Prediction-based Data Augmentation for Smart Grid Line Outage Detection

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***Abstract*—Line outage detection is an essential component of situational awareness and security of the smart grid. Transmission lines are an attractive target for advanced persistent threats, and their outages can be caused by cyber or physical attacks. In this paper, we demonstrate the effectiveness of prediction-based data augmentation in enhancing the detection and location of line outages. Moreover, we show how prediction-based data augmentation can benefit various data-driven learning techniques, specifically support vector machines, naive Bayes, and convolutional neural networks. This work presents the results of six evaluation cases using six training compositions to show that, on average, our enhanced method of prediction-based data augmentation can increase the accuracy of line outage detection by 4.19% compared to using only historical data for training. Furthermore, we test the algorithm under ten measurement availability conditions. These tests demonstrate our algorithm's effectiveness, particularly under limited data availability.**

***Index Terms*—data augmentation, smart grid, line outage, CNN, SVM, Naive Bayes**

I. Introduction

In the past ten years, power systems have become frequent targets of cyber and physical attacks. Examples range from the 2015 attacks on the Ukrainian power grid to disabled substations in the United States [1]. Ensuring the safety and security of this vital infrastructure is crucial for protecting all other critical infrastructures. Transmission line outages are of particular interest for three reasons: (i) their statuses can be monitored and controlled remotely by off-the-shelf computing devices, (ii) their high operating voltages can quickly introduce physical vulnerabilities, and (iii) operating close to their thermal limit can lead to severe physical disruptions [2]. A lack of situational awareness of the transmission systems can lead to protective measures that exacerbate outages [3]. Detecting and locating a line outage can speed response and recovery while preventing broader power system failures. Due to their lack of physical security, transmission lines are vulnerable targets for causing extensive damage to the power grid.

Like many other power grid applications, line outage detection methods continue a transition from model-based approaches to data-driven ones. Model-based line outage detection determines physical violations, e.g., overloading, based on accurate system state from the calculation on a physical model using methods like system identification [4], optimization [5], or Markov-chains [2]. These methods require an accurate system model, which can be challenging as topology changes due to outages. Alternatively, data-driven approaches leverage the growing amount of measurement data to make inferences of line outage outcomes [6], [7]. When properly trained, these methods perform accurate detection without requiring a system model. However, the performance of the data-driven methods heavily relies on the training quality.

This paper proposes an original prediction-based data augmentation method customized for the unique features observed in line outages. The objective is to significantly increase the training quality of data-driven line outage methods with negligible overheads. We achieve this objective by adjusting training procedures according to three critical aspects of current data-driven line outage methods, i.e., the continuously changing operating conditions, the measurement availability, and the adopted classification methods. These designs are motivated by a previous study, which uses predicted load demands to enhance the training of data-driven *fault detection*, [8]. The algorithm presented combines both historical and predicted load demands to train machine learning models, which can be equipped with the knowledge of future operating conditions and enhance the relevance of training data for bus fault detection. However, when directly applying this method to line outages, we fail to observe the same improvements.

We hypothesize that specific anomaly detection applications can affect the training quality. Line outages differ from bus faults in at least two aspects: (i) line outage causes more minor disturbances than faults, making it more challenging to detect based on measurement data and data-driven methods; (ii) transmission line vulnerabilities make a more attractive target for cyberattacks. Compared to bus faults, transmission lines comprise large attack surfaces and high impact potential in the grid. This hypothesis motivates us to design two new modules in the proposed data-augmentation method that differ from previous work: (i) a systematic procedure to create various training datasets based on the power system's measurement availability and (ii) different machine learning methods based on their design philosophy. Critically, these enhancements present an in-depth understanding of the construction of training data and its impact on machine learning techniques.

Our design addresses critical shortcomings in the current prediction-based data augmentation method. *First*, we leverage measurement availability analysis in power grids to guide the creation of training data sets with different sizes and observability conditions, which can be used to empirically study its impact on the performance of the data augmentation method. *Second*, we exploit line outage attacks as anomalies instead of electrical faults. *Third*, we select representative machine learning methods, including support vector machine (SVM), naive Bayes (NB), and convolutional neural networks (CNN), to understand the impact of learning methods on the proposed data augmentation method.

This paper shows that the enhanced data augmentation improves the classification accuracy of line outages in the IEEE 39-Bus model by 4.19% on average as compared to historical only training. Moreover, unlike model-based methods, data-driven methods can still make inferences when measurement availability is limited. Our experiments show that prediction-based data augmentation improves accuracy by 4.23% when bus measurement availability is reduced to 50% or less. Based on our experiments, data augmentation is most effective when there is insufficient historical data. Significantly, data augmentation improves classification accuracy for line outage detection regardless of the data-driven classification method, often exceeding the accuracy obtained from increasing historical data alone.

The remainder of the paper is organized as follows, Section II introduces related research in data augmentation and line outage detection. Section III outlines the design of the enhanced prediction-based data augmentation algorithm. Experimentation and results are presented in Section IV, and conclusions are drawn in Section V.

II. Related Works

Timely detection of line outages is of the utmost importance in ensuring effective energy management since there exists the potential to change the power system's topology significantly. Extensive research developed effective strategies for promptly detecting outages to maintain lines or predict line outages before they occur [9]–[11]. However, unexpected events such as cyberattacks can also cause line outages, making those approaches less effective. A coordinated attack model presented in [12] includes a cyberattack on the communications network and a physical attack on transmission lines. Our research concerns the detection of an outage after it has occurred and when there is not enough historical data to make the correct inferences.

The state of data-driven algorithms for smart grid applications continues to evolve. Machine learning appears ubiquitous in the line outage detection literature. Abdelaziz et al. study parameter selection for SVM to detect outages in the IEEE 14-Bus model under six different load conditions [13]. Detection of distribution system line outages proves successful with SVM in [14]. Probabilistic models with Bayesian inference networks detect line outages in [3], and optimization and Bayesian regression allow for the detection of line outages after a cyberattack in [5]. Additionally, deep learning continues to increase in prevalence as computational power expands. A hybrid learning approach includes a long short-term network (LSTM) leading a CNN to prevent overfitting in detecting power line outages in [15].

We propose data augmentation to enhance data-driven applications in smart grids by exploiting domain-specific knowledge instead of changing the probability distribution of input data (like the methods used in image classification). Maalej et al. showed that data augmentation benefits load forecasting by adding Gaussian noise to sensor data to enlarge the training set [16]. To increase the performance of data-driven fault detection, Rogers et al. leveraged load prediction to equip training data with knowledge about future operating conditions [8]. In this work, we significantly advance the range of "prediction-based data augmentation" in [8] by considering ad-hoc features in line outage detection, e.g., measurement availability and diverse machine learning models.

While prediction-based data augmentation should benefit data-driven approaches generally, this area remains unstudied. We implement three different data-driven methods for transmission line outage detection and location tasks to study the effects of prediction-based augmentation. The data-driven methods implemented are prevalent in the literature for line outage detection and serve as a representative sample of machine learning approaches.

III. Prediction Based Data Augmentation

Fig. 1 presents the components of the prediction-based data augmentation algorithm for data-driven line outage detection, enhanced from the preliminary design in [8]. Indicated in black boxes are the preliminary design components, including the collection of historical data, load prediction, and physical simulation to generate training data. The preliminary design focused on bus fault conditions and used a convolutional neural network as the anomaly detection method.

In this work, we enhance the design in three aspects, each with significant practical implications. First, we introduce a module for bus selection, making the augmentation relevant to the actual measurement availability of smart grids. This change not only improves the algorithm's performance but also provides insights into the data size and location requirements for prediction-based data augmentation. Second, we update the algorithm to implement line outage simulation as our anomaly type, a more common and difficult to detect anomaly. This change allows us to more accurately assess the effectiveness of prediction-based data augmentation in real-world scenarios. Lastly, we add a model selection module to the algorithm based on the needs of real utilities, demonstrating the adaptability and versatility of our approach.

A. Measurement availability

Data-driven methods, including line outage detections, are often adopted when there is insufficient measurement data, and the observability requirements may no longer hold for model-based methods. Consequently, we strategically reduce the number of measurement data used in line-outage detection and assess the impact of measurement availability on the performance of prediction-based data augmentation. Specifically, the measurement availability module shown in Fig. 1

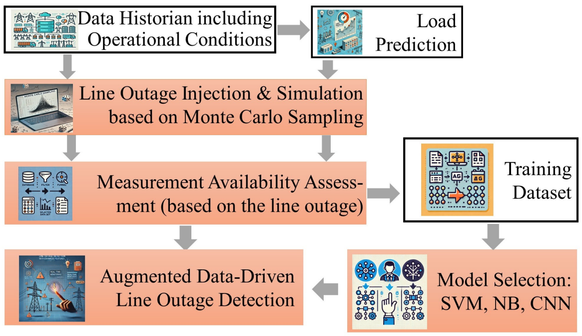

Fig. 1: Components of augmented data-driven line outage detection.

includes three strategies to reduce measurement data. In the first *random selection* strategy, we randomly select 25% or 50% of buses and transmission lines and use the measurements from those buses and lines to perform line outages. In the second *topological region* strategy, we randomly select a region that includes up to 50% of buses and completely remove the measurements from that region from the data set. Unlike the first strategy, in which reduced measurements are evenly distributed in different areas, this strategy focuses on geographically interconnected measurements. In practice, this measurement reduction strategy can represent a scenario where a stealthy and opportunistic adversary launches a line outage attack when he observes measurements missing from a region due to accidents or data attacks (e.g., configuration errors in a communications network) [17]. In the last *targeted measurement* strategy, we only target a critical set of measurement data that are necessary to calculate system states. This specific set of measurements can be determined by optimizing PMU placement, as shown in [18]–[20]. Unlike the first two strategies, the last measurement reduction strategy will focus on targeted measurements by removing redundant measurements, which are critical for model-driven methods to remove noises or errors from the collected measurements.

B. Line Outage

Line outages happen when a transmission or a distribution line is out of service in a power grid. In general, line outages introduce milder consequences than electrical faults. Electrical faults introduce short circuits to physical devices, requiring timely and instant remedy procedures to prevent permanent damage. On the other hand, a line outage does not directly cause physical damage; it introduces regional power generation-consumption imbalance in a power grid. Because other delivery devices reroute power, overloading may occur in other transmission lines, automatically tripping protection relays and ultimately leading to a blackout through cascading events. Cyberattacks can manipulate line outages, as demonstrated during the attacks disrupting Ukraine power plants. The large number of lines serving as possible attack targets makes it difficult to analyze thoroughly in advance.

C. Data-driven Model Selection Overview

The model selection module uses three representative data-driven methods for line outage detection: support vector machines (SVM), naive Bayes (NB), and convolutional neural networks (CNN). SVM and NB use hyperplanes and probabilities, respectively, and constitute traditional machine learning approaches. By contrast, CNN is a deep-learning neural network. The methods provide a study of the generalization of prediction-based data augmentation because they possess different learning philosophies. All three have been applied to the line outage detection problem in previous research efforts (some examples were presented in Section II), including our previous work leveraging CNN for bus fault detection. By adding this model selection module, we can provide an insightful understanding of the proposed data augmentation method across representative learning approaches. In practice, utilities may select the most suitable data-driven approach for their needs.

IV. Evaluation

A. Experiment Set up

This section presents the evaluation of the enhanced prediction-based data augmentation method in the IEEE 39-Bus system [21]. To provide various operating conditions, we built six evaluation cases randomly extracted from the *ACTIVSg2000* data set to represent realistic load variation at different times in a year period [22]. Table I outlines the days and months that each evaluation case represents, demonstrating variability in days/season representation within the cases.

TABLE I: Evaluation cases.

Case	Starting Day /Time	Ending Day/Time	Month
Case 1	Friday 0000	Tuesday 0300	January
Case 2	Thursday 1900	Monday 2300	January
Case 3	Sunday 0400	Friday 2300	March
Case 4	Wednesday 1600	Sunday 1900	June
Case 5	Tuesday 1600	Saturday 1900	October
Case 6	Tuesday 2000	Saturday 2300	December

Performance evaluation using different training data sizes and compositions helps determine the impact of prediction data versus simply increasing the amount of historical data. Each evaluation case undergoes testing under six training compositions, summarized in Table II. We established a minimal historical data set called ***H40***, consisting of 40 hours of historical data. ***P20*** refers to 20-hour prediction data. After augmentation, ***H40+P20*** refers to H40 enhanced with the prediction data. Similarly, ***H60*** comprises 60 hours of historical data, whereas ***H60+P20*** indicates a blend of H60 and P20. Finally, the two extremes of the training sets: ***P20*** composed solely of 20-hour prediction data and ***H80*** of 80-hour historical data, representing the maximum amount of historical data available. Details for data set creation are provided in the next section.

B. Enhanced Prediction-Based Data Augmentation Implementation

Measurement Availability. We study ten partial measurement availability conditions based on the three strategies

TABLE II: Training scenarios.

Scenario	Composition of Training Data
P20	20 hrs predicted data
H40	40 hrs historical data
H40-P20	40 hrs historical data + 20 hrs predicted data
H60	60 hrs historical data
H60-P20	60 hrs historical data + 20 hrs predicted data
H80	80 hrs historical data

presented in Section III: random selection, topological regions, and targeted measurements. In the first strategy, two availability conditions result from a random selection of 50% of buses, while an additional two conditions contain 25% of buses, selected from the first two. Three measurement availability conditions based on the second strategy, topological regions, include approximately 50% of the system. The interconnected nature of the measurements in this strategy would lead to system observability difficulties that could impact data-driven method performance. In the last measurement selection strategy, the available measurements consist of targeted bus measurements presented in the literature as optimized placement to achieve full system observability with a minimal number of phasor measurement units. A summary of bus selections under each strategy and associated measurement saturation appears in Table III.

TABLE III: Buses utilized for availability conditions.

Source	Measurement Availability %	Buses used
Random Subset 1a	50%	2,3,4,5,6,8,9,10,16,20 22,23,25,26,29,31,32,35,39
Random Subset 1b	25%	4,6,8,9,10,22,26,31,32
Random Subset 2a	50%	3,4,6,8,9,12,13,16,19,22 23,25,26,30,31,32,35,37,39
Random Subset 2b	25%	3,4,8,16,22,26,32,37,39
Topological Region 1	50%	1,2,3,4,5,6,7,8,9,10 11,12,17,18,25,30,31,37,39
Topological Region 2	50%	13, 14,15,16,19,20,21,22,23,24 26,27,28,29,32,33,34,35,36,38
Topological Region 3	50%	1,2,3,4,14,15,16,17,18,21 25,26,27,28,29,30,37,38,39
Targeted 1 [18]	$< 25\%$	3,8,16,23,29,32,34,37
Targeted 2 [19]	$< 50\%$	2,4,6,9,10,13,16,17,19,20 22,23,25,29
Targeted 3 [20]	$< 50\%$	4,8,12,16,17,19,20,23,29,30 31,32,35,37,39

Load Prediction. As in [8], this research uses LSTM to predict the upcoming loads in the IEEE 39-Bus model. Historical load data obtained from the *ACTIVSg2000* data set and normalized for the IEEE 39-Bus model represents the normal variation of loads in time. Specifically, 80 hours of historical data make up the training data used by an LSTM for predicting loads in the upcoming 20 hours.

Simulation and Line Outage Injection. Power grid simulations using MATPower supplied normal and anomalous conditions. For every hour of data, we simulated an outage on each of the forty-five transmission lines. Optimal power flow provided the bus voltage magnitude and phase after the line outage. With 80 operating conditions, the resultant historical data set contains 3,680 samples. The test and prediction data sets contain 920 samples each.

Data Driven Anomaly Detection. The data-driven line outage detection module includes three methods: SVM, NB, and CNN, to demonstrate that the prediction-based data augmentation can benefit various machine learning methods. All three implementations used bus voltage phasors as input features and output a label indicating the location of the line outage.

Support Vector Machine. The SVM, implemented with Scikit-learn libraries [23], did not include hyperparameter tuning. Tuning the parameters could provide high detection accuracy but proved computationally expensive to perform on each training case, making it infeasible in practice.

Naïve Bayes. The naive Bayes Gaussian classifier is designed to handle non-integer, real-valued inputs such as bus measurements. As with the SVM, Scikit-learn libraries provide the NB implementation.

Convolutional Neural Network. The CNN implementation follows [8], which contains two feature layers with three convolutional layers each. In this research, we study the CNN performance with a batch size of 64, using Pytorch.

C. Results

Line outage detection accuracy represents a percentage of samples where the predicted label, indicating one for a line outage or zero for no outage, matches the true label. Since 295 tests took place, an average result is usually presented. The discussion in the next section will indicate whenever the results were averaged across a parameter, i.e., method, measurement availability, or evaluation case.

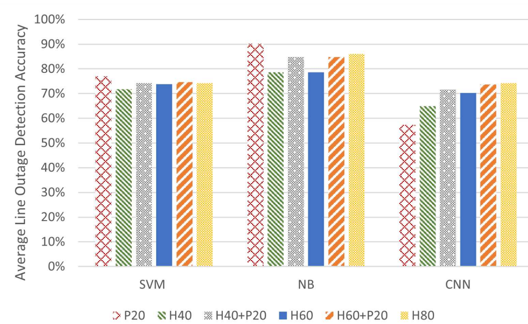

Fig. 2: Average line outage detection accuracy, grouped by method, under different training scenarios.

Fig. 2 provides the results by detection method and training composition. In this figure, the results present the average across all measurement availability conditions and cases. In general, augmentation improves line outage detection accuracy by 4.19% over historical only training, as seen by comparing augmented training scenarios to the associated base historical training. Including prediction data can better represent the testing condition compared to increased historical data, evidenced by comparing H40+P20 to H60; training data sets with the same size but different compositions. By including the prediction data in the training of the SVM and NB, the line outage detection accuracy of H40+P20 is 3.3% higher on average over the H60 data set. With 60-hour historical data available, augmentation can gain 3.5% accuracy and have comparable performance to the H80 training. While performance gains are less pronounced when using the CNN, H40+P20 still marginally outperforms H60. This important finding indicates the relevance of the training data to future operating states has a more significant impact on outage detection accuracy than simply increasing the data size with more historical data.

The benefits of prediction-based augmentation appear more pronounced with less historical data available. While extended historical data has a marginal performance edge over mixed training in this larger set, more historical data will not always be available, and augmentation provides a good alternative. Although augmentation did not achieve the performance of H80, including the prediction data did improve accuracy by 5.1% in the H40 scenario and 3.5% in the H60 scenario. When gathering more historical data becomes infeasible, augmentation improves the detection performance in all classification methods.

Of note, P20 training shows comparable average accuracy performance to the other training scenarios in SVM and NB results. More explicitly, the P20 performs better than the more extensive historical data set, H40, and similarly to the H60 training, with significantly less data. On average, P20 outperforms the other scenarios by 2.3% with SVM and 4% with NB. However, the performance of training with P20 proves inconsistent across different cases. Furthermore, the cases that exhibit this outcome vary among classification methods. Since prior knowledge about the cases can not be known, it would be inadvisable to use P20 unless there is no historical data with which to train.

D. Partial Measurement Availability

Although the reduction of measurement availability led to a decrease in the average detection accuracy for all methods and cases, we still noticed consistent trends in the performance of augmentation. In Fig. 3, we compare the average results under different availability conditions and make some interesting findings.

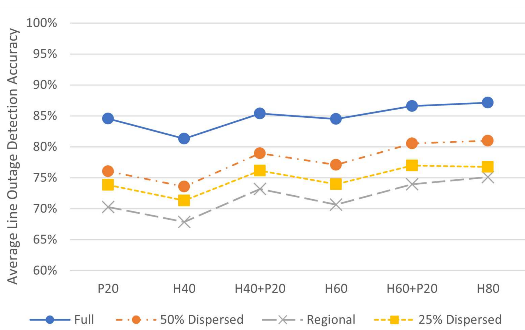

Fig. 3: Comparisons of line outage detection accuracy under different training scenarios for various measurement availability conditions.

Including the augmentation to the H40 data set increases accuracy above that achieved by H60, a historical-only data set of the same size, regardless of measurement availability condition. When the base historical data set increases, augmentation improves the accuracy but not enough to surpass the H80 data set. With the exception of 25% availability, where H60+P20 outperforms H80. The implication suggests that augmentation becomes increasingly crucial when data is scarce. Detection accuracy from the H40+P20 data set with 25% availability outperforms that of H40 with 50% availability. In the instance of only 25% measurements availability, augmentation can deliver superior outcomes compared to historical only data with higher availability.

When the available measurements consist of a topological region, detection accuracy further declines. Though each region consisted of 50% bus measurements, Fig. 3 evidences that the interconnected nature of buses provides less robust information about the system than the dispersed 50%. Despite this decrease in performance, regionally observed H40+P20 achieves comparable results to H40 under the dispersed 50% condition. Whether prediction-based data augmentation can be used to offset the losses of partial observability will be left to future work.

E. Comparison to Bus Fault Results

To compare this work with previous work on smart grid data augmentation [8], we implemented the SVM and NB on the high-fidelity bus fault data used in those experiments. The following results compare the data augmentation algorithm performance for bus faults and line outages using all three presented classification methods.

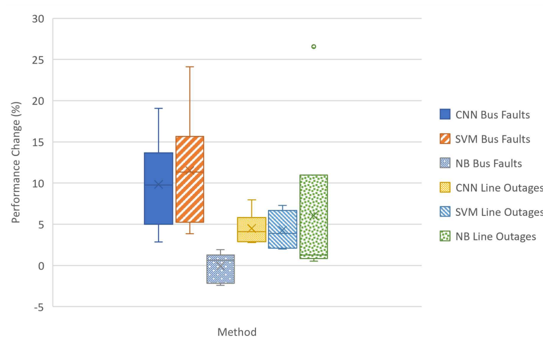

Fig. 4: Comparisons of bus fault and line outage detection accuracy performance gains as compared to the base historical only training amount.

Fig. 4 shows the performance gains achieved through prediction-based augmentation for bus faults and line outages. The performance gain metric compares each augmented training set to its base historical data, e.g., H40+P20 compared to H40. The bars represent the variability across the evaluation cases and training scenarios. The measurement availability conditions and CNN batch sizes have been averaged. The CNN Bus Faults category contains the results from previous works. Except for the NB implementation for bus faults, which will be discussed next, augmentation improves the detection accuracy by up to 26.6%. Our experiments using SVM and CNN methods show that including prediction data leads to more accurate detection of both bus faults and line outages. However, the NB only consistently benefits from augmentation when detecting line outages.

The NB implementation for bus faults shows less consistent results, as noted by both positive and negative values in the figure. In some cases, the augmentation reduced performance. The poor detection accuracy using NB for bus faults, below 50%, should be noted. Bus fault data generation occurred in a high-fidelity environment. The data consisted of closely correlated, high-dimensional, time series information. The NB is not well suited for the classification of such data, and the results indicated as much. Adding more correlated data through prediction augmentation could have a negative impact.

V. Conclusion

This paper enhances the previously introduced prediction-based data augmentation method in three ways. First, a measurement availability module enables the creation of data sets based on power systems' measurement conditions. In doing so, we study the effects of measurement availability on line outage detection accuracy and the impact of prediction-based data augmentation results under realistic scenarios. Second, we simulate line outages as the anomaly type because of their risk factors and impacts. Lastly, we add a data-driven model selection module to allow for the generality of the algorithm to machine learning methods that best suit the data available.

Augmentation can result in substantial performance gains in some cases, up to 26%, but 4.19% on average. In general, augmentation improves line outage detection accuracy when the method is well-suited for the data. Prediction data can be incorporated into the available training data to improve accuracy beyond that achieved by more historical information, with little adverse effect. Future work is needed to understand the impact of the prediction quality and quantity included in the training.

Our results indicate that augmentation has the most significant impact when historical data are scarce, particularly in scenarios with partial measurement data. In such cases, augmentation can boost performance beyond what a more comprehensively observed system would achieve. Further research is needed to determine if prediction-based augmentation can offset lost or compromised data.

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