# OBJECT DETECTION BASED EXPERTSYSTEM OF AN ELECTRIC VEHICLE CHARGING STATION

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## *ABSTRACT*

*The shift in power systems from large power stations towards smaller decentralized generation units imposes new challenges on grid operators regarding power quality. The steady increase of power electronics connected to the grid results in elevated harmonic distortion levels, inducing additional losses and causing malfunctioning of control devices. This development has led to a rising number of monitoring systems, in order to ensure adequate power quality within the mandatory limits and boundaries. Consequently, detection and classification of power quality disturbances is a vital component of the mentioned systems. This paper proposes a new method for detecting power quality issues and identifying their underlying causes, based on historical data. The implemented automated image classification algorithm continuously analyses the FFT spectrogram of disturbances and simultaneously determines the type of disturbance and its cause without the need of a segmentation and feature extraction process. The results are validated using measurement from an electric vehicle car charging station.*

## INTRODUCTION

With the ongoing changes in energy production, transmission and consumption in electric power systems, ensuring power quality within acceptable limits has become an increasingly demanding task. In recent years the role of the customers in the electricity market has shifted from a predictable energy consumer to a more proactive and complex role. Considering the continuous growth of consumer side distributed generation and the increasing popularity of battery electric vehicles (BEV), reasonable concerns arise amongst system operators. A large-scale integration of BEV's might lead to an increase in load unbalance and harmonic emission levels for lower and higher frequencies [1]. The current and voltage distortions are caused by the BEV's integrated power-electronic based rectifiers, providing the vehicles battery with direct current (DC). Aside from elevated harmonic distortion levels, BEV can inject transients during the charging process or upon connection of the vehicle to the grid. The time that the transients are present in the system is short, but during a transient period, the components in the systems are subjected to high current and high-voltage peaks that can cause considerable damage [2]. Even if failures do not occur, poor power quality and harmonics increase losses and decrease the lifetime of power system components and end use devices [3]. Consequently, comprehensive monitoring and analysis of power quality disturbances injected by BEV's is necessary, in order to evaluate effective preventive and mitigating measures.

The major challenge in power quality classification is not necessarily the classification process of a disturbance itself, but the determination of the underlying cause. This typically requires large historical datasets, reviewed and labelled by domain experts. Due to the short duration of many power quality disturbances, high meter sampling rates are required. In order to handle the large occurring data sets, applied signal processing techniques must function in a fast and efficient manner. A common approach is to aggregate measurements by calculating the root mean square (r.m.s.) over one or more periods. This significantly reduces the memory that is needed for saving the event and allows the monitoring system to process more data before it runs out of memory [4]. A significant drawback of r.m.s. data is the loss of information when classifying short-lived events such as switching transients.

The recent rise of convolutional neural networks (CNN), particularly in the field of visual pattern recognition, has enabled new approaches and possibilities when processing large datasets. These visual classifiers can be utilized for detecting power quality disturbances. The proposed method is an r.m.s. based classifier combined with an expert system, monitoring the spectrograms of current and voltage harmonics with an object detection algorithm (ODA). The ODA has the ability to recognize and associate unusual spectral patterns to a specific, predefined cause, utilizing the visual features of the spectrogram. The method enables the detection of short-term power quality disturbances, such as transients, which leave distinctive patterns in spectrograms, composed by their spectral components. The ODA is designed to search for these distinctive patterns and to identify them within the affected spectrogram. This allows a simultaneous classification of disturbance type and cause, without the need of an initial segmentation and feature extraction process. However, this approach requires large historical datasets of harmonic measurements in order to acquire sufficient training data. Furthermore, affiliating power quality problems with their corresponding cause requires a comprehensive analysis of observed power quality issues at a given measurement site.

Reoccurring disturbances such as transients injected by a BEV during the charging process can be identified within the corresponding spectrogram. More complex spectrograms with multiple transients and elevated harmonic emission can be detected and distinguished as well. Assuming sufficient training data size is available, any noticeable pattern observed in the frequency domain can be generalized by the ODA. By formulating a visual classification problem, large data sizes can be processed time efficient without the need of any preprocessing and allows the algorithm to improve with experience and data.

## POWER QUALITY CLASSIFICATION

Generally, power quality disturbances are divided into events and steady state variations [5]. Events are larger signal deviations that only occur occasionally, for example voltage interruptions or switching transients. Power quality variations on the other hand refer to the deviation of voltage and current from the nominal, invariably present in the signal and can be measured at any time. Examples for variations are waveform distortions such as harmonics, notching and flicker.

Accurate and precise classification is essential in order to reasonably assess power quality disturbances levels and conclude suitable preventive measures. A key aspect of PQ monitoring systems is not only to determine the type of disturbance, but also to estimate a corresponding cause and reason why the event occurred. Conventional PQ classifiers consist of several signal-processing components with the objective to detecting and identifying disturbances in the signal. These components will be briefly presented in the following section. A more detailed description of the automated power quality classifiers can be found in [6].

### Segmentation

Segmentation is used to pre-process the measured signal in order to detect measurements with significant deviations from their expected value. If any sudden changes within the monitored measurements are observed, segmentation is triggered and identifies the affected data points. Commonly used segmentation methods are Kalman-filters, high pass filters and wavelet transformation. Detected segments are split into transition segments and event segments and passed on to the feature extraction.

### Feature Extraction

Feature extraction converts raw measurement data into a more effective data representation for the subsequent classification process. The performance of the classifier is heavily influenced by the selection and weighting of features. One of the most prominent method for analysing the spectral components of a signal it the fast fourier transformation (FFT). FFT is utilized to transform a given signal from the time domain into the frequency domain. With this tool is possible to have an estimation of the fundamental amplitude and its harmonics with a reasonable approximation [7].

### Classification

The methods for PQ classification can broadly divided into deterministic classifiers and statistical classifiers. Deterministic classifiers, such as rule based expert systems and fuzzy systems, can be implemented with limited amounts of data. Statistical based classifiers require extensive amounts of data for training. Lack of PQ data availability is often a significant problem for the deployment of the recently popular deep learning approaches. A major advantage of the statistical methods such as artificial neural networks (ANN) is the improvement over time with experience. This enables the algorithms to approximate functions and recognize given disturbances by experience, not by predefined rules.

However, merely detecting the power quality type is generally not sufficient. The ideal classifier should able to link any detected disturbance with a cause in order to decide on preventive measures. In order to determine the causes of power quality disturbances comprehensive understanding of the power network and its components is required, often referred to as expert knowledge. Embedding expert knowledge into non-rule based classifiers is a challenging task due to the lack of generalization and the strong dependence on measurement location and external variation factors.

According to [8] the key issues for PQ classification are the detection and classification of multiple disturbances simultaneously, denoising the measurement signal and selecting the optimal features. Furthermore, most publications validate classification methods with synthetic generated data increasing the comparability of accuracy between systems.

## OBJECT DETECTION MODEL

The major design criteria for the proposed expert system are the efficient processing of large datasets, simultaneously detecting type and cause of a disturbance, with the ability of identifying multiple disturbances separately. Severe changes in harmonic amplitudes caused by power quality disturbances are reflected within spectrograms, leaving distinctive visual patterns, which can be recognized by image classifiers. Deep learning allows algorithms to learn from experience and understand problems in terms of a hierarchy of concepts, with each concept defined in terms of its relation to simpler concepts [8]. The ODA approach avoids the need for human operators to define specific knowledge-based rules. Visual classification is an active research field in deep learning, a machine learning subfield. The CNN is a widely used deep learning approach for detecting objects within images. Further details on CNN can be found in [5] and [6]. Figure 1 shows the spectral pattern of a transient in the frequency domain with the corresponding trend in its waveform. The spectrogram displays a current transient

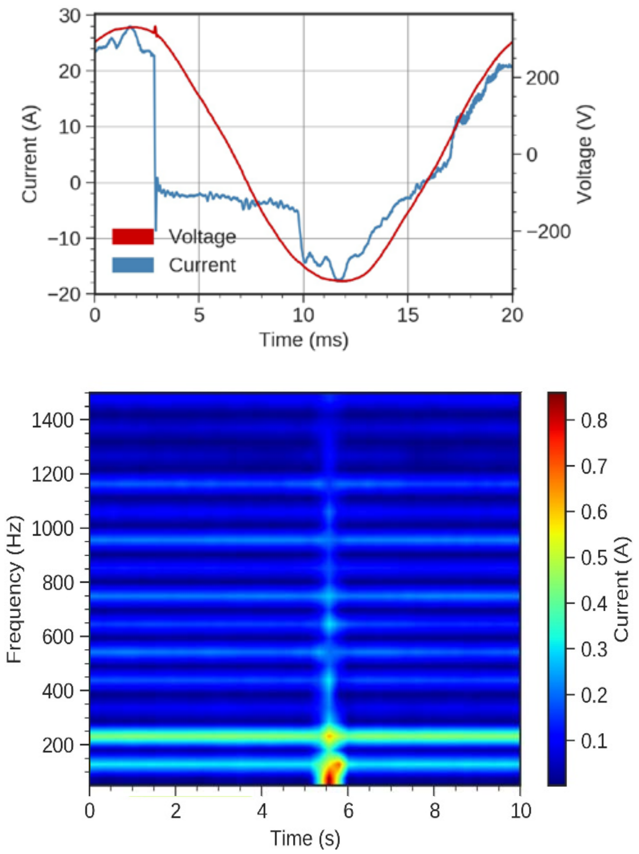


*Figure 1: Transient in waveform data (top). Transient in the spectrogram of aggregated harmonic r.m.s. values (bottom)*

disturbance over one period measured at a BEV charging station. The figure shows the elevated harmonics of the transient, causing a vertical line throughout the spectrogram. Since classifiers are generally provided with r.m.s. values of current and voltage, a direct classification of the transient data is difficult. However, the spectrogram composed of ten period r.m.s. current harmonic obtained by FFT, shows a clearly noticeable pattern at the 5.5s mark. This can be explained by the harmonic components of the transient, which significantly differ from steady state harmonic amplitudes. It is important to point out that the identification of the current transient itself can be achieved by less complex classification approaches, such as KNN (k-nearest neighbours) or Support vector machines (SVM). However, by utilizing an ODA approach multiple predefined classes within a single spectrogram can be identified. This allows a direct association of a detected disturbance to a corresponding cause. The ODA was implanted with Tensorflow, introduced in 2015. Tensorflow is a widespread open source machine learning framework, gaining increasing popularity in recent years. The implementation steps for the ODA will be discussed in the following sections.

### Model preparation

Although the segmentation and feature extraction procedure is not required during the deployment of the ODA, an initial analysis of the data is necessary in order to generate the training data. For the data preparation, historic PQ measurements are analysed and observed disturbances collected. The number of classes depends on the observed PQ issue. If the training data set size for each class is sufficient, the corresponding spectrograms can be generated. Since the visual representation of the harmonic spectrogram is most decisive feature, the image plotting settings are important hyperparameters for the ODA. The selected frequency and time range also greatly influence the accuracy of the algorithm. After the images are created, the areas within the spectrograms must be linked to one or multiple classes. This step is required to mark the areas in the images for later detection. Once the images are prepared and the hyperparameters of the model are set, the training process can be initialized.

### Model training and testing

During the training process, the CNN adjusts its weights in order to link the patterns in the input data to the corresponding target class. Once the model is trained, the performance is reviewed on a test data. This allows an assessment of the model of how well the classifier performs on unseen data (test data). This step is often referred to as generalization. If the accuracy of the ODA is within acceptable limits, the model can be deployed for the actual classification task. The accuracy on test data is heavily influenced by the quality of the provided training data. For adequate classification accuracy at least 250 images per class are necessary.

### Model deployment

Once the model achieves acceptable classification accuracy, it can be deployed to monitor measurements. The ODA is provided with a continuous stream of voltage and current spectrograms, for each phase respectively. The streamed spectrograms must be generated with identical the hyperparameters as the training data. To reduce the classification error, a statistical certainty limit of the ODA should be set at 75%.

## RESULTS

The ODA model was trained with datasets measured at a BEV over a three-month period, including current and voltage harmonics up to 1.5 kHz. Transients injected by the connected BEV's were found to be the most frequent disturbance. Thus, the focus of the model relies on the detection of transients since adequate training data sizes were available. One of the most common observed disturbance patterns were transients triggered at the beginning of a charging process of a BEV. Figure 2 shows a sequence of spectrograms and the corresponding current

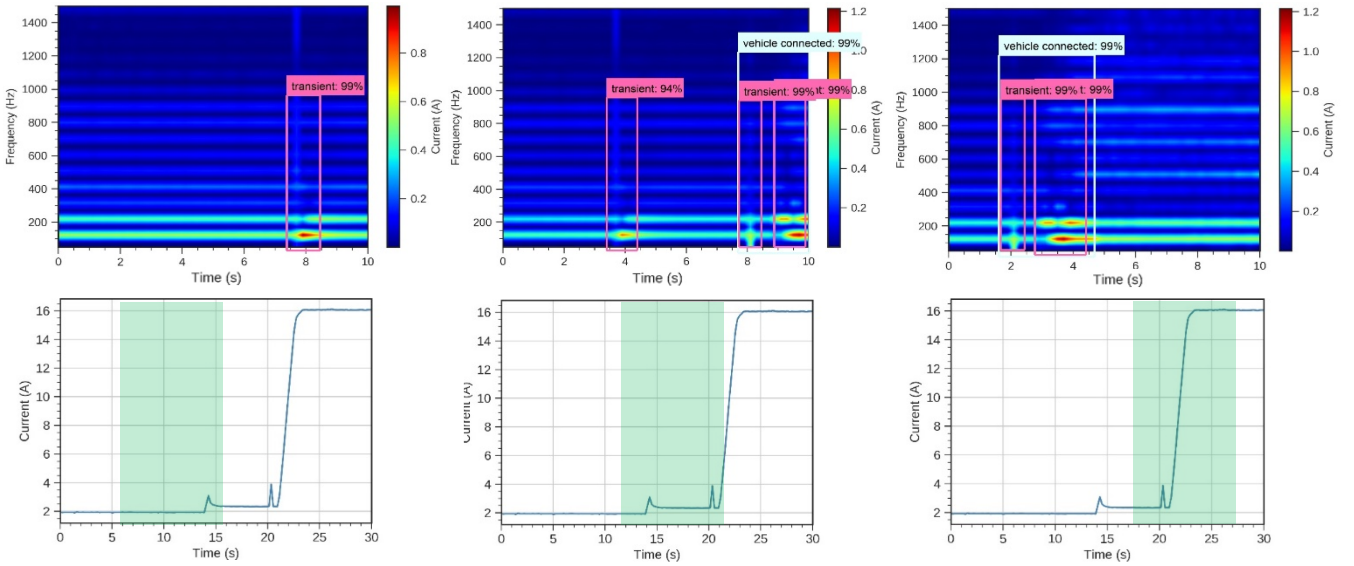


*Figure 2: Spectrograms recorded during charging of a BEV (top) processed by the ODA. Current (r.m.s.) during the charging process with the green areas referring to the section of the above spectrogram (bottom).*

measurements recorded during a charging process of a BEV. The images are sequentially processed by the ODA. The second row of fig. 2 displays the trend of the r.m.s. current during the charging process. The green areas within the graphs represent the section of the spectrogram above, each over a 10 second timeframe. Spectrograms without a disturbance typically contain dominant uneven harmonics but a homogeneous horizontal colour distribution. The colour scale of the images changes dynamically, normed on the maximum amplitude of the given harmonic measurements. In spectrogram 1 (top left) a maximum current value occurs at the third harmonic due to a transient. The transient contains a high number of elevated harmonic amplitudes, leaving a distinctive pattern in the spectrogram in form of a vertical line. The ODA is able to recognize the pattern and labels the affected area. The following spectrogram (top middle) contains a second transient, followed with the increased current drawn by the BEV. The connection of the vehicle results in higher uneven harmonics with an initial peak in the third and fifth harmonic. This specific pattern allows the ODA to associate the detected transients with the charging process, determining the cause of the disturbance. The spectrograms are generated continuously with the latest recorded measurements and scanned by the ODA, for each phase respectively.

The images are created with ten period r.m.s. values of harmonic amplitudes. The model was provided with an updated spectrogram every second, each spectrogram with a 10s timeframe with frequency up to 1.5 kHz. The timeframe was selected based on the duration of the observed disturbance patterns. As previously mentioned, the most common observed disturbance within the measurements were transients. The transients occurred upon connection of the BEV's to the charging station, during the charging process and at disconnection of the vehicles. Rarely, transients occurred when no BEV were connected. However, since a minimum of approximately 250 images per label is required for the ODA to achieve acceptable classification accuracy, power quality issues observed seldom are difficult to detect with this method. The connection and disconnection power electronic devices is generally reflected in some way the harmonic spectrogram. The ODA can also be trained to recognize such patterns, unrelated to power quality issues. The class of BEV's charging processes can be further divided into single phase and three phase BEV disconnection, if the spectrograms of other the phases are taken into account. Figure 3 shows the pattern of a spectrogram caused when a second BEV is connected to the same phase. Both of the transients occurring during the process were recognized and the affected area marked by the ODA. Another frequent observed cause of transients was the disconnection of a BEV. The corresponding spectrogram is illustrated in figure 4.

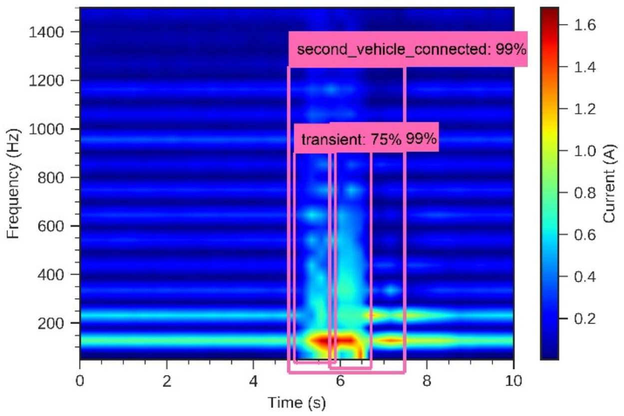


*Figure 3: Spectrogram of a second vehicle connecting to the charging infrastructure.*

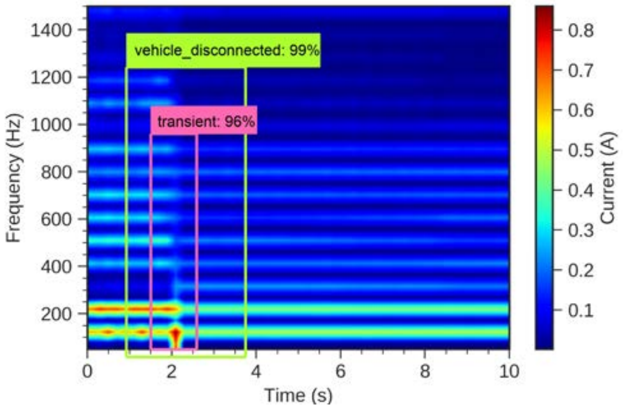


*Figure 4: Spectrogram of a transient injected by the disconnection of a BEV*

The spectrogram shows a drop in harmonic amplitudes as soon as the BV disconnects. The ODA was trained to detect four classes with varying sample sizes, listed in table 1. For the test data sets, 20% of each class was selected respectively. The remaining 80% of the samples were used for training the model. The ODA training process was aborted after 20.000 iteration steps, since the accuracy of the model stagnated.

Table 1. Model classes and accuracy

| Class | Description | Samples | Accuracy in % |
|---|---|---|---|
| A | BEV connected | 594 | 95.5 |
| B | Second BEV connected | 230 | 93.1 |
| C | Transient | 2972 | 96.3 |
| D | BEV disconnected | 266 | 92.3 |

The results show an acceptable model accuracy for the classes A and C, where large training size was available. For the classes B and D lower accuracy was achieved due to less available training images.

## SUMMARY

The presented ODA method is able to identify power quality disturbances based on the visual patterns within spectrograms. The main objectives of the approach are the abilities to process large datasets, detect multiple power quality disturbances simultaneously and link the identified disturbances to a corresponding cause. By utilizing an image classifier, large datasets can be processed fast and with adequate accuracy. With this semi-supervised approach, the algorithm is able to improve with experience over time. Retraining the model allows adding more classes after deployment. However, the ODA requires a training process involving a comprehensive review of historical datasets in order to define the initial labels of the model. Since large datasets for training the model are necessary, power quality disturbances observed seldom are difficult to detect due to the lack of available training data.

The method was trained with data measured at an electric vehicle charging station, recorded over a three month period. The results show that the ODA was able to identify multiple transients within a spectrogram and mark the affected areas. The model was also able to determine the corresponding causes of the detected transients. Acceptable classification accuracy was achieved for all trained labels. In order to increase the performance, larger training data sizes should be generated and the hyperparameters of the model optimized.

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