SPECTRAL ANALYSIS FOR TRACKING TRANSIENT EFFECTS IN DISTRIBUTION GRIDS

Patrick LEHNEN
TH Köln - Germany
patrick.lehnen@th-koeln.de

Patrick MACK
TH Köln - Germany
patrick.mack@th-koeln.de

Markus DE KOSTER
TH Köln - Germany
markus.de_koster@th-koeln.de

Ingo STADLER
TH Köln - Germany
ingo.stadler@th-koeln.de

Eberhard WAFFENSCHMIDT
TH Köln - Germany
eberhard.waffenschmidt@th-koeln.de

ABSTRACT

In the face of the challenges posed by climate change and the rapid integration of renewable energy sources, the resilience of power distribution grids has never been more crucial. Our research introduces a novel methodology aimed at increasing grid resilience by leveraging advanced analytics enabled by simulations. We propose an algorithm to locate failures and power quality issues in the presence of modern high-power, non-linear inverter-based assets like photovoltaics (PV), battery electric vehicle (BEV) charging stations, and heat pumps.

This paper explores the use of neural networks for identifying the injection point of transients and comprises two distinct experiments. Initially, we demonstrate a proof of concept using the amplitude of the third harmonic across all buses in the CIGRE-LV 44-bus distribution grid, achieving a validation accuracy of 100%. Recognizing the impracticality of full observability in real-world scenarios, we strategically reduce measurements to three buses, achieving 84.7% accuracy with a neural network. This method results in top-3 and top-5 categorical accuracies that improve to 97.3% and 98.8%, respectively, giving valuable intuition where the sources might be located.

INTRODUCTION

This paper is embedded in a research project to assess power quality issues in the German electricity grid. In the face of declining energy generation from conventional linear sources like coal and nuclear power plants and the rapid integration of renewable energy sources, it is necessary to monitor the power quality extensively [1, 2]. As monitoring the whole grid is not possible, there is a need for methods that will work in an imperfect information setting.

This study focuses on leveraging neural networks to localize transients within a distribution grid using harmonic analysis, specifically using the third harmonic component (150 Hz) as the diagnostic feature. Validation of our methodology is carried out on a simulation of a reference grid, into which we integrate PV, BEV-charging, and heat pumps. This simulated environment enables a detailed exploration of the impacts of these assets on grid stability and resilience. Central to our methodology is the analysis of harmonics across different buses. By evaluating the residuals of these frequencies against the normal operating state, we can predict the injection points of transients into the distribution grid. This spectral analysis aids in fault detection and can be used as a foundation for predictive maintenance strategies, as high harmonic loads can lead to accelerated aging of assets [3].

This paper is structured as follows: Section 2 provides a background on distribution grids, harmonic analysis, and neural networks. Section 3 details the simulation environment and data collection methodology. Sections 4 and 5 discuss the experiments with full and limited observability, respectively. Finally, section 6 presents the discussion, and section 7 concludes with a summary of findings and suggestions for future work.

BACKGROUND

Transients are brief yet significant deviations in voltage or current. They can disrupt grid operations, damage equipment, or increase the aging of components. Electrical devices often generate transients through normal operating processes, such as switching operations or motor inrushes. Non-linear loads like rectifiers and inverters, which draw current in short pulses, as well as non-linear generators like photovoltaic and wind power systems, can also produce transients during normal operation. In the worst-case scenario, transients can result from short-circuits, fault conditions, or lightning strikes. These transient sources can influence the power grid and cause disturbances that may be detrimental to power quality. Identifying and localizing transient sources is therefore necessary to implement appropriate measures to minimize their impacts.

We simulated transients in the OpenDSS simulation environment using the 44-bus CIGRE-LV distribution grid [4]. A large dataset is necessary to enable data driven methods like neural networks to work properly. For this study, we simulated thousands of different transients, voltage sags and swells and a multitude of harmonic sources like inverters, photovoltaic systems and electric vehicle charging points, to generate an extensive dataset. The simulations let us generate and analyze a multitude of harmonic signatures of these transients. Exemplary transient and harmonic effects we simulated can be found in Figure 1.

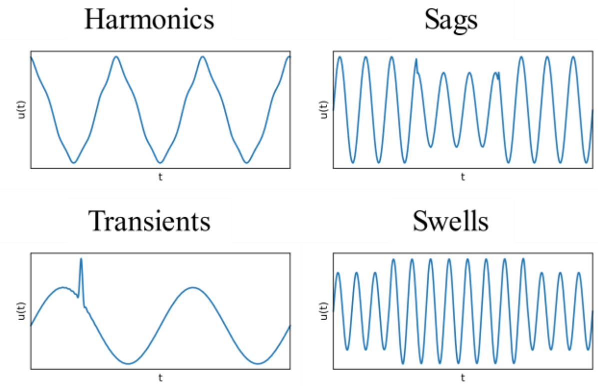

Figure 1: Examples of different power quality issues simulated in an OpenDSS environment.

The proposed methodology is supposed to have a real-world application in a wide-area monitoring systems (WAMS), where the ability to quickly and accurately pinpoint the source of transients in the distribution grid can enhance grid resilience and facilitate timely mitigation measures.

This research presents a novel approach for locating the source of transients in electrical distribution grids using neural networks and harmonic analysis. We train a neural network that can accurately predict the injection point of transients within the distribution grid.

Several studies have proposed methods for fault localization in distribution grids before. A fault localization scheme based on transient behavior, using local data to locate faults within milliseconds was introduced in [5]. An algorithm for event detection, classification, and localization in active distribution grids was developed in [6], achieving an enhanced localization accuracy of 94,5% through data-driven system identification. Another approach using a time-frequency based algorithm for fault detection and localization using the Stationary Wavelet Transform and Artificial Neural Networks was discussed in [7]. For event detection and localization [8] proposed an online algorithm in an unbalanced three-phase distribution systems, demonstrating accurate and timely detection of tripped lines.

Some of the mentioned papers require a large amount of measurement devices or are only able to localize hard grid errors like faulty lines, short circuits and topology changes. While [6] can locate soft transients e.g. from PV-systems, in a 24-bus grid, the proposed system is only capable of predicting distances from the measurement device to the fault, which may be impractical in distribution grids with a higher branching factor or more nodes in general.

The third harmonic, occurring at 150 Hz in a 50 Hz system, is of particular interest in this study. Harmonic analysis involves measuring and analyzing these harmonic components to diagnose and understand various power quality issues. The amplitude and phase angle of the third harmonic can provide critical insights into the system's behavior and the location of disturbances such as transients.

In all our experiments we use a dense residual neural network [9] with three residual connections, batch-normalization [10] and ReLU activation functions. We use softmax as the classification layer and 20% dropout for regularization. This setup results in a model with roughly 46k parameters, making it lightweight with fast inference times.

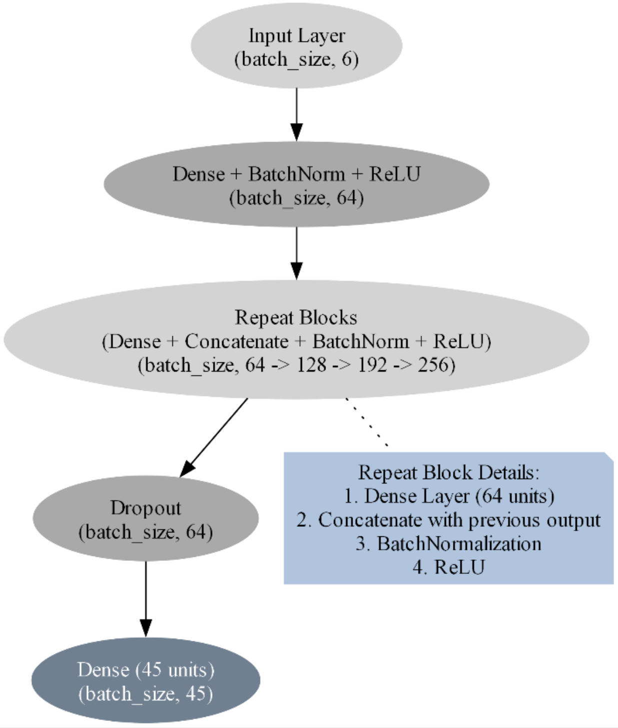

Figure 2: The dense neural network with residual connections and the repeating blocks in the middle. We use the same model for both experiments, excluding the input layer.

All experiments are run on an Intel Core I9 13900KF with 64 GB of RAM and a RTX4090.

Simulation Environment:

The experiments were conducted in the OpenDSS simulation environment, using the 44-bus CIGRE-LV distribution grid as the test system.

The transients and harmonics were synthetically simulated and afterwards fed as spectra into the OpenDSS simulation, to generate a comprehensive grid state. This grid state is the base of our training data set.

We chose the third harmonic for our algorithm, as it is one of the most dominant non-fundamental frequency components due to common harmonic-generating sources and due to phase-angle-alignment for harmonics that are multiples of three, making it more pronounced and measurable compared to higher-order harmonics. The third harmonic also maintains a stronger and clearer signal across the network, making it more reliable for analysis and localization, as higher order harmonics tend to be more attenuated due to the impedance characteristics of distribution lines which generally increase with frequency. Additionally, the third harmonic is more likely to be influenced by common network disturbances, making it a good indicator of system disturbances and a more informative signal for neural network-based localization methods.

However, the delta-wye transformers between the medium-voltage and low-voltage section suppresses harmonics that are multiples of three. Thus, a spread of disturbances will not be recognizable in sections that are unmonitored by measurement devices.

EXPERIMENT 1: FULL OBSERVABILITY, WITH 44 MEASUREMENT BUSES

The objective of the first experiment is to evaluate the performance of the neural network-based transient localization model in a scenario with full observability of the distribution grid. For this, we collect the amplitude of the third harmonic per bus resulting in a vector with 44 entries at the time of transient occurrence. Afterwards we normalize the dataset subtracting the mean per vector and scale between 0 and 1 as can be seen in the following formula 1.

$$x = \frac{h - \emptyset h}{\max(h - \emptyset h)} \tag{1}$$

Where x is the scaled dataset and h the vector of the third harmonic amplitudes. We also include states without any transient effects to be able to predict normal grid operation states. The resulting vector over all buses can be seen in Figure 3.

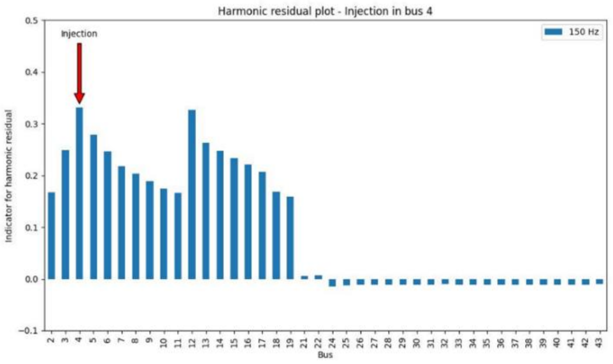

Figure 3: Exemplary data point showing how the harmonic residual is propagated through the grid. The bus where the transient is injected is marked with the red injection arrow.

The injection plot shows how a transient leads to a distinctive propagation pattern after the normalization with equation 1. The simple approach of searching for the maximum value in the resulting vector does not yield accurate results, as noise may lead to false classification events for buses that are close to each other. Furthermore, neural networks can leverage the distinctive pattern, as the propagation of the transient effect contains information of its origin as well. Figure 4 further visualizes the same transient spread as shown in Figure 3.

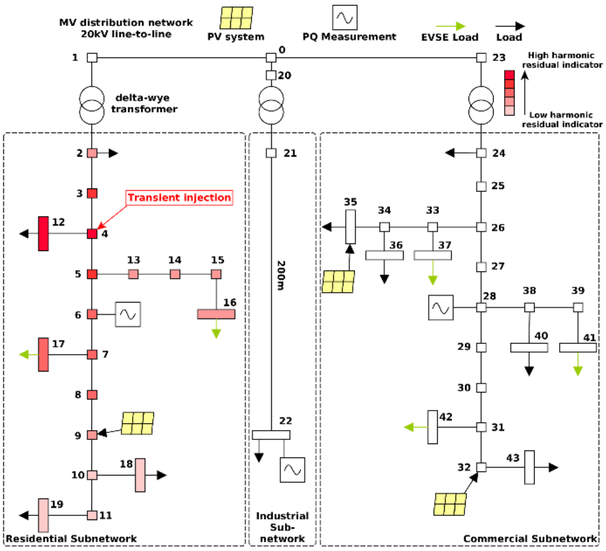

Figure 4: Visualization of the propagation of a transient in the CIGRE-LV grid. [4]

The injected transient in the residential network has little effect in the other subnetworks. The delta-wye-connected transformers completely suppress the propagation of the triplen harmonics. The electrical characteristics of the network, such as line impedances, transformer connections, and load distributions, influence how the third harmonic propagates across the buses.

We simulated a comprehensive dataset of 215,000 data points, with 10% of those data points for validation and 10% for testing purposes.

The neural network model is trained and evaluated using the dataset to predict the bus location where transients are injected. The results of this experiment are promising, as the neural network achieves 100% validation accuracy, correctly identifying the bus location for all the transient events in the validation and testing set of 21,500 data points each. We introduce 2% gaussian noise to simulate real-world measurement errors or minor disturbances, but the model maintains its 100% performance in accurately localizing transients, despite these random perturbations.

As full observability is not achievable in the real world, since measurement devices are costly, we reduce the number of measurement devices in the following experiment.

EXPERIMENT 2: LIMITED OBSERVABILITY WITH 3 OF 44 MEASUREMENT BUSES

The objective of experiment 2 is to assess the performance of the neural network-based transient localization model in a scenario with limited observability, where measurements are only available from three strategically selected locations within the distribution grid.

We also include the phase angle as information for the neural network, as this has positive effects on the performance. The neural network model is trained and evaluated using the limited information from the three measurement points.

For this experiment, we use the same neural network from experiment 1, though we have to change the input layer to accept only six inputs. The data preprocessing is changed as well, as we only scale the amplitude and the angle of all observations to lie in a range of 0 to 1 by max scaling.

The overall accuracy of the model in the limited observability scenario drops to 84.7%. However, the Top-3 and Top-5 categorical accuracies reach 97.3% and 98.8%, respectively, meaning that in 97.3% of cases, the correct bus is among the top three predictions made by the neural network. This high Top-3 accuracy suggests that even though the network may not always pinpoint the exact bus, it consistently narrows down the possibilities to a small subset of buses. Those Top-K accuracy results also indicate that the neural network model is robust and capable of generalizing well even with the loss of information in comparison to the first experiment.

DISCUSSION

An overview of the results is shown in Table 1. The in-depth evaluation shows that the neural network can identify the correct direction and general area where the transient is injected, as presented in Figure 5.

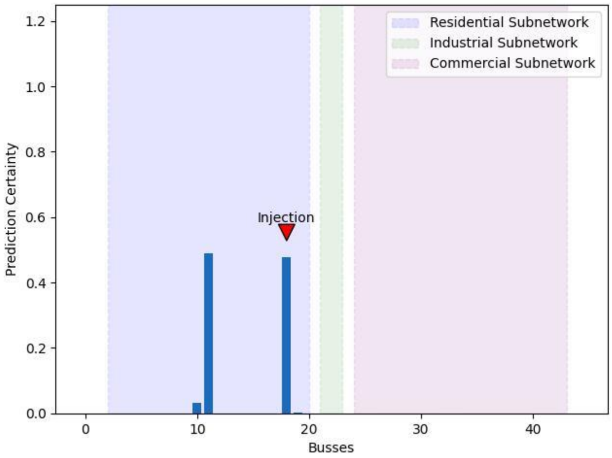

Figure 5: The plot shows the prediction of the neural network, with the prediction value on the y-axis and the number of the corresponding bus at the x-axis. It can be seen in Figure 4 that the three most probable buses, (10, 11 and 18), are directly connected and in the same general area of the grid.

The decrease in accuracy from the full observability scenario is expected and can be attributed to several factors, like the loss of spatial resolution and the increased ambiguity in the data. The limited number of measurement points introduces ambiguity in the data as multiple injection buses may now have similar harmonic responses at the selected measurement points, making it difficult for the neural network to differentiate between them.

The strategic selection of measurement points is critical, as the placement of these points directly affects the neural network's ability to learn distinct patterns associated with each bus in the distribution system.

Table 1: Results for the two different observability scenarios in comparison with other methods

Observability	Accuracy	Top 3 Acc.	Top 5 Acc.
44 of 44 buses measured [Ours]	100.0%	-	-
3 of 44 buses measured [Ours]	84.7%	97.3%	98.8%
13 of 13 buses [8]	98.5%	-	-

Comparing our work with other authors is not directly possible in most cases, as the methodology differs significantly. For example the authors of [5] do not try to predict the correct bus, but rather the distance of the fault to the measuring device, which may result in ambiguous predictions. Comparing our work with [8] shows that our approach is even able to localize softer transient effects than the examined line tripping events, which will have an easier to detect, strong transient feedback.

If the transformers in a subnetwork are not configured in a delta-wye setup or non-triplen harmonics are used, our approach may even be applicable in localization of transients in other subnetworks.

Limitations:

Although the proposed algorithm demonstrates promising results in the simulated environment, several limitations and considerations need to be addressed before its practical deployment. The model's performance should be further validated on real-world distribution grid data, and its robustness to various practical challenges needs to be investigated.

As the experiments were conducted in a simulation environment, they may not fully capture the complexities of a real-world distribution grid. Additionally, the study was limited to a single grid, requiring the model to be retrained for any new grid. While the dataset used for training and evaluation was comprehensive, it may not be representative of all possible transient scenarios that could be encountered in practice. The network topology and grid characteristics can have a significant impact on the performance of the proposed approach, and further validation is required to assess its broader applicability.

FUTURE WORK

The study demonstrates the potential of neural networks for transient localization in distribution grids, even with limited observability. To further enhance the performance and applicability of this approach, the following five improvements are worked on:

1. Investigating optimal strategies for the placement of measurement devices can improve spatial resolution and reduce ambiguity in the data. This includes employing techniques to strategically select measurement locations that capture the unique characteristics of different regions within the distribution grid.
2. The dataset will be expanded to incorporate a wider range of load profiles and transient scenarios. Enhancing the dataset in this manner is expected to aid the neural network model in improved generalization, increasing its robustness and achieving better accuracy overall.
3. The integration of real-world data from the ongoing research project is underway to reflect the complexities of actual power systems. This integration is necessary for validating the model's applicability and effectiveness in real-world settings.
4. The exploration of alternative neural network architectures and techniques, such as advanced feature extraction methods or grid embeddings, is an active area of research. Such methods may further improve the localization accuracy and extend the applicability of the neural network model to different grid configurations.
5. Efforts are being directed towards implementing the approach within a Wide-Area Monitoring System framework. This implementation aims to enable real-time monitoring and response to transient events in distribution grids, thereby enhancing overall grid resilience.

CONCLUSION

In this study, we demonstrate a novel methodology for enhancing resilience within power distribution grids, by analyzing the source of transients in the distribution grid. The presented data driven approach is one way to address and quantify the change caused by the integration of high-power, non-linear inverter-based assets on power quality. Such information is critical for the smooth operation of future distribution grids.

Our experiments, conducted within an OpenDSS simulation environment on a 44-bus CIGRE-LV reference grid, validate the proposed algorithm's capability to localize transient and power quality issues originating from photovoltaics, battery electric vehicle charging stations, and heat pumps. The first experiment, designed as a proof of concept, achieves a validation accuracy of 100%. In a more applicable real-world setting, our second experiment employs limited observability, maintaining noteworthy accuracy levels of 97.3% for the best three predictions while significantly reducing the measurement devices required.

Our research shows that grid management and maintenance strategies may benefit from this approach and can increase grid resilience in the future, as we are able to timely detect and localize any transients in the supervised grid. This allows for rapid intervention if assets are not operating in their expected range and may lead to lesser harmonic stress for the surrounding assets, reducing the wear of components. The ability to monitor and adjust for the effects of new renewable load profiles and generation patterns helps maintain grid stability.

There are many possible ways to enhance the quality of the algorithm, e.g. through optimization of measurement device placement to further enhance the model's accuracy and efficiency in real-world environments. Additionally, expanding our dataset to encompass a broader range of load profiles, transient scenarios and maybe even transferring the same neural network to other grids will be crucial in advancing the model's robustness, adaptability and scalability.

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