the performance of the detection of a specific PV misconfiguration.

VI. CONCLUSION

A. ACHIEVEMENTS AND CONCLUSION

The problems raised by the transformation of the electric energy grid need novel solutions such as controls on a device that support the grid to work within operational limits. Due to a lack of sensors in the distribution grid, DSOs need solutions for monitoring the correct execution of these controls, in order to be able to guarantee a reliable and safe operation of the grid. The integrated monitoring application presented delivers just that tackling the first two objectives set initially. The detection method, as well as the disaggregation method, were both evaluated and then combined to form an easy-to-integrate and deploy monitoring solution that can act as a decision support tool for DSOs pointing them to misconfigurations of controls at a regular interval. A PV inverter and a DSM use case were presented and used for the experiments. The application presented makes use of data already available to the grid operator, with the sole extension of a PV generation estimation and voltage measurements at certain points in the grid to mine information about loads' consumption. This satisfies the third goal defined. The former are considered rather easy to obtain as they are historic for the past day. The latter constitutes only a small extension to sensing capabilities in the low-voltage distribution grid. Figure 12 sketches the problems stated and the contributions made in a condensed way. The contributions include the development of a detection and classification of abnormal transformer measurement data as well as an assessment of necessary data quality and an approach to Data Mining through Disaggregation. Life-like data were collected in a laboratory environment and recreated through simulation to give more validity to the results. These results give insights into the performance of the individual parts as well as of the complete monitoring application. The performance achieved in all scenarios is sufficiently satisfying to serve as a reliable and helpful tool for better monitoring of distribution grids, which fulfills the last aims set in the beginning. The limitations are mainly set by the assumptions on a correctly configured initial state before the calibration of the monitoring solution is conducted. This means previously present misconfigurations can not be detected, only newly occurring ones.

B. OUTLOOK

The application is meant to be working online as a decision support tool for DSOs. Therefore, a field trial assessing the transformer profile disaggregation approach as well as the complete monitoring solution would be beneficial to further improve the application as well as check its robustness. Furthermore, a trial in more diverse grid setups as well as larger grid setups is of interest, to be able to judge the application's scalability. To test the application's adaptability, the integration of new use cases regarding misconfigurations or devices is to be done in future work as well. The examples presented can also serve as templates for integrating other devices' misconfigurations. These are to include EVSEs and HPs.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper or pose a conflict of interest of any sort.

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