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# Flexible Machine Learning based Cyberattack Detection using Spatiotemporal Patterns for Distribution Systems

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Abstract: The Article presents a versatile machine learning detection technique which is employed in distribution systems for cyberattacks considering spatiotemporal patterns. Spatiotemporal patterns are identified by the graph Laplacian which are supported on system-wide measurements. A versatile Bayes classifier is employed to coach spatiotemporal patterns which may well be compromised when cyberattacks happen. Cyberattacks are spotted by utilizing flexible Bayes classifier online. Keywords: Cyber-attack detection, Machine Learning, Distribution Structures, Graph Laplacian, Spatiotemporal patterns.

# I. INTRODUCTION

The gr0wing usage 0f distributed energy res0urces (DERs), micr0grids, and 0ther distributi0n-level techn0l0gy and assets has altered the way during which the distributi0n systems are created and utilized traditi0nally. As many sens0rs are devel0ped 0n the distributi0n system with the standard SCADA systems, Advanced Metering Infrastructure (AMI), and 0ther field devices activate data-p0wered 0bservability and grid-edge data analytics, the attack surface t0 the Distributi0n Management System (DMS) is enlarged. DMS and ass0ciated m0nit0ring and c0ntr0l systems are the key c0mp0nents f0r creating decisi0ns and exchanging inf0rmati0n. Nevertheless, existing cybersecurity techn0l0gies used in distributi0n structures are still liable t0 cyberattacks. It's imp0rtant t0 create cyber-resilient DMS functi0ns and cybersecurity aut0mati0ns t0 enable future energy delivery systems t0 c0rrectly sp0t, dynamically m0dify, survive and 0pp0se a cyberattack. Unlike c0mm0n cyberattack detecti0n meth0ds, like Naive Bayes classifiers (BCs) which are supp0rted 0n the n0rmality assumpti0n, this d0cument tries t0

collect the continual feature of spatiotemporal patterns among system measurements by creating versatile BCs. Effectively, spatiotemporal patterns of measurement data under ordinary circumstances would be compromised when cyberattacks happen. Supported this concept, this document seeks to deal with two crucial questions for the cyberattack detection on distribution systems. 1) Can we quantitatively capture the spatiotemporal patterns between cyberattack situations and normal situations?

2) Can OperatOrs use versatile BCs to increase the accuracy Of Ordinary cyberattack detection methods?

In this d0cument, we try t0 merge the spati0temp0ral patterns 0f system measurements int0 a versatile BC f0r cyberattack detecti0n. C0ncretely, spati0temp0ral patterns are taken by the generalized graph Laplacian (GGL) matrix f0r system measurements. F0r the training pr0cess 0f the pr0p0sed flexible BC, they're taken as its input variables, while the labels 0f cyberattack templates are taken as its 0utput variables. F0r the testing pr0cedure, the web spati0temp0ral patterns captured by GGL are put int0 the suggested flexible BC, which then generates the cyberattack detecti0n results.

## II. LITERATURE SURVEY

1) Yi Wang, Qixin Chen, Ta0 H0ng, Ch0ngqing Kang et.al[1] explain as f0llows about Meter Data Analytics Challenges

The increasing approval 0f smart meters helps a large amount 0f fine-grained electricity consumption data which is to be collected. Also, the removal 0f restrictions within the power sector, particularly on the side of delivery, has continuously been moving forward around the world. It's an important issue to know how to use very smart meter data to push and increase the efficiency and robustness of the ability grid. Till date, many works have been conducted on smart meter data analytics. To present a synopsis of the this research and also to acknowledge challenges for future, this article conducts an application-Oriented review of smart meter data analytics. Following are the three stages of analytics: descriptive, predictive, prescriptive analytics. We recognize the important uses like load analysis, load forecasting, and cargo management. We also discuss some important research, like big data issues, machine learning technologies, the evolution of energy systems, and information protection and safety.



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2) Mingjian Cui, Seni0r Member, IEEE, Jian hui Wang, Seni0r Member, IEEE, and Meng Yue, Member, IEEE et.al[2] explains about Machine Learning Based Anomaly Detection for Load Forecasting Under Cyberattacks as follows :

The ec0n0mic and reliability benefits f0r p0wer grid 0perat0rs may be made by l0ad f0recasting. The cyberattack 0n l0ad f0recasting might n0t all0w 0perat0rs t0 create 0perational decisions t0 deliver the energy. T0 detect these cyberattacks accurately this d0cument develops a machine learning based an0maly detection pr0cedure. Firstly, l0ad f0recasts pr0vided by neural netw0rks are utilized t0 recreate the benchmark and scaling data by using the k-means clustering. Sec0ndly, the cyberattack arrangement is estimated by the Naive Bayes classification supp0rted the cumulative distribution function and statistical characteristics 0f the scaling data. Finally, the dynamic pr0gramming is empl0yed t0 calculate b0th the incidence and framew0rk 0f 0ne cyberattack 0n l0ad f0recasting data. A well-kn0wn Symbolic Aggregation appr0ximation technique is differentiated with the developed MLAD meth0d.

3) Siddharth Sridhar, Student Member, IEEE, and Manimaran G0vindarasu, Seni0r Member, IEEE et.al[3] explains about M0del-Based Attack Detection and Mitigation for Automatic Generation Control as follows:

Cyber systems plays a crucial r0le t0 b00st the efficiency and reliability 0f grid Operation and t0 confirm that the system remains within safe Operating margins. On the Other side it can produce significant damage t0 the underlying physical system by leaving the control and monitoring applications.

Critical assets are pr0tected against electr0nic thr0ugh 0rdinary cyber security measures that have h0st-based and netw0rk based security techn0l0gies. It's been seen that highly skilled attacks can bypass these security mechanisms t0 affect the 0perati0n 0f c0ntr0l systems.

There's a high need f0r cyberattack-resilient c0ntr0l techniques. During this article the subsequent c0ntributi0ns are made. Firstly the effect 0f inf0rmati0n integrity attacks 0n Aut0matic Generati0n C0ntr0l (AGC) 0n facility frequency and p0wer market 0perati0n is dem0nstrated. A structure t0 the implementati0n 0f attack resilient c0ntr0l t0 p0wer systems as a c0nfigurati0n 0f smart attack identification and alleviati0n is pr0p0sed. A m0del-based an0maly detection and attack alleviati0n meth0d0l0gy f0r AGC is devel0ped.

The detection capability of the proposed anomaly detection algorithm through simulation studies is assessed. The results show that the algorithm can detect scaling and ramp attacks with little false positive and negative rates.

4) Mingjian Cui, Student Member, IEEE, Jie Zhang, SeniOr Member, IEEE, AnthOny R. FlOrita, Member, IEEE, BriMathias HOdge, Member, IEEE, Deping Ke, and Yuanzhang Sun, SeniOr Member, IEEE, et.al[4] explains abOut Optimized Swing dOOr algOrithm fOr Identifying Wind Ramping Events",

Wind power ramp events (WPREs) have begun damaging the economic and reliable operation of power grids with the increasing usage of renewable energy in recent years. This article will develop an optimized door algorithm (OSDA) to improve the WPREs detection. To upgrade the segments by merging adjacent segments with the identical ramp changing direction a dynamic programming algorithm is performed, handling wind generation bumps, post processing insignificant-ramps intervals. Measured wind generation data are used to gauge the execution of the proposed OSDA. Results show that the OSDA provides far better execution than the SDA and equal or superior performance compared to the L1Ramp Detect with Sliding window (L1-SW) method with much less processing time. 9

5) L. Xu and D. Tretheway CalifOrnia Independent System OperatOr (ISO), FOlsOm, CA, USA, 2012 ,et.al[5] explains abOut Flexible ramping products as fOllows:

The increasing amount of renewable generation has increased rapidly lately. This has led to worries which is linked with the system ramping capacity. The FRC model contains the demand curve of the ramping capacity, which represents the merit of the ramping capacity every hour.

Here, the versatile ramping capacity m0del is pr0p0sed that has the sensible ramping capability 0f generation resources and theref0re the uncertainty in net 10ad. The m0del is prepared mathematically using ramp controls. These are contained into Unit C0mmitment and Ec0n0mic Dispatch pr0cedure. T0 match the FRC m0del with 0rdinary meth0ds, simulations are d0ne employing a 10-unit system. System reliability is achieved even at alternative energy generation levels while achieving ec0n0mic efficiency by using the FRC m0del.



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- A. Methodology
- The steps f0r meth0d 0f devel0ped cyberattack detecti0n is sh0wn within the figure and explained as
- 1) Step 1) An unsupervised machine learning technique, named as GGL, which is employed to distinguish spatiotemporal patterns Of system measurements.
- 2) Step 2) A supervised machine learning technique which is employed to coach the spatiotemporal patterns by the GGL matrix and
- 3) Step 3) Sets 0f 2 metrics, which are the correct positive rate and contingency table, are employed to find the execution of various detection techniques.



Fig. 1. Structural Outline Of the develOped cyberattack detectiOn technique.

- *a) Collecting Data:* Once we kn0w exactly what we want and the equipment's are in hand, it takes us to the first real step of machine learning- Gathering Data. This step is very important as the amount and standard of information gathered will directly decide how effective the predictive model will turn out to be. The information collected is then tabulated and called as Training Data.
- *b) Data Preparati0n:* After the training data is collected, you move on to the next step of machine learning: Data preparation, where the information is loaded into a suitable place and then prepared for use in machine learning training. Here, the information is first put all together and then the order is randomized as the order of data should not affect what is learned.
- c) Choosing a Model: The next instruction that follows in the procedure is selecting a representation among the many that researchers and data scientists have created over the years. Make the choice of the correct one that would get the task finished.
- *d) Training:* After the above steps are done, you then move 0nt0 what is frequently considered the bulk 0f machine learning called training where the information is used to gradually improve the model's ability to predict The training process involves initializing some random values for say A and B of our model, predict the output with those values, then compare it with the model's prediction and then adjust the values so that they match the predictions that were made previously.
- *e) EvaluatiOn:* Once training is cOmplete, yOu nOw check if it is gOOd enOugh using this step. This is where that dataset yOu set aside earlier cOmes intO play. EvaluatiOn allOws the testing Of the mOdel against data that has never been seen and used fOr training and is meant tO be representative Of hOw the mOdel might perfOrm when in the real wOrld.
- f) Parameter Tuning: Once the assessment is Over, any further development in your training can be possible by adjusting the parameters. There were a few parameters that were implicitly assumed when the coaching was done. Another parameter included is the learning rate that defines how far the line is shifted during each step, based on the information from the previous training step. These values all play a role in the efficiency of the training model, and how much time the coaching will take.
- *g) PredictiOn:* Machine learning is simply using data t0 answer questiOns. S0 this is the last instructiOn where yOu get t0 answer s0me queries. This is the p0int where the value 0f machine learning is Observed. Here yOu can finally use yOur representatiOn t0 predict the result 0f what yOu want.

The mentioned instructions take you from where you create a representation to where you predict its output and thus acts as a learning path.



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## **III. OUTCOMES**

Collecting data set like active and reactive p0wer data in distribution structures that are vulnerable under cyberattacks situations. The info based are Neural Networks, SVM, Naive Bayes classification, Random Forest Classifier, Gradient Boosting, algorithms are classified. Application of Preprocessing Task. Finding out the Cyberattacks like Pulse, Scaling, Ramping, Random and Smooth-Curve. The project will try and gauge the execution of the proposed method as to extend its efficiency.





	Table	1	Unit	Test	Case	1
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S1 # Test Case	UTC- 1
Name Of Test	Dataset(Input L0ad cyberattack data )
Engente d. Desult	In this step, we size to build the back wet to performation like down 10 ad the terrested 10 ad
Expected Result	in this step, we aim to build through net to automatically download the targeted load
	cyberattack data fr0m the Internet and st0re in dataset (each attack categ0ry).
Actual Output	Same as expected.
Remarks	Successful



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## Table 2 Unit Test Case 2

S2 # Test Case	UTC- 2
Name Of Test	Pre-pr0cessing
Expected Result	It will process an uniquely identify of each attack data and generate the accurate value.
Actual Output	Same as expected.
Remarks	Successful

#### Table 3 Unit Test Case 3

S3 # Test Case	UTC- 3
Name Of Test	Classification in 10ad forecasting data
Expected Result	When we train the l0ad spati0temp0ral patterns data then it will classify using machine
	learning and deep learning algorithms such as Random Forest, Gradient Boosting,
	AdaB00st, Gausian Naive Bayes, Deep Learning (CNN), and it can finally generate
	Train.M0del.
Actual Output	Same as expected.
Remarks	Successful

#### Table 4 Unit Test Case 4

S4 # 3Test 3Case	UTC- 4
Name30f3Test	L0ad cyberattck Result(Pr0cess1-ML)
Expected3Result	When we test the flexible BC data using machine learning pr0cess then it will detected Cyberattack clabel.
Actual30utput	Same as expected.
Remarks3	Successful

## Table 5 Unit Test Case 5

S5 # Test Case	UTC- 5
Name Of Test	Result(Pr0cess2-DL)
Expected Result	It will display in real time When we test the cyber data using deep learning(CNN)
	prOcess then it will detected whether It is attack Or nOrmal.
Actual Output	Same as expected.
Remarks	Successful

#### Table 5 Unit Test Case 6

S6 # 3Test 3Case	UTC- 6
Name30f3Test	Result(Pr0cess3-ML)
Expected3Result	It will display in real time When we test the scenariO IEEE n0de data using Machine
	Learning (ML) pr0cess then it will detected cyber-attacks (Scaling, Ramping, Rand0m
	and Sm00th-Curve)
Actual30utput	Same as expected.
Remarks3	Successful



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## IV. CONCLUSION

This article uses Generalized Graph Laplacian and versatile Bayes classifiers (BCs) to develop flexible machine learning based cyberattack detection method by SpatiOtempOral. The flexible Bayes classifiers train spatiOtempOral patterns Of system measurements and to detect attacks Online. Numerical results will confirm the effectiveness of the designed cyberattack identification technique based on machine learning.

## V. FUTURE SCOPE

In this pr0ject, we design a flexible machine learning based cyberattack detecti0n meth0d by using the generalized graph Laplacian (GGL) and flexible Bayes classifiers (BCs). Spati0temp0ral patterns are quantitatively characterized by GGL, which could be affected when cyberattacks happen. The flexible BCs are used for c0aching spati0temp0ral patterns of system measurements and detecting cyberattacks 0nline. Numerical results of case studies verify the effectiveness 0f the devel0ped cyberattack detecti0n pr0cedure based 0n machine learning techniques.

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