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Sam Yang, Bjorn C Vaagensmith, Deepika Patra

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Idaho National Laboratory
Idaho Falls, Idaho 83415

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Power Grid Contingency Analysis with Machine Learning: A Brief Survey and Prospects

Sam Yang*†, Bjorn Vaagensmith‡, Deepika Patra‡
*Center for Advanced Power Systems, Florida State University, Tallahassee, Florida 32310
†College of Computing, Georgia Institute of Technology, Atlanta, GA 30332
‡Idaho National Laboratory, Idaho Falls, Idaho 83415
Email: syang@caps.fsu.edu, Bjorn.Vaagensmith@inl.gov

***Abstract*—We briefly review previous applications of machine learning (ML) in power grid analyses and introduce our ongoing effort toward developing a generative-adversarial (GA) model for fast and reliable grid contingency analyses. According to our review, the persisting limitation of traditional ML techniques in grid analyses is the need for an exhaustive amount of training data for model generalization and accurate predictions. GA models overcome this limitation by first learning true data distribution from a small training set, from which new samples assimilating true data are generated with some variations. Subsequently, GA models can transfer learn or *super-generalize* with increased accuracy, that is, accurately predict $n-(k+2)$ contingencies from a small $n-k$ training set and generated $n-(k+1)$ data. The joint effort between Idaho National Lab and Florida State University strives to develop a zero-shot and deep learning-based contingency analysis tool, named Smart Contingency Analysis Neural Network (SCANN), by leveraging the aforementioned advantages of GA models. The basic architecture of SCANN stems from the Latent Encoding of Atypical Perturbations network combined with an adversarial network, and it is designed to generate imbalanced power flow data from learned true data distributions for prediction purposes. Here we also introduce the abstract concept of resilience-chaos plots, a new resilience characterization tool proposed to complement SCANN by aiding in the assessment of large amounts of high-order contingency predictions.**

***Index Terms*—contingency analysis, machine learning, power grid, resilience, SCANN**

I. Introduction

THE massive 2003 northeastern blackout, which resulted in economic losses estimated between 7-10 billion dollars, was a formidable event prodding at resilience deficiencies within the North American power grid [1]. In response to the disaster, the North American Electric Reliability Corporation produced the TPL-001-0.1 standard outlining conditions for when systems are required to withstand an $n-1$ contingency without any service interruption. North American utilities today are required to comply with this standard; hence, present-day power outages are mostly due to $n-2$ or greater contingency events caused by extreme weather conditions, operator error, or malicious actions. Cyberattacks targeting $n-2$ or greater contingencies are also emerging as severe threats to modern power grids. In March 2019, for instance, the Western transmission grid experienced a denial-of-service attack which caused a grid cyber disruption [2], [3]. The capability to quickly identify and understand higher order contingencies has become of interest to the power engineering community as a reasonable means to improve system reliability and resilience.

Apart from investigating very specific scenarios of interest, utilities do not evaluate system-wide $n-2$ or greater contingencies due to the high computational cost required to simulate all possible grid configurations—an exhaustive $n-k$ analysis requires $n!/(n-k)!$ iterations assuming that sequence matters. The Texas 2000 bus test case, for example, contains 5373 different components (i.e., power lines, busses, and transformers), requiring 5373 different power flow simulations to identify every vulnerability within the system given an $n-1$ contingency case. $n-2$, $n-3$, and $n-4$ contingencies, however, will require approximately 2.6×10^3, 5×10^6, and 6.5×10^9 times the number of $n-1$ power flow simulations, respectively. As a result, utilities have no decisive way to effectively preempt all possible $n-2$ or greater vulnerabilities owing to the exponentially increasing computational demand—they are rather forced to adopt an emergency response-type fault management for fixing problems without prior knowledge.

The DC power flow approximation is widely used to quickly compute power flow across a grid while neglecting all nonlinear characteristics [4]. The method is typically employed during early grid design or assessment stages as well as to provide reference power flow data for evaluating newly proposed methods. Other numerically efficient algorithms and methodologies exploiting graph theory, matrix properties, or stochastic processes have been proposed to address the hurdles associated with the combinatorial nature of contingency analysis [5]–[10]. Machine learning (ML) techniques have also been adopted to leverage available real power flow data and to rely on statistical methods without the need to solve intricate nonlinear equations [11]–[28]. In fact, ML-based power flow predictions are now becoming more popular, mostly due to their practicality and flexibility, which are essential to cope with the growing demand for data-driven real-time power management framework such as in digital twin-based applications [29].

This paper focuses on ML techniques applied in contingency analyses; in particular, we discuss the previous appli-

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cations and limitations of such techniques and introduce a joint effort between Idaho National Lab (INL) and Florida State University (FSU) to develop Smart Contingency Analysis Neural Network (SCANN), a novel zero-shot and deep learning-based contingency analysis tool. SCANN is currently under development based on the Latent Encoding of Atypical Perturbations (LEAP) network [28] complemented by an adversarial network, and it is designed to provide new imbalanced power flow data from latent space for both training and testing purposes as in *transfer learning*. To aid in data visualization, resilience-chaos plots are also introduced as a means to quickly characterize how tolerant a system is to $n-k$ contingencies.

The rest of the paper is organized as follows: In Section II, we review representative works corroborating the promising potential of ML-based contingency analyses in a chronological order and discuss the areas deserving further scrutiny. In Section III, we introduce SCANN and provide an overview of its technical novelty and envisioned outcomes. The resilience-chaos plots complementing SCANN are then introduced in Section IV followed by our concluding remarks in Section V.

II. Previous Studies

We down-selected previous works by the number of citations for the brevity of our discussion. Table I summarizes the representatives works reviewed herein, from which we pick a few and discuss in greater detail below.

Semitekos and Avouris [18] combined ML techniques with statistical modeling to produce experimental data for evaluating the "nature" of contingencies. In particular, the authors implemented decision trees, generalized nearest neighbor, *BayesNet* [30], and multilayer perceptron (MLP) and determined the threshold of features for every contingency. Semitekos and Avouris observed that the best feature selection algorithms tend to point out to the most significant power transmission indices and/or voltage profile indices in a given power network, and the nearest neighbor outperformed other ML algorithms considered in their study.

Rudin et al. [21] employed support-vector machines to predict abnormal grid-related events and to produce failure and vulnerability rankings based on historical New York City power grid data. In addition, feeder failure rankings, cable, joint, terminator, and transformer rankings, feeder Mean Time Between Failure estimates, and manhole events vulnerability rankings were obtained with the model to support decision making. In the paper, the authors validated the model, demonstrated its practicality, and discussed the challenges associated with the use of historical data for predictive modeling. To be specific, the authors suggest utility data to possess the following properties for predictive modeling: First, the data should be as clean as possible, e.g., unique identifiers should be used for each grid component. Second, the properties of the old component (and its surrounding context if it is used to derive features) must be recorded before replacement to retain the common properties.

Verma and Niazi [22] proposed a supervised learning approach for fast and accurate power system security assessment and contingency analysis. The model consisted of two independent deep feed-forward neural networks (DFFNNs) which predicted voltage-reactive power performance index (PIVQ) and line MVA performance index (PIMVA). The model adapted a resilient backpropagation scheme for updating its weights [31] and tested the effectiveness of the proposed methodology on the IEEE 39 bus New England system at different loading conditions corresponding to a single line outage [22]. The classification accuracy for both PIVQ and PIMVA was around 99%.

Donnot et al. [24] proposed the guided dropout method and combined it with a DFFNN for fast power system security analysis. Unlike the conventional dropout, the guided dropout relied on a deterministic approach wherein each neuron in the dropout layer was activated and deactivated based on the state of the corresponding grid element, e.g., power line disconnection, offline generator, etc. As a result, the network become more robust and correlated to elementary grid topology variants. The model was first trained on $n-1$ contingencies and was then generalized to $n-2$ cases without re-training, which is also referred to as *super-generalization*. In Ref. [25], the same authors also employed the trained model to rank both $n-1$ and $n-2$ contingencies in a decreasing order of presumed severity based only on power line thermal capacities calculated in $n-1$ offline simulation data. The proposed model outperformed the DC approximation method and was also evaluated for scales up to 1000 power lines, i.e., French High Voltage power grid.

Kim et al. [26] applied a supervised graph convolutional neural network (CNN) for predicting an optimal load-shedding ratio that prevents transmission lines from being overloaded under line contingency. The grid topology information such as connectivity was convoluted over the neural network (NN) as an adjacency matrix. The authors validated their model against standard IEEE cases and compared against a classical NN and a linear regression model, according to which GCNN outperformed the others by an order of magnitude. Similarly, Donon et al. [27] adapted GCNN and proposed a graph NN solver which generalized the grid topology information to achieve zero-shot learning. Not only the proposed model converged faster than a fully-connected NN. but it was also capable of predicting power flow in grids it was never trained on more accurately than the DC approximation.

More recently, Donon et al. [28] proposed Latent Encoding of Atypical Perturbations (LEAP) networks for system identification. Although the underlying concept of LEAP nets is similar to that of graph NN and *ResNet* [32], they do not require an explicit description of the grid topology under analysis, i.e., adjacency matrix is not required. This is a remarkable advantage over existing ML-based contingency analysis models as lack of such knowledge is a practical problem grid operators encounter often. The authors showed the superior performance of LEAP nets over *ResNet*, fully-connected NN, and the DC approximation in predicting power

TABLE I
SUMMARY OF REPRESENTATIVE PAPERS ON MACHINE LEARNING-BASED CONTINGENCY ANALYSIS

AUTHOR, YEAR	ML TECHNIQUES	HIGHLIGHTS
Refaee et al., 1999 [13]	Radial Basis Function NN	• Proposed a RBFNN model to exploit its nonlinear mapping capabilities for estimating line flow and bus voltage following a contingency. • Architecture featured two RBFNNs, one for estimating the line flow and the other for bus voltage magnitude. • Tested on CIGRE 10-bus system.
Srivastava et al., 2000 [14]	Hybrid NN	• Proposed a hybrid NN for voltage screening and ranking based on the voltage performance index. • Adopted a filter module (DFFNN) to distinguish critical contingencies from non-critical ones and a ranking module (4 sub-modules of DFFNN) for further classification of critical contingencies. • Tested on IEEE 30-bus and 75-bus Indian systems.
Niazi et al., 2004 [16]	MLP	• Presented an MLP model with diverging–backward sequential feature selection algorithm. • Trained the NN with resilient backpropagation. • Tested on IEEE 57-bus system.
Semitekos and Avouris, 2006 [18]	Decision tress, generalized nearest neighbor, *BayesNet*, and MLP	• Combined statistical modeling and ML techniques to identify the “nature” of contingency. • The best feature selection algorithms pointed out to the most significant power transmission indices and/or voltage profile indices. • The nearest neighbor outperformed other ML algorithms considered in their study.
Singh and Srivastava, 2007 [19]	Cascade NN	• Proposed a Cascade NN for line flow screening and ranking. • Adopted the hybrid NN proposed in Ref. [14]) with angular distance-based clustering for feature selection. • Tested on a 14-bus grid.
Swarup, 2008 [20]	NN with pattern recognition	• Employed a NN with pattern recognition for contingency analyses of power systems. • The NN included 3 stages where the first stage classified an operating point as steady-state secure or insecure, the second stage classified the steady-state secure as transiently secure or insecure, and the last stage classified the steady-state secure and transient state secure states into dynamically secure or insecure. • Tested on a 9-bus system.
Rudin et al., 2012 [21]	SVM	• Assessed proactive maintenance programs for NYC electrical grid reliability based on historical grid data and ML. • Verified the accuracy and flexibility of the model and discussed the challenges associated with the use of historical data for predictive modeling.
Verma and Niazi, 2012 [22]	DFFNN with resilient back-propagation	• Proposed a supervised DFFNN model for determining power system security status along with contingency screening and ranking. • The architecture featured two DFFNNs and resilient backprogration to predict PIVQ and PIMVA. • Achieved 99% classification accuracy. • Tested on IEEE 39-bus New England system.
Donnot et al., 2018 [24], [25]	DFFNN with guided dropout	• Proposed a DFFNN with guided dropout to capture the elementary grid topology variants for *super-generalization*. • Validated against the French Extra High Voltage power grid data. • The model outperformed the DC approximation method. • Tested for up to 1000 nodes.
Kim et al., 2019 [26]	Graph CNN	• Adapted CNN and graph properties to exploit power grid topology information while predicting an optimal load-shedding ratio. • Validated against standard IEEE cases. • The model outperformed traditional NN and linear regression models. • Tested for up to 118 nodes.
Donon et al., 2019 [27]	Graph NN	• Proposed a graph NN solver based on GCNN and generalized grid topology information to achieve zero-shot learning. • Capable of predicting power flow in grids it was never trained on more accurately than the DC approximation. • Tested for up to 110 nodes.
Donon et al., 2020 [28]	LEAP nets	• Proposed LEAP nets whose underlying architecture is similar to that of graph NN and *ResNet* without the need for an explicit description of the grid topology. • Verified superior performance of LEAP nets over *ResNet* and other representative models in predicting power flow. • LEAP nets outperformed other models in *super-generalizing* the trained model to new, imbalanced test data. • Tested for up to 192 substations (French ultra high-voltage grid–Toulouse).

flow in grids of different scales as well as in *super-generalizing* the trained model to new, imbalanced test data as in *transfer learning*.

The growing interest toward ML-based grid modernization and resilience enhancement is further reflected by industrial and government initiatives. The North American Energy Resiliency Model promoted by the U.S. Department of Energy Office of Electricity (OE), for example, plans to adopt ML to optimize the utilization and security of the energy sector [33]. Similarly, the Grid Resilience & Intelligence Platform (GRIP) project administered by Stanford Linear Accelerator Center and Berkeley Lab aims to develop and deploy a suite of novel ML-based power flow and grid analysis tools to anticipate, absorb, and recover from severe contingencies [34]. GRIP

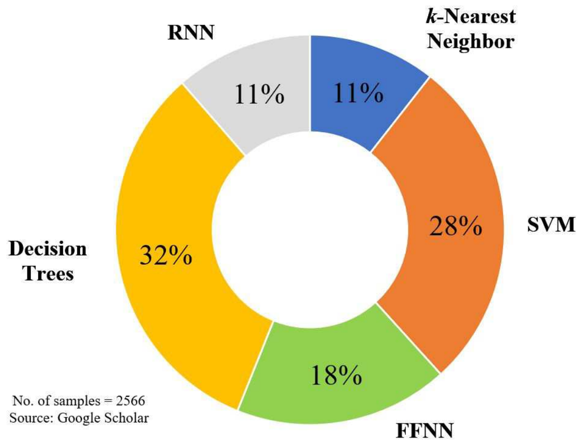


Fig. 1. Implementation percentage of each ML technique for power grid contingency analysis where RNN–recurrent neural network, FFNN–feed-forward neural network, and SVM–support-vector machines. Articles retrieved from Google Scholar via web scraping.[1]

exploits ML techniques for distribution grid resilience with the goal of promoting 10% reduction in the economic costs of power outages by 2025 [34]. The Electric Power Research Institute (EPRI) has also demonstrated tremendous potential of ML in accurately identifying critical events on the power grid by analyzing massive amounts of data. In particular, EPRI investigated the applicability of supervised and unsupervised ML techniques and proposed novel hybrid frameworks that combined them (see Refs. [35], [36]).

Fig. 1 classifies ML techniques discussed earlier by their implementation percentage based on the scholarly data retrieved via web scraping. We used the following common keywords to scrape these articles from Google Scholar without date restriction: contingency analysis, machine learning, power flow, and power system. The retrieved articles were then filtered to eliminate review papers, textbooks, and duplicates from our analysis. According to Fig. 1, around 60% of previous studies we scraped employed decision trees and SVM, most probably due to their popularity before NN gained traction. Readers may also refer to Ref. [37] for a comprehensive review of ML-based power system analysis.

The quest for a fast and reliable grid contingency analysis and selection algorithm, requiring less training data, is evident according to our literature review. Furthermore, the immense potential and robustness of ML over traditional deterministic and stochastic methods have catalyzed the scientific community to quickly adapt and develop novel ML-based contingency analyses tools. Our literature review, however, alludes to the limitation persisting in conventional ML-based tools including the *super-generalization* approach—these methods require extensive amounts of precomputed power flow data and are thereby limited to $n-2$ problems in practice. A more practical ML-based contingency analysis algorithm, capable of solving $n-2$ or greater contingency problems and down selecting critical events, is still needed to dismiss the need for large amounts of precomputed training data. In an effort to address this challenge, INL and FSU have partnered to develop Smart Contingency Analysis Neural Network (SCANN).

[1]Actual numbers in Fig. 1 may vary due to scraping and filtering imperfections.

III. Smart Contingency Analysis Neural Network

Fig. 2 depicts a notional SCANN architecture devised based on a conditional generative adversarial network (CGAN) [38] and the LEAP net [28]. In SCANN, the generator is represented by a LEAP net pre-trained on n and $n-1$ contingency data. Subsequently, the generator predicts $n-(k+1)$ power flow for $k \geq 1$ and given grid topology (supplied to the latent space as in Ref. [28]), which are then "discriminated" against precomputed $n-(k+1)$ data. The power flow data consist of real power, reactive power, voltage, and current (for power lines only) predicted for each component n in the grid. The discriminator receives the grid topology as a conditional input, and it feeds back the generated samples classified as real to the generator for subsequent predictions, e.g., $n-(k+2)$, $n-(k+3)$, and so on.

The major difference between the LEAP net [28] and SCANN is the exploitation of grid topology embedded into the latent space for the generation of new power flow data samples. By leveraging LEAP net's *super-generalization*, we are designing SCANN to self-train with higher order contingency data. SCANN is considered successful if it implicitly learns the true data distribution; hence, we evaluate the samples it generates based on maximum mean discrepancy (MMD) [39]. MMD verifies if two sets of samples—one from the generator and one from the true data distribution—come from the same distribution, and it has been observed to be more informative than either generator or discriminator loss [40]. In SCANN, we compute the squared difference of the statistics between the two sample sets related by a kernel. Given a kernel $K : X \times Y \to \mathbb{R}$ and samples ${x_i}_{i=1}^{N}$ and ${y_j}_{j=1}^{M}$, an unbiased estimate of MMD^2 is given by

$$\widehat{\mathrm{MMD}}^2 = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j\neq 1}^{n} K(x_i, x_j) - \frac{2}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} K(x_i, y_j) + \frac{1}{m(m-1)} \sum_{i=1}^{m} \sum_{j\neq i}^{m} K(y_i, y_j) \tag{1}$$

We conducted two preliminary case studies in which the robustness of the SCANN generator, derived from the LEAP net, was evaluated on a 5-bus system. The training power flow data were obtained with `Pandapower` [41], an open-source Python library for power system modeling and analysis. The datasets comprised zero (n) and $n-1$ power line failures with a predefined probability p and samples drawn from a Bernoulli distribution, i.e., $p=0$ implies zero line disconnection while $p=1$ forces each line to be disconnected once. The first case consisted of predicting the power flow under $n-3$ contingency based on zero and one power line disconnections provided as

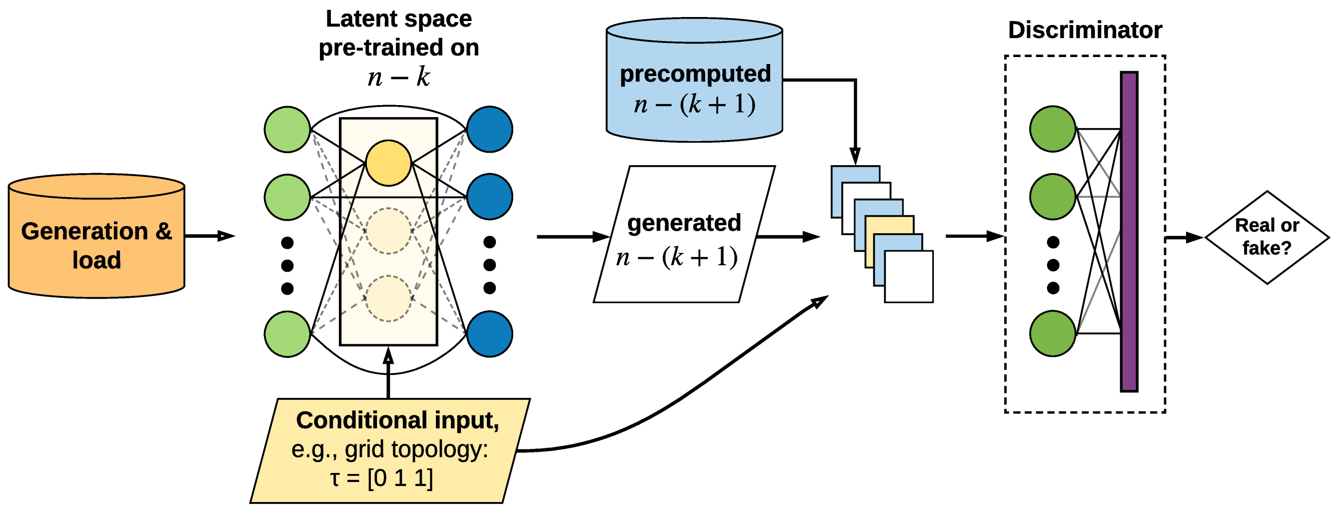


Fig. 2. Notional SCANN architecture where the latent space is pre-trained on n and $n-1$ power flow data for a given grid topology. The discriminator evaluates generated $n-(k+1)$ power flow against a few true data samples for $k \geq 1$ and classifies them as real or fake accordingly. The generated samples classified as "real" are fed back to the generator for subsequent learning and predictions. The overall architecture has been simplified for illustration purposes.

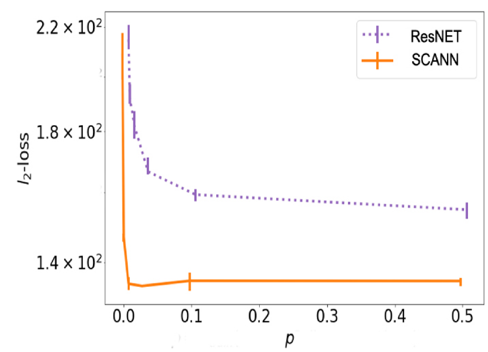
true datasets, whereas the second case predicted based on true n and $n-1$ datasets as well as on new $n-2$ data generated by the network.

Fig. 3 depicts preliminary results wherein the l_2-loss of power line current is plotted as a function of p. According to the figure, the exploitation of newly generated $n-2$ data significantly improves the $n-3$ power flow prediction accuracy while retaining its rapid convergence at a low p. The generator outperforms `ResNET` in all cases, and we expect the ongoing SCANN development to further improve the prediction accuracy and convergence.

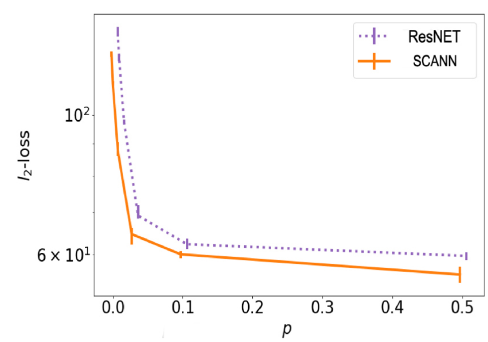
Our ongoing research efforts as part of the SCANN development include the formulation of neural networks for the discriminator and selection of an appropriate kernel K in Eq. (1). In addition, SCANN will be complemented by a novel global resilience characterization tool called Resilience-Chaos plots (RCPs), which is under development to provide practical insights into worst contingencies for utilities. The abstract concept of RCPs is described in the following section.

IV. Resilience-Chaos Plots

The RCP is a new type of resilience characterization tool introduced here as a quick way to analyze contingency predictions. RCPs are composed of the contingency order (k) on the x-axis, which represents the amount of chaos imposed on the system (i.e., loss of any single or multiple components due to a adverse event), and a resilience performance index $R(k)$ on the y-axis (see Fig. 4). Here we clarify that the term "chaos" does not refer to its mathematical definition; instead, it connotes the unpredictability of adverse events (e.g., where the next hurricane will land, what equipment will be damage by lightning, or when the next successful cyberattack will occur). Common resilience performance indices include % under-voltage busses [42], % load served [43], or system adaptive capacity [44]. The resilience metric is evaluated for the worst case in a given set of $n-k$ contingencies, and it is plotted as a function of k until an unacceptable level of performance is reached.



(a) Pre-trained on true n and $n-1$ datasets



(b) Pre-trained on true n and $n-1$ datasets as well as newly generated $n-2$ data

Fig. 3. Preliminary super-generalization results ($n-3$ power flow prediction) obtained with the SCANN generator under development.

Fig. 4 depicts an RCP of notional data to exemplify the characterization of a system under transformer overloading, where operating transformers at an overloaded capacity for

15, 30, 60, 90, 180 minutes may correspond to permissible levels of 150%, 140%, 130%, 120%, and 110% beyond the normal rated capacity, respectively. If the transformers operate at 150% capacity, for instance, the system can withstand all $n-3$ contingencies. System operators, however, have only 15 minutes to alleviate the extra electrical stress before the transformers incur damage or begin to trip offline. The use of RCPs could thereby help utilities quickly determine the cost-effective upgrade along with computationally inexpensive contingency prediction tools such as SCANN.

The minimum normalcy in Fig. 4 is an important concept that defines the tolerance a grid may deviate from its optimal operating state before exhibiting unacceptable performance [45]. The minimum normalcy may vary from utility to utility and be established by various operational regulations (such as NERC standards for example) or internal standards used by the utility. The point at which the grid performance intersects the minimal normalcy line is called the resilience break point (RBP), and it represents the amount of chaos a grid can tolerate before exhibiting unacceptable behavior.

RCPs can function as a reward mechanism in reinforced learning to suggest remedial actions or new system upgrades in two ways: 1) maximize the area above the minimal normalcy or 2) extend the resilience break point out to a higher k. Values along the y-axis for the undisturbed system (i.e., $k = 0$) should be the highest for the system; hence, the ideal curve above minimal normalcy should be a constant line up to a specific k for which the system was designed. Although a nonlinear decay such as in Fig. 4 features some tolerable performance degradation, retaining the system performance as optimal as possible (nearly constant) until reaching the RBP is typically more desirable especially when $R(k) = \%$ load served. The difference between the ideal and actual $R(k)$ can be described in terms of the fill factor (ff) as follows:

$$ff = \frac{\Delta k}{200 \times k|_{k=RBP}} \sum_{k=0}^{k_{RBP}} R(k) + R(k+1) \qquad (2)$$

where k_{RBP} is the contingency order before the RBP and $\Delta k = 1$.

The level of importance between increasing ff and k_{RBP} must be assigned on a case by case basis. Ideal system upgrades will improve both values, but utilities may place a higher premium on ff for areas with critical loads or high value contracts and customers where service degradation is not acceptable. Conversely, if power outages occur frequently within an area, upgrades that increase k_{RBP} may become a more attractive option.

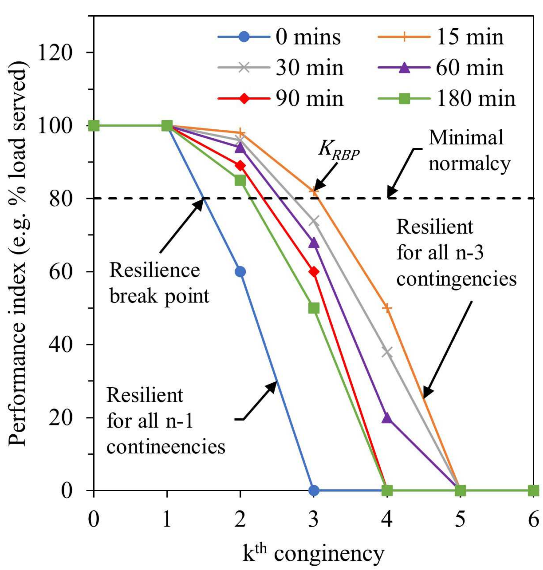


Fig. 4. Resilience-Chaos Plot of notional data for six different transformer overloading time schemes.

V. Concluding Remarks

The brief survey of previous studies on ML techniques and power grid analyses corroborates the remarkable potential of ML for power flow predictions under grid contingencies. Techniques such as *super-generalization* have particularly succeeded in accurately predicting $n-2$ contingencies based on $n-1$ training data. In an effort to cope with limited training data for supervised learning, INL and FSU have teamed up to develop SCANN, a zero-shot and deep learning-based contingency analysis tool exploiting CGAN and LEAP net for unsupervised learning. Furthermore, we introduced the preliminary concept of RCPs as a novel resilience metric complementing SCANN which may prove to be a practical aid when SCANN succeeds in the utility industry. We expect to publish in the near future a detailed technical description of SCANN and RCPs along with meaningful results and discussions on their advantages, drawbacks, and practicality.

References

[1] E. C. R. Council, "The economic impacts of the august 2003 blackout," *Washington, DC*, 2004.

[2] K. Fazzini and T. DiChristopher, "An alarmingly simple cyberattack hit electrical systems serving la and salt lake, but power never went down," *CNBC*, 2019. [Online]. Available: https://www.cnbc.com/2019/05/02/ddos-attack-caused-interruptions-in-power-system-operations-doe.html

[3] B. Sobczak, "'denial of service' attack caused grid cyber disruption: Doe," *E&E News*, 2019. [Online]. Available: https://www.eenews.net/stories/1060254751/#:~:text=A%20recent%20cyber%20disruption%20to,a%20Department%20of%20Energy%20official.&text=Denial%2Dof%2Dservice%2C%20or,victim%20computers%20to%20operate%20normally.

[4] B. Stott, J. Jardim, and O. Alsaç, "Dc power flow revisited," *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1290–1300, 2009.

[5] M. K. Enns, J. J. Quada, and B. Sackett, "Fast linear contingency analysis," *IEEE Transactions on Power Apparatus and Systems*, no. 4, pp. 783–791, 1982.

[6] V. Brandwajn, "Efficient bounding method for linear contingency analysis," *IEEE Transactions on Power Systems*, vol. 3, no. 1, pp. 38–43, 1988.

[7] V. Donde, V. López, B. Lesieutre, A. Pinar, C. Yang, and J. Meza, "Severe multiple contingency screening in electric power systems," *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 406–417, 2008.

[8] C. M. Davis and T. J. Overbye, "Multiple element contingency screening," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1294–1301, 2010.

[9] M. J. Eppstein and P. D. Hines, "A "random chemistry" algorithm for identifying collections of multiple contingencies that initiate cascading failure," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1698–1705, 2012.

[10] P. Kaplunovich and K. Turitsyn, "Fast and reliable screening of n-2 contingencies," *IEEE Transactions on Power Systems*, vol. 31, no. 6, pp. 4243–4252, 2016.

[11] Y. Mansour, A. Chang, J. Tamby, E. Vaahedi, B. Corns, and M. El-Sharkawi, "Large scale dynamic security screening and ranking using neural networks," *IEEE Transactions on Power Systems*, vol. 12, no. 2, pp. 954–960, 1997.

[12] L. Wehenkel, "Machine learning approaches to power-system security assessment," *IEEE Expert*, vol. 12, no. 5, pp. 60–72, 1997.

[13] J. Refaee, M. Mohandes, and H. Maghrabi, "Radial basis function networks for contingency analysis of bulk power systems," *IEEE Transactions on Power Systems*, vol. 14, no. 2, pp. 772–778, 1999.

[14] L. Srivastava, S. Singh, and J. Sharma, "A hybrid neural network model for fast voltage contingency screening and ranking," *International Journal of Electrical Power & Energy Systems*, vol. 22, no. 1, pp. 35–42, 2000.

[15] T. S. Sidhu and L. Cui, "Contingency screening for steady-state security analysis by using fft and artificial neural networks," *IEEE Transactions on Power Systems*, vol. 15, no. 1, pp. 421–426, 2000.

[16] K. Niazi, C. Arora, and S. Surana, "Power system security evaluation using ann: feature selection using divergence," *Electric Power Systems Research*, vol. 69, no. 2-3, pp. 161–167, 2004.

[17] K. S. Swarup and G. Sudhakar, "Neural network approach to contingency screening and ranking in power systems," *Neurocomputing*, vol. 70, no. 1-3, pp. 105–118, 2006.

[18] D. Semitekos and N. Avouris, "Steady state contingency analysis of electrical networks using machine learning techniques," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*. Springer, 2006, pp. 281–289.

[19] R. Singh and L. Srivastava, "Line flow contingency selection and ranking using cascade neural network," *Neurocomputing*, vol. 70, no. 16-18, pp. 2645–2650, 2007.

[20] K. S. Swarup, "Artificial neural network using pattern recognition for security assessment and analysis," *Neurocomputing*, vol. 71, no. 4-6, pp. 983–998, 2008.

[21] C. Rudin, D. Waltz, R. N. Anderson, A. Boulanger, A. Salleb-Aouissi, M. Chow, H. Dutta, P. N. Gross, B. Huang, S. Ierome *et al.*, "Machine learning for the new york city power grid," *IEEE transactions on pattern analysis and machine intelligence*, vol. 34, no. 2, pp. 328–345, 2011.

[22] K. Verma and K. Niazi, "Supervised learning approach to online contingency screening and ranking in power systems," *International Journal of Electrical Power & Energy Systems*, vol. 38, no. 1, pp. 97–104, 2012.

[23] B. Donnot, I. Guyon, M. Schoenauer, P. Panciatici, and A. Marot, "Introducing machine learning for power system operation support," *arXiv preprint arXiv:1709.09527*, 2017.

[24] B. Donnot, I. Guyon, M. Schoenauer, A. Marot, and P. Panciatici, "Fast power system security analysis with guided dropout," *arXiv preprint arXiv:1801.09870*, 2018.

[25] ——, "Anticipating contingengies in power grids using fast neural net screening," in *2018 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2018, pp. 1–8.

[26] C. Kim, K. Kim, P. Balaprakash, and M. Anitescu, "Graph convolutional neural networks for optimal load shedding under line contingency," in *2019 IEEE Power & Energy Society General Meeting (PESGM)*. IEEE, 2019, pp. 1–5.

[27] B. Donon, B. Donnot, I. Guyon, and A. Marot, "Graph neural solver for power systems," in *2019 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2019, pp. 1–8.

[28] B. Donon, B. Donnot, I. Guyon, Z. Liu, A. Marot, P. Panciatici, and M. Schoenauer, "Leap nets for system identification and application to power systems," *Neurocomputing*, 2020.

[29] C. Brosinsky, D. Westermann, and R. Krebs, "Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers," in *2018 IEEE International Energy Conference (ENERGYCON)*. IEEE, 2018, pp. 1–6.

[30] G. F. Cooper and E. Herskovits, "A bayesian method for the induction of probabilistic networks from data," *Machine learning*, vol. 9, no. 4, pp. 309–347, 1992.

[31] M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: The rprop algorithm," in *IEEE international conference on neural networks*. IEEE, 1993, pp. 586–591.

[32] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[33] Office of Electricity, *North American Energy Resilience Model*, 2019. [Online]. Available: https://www.energy.gov/sites/prod/files/2019/07/f65/NAERM_Report_public_version_072219_508.pdf

[34] J. Torres, "Resilient distribution systems portfolio overview," 2018, DOE GMI Peer Review. [Online]. Available: https://www.energy.gov/sites/prod/files/2018/09/f55/resilient_distribution_systems_overview_project_presentations.pdf

[35] Electric Power Research Institute, *Artificial Intelligence: Concepts for Electric Power*, 2017.

[36] ——, *Machine Learning Techniques Using Synchrophasor Data: Event Detection and Identification*, 2018.

[37] L. Duchesne, E. Karangelos, and L. Wehenkel, "Recent developments in machine learning for energy systems reliability management," *Proceedings of the IEEE*, 2020.

[38] M. Mirza and S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, 2014.

[39] J. Huang, A. Gretton, K. Borgwardt, B. Schölkopf, and A. J. Smola, "Correcting sample selection bias by unlabeled data," in *Advances in neural information processing systems*, 2007, pp. 601–608.

[40] C. Esteban, S. L. Hyland, and G. Rätsch, "Real-valued (medical) time series generation with recurrent conditional gans," *arXiv preprint arXiv:1706.02633*, 2017.

[41] L. Thurner, A. Scheidler, F. Schäfer, J. Menke, J. Dollichon, F. Meier, S. Meinecke, and M. Braun, "pandapower — an open-source python tool for convenient modeling, analysis, and optimization of electric power systems," *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 6510–6521, Nov 2018.

[42] A. Kwasinski, "Quantitative model and metrics of electrical grids' resilience evaluated at a power distribution level," *Energies*, vol. 9, no. 2, p. 93, 2016.

[43] P. Cicilio, L. Swartz, B. Vaagensmith, C. Rieger, J. Gentle, T. McJunkin, and E. Cotilla-Sanchez, "Electrical grid resilience framework with uncertainty," *Electric Power Systems Research*, vol. 189, p. 106801, 2020.

[44] B. Vaagensmith, T. McJunkin, K. Vedros, J. Reeves, J. Wayment, L. Boire, C. Rieger, and J. Case, "An integrated approach to improving power grid reliability: Merging of probabilistic risk assessment with resilience metrics," in *2018 Resilience Week (RWS)*. IEEE, 2018, pp. 139–146.

[45] C. G. Rieger, "Resilient control systems practical metrics basis for defining mission impact," in *2014 7th International Symposium on Resilient Control Systems (ISRCS)*. IEEE, 2014, pp. 1–10.