ELECTRIC VEHICLE CHARGING STATION FAULT DETECTION: A MACHINE LEARNING APPROACH

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ABSTRACT

The number of electric vehicles on the roads is increasing, and the number of fast DC charging stations is following this trend. However, the advantages of DC electric vehicle charging stations (ECVS) in terms of efficiency and power output compared to their AC counterparts are accompanied with protection problems. To address these problems, a recurrent neural network-based fault detection method that can detect both solid and arc faults in EVCS is presented.

INTRODUCTION

We are witnessing global warming caused by greenhouse gases, a significant proportion of which are emitted by today's fleet of vehicles with internal combustion engines. Road transport in the European Union is responsible for 72% of the total CO2 emissions from the transport sector, of which 60.7% are caused by cars [1]. Replacing the car fleet with electric-powered, zero-emission cars is seen as a step towards a 90% reduction in transport-related greenhouse gas emissions by 2050 as part of the climate-neutral targets of the European Green Deal [2]. Such transition requires extensive development of the supporting infrastructure, which in the case of battery-powered electric vehicles (BEVs) are the network of charging stations. Availability of chargers, continuity of supply and charging speed are parameters to be maximized to increase the convenience for BEV users [3]. To reduce charging time while increasing efficiency, fast DC charging stations are widely used. However, the DC systems are characterized by faster transients, and, unlike the AC systems, there is no natural zero crossing of the voltage, which complicates the DC system protection. Therefore, fault detection should be fast enough to detect faults before the current reaches a high magnitude. In addition, the fault response could resemble a sudden load change, which further complicates fault detection.

RELATED WORK AND CONTRIBUTION

The protection of charging stations has been addressed in several international standards, such as IEC 61851-23:2014, which presents guidelines for overvoltage and short-circuit faults. Researchers have also presented approaches to charging station protection based on overcurrent, over/undervoltage and over/underfrequency protection schemes [4]. In recent years, the research focus has shifted to digital signal processing and intelligent classification methods because of their ability to distinguish between events with high accuracy even in a complex microgrid environment [5]. For example, an EVCS fault detection method based on the wavelet transform is used to detect open-circuit faults of the inverter switching devices [6].

In contrast to solid, faults with varying and often nonlinear resistance also occur. This type of faults, called arc faults, is often caused by the loss of a connection, an insulation fault, a cut wire, a defective connector, and other causes [7]. Arc faults can be significant and therefore easily detected, but they can also be very low and not so easily detected, depending on the cause of the fault and whether it is a series or parallel fault [8]. In addition, the current waveform is unusual and strongly depends on the length of the gap and the environmental conditions. Therefore, different approaches have been developed to detect arc faults. The most popular approach is to extract current and voltage fault features using signal processing methods. Recently, a method based on mathematical morphology has been proposed [9], but there are also somewhat less complex methods based on Fourier and wavelet transforms [10]. A machine-learning-based model of nonlinear dependencies between the features and the operating state was also used for arc detection [11]. In [12], a machine learning approach to arc fault detection is discussed with a focus on the feature selection.

Methods for microgrid fault detection based on digital signal processing and intelligent classification have already been proposed by different authors [13]. Among other intelligent classifiers, a recurrent neural-network-based fault detection method for a DC microgrid was proposed in [14]. The method, based on a recurrent neural network (RNN) classifier, proved accurate for fault detection and location, including pole-to-pole and pole-to-ground faults. The observed microgrid included photovoltaic and a battery storage systems, which respond differently to the faults, which was used to determine the fault location. However, the method should be extended in case there are loads/sources with the same fault response. An electric vehicle charging station meets these requirements as it contains loads with similar characteristics. These loads are also active, which makes fault detection even more difficult. However, the topology of a EVCS is similar to that of a microgrid, which makes the extension of the method less complicated. Furthermore, the faults that the method can detect are limited to solid, constant resistance faults. To further improve the method, detection of arc faults is being considered.

The outcome of our work is the improvement of the microgrid fault detection method and its application to a charging station. The improved method uses more features, which affects the design of the classifier and the training process, but the basic framework of the method remains unchanged. The main contribution of the paper is an RNN-based method for fault detection in EVCS, which can also distinguish between the solid and arc faults.

FAULT SIMULATION SETUP

Simulation setup

Electric vehicle charging stations come in different topologies, namely: topologies with back-to-back AC/DC/DC converters, multiport stations with a common AC-link, and transformerless charging stations [15]. Topologies with back-to-back AC/DC/DC converters are characterized by their modularity, simple control, and high reliability. Generally, this type of EVCS is connected to the grid via a Yg/Δ voltage transformer and a voltage source converter (VSC). DC/DC converters are connected to the common bus, whose voltage is controlled by a VSC, and supply power to the vehicle. The described topology corresponds to a microgrid where all sources and loads are connected to a common bus, which facilitates the adaptation of the mentioned RNN-based fault detection method. Therefore, this EVCS topology is modelled according to the model presented in [16]. The simulation setup is shown in Fig. 1. The batteries representing the loads of the electric vehicle are charged from the DC/DC chargers operating in either constant current (CC) or constant voltage (CV) mode. The simulation setup was implemented in Matlab Simulink environment. To reduce the complexity of the model, two chargers with corresponding batteries were implemented, both active at the same time. The faults are located between the charger and any of the two electric vehicle batteries. Cases where the batteries operate in the same, but also in different control modes are considered, as the fault behaviour may depend on the control scheme [17].

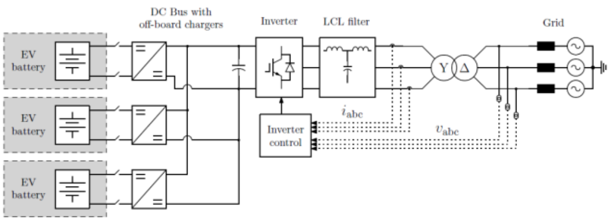

Fig. 1 *Electric vehicle charging station model* [16].

Faults

Two types of faults are considered: pole-to-pole (PP) and arc faults. Pole-to-pole faults are characterised by a fast-rising, high-magnitude current that easily results in equipment destruction. Arc faults, on the other hand, are variable in intensity and duration. Therefore, it is expected that arc faults are more difficult to detect, which poses a challenge to the existing fault detection (FD) methods. Before presenting the proposed FD method, PP and arc faults are described.

Pole-to-pole fault

Pole-to-pole fault behaviour is a well-studied topic in both the AC and DC systems. When two poles are short-circuited, i.e., the fault impedance is very low, a fast-rising, high-magnitude current starts flowing. The devastating consequences of this fault can only be mitigated if the fault is detected and eliminated immediately. In case of a PP fault on the cable connecting the electric vehicle and the charger, the battery contributes significantly to the fault current [18].

The charging station fault contribution in the case of constant current charging is limited since the control manages to follow the current reference. However, if the voltage control is engaged and a fault occurs, the control will try to match the voltage reference, resulting in a high current, as in Fig. 2. In normal operating conditions, the current in the CV mode is lower than in the CC mode. A fault in Fig. 2 occurs at t=3 s. The low fault impedance leads to a high battery discharge current and consequently reduced battery voltage. If the current control mode is active during such event, the charger's output current remains unaffected as the control is inherently not dependent on the output voltage. However, when the output voltage is controlled, the difference between the setpoint and the actual value is high, resulting in a high duty cycle of the converter switches and a high current.

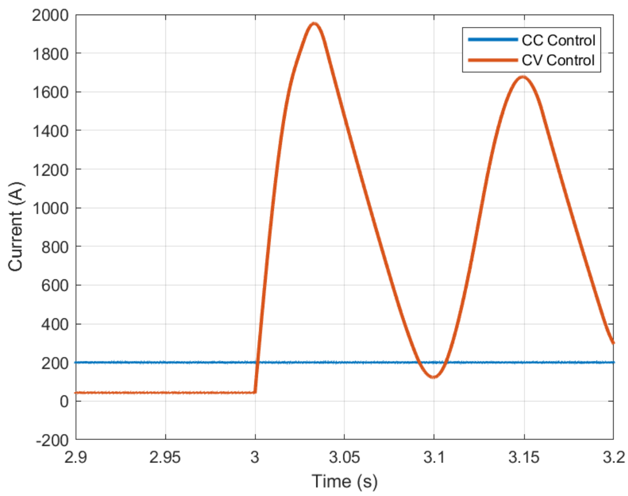

Fig. 2 *Converter fault current for different control modes.*

In case when more than one battery is connected, the fault behaviour becomes more complex. If the charger is in the CC charging mode and a fault occurs, only its output voltage is affected. All other batteries are not affected by this fault. However, if the charger is in the CV mode when a fault occurs, its high current will discharge the DC capacitor and reduce the DC bus voltage. Consequently, all other batteries are also affected and contribute to the fault, regardless of their charger's operating mode.

Arc fault

Arc faults are best described as faults with variable voltage and current, nonlinear resistance, and a portion of randomness. There are several approaches to modelling arc faults: i) numerical, where a 3D simulation model is used to investigate the arc behaviour [19], ii) empirical, where an arc voltage-current characteristic is formulated as a nonlinear equation that depends on the magnitude of the arc current and the gap [20], and iii) heuristic, where fluctuations in gap voltage and current are modelled by choosing the random distance ratio between the gap width and the extinction width at which the arc is extinguished [21]. The accuracy of the latter approach was experimentally demonstrated for a series arc fault in a low-voltage DC microgrid in [21]. The authors pointed out that the complexity of the model implementation is significantly reduced because the time-varying resistance replaces the necessary knowledge about the physical (or temporal) parameters of the arc. The said heuristic model was implemented in MATLAB Simulink environment for monitoring arc faults in photovoltaic systems, as a first step towards developing the FD algorithm [22]. The same procedure is used in this work, as the arc FD method is first tested on the simulated data. Before presenting the challenges of detecting arc faults using neural networks, the heuristic model used is briefly explained.

Arc voltage is described by a sum of two nonlinear terms V_q and e_{gap}:

$$V_{arc} = V_q + e_{gap} \quad (1)$$

$$V_q = V_{dc}(0.5 + 0.5\tanh(\alpha(q-1))) \quad (2)$$

$$e_{gap} = 0.5\left(a + bx_{gap}\right)(\tanh(\lambda q) - \tanh(\lambda(q-1)) \quad (3)$$

where a denotes gap electromotive force (EMF), b EMF slope, α slope of V_q, λ slope of e_{gap}, and q a random function. Arc current is given with:

$$I_{arc} = I_q - j_{gap} \quad (4)$$

$$I_q = I_{load}(0.5 - 0.5\tanh(\alpha(q-1))) \quad (5)$$

$$j_{gap} = \frac{e_{gap}}{R_{gap} + R_{load} + R_g} \approx \frac{e_{gap} I_{load}}{V_{dc}} \quad (6)$$

where j_{gap} can be neglected if the load resistance is high. Furthermore, parameter q, which denotes the ratio between the gap width (x_{gap}) and arc extinction width ($x_{\text{extinction}}$) is randomized to emulate the arc behaviour. It is given by:

$$q_t = q_{t-1} + c * rand(0,1)^d \quad (7)$$

The constants a, b, c, d, α, λ can be chosen according to [21], but are relaxed in this work according to [22] to represent a faster decay of the arc. As can be seen from (7), the value of q at time step t depends on its value at the previous time step and a random number whose interval is determined by constants c and d. This means there are no two identical arc fault signatures and determining whether a fault has occurred becomes difficult.

The problem arises from the nature of the neural network attempting to model the unknown function. If the samples characterizing a particular event are random, the neural network may not find the pattern required for successful classification. In this specific problem, the randomness of the voltage and current measurements provided to the neural-network-based classifier could lead to a failure. Therefore, the neural network should be provided with additional features that contain more information about the fault. The waveform of the series arc observed in this paper can be seen in Fig. 3. The change in the voltage after a fault occurs at t=3 s is obvious. However, the randomness of the response becomes more visible when the temporal resolution is increased.

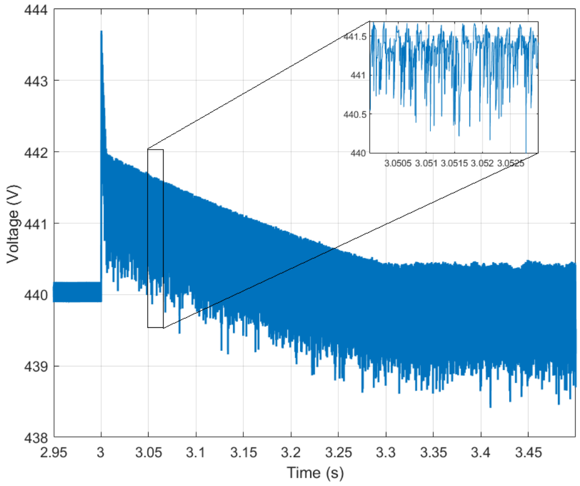

Fig. 3 *Charger output voltage after series arc fault.*

FAULT DETECTION METHOD

An advantage of machine learning algorithms is the ability to construct complex dependencies from data. Deep learning models, a subset of machine learning models, are able to design features implicitly, relieving the user of difficult feature selection. However, user-defined features can be added if this contributes to the model accuracy. The fault detection method proposed in [14] used only the current and the voltage as inputs, but with the inclusion of arc faults this feature set should be expanded.

Recurrent neural networks

Recurrent neural networks can model an interdependence between the successive data samples and use this knowledge to produce the output, unlike classical neural networks that produce the output based only on the current inputs. How is this achieved can be seen by comparing the formulations of the hidden layer of a standard feed-forward neural network (FFNN) with that of a recurrent neural network. Equation (8) shows how the hidden layer of an FFNN is obtained. The input is represented by $\mathbf{x}^t$, $\mathbf{h}^t$ is the output of the hidden layer, and g arbitrary nonlinear function, usually tanh or rectified linear unit (ReLU). Matrices **U** and **b** are obtained after the classifiers' training.

$$\boldsymbol{h}^t = g(\boldsymbol{U}\boldsymbol{x}^t + \boldsymbol{b}) \quad (8)$$

A recurrent NN has an additional term in the hidden layer, as shown in Equation (9).

$$\boldsymbol{h}^t = g(\boldsymbol{U}\boldsymbol{x}^t + \boldsymbol{W}\boldsymbol{h}^{t-1} + \boldsymbol{b}) \quad (9)$$

Here, the past state of the hidden layer is considered using the matrix **W,** which is also obtained during the training process. Now the output at each time step depends not only on the current input but also on the past states of the hidden layer. In addition, the RNN is free to decide how far into the past it wants to look, so that the user no longer has to determine the length of the time window.

Method

Since the EVCS contains two identical loads, determining which one is faulty requires independent measurements from each load. Current and voltage measurements at the output of the charger can be used for fault detection. These measurements are already available because the control system uses the same measurements for charging control. As already described, the faults affect the entire charging station or only one load, depending on the control mode of the faulty charger. Therefore, it is important that the measured values from all instances are available to the classifier. However, from the fault analysis, it appears that the charger's output current remains unchanged in certain cases, but the voltage is affected in all considered cases. To minimize the number of classifier inputs it is sufficient to use only the voltage measurements at the charger output.
A proper selection of features is required for the detection of arc faults. Since the arc fault is modelled as a random sequence, it is questionable whether the neural network used for classification can implicitly design the features. Therefore, additional features are proposed in [12]. The authors used the wavelet transform of the signal together with the moving average of the current as features for the classifier. This approach was used to address the noisy response problem of the arc fault. First, a suitable mother wavelet was selected, and then the decomposition level coefficients containing the information about the frequency spectrum of a signal were selected. The approximation coefficients represent the denoised original signal and the detail coefficients represent the high frequency components. The moving average helped tracking the arc current, which shows a negative trend after the occurrence of an arc fault.
In this paper, the same procedure is used. The voltage signal is divided into segments with a length of 10 samples and the wavelet transform is applied. The obtained coefficients are then passed on to the RNN together with the mean value of the voltage segment. The same features are used for PP fault detection, as their occurrence is also visible as a change in the coefficient magnitude. An overview of the method is shown in Fig. 4. Approximation coefficients provide a stable, denoised signal that is easier to model. The RNN's ability to model past the dependencies is less difficult when the signal does not change amplitude at high frequency. However, high frequency components are useful when sudden changes occur in the signal. This can be seen in Fig. 5, which shows the level 2 approximation and detail coefficients during PP fault. The approximation coefficient follows the falling voltage, but the increase in the magnitude of the detail coefficient shows that a sudden change in the signal has occurred.
The neural network is trained on the dataset obtained from the simulation. The dataset was divided into the training and the test part in a ratio of 80/20%. Three classes can be distinguished: normal operating condition, PP fault and arc fault.

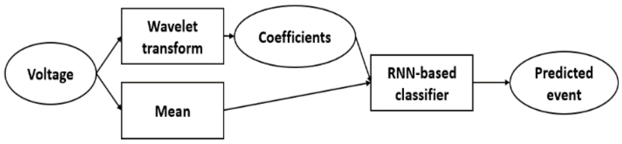

Fig. 4 *Method overview.*

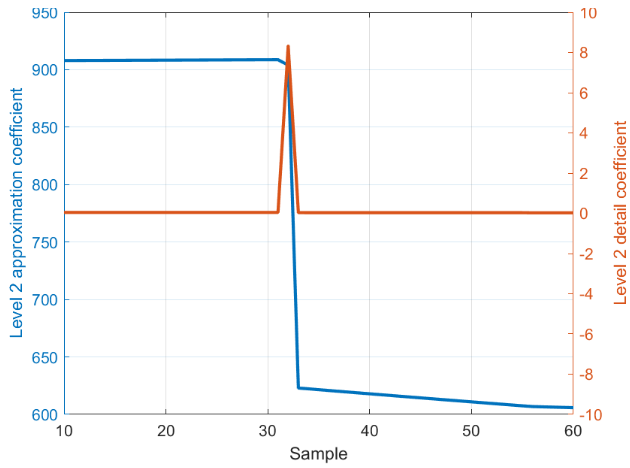

Fig. 5 *Level 2 coefficients during PP fault.*

The number of sequences per class can be found in Table 1. PP fault resistance is set between 0.1 and 1 Ω. The characteristics of the arc fault are varied by changing the gap parameters.

Table 1 *Number of sequences per event.*

Class	No. sequences
Normal operation	60
PP fault	40
Arc fault	20

RESULTS

Classification results are measured with two metrics: accuracy and F1-score. Accuracy is the ratio of correctly classified samples and the total number of samples, while F1-score is meant for unbalanced classes and is more conservative. The classes here are slightly unbalanced because the majority of the sequences start with the normal operating state.
The classifier's score is shown in Table 2. The features provided to the RNN-based classifier proved to be very discriminative as the result is high for both metrics. The decomposition of the variable noisy signal into the low and high frequency components proved to be a good basis for classification. As it turns out, the suggested features can be used not only for arc fault detection but also for the PP faults.

Table 2 *RNN-based classifier score.*

Accuracy	F1-score
98.05 %	96.90 %

CONCLUSION

This paper presents an RNN-based fault detection of fast-charging DC EVCS. The method uses features obtained by wavelet transform and signal averaging to detect both solid and arc faults. The control dependent fault response is considered in the development of the method. The method has shown to be capable of detecting both solid and arc faults, with high accuracy of 98.05% and F1-score of 96.90%.

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