


An Unsupervised Method for Fault Detection in Transmission Lines Using Denial Constraints


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Abstract This paper presents a denial constraint (DC) discovery approach for detecting faults in utility companies' electric transmission lines. Transmission lines rely on a protection system that continually streams and stores waveform data with three-phase current and voltage information. Considering that those data are stored in a relational database, we use the high expressive power of DCs to capture the expected behavior of a transmission line, as they are ideal for representing rules in databases. Since defining DCs in our scenario requires expensive domain expertise and, worse, is an error-prone task, we use a state-of-the-art algorithm to discover reliable DCs. Unfortunately, the amount of data in the studied scenario makes state-of-the-art DC discovery algorithms impractical due to the long execution times. In response, we propose a novel DC discovery approach using streaming windows to address this issue. Our hypothesis is that DCs discovered in pre-fault windows significantly differ from those in post-fault windows and can be used as a fault detection approach. We use this intuition to detect faults without human intervention (*i.e.*, an unsupervised method). The extensive experimental evaluation on a dataset with diversified fault events shows that our approach can detect faults with 100% accuracy.

Keywords: Fault Diagnosis, Intelligent Systems, Power Transmission, Denial Constraint, Data Dependency Violation

1 Introduction

Electrical power systems rely on transmission lines to deliver electrical power to customers. These lines usually travel long distances and are exposed to several elusive glitches and transient events that can disturb electrical power transmission. These events include, for example, storms and fire under the lines. Unfortunately, such disturbances cause faults that end up interrupting the electrical supply. Generally speaking, a fault can be defined as any abnormal condition in the components of a power system, such as an increase in current flow to one or more phases [Prasad *et al.*, 2018; Furse *et al.*, 2021; Ensina *et al.*, 2024].

Electrical substations are the interface between the transmission lines and the distribution grid. The substations contain a protection system to guarantee the stability of the network and minimize any possible damage caused by faults [Singh and Vishwakarma, 2015]. The goal of the protection system is to accurately and quickly detect the fault and enable the repair and restoration of the faulty line as soon as possible [Aleem *et al.*, 2015]. Such systems contain a protection relay or a digital fault recorder that samples line signals to produce a data stream with sample points. Each point represents information on the distribution of load into three phases (A, B, and C) for the current and voltage signals in the circuit. The sample points are stored in a relational database and can be queried to represent waveforms of changing cur-

rents. Figure 1 shows an example of electric current signal waveforms with the incidence of a fault near 0.05 seconds. As can be observed, a failure affects the normal operating condition of the power system, which contains balanced and symmetrical loads, *e.g.*, similar amplitudes of the current signal among the phases during the pre-fault cycles.

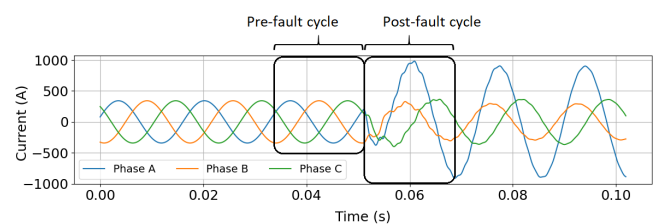


Figure 1. Waveforms of a faulty transmission line, involving the phase A and the ground (AG).

There are three essential tasks in fault diagnosis: detection, classification, and location. Of course, an effective classification and location rely on accurate fault detection. So it is possible to segment the oscillography into pre-fault and post-fault cycles, as represented in Figure 1. Such segmentation is required by several machine learning-based approaches found in the specialized literature. Thus, detecting the fault inception is crucial to allow the execution of the other two tasks since the segmentation, as mentioned above, is intrinsically dependent on this instant for a correct demarcation, which can directly affect the methods' performances for fault

classification and location.

As highlighted by Ferreira *et al.* [2016], some proposals for fault diagnosis assume that the detection phase is accomplished by the protection system itself (*e.g.*, protection relays). Although such an approach works well for online applications, it is not valid for offline applications. It requires an approach to identify the failure inception since a fault record presents pre-fault and post-fault signals, as demonstrated in Figure 1. Developing an integrated tool including the three essential tasks in fault diagnosis is still a challenge. However, treating each task individually enables some advantages, such as high cohesion and independence among them, which can result in better generalization and adaptability capabilities. Due to these advantages, we investigate the fault detection task individually.

We present a novel unsupervised approach to detect faults based on denial constraints (DCs), acting as an offline application. Since DCs are ideal for representing the complex data business rules in databases [Chu *et al.*, 2013], we use the formalism to represent the expected behavior of a transmission line so that it is possible to detect faults when there is a deviation from this behavior. For example, consider the following constraint, often found in transmission lines: “The electric current and voltage among the phases in a transmission line must be similar.” A DC capturing such constraint, denoted as φ_1 , can be expressed as follows: “There are no two records in the database where the electric current values differ between the phases A and B, and one of the records has a bigger phase A voltage.” We defer the formal definition of DCs to Section 4.

Our method differs from traditional approaches based on machine learning algorithms by eliminating the need for feature extraction, as we directly utilize the raw data. Additionally, our method is unique in that it is the first to detect faults based on an important data management technique, *i.e.*, denial constraint. Thus, our approach enables the direct identification of fault inception from the database for the specific event of interest without loading the entire time series into dedicated systems.

The computational costs of DC discovery are directly influenced by the size of the dataset, specifically, the number of rows and columns it contains [Chu *et al.*, 2013]. As a result, in our context, the sheer amount of data generated by the protection system makes traditional DC discovery impractical due to the long runtimes. In response, we contribute with an approach for discovering DCs in streaming windows. We hypothesize that DCs discovered in pre-fault windows greatly differ from those in post-fault windows and can be used to detect faults. A fault in a transmission line is detected by comparing the ratio of DC violations in each window to an expected threshold. It is noteworthy that this paper is an extension version of the work published originally in Tamalu *et al.* [2023]. In this paper, we increased the discussion about the related work (Section 2), added more details about our method (Section 4), and included and analyzed more results about our approach (Section 5.3), especially concerning the variation of fault parameters.

The main contributions of this work are summarized as follows:

- A DC discovery approach for streaming data;
- An application of DCs and DC discovery for fault detection in electric transmission lines;
- An unsupervised method for fault detection as an offline application;
- An empirical evaluation showing that our approach detects faults in transmission lines for all fault events assessed (100% of accuracy).

This paper is organized as follows. Section 2 describes the related work. Section 3 describes the database used in this study. Section 4 reports the proposed method for fault detection based on DC. Section 5 presents and discusses our results. Finally, Section 6 concludes this work.

2 Related Work

The literature contains several methods for fault detection. Typically, traveling wave (TW)-based methods are used in industry to address the problem of fault analysis, including the detection step [Shakiba *et al.*, 2023]. However, most recent methods are primarily based on machine learning, as demonstrated in recent reviews carried out by Kanwal and Jiriwibhakorn [2023] and Shakiba *et al.* [2023].

The authors in Ferreira *et al.* [2020] used six neural networks for fault detection using voltage and current representation for a single transmission line terminal (bus). Belagoune *et al.* [2021] proposed an LSTM-based method for fault diagnosis, including the detection task. Coban and Tezcan [2021] used Discrete Wavelet Transform (DWT) on the measured single terminal current signals before fault detection, in which the three-level wavelet energy values obtained for each of the three-phase currents were used as input features for the detector based on the SVM algorithm.

Chen *et al.* [2018] presented a method for fault detection in power transmission lines based on a sparse convolutional autoencoder, automatically learning features from a dataset of voltage and current signals. In turn, Asadi Majd *et al.* [2017] used the kNN algorithm with a sliding window with a length of a half cycle moved on the squared normalized current waveform of each phase to detect the fault inception.

Another technique widely used for fault diagnosis is the Wavelet Transform (WT) and its variants, such as Wavelet Packet Transform (WPT) and Discrete Wavelet Transform (DWT). Adly *et al.* [2020] used the WPT coefficients to create a logical decision about the occurrence or not of the fault. Similarly, Masood *et al.* [2017] decomposed the current signal by the DWT technique, comparing the resulting coefficients with a pre-defined threshold value to determine the fault inception.

On the other hand, Gilbert and Morrison [1997] discussed about statistical approaches for fault detection, such as calculating the median using a sliding window over voltage or current oscillographies. Other approaches can be found in specialized surveys and reviews [Yadav and Dash, 2014; Mishra and Ray, 2018; Raza *et al.*, 2020; Kanwal and Jiriwibhakorn, 2023; Shakiba *et al.*, 2023].

The machine learning methods discussed earlier rely on supervised learning, which presents a drawback since they depend on labeled data to train the algorithms. In contrast,

our approach overcomes this limitation by operating without supervision, meaning it does not require labeled data. Consequently, it can detect faults autonomously. This paper introduces a novel approach based on denial constraints (DCs), typically employed to represent intricate data relationships in databases. The proposed approach employs DCs for fault detection without employing a traditional machine learning algorithm.

3 Fault Database

The Fault Analysis Database (FADb) is a public dataset with several fault simulations [Ensina *et al.*, 2022]. These events were based on the IEEE 9-bus power system [Høidalen *et al.*, 2019], which approximates a real power system. For this purpose, we used the ATPDraw and ATP (Alternative Transient Program) to model the system and run all simulations, providing representative time series of failures. These tools are widely used in the research community for electrical circuit studies, particularly in power systems considering the investigation about fault analysis and their effects.

We use a transmission line with the following properties: 500 kV, 414 km, and 60 Hz. In special, this specification represents the longest transmission line in a network of a public electric utility company in Brazil (Energy Company of Paraná – COPEL). The available data represent voltage and current signals for each of the three phases at both terminals for a sampling rate of 10 kHz. The oscillography of each simulation starts without failure, which occurs in distinct instants inserted into the same cycle. Also, the fault parameters used in the simulations are as follows:

- **Type:** AG, BG, CG, AB, AC, BC, ABG, ACG, BCG, \overline{ABC} ;
- **Location:** 1 to 100% of line extension, with intervals of 1%;
- **Resistance:** 0.01 to 200 Ω , with intervals of 10 Ω ;
- **Inception time, in seconds (s):** 0.091 s, 0.093 s, 0.095 s, 0.097 s, 0.099 s, 0.101 s, 0.103 s, and 0.105 s.

In particular, the letters A, B, and C represent each of the three phases of a transmission line, while the letter G corresponds to the ground action in a fault. The combination of initials indicates faults involving multiple phases or the ground. For example, AG indicates a fault involving the phase A and the ground, as well as AB represents a fault between the phases A and B without the action of the ground. For more technical details, see the following references [Yadav and Dash, 2014; Aleem *et al.*, 2015; Grainger *et al.*, 2016].

The FADb repository contains 168,000 fault events combining each of the previously mentioned parameters. The available archives ensure reproducibility of the results and the generation of new fault events considering other values of the parameters. All simulation data are available in our repository¹.

¹<https://1drv.ms/u/s!ArMEeMx4MYDNimHVxiDx3b4CI3iL?e=8GfXg7>

4 Denial Constraint Approach

The goal of a DC is to identify conflicting relationships of combinations of column values with sets of predicates. A DC specifies a conjunction of predicates that cannot be true for any pair of tuples. We use the formalism of a predicate, as $p: t.X \theta t'.Y$, where X, Y are columns of a table r with schema R ; t, t' is a pair of distinct tuples of r ; and $\theta \in \{=, \neq, <, \leq, >, \geq\}$ is a comparison operator, see Chu *et al.* [2013] for additional DC definitions. We can specify a DC φ as follows:

$$\varphi: \forall t, t' \in r, \neg(p_1 \wedge \dots \wedge p_m)$$

Using the above notation, we express our example rule, as $\varphi_1: \forall t, t' \in r, \neg(t.IA \leq t'.IA \wedge t.IB \leq t'.IB \wedge t.VA \geq t'.VA)$, where IA is the current at phase A, IB is the current at phase B and VA is the voltage at phase A.

$$\varphi_1: \forall t_\alpha, t_\beta \in r, \neg(t_\alpha.IA \leq t_\beta.IA \wedge t_\alpha.IB \leq t_\beta.IB \wedge t_\alpha.VA \geq t_\beta.VA)$$

Fault detection with the DC approach is divided into three parts: data streaming and processing windows (Section 4.1), discovery of DCs (Section 4.2) and fault detection using these DCs (Section 4.3).

4.1 Data Streaming and Processing Windows

We use data streaming notation to represent the signals of current and voltage converted by an oscilloscope [Braverman and Ostrovsky, 2010]. A data stream is a finite sequence of n observations $T = \{x_0, x_1, \dots, x_{n-1}\}$ read in an increasing order of the index i , as $0 \leq i < n$. A single data observation x_i contains information of electric current and voltage from the three phases of the transmission line at the i^{th} index.

The transmission line signal is humongous, generating gigabytes of data per second. For example, the dataset used in our experiments stores about 96 GB of data. We propose splitting the stream into small finite sets, called W_j windows, to facilitate DC discovery. We use two different window types: a fixed-size tumbling window and a sliding window. A tumbling window is a non-overlapping batch of the data stream, such as $W_y \cap W_k = \emptyset$ which enables DC discovery with small runtimes. A sliding window traverses a number of tumbling windows to detect faults using the discovered DCs. Sliding windows overlap data observations $W_y \cap W_k = \{x: x \in W_y \wedge x \in W_k\}$.

4.2 Denial Constraint Discovery

The FADb dataset (Section 3) contains twelve attributes with voltage and current values for the three phases for both terminals of the transmission line regarding a given instant of time of the time series. In this scenario, we used only the data available for a single terminal (six attributes), aiming to avoid the requirement of data synchronization between both sides of the transmission line in a real operation system.

DC discovery is one of the most computationally expensive data profiling tasks, so care must be taken with such processes [Chu *et al.*, 2013; Abedjan *et al.*, 2015]. Instead of discovering the DCs using the entire dataset, we discover DCs in tumbling windows (batches with 1,000 samples). We use the state-of-the-art DC discovery algorithm, DCFinder,

as provided by Pena *et al.* [2019]. Our goal is to discover the DCs and capture the expected behavior of a transmission line without and with faults in pre-fault and post-fault windows, respectively. We selected a subset of fault events to use in discovering DCs. So, we used a subset of 1,000 simulations from FADb dataset (Section 3) for this purpose with the following diversified and representative fault parameters:

- **Fault type:** AG, BG, CG, AB, AC, BC, ABG, ACG, BCG, ABC;
- **Fault location:** 1%, 25%, 50%, 75%, and 100% of line extension;
- **Fault resistance:** 0.01 Ω , 50 Ω , 100 Ω , 150 Ω , and 200 Ω ;
- **Fault inception time:** 0.095 s, 0.097 s, 0.103 s, and 0.105 s.

4.3 Fault Detection

We use the term $(t, t') \not\models$ to denote that the pair of tuples t, t' violate the DC. Our fault detection mechanism is based on the degree of approximation shown in Equation 1, which measures the ratio of the number of tuple pairs violating a DC divided by all the tuple pairs in a batch [Chu *et al.*, 2013].

$$g(r) = \frac{|\{(t, t') \in r \mid (t, t') \not\models\}|}{|r| \cdot (|r| - 1)} \quad (1)$$

We calculate the degree of approximation of the batch samples with the DCs previously discovered for each sliding window in previous steps. Then, we compare the degree of approximation with a threshold value to determine the occurrence or not of a fault. A fault is detected if the degree of approximation of a window is higher than the threshold value. In this scenario, there are two parameters to be considered: the window length and the threshold of the degree of approximation. The values evaluated in this work are presented as follows:

- **Window length (w):** 50, 100, 200, 400, and 800;
- **Degree of approximation threshold (DAT):** 0, 1×10^{-5} , 1×10^{-4} , 5×10^{-4} , 1×10^{-3} , 5×10^{-3} , 1×10^{-2} , 2×10^{-2} , 4×10^{-2} , and 6×10^{-2} .

To measure the effectiveness of our approach, we use the precision (Equation 2) and F1-Score (Equation 3) as evaluation metrics. We calculated each of these metrics in every window of every simulation.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$F1 - Score = \frac{TP}{TP + \frac{FN + FP}{2}} \quad (3)$$

In the above equations, TP, FP, and FN represent, respectively, the values of True Positive, False Positive, and False Negative. Figure 2 depicts an overview of the approach. We observed the sliding window depicted in blue color when running across the batches without faults in white color and purple color when running across the batches with faults in orange color. We also observe the degree of approximation and the evaluation by batch with DAT of 0.2.

5 Results and Discussion

We present in this section the results for the discovery of denial constraints and evaluation of the performance of these DCs for fault detection, acting as an offline application.

5.1 Discovery of Denial Constraints

During the initial phase, we executed DCFinder on the simulations without employing batching or partitioning techniques. This led to the identification of 140,879 unique DCs, with an average of approximately 1,300 DCs per simulation. However, the substantial number of DCs posed a challenge as it rendered subsequent stages of the process, such as obtaining coverage metrics and evaluating the constraints, impractical due to the extensive time required. Moreover, without data batching, it was not feasible to differentiate constraints discovered in fault-free samples, which are crucial for fault detection.

By batching selected simulations in groups of 1,000 samples, 153,052 unique DCs were discovered, resulting in an average of around 555 DCs per batch. This high number of discovered DCs allowed for the distinction between constraints present in samples without faults and those with faults, overcoming previous limitations.

Finally, the application of batching and partitioning (use of voltage and current samples only from a single terminal of the transmission line) reverberates in a drastic reduction in the number of DCs, finding 695 unique DCs and an average of approximately 18 DCs per batch, which demonstrates the relevance of the number of attributes, as it determines the size of the predicate space. Even more important, the partitioning process enables the discovery of constraints with predicates with attributes of a single bus. So, fault detection with these DCs does not require synchronization of data collected on both transmission line terminals, which is more consistent with a real operating environment.

From the 695 constraints found, 100 were found in batches with samples without fault presence, and 694 were found in batches with failure samples, *i.e.*, only one DC was found exclusively in batches without failure, while the other 99 constraints of the batches without fault also appeared in batches with failure samples. This proportion in the number of times a DC was found in batches with and without fault varied a lot; for example, we obtained a constraint that was found in all 500 batches without fault and which was also found in only 62 batches with failure, since another DC that was found in all batches with no failure was also found in 3,386 batches with fault. The mean coverage of each of the 100 DCs found in batches without fault also varied. Trivial constraints with only one predicate obtained an average coverage of 1.0, other trivial ones with only two predicates had an average coverage of approximately 0.5, while non-trivial constraints varied between approximately 0.666 and 0.833.

The lengths of these 100 constraints ranged between two and six predicates, being the vast majority (79%) with five or six predicates. Disregarding the most trivial constraints (with one and two predicates), the shortest length was four; thus, the majority succinctness was 1×10^5 , 0.666, and 0.833. Analyzing which types of dependency the constraints found

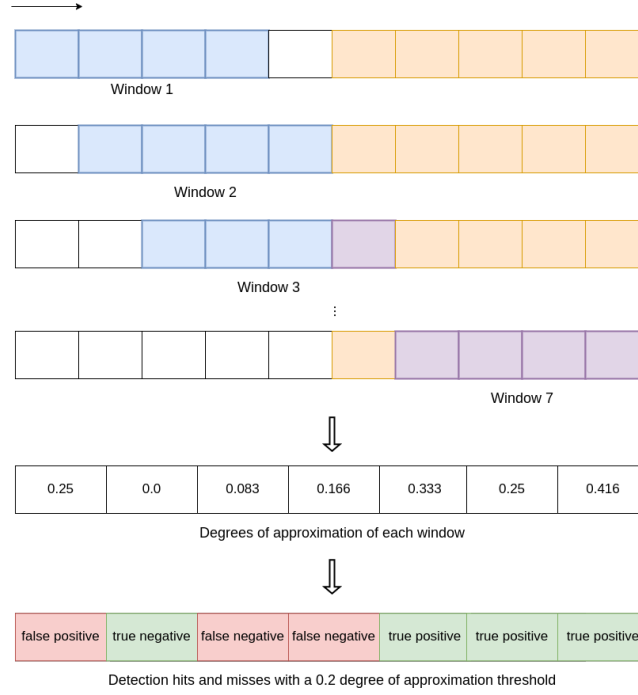


Figure 2. Fault detection with sliding windows and DC violations by batch.

represented, we noticed that we obtained a large amount of bidirectional order dependencies, such as: $\varphi_e : \forall t_x, t_y \in r, \neg(t_x.IC \leq t_y.IC \wedge t_x.IA \leq t_y.IA \wedge t_x.IB \leq t_y.IB)$

which is coherent since the three phases have symmetric and balanced current values during the normal operating state. So, the ordering by the current of one of the phases must also order the values of another phase, even if in a different direction (ascending or descending). We also had unique combinations of trivial columns: $\varphi_f : \forall t_x, t_y \in r, \neg(t_x.VA = t_y.VA \wedge t_x.IC = t_y.IC)$.

In turn, other dependencies did not fit any known definition, but presented a pattern where there is a predicate with the equality operator and two others with the inequality operators, such as: $\varphi_g : \forall t_x, t_y \in r, \neg(t_x.IC \leq t_y.IC \wedge t_x.VA \leq t_y.VA \wedge t_x.IA = t_y.IA)$. The complete set with all DCs found is available as a supplementary material².

5.2 Performance of the Proposed Approach

We used different simulations for the discovery of DCs and fault detection. The performance of our approach, considering the F1-Score measure, is shown in Figure 3. The performance of our approach increases for higher values of the window length together with lower values of the degree of approximation threshold. This suggests that DCs discovered at larger window sizes better capture the behavior of a transmission line and perform better in detecting DC violations.

We did not present performance results for window sizes larger than 800 due to the increase in the computational cost for larger windows, at the same time that there is no significant performance gain compared to $w = 800$. We did some additional experiments and observed that no performance

gain was achieved for these cases. On the other hand, smaller window sizes demonstrate worse results, which would be even lower for $w < 50$. It is also possible to observe in Figure 3 that values higher than 6×10^{-2} for the DAT indicate a considerable performance loss for all combinations with window sizes.

In general, the pair of parameters composed of $w = 800$ and $DAT = 0$ initially seems to be the best configuration. However, if we analyze the precision measure (Figure 4), we identify that this pair is the only one that presented FP suggesting possible overfitting. The occurrence of FPs is a problem in the fault detection context since it indicates that a window without electric fault data contains an anomaly. Thus, the absence of FP is essential to guarantee the accuracy of data for posterior fault classification and location tasks by machine learning approaches. This can impact in a performance loss for fault classification and location tasks, which these activities are directly related to the instant of the fault inception, determined by the fault detection task in an oscillography. Thus, it is essential the absence of FP in order to the data segmentation for a posterior fault classification and location be as accurate as possible.

In response, we consider $w = 800$ and $DAT = 1 \times 10^{-5}$ as the best pair of parameters for our approach. This pair of parameters does not present any FP and holds an F1-Score of 98.41%. It is crucial to mention that our method identified the fault incidence for all test cases (accuracy of 100%), but for some events our approach did not recognize the initial batch that contained the first failure samples as faulty, which penalized the performance and justifies the F1-Score of 98.41%. Thus, our method detected the fault incidence for all test events, but not necessarily in the first batch that the failure began.

²https://github.com/leandroensina/FaultDetection_DC_SBBD

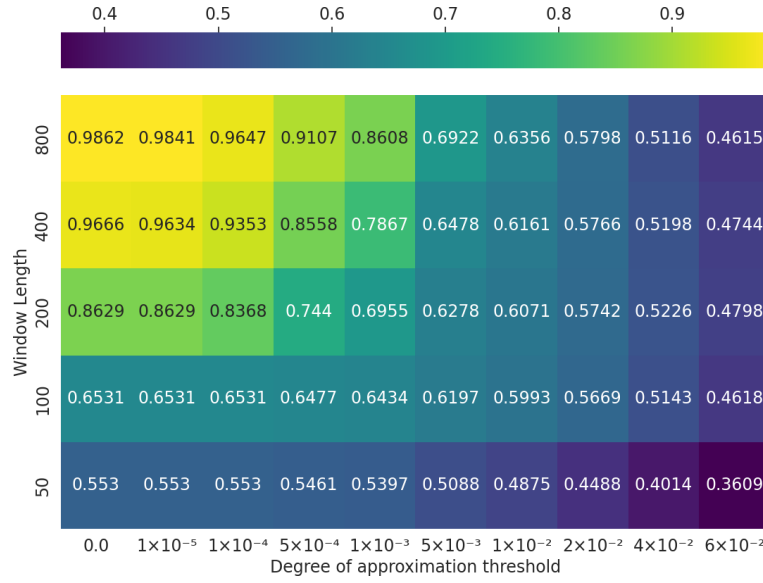


Figure 3. F1-Score for fault detection for each pair of parameters windows length and degree of approximation.

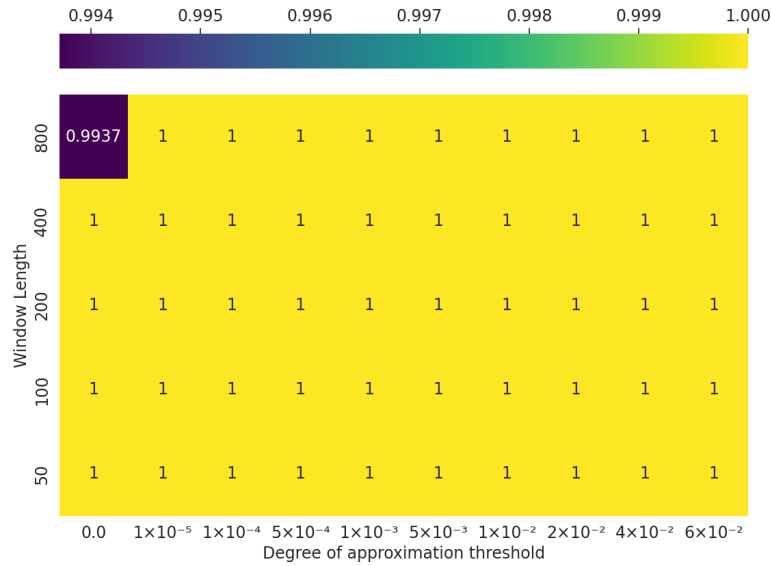


Figure 4. Precision for fault detection for each pair of parameters windows length and degree of approximation.

Also, this pair of parameters requires only about 20 samples to determine the fault inception after its real beginning, as can be observed in Figure 5, where the smaller the value, the better the performance. We discovered 695 DCs in all the simulation data, where 100 were discovered in pre-fault windows and 694 in post-fault windows. DCs discovered in pre-fault windows significantly differ from those in post-fault windows and perform best in discovering faults.

In other words, we discover the DCs present in time series without anomalies and use these DCs with sliding windows and the degree of approximation to detect anomalies. This strategy can also be used in several other areas of study that have time series and different attributes, such as IoT and the stock market.

The degree of approximation takes into account the number of pairs of tuples that violate a DC, but there are other possible metrics that we let for future work, such as the amount of tuples involved in violations and the minimum amount of tuples that need to be removed for the constraint not to be violated.

We also compared the performance of our method against two related works previously described in Section 1 [Asadi Majd *et al.*, 2017; Coban and Tezcan, 2021]. Both works were selected because they represent two methods based on the machine learning approach, which is widely adopted for fault detection, demonstrating accurate performances and versatility to other transmission lines than the one in which they were proposed. It is worth mentioning that we replicated both methods using the same dataset used to evaluate our approach. The results demonstrate that both approaches based on supervised machine learning algorithms also detected the fault for all test events (accuracy of 100%), just like the proposed unsupervised approach.

However, our method does not require supervision (*i.e.*, labeled data) to infer the fault (anomaly) incidence, in other words, a human specialist delimiting if each sample or data window represents a failure for the algorithm training. This aspect can also reverberate in a better generalization of the proposed approach compared to supervised methods for fault detection. The utilization of supervised machine learning

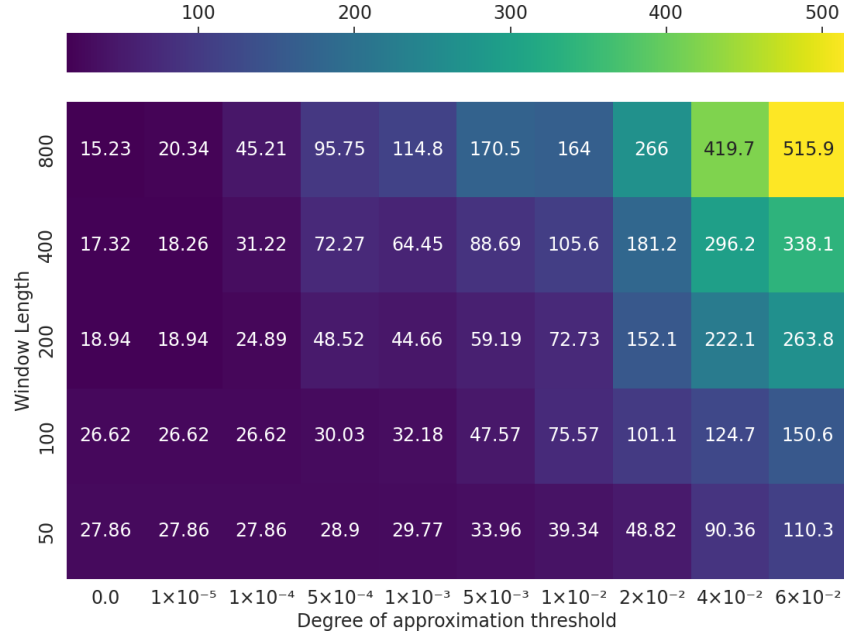


Figure 5. Average of samples for fault detection after the real fault inception for each pair of parameters.

methods might necessitate separate training for each supervised transmission line. This is due to the variations in voltage and current signal amplitudes observed during the operation of each transmission line, influenced by factors such as generator power fluctuations, transmission line length, and voltage [Ensina *et al.*, 2022]. Consequently, it is likely that these approaches will require an individual model for each supervised line.

On the other hand, our approach can indiscriminately identify faults despite these factors since the transmission lines present predominantly properties like symmetrical and balanced voltages/currents until the inception of a fault. Thus, the DCs found in this work are valid to use in other transmission lines (*e.g.*, other datasets) for fault detection. The DCs are based on the correlation among the behavior of the voltage and current waveforms, according to the properties previously mentioned, and not by features extracted from the signals or predefined threshold values (*e.g.*, constants).

Methods relying on feature extraction, such as those based on machine learning algorithms, may encounter challenges when confronted with varying feature values from other transmission lines exhibiting different amplitudes of voltage and current signals. This can lead to a lack of generalization capacity, as mentioned in Ensina *et al.* [2022]. Instead, the proposed approach aims to eliminate the need for feature extraction, seeking to improve the method's capacity to adapt effectively to new, previously unseen data originating from other power systems (different datasets). Further exploration of this analysis is planned for future investigations.

The primary limitation of our approach lies in the computational expense associated with initially discovering the Denial Constraints (DCs). However, once these DCs are identified, the average time required for the approach, using a window length of $w = 800$, to calculate the degree of approximation and perform classification amounts to approximately 331.54 milliseconds (ms). It is noteworthy that the runtime cost exhibits a linear pattern concerning the window length,

with times ranging from 20.75 ms for $w = 50$, 40.39 ms for $w = 100$, 78.37 ms for $w = 200$, 159.17 ms for $w = 400$, up to 331.54 ms for $w = 800$.

Figure 6 shows that our method could detect the fault occurrence in all simulations when using windows length greater than or equal to 200 with a *DAT* less than or equal to 1×10^{-4} .

Intuitively, we initially thought that smaller windows would have their degrees of approximation more sensitive to changes in the number of violations than larger windows, which did not happen as can be observed. In order to clarify the reason for this behavior, we sought to make additional analysis to answer this question. We hypothesize that larger windows include more samples and, consequently, more pairs of tuples that constitute a violation, while smaller windows have fewer pairs of tuples that represent a violation. Therefore, combining larger windows with a lower *DAT* leads to a reduction in the number of false negatives.

5.3 Analysis for the Fault Parameter Variation

In this section, we analyze our method considering the influence of the variation of each fault parameter. The results correspond to the best configuration for our approach such as previously discussed and justified ($w = 800$ and $DAT = 1 \times 10^{-5}$).

Table 1 shows the results for different fault inception times, demonstrating similar performances among them and, consequently, that this parameter does not significantly affect our method. This parameter is important because it represents the uncertainty associated with the time when a fault starts. It is noteworthy that the values for this parameter differ from those reported in Section 4.2 since we used different fault events for DC discovery and to assess the method.

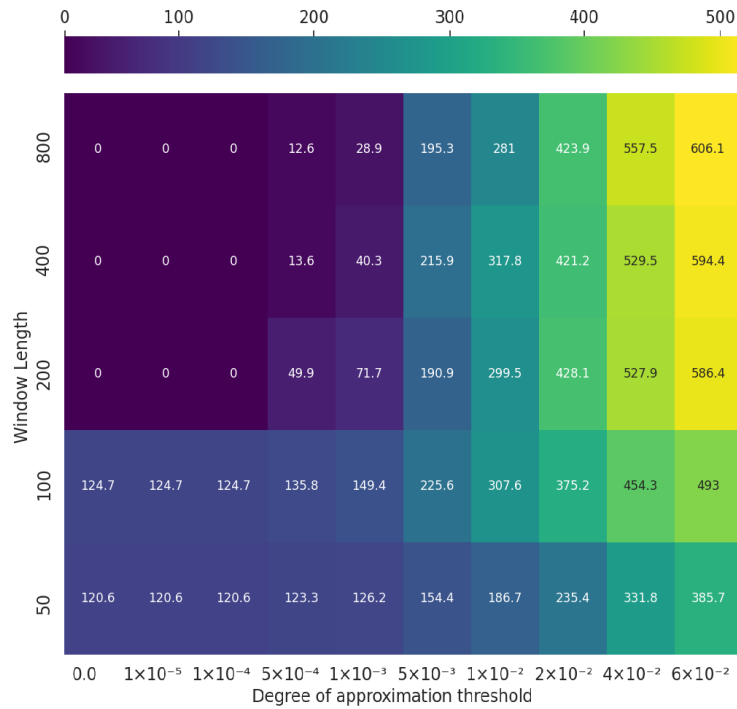


Figure 6. Average of simulations in which no faults were detected.

Table 1. Performance evaluation for different fault inception time.

Fault inception time	F1-Score	Precision
0.091 s	0.9845	1.0000
0.093 s	0.9839	1.0000
0.099 s	0.9844	1.0000
0.101 s	0.9837	1.0000

Table 2 presents the results individually for each fault type. In this analysis, we can observe distinct behaviors among some fault types, especially regarding CG, AB, and AC types, which demonstrated worse results, with the F1 score being lower than 98%. Nonetheless, it is crucial to emphasize that these results represent the overall performance considering all windows obtained from the oscillography. In other words, for these types of faults, it was not possible to identify the occurrence of the fault in the first windows, requiring additional windows to actually recognize the failure inception. The results reported in the last section demonstrated that our method achieves 100% accuracy, *i.e.*, our method identified the anomaly inception for all fault events but not necessarily in the first data windows.

Table 2. Performance evaluation for each fault type.

Fault type	F1-Score	Precision
AG	0.9801	1.0000
BG	0.9860	1.0000
CG	0.9665	1.0000
AB	0.9754	1.0000
AC	0.9611	1.0000
BC	0.9972	1.0000
ABG	0.9951	1.0000
ACG	0.9899	1.0000
BCG	0.9922	1.0000
ABC	0.9962	1.0000

Similar findings can be identified in Tables 3 and 4, which report the performance of varying fault resistance and location, respectively. Faults that are closer to the terminal used for data collection, as well as faults with lower resistances, present more significant changes in the behavior of the three-phase current signal (*i.e.*, higher post-fault amplitudes), which we expected would be easier to detect by our method. Curiously, the results were inferior for these scenarios, requiring extra sliding windows to identify the fault.

Table 3. Performance evaluation for different fault resistances.

Fault resistance	F1-Score	Precision
1 Ω	0.9794	1.0000
50 Ω	0.9734	1.0000
100 Ω	0.9831	1.0000
150 Ω	0.9908	1.0000
200 Ω	0.9936	1.0000

Table 4. Performance evaluation for different fault locations.

Fault location	F1-Score	Precision
1 %	0.9635	1.0000
25 %	0.9851	1.0000
50 %	0.9863	1.0000
75 %	0.9917	1.0000
100 %	0.9935	1.0000

6 Conclusion and Future Work

This paper presented a DC-based approach for accurate fault detection in electric transmission lines. Since DCs capture complex rules in databases, we used them to represent the behavior of transmission lines with and without faults. We showed that the DCs discovered in pre-fault windows significantly differ from those in post-fault windows and can be used to detect faults. The results demonstrated accuracy and precision of 100% for this task, requiring only about 20 samples to determine the inception of the fault with a window size of 800 and a degree of approximation of 1×10^{-5} .

Future works include (1) the evaluation of the method using more failure events from the FADb dataset and examples of real fault data. Considering the DC algorithm employed in our approach, future works also include (2) testing the C-FASTDC algorithm [Chu *et al.*, 2013] as it allows discovering DCs with constant values not covered by the DCFinder; (3) applying our DC approach in other data streaming applications to detect elusive events, like IoT and stock market; (4) assessing the predicates of the DCs for the fault classification task.

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Authors' Contributions

All authors contributed to the conception and writing of this study. Nicolas Tamalu performed the experiments. All authors read and approved the final manuscript.

Competing interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Availability of data and materials

The dataset used in our study is available in <https://1drv.ms/u/s!ArMEeMx4MYDNimHVxiDx3b4CI3iL?e=8GfXg7>.

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