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Generative Adversarial Networks-Based Synthetic PMU Data Creation for Improved Event Classification

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ABSTRACT A two-stage machine learning-based approach for creating synthetic phasor measurement unit (PMU) data is proposed in this article. This approach leverages generative adversarial networks (GAN) in data generation and incorporates neural ordinary differential equation (Neural ODE) to guarantee underlying physical meaning. We utilize this approach to synthetically create massive eventful PMU data, which would otherwise be difficult to obtain from the real world due to the critical energy infrastructure information (CEII) protection. To illustrate the utility of such synthetic data for subsequent data-driven methods, we specifically demonstrate the application of using synthetic PMU data for event classification by scaling up the real data set. The addition of the synthetic PMU data to a small set of real PMU data is shown to have improved the event classification accuracy by $\mathbf{2}$ to $\mathbf{5}$ percent.

INDEX TERMS Event classification, phasor measurement unit, generative adversarial network, neural ODE.

I. INTRODUCTION

PHASOR Measurement Units (PMU) have been deployed in the bulk transmission grid at an accelerated pace after the 2003 U.S. Blackout [1]. Similarly, a number of other high-resolution and time-synchronized measurement devices such as frequency disturbance recorders (FDRs) have been pilot-tested and deployed into the power grid. Collectively, these measurement devices enable improved monitoring and control of power system dynamics at a higher resolution.

As an important application for improving the situational awareness, the event classification is usually triggered upon the detection of an event. A timely and accurate event classification result can further serve as the basis for remedial, preventive and proactive controls. Based on the current literature, there are two categories of approaches for event classification: model-based approaches and data-driven approaches. Several model-based approaches are briefly summarized in [2] and its references, which will not be discussed in detail here. It should be noted that all model-based event classification approaches would encounter certain difficulties when there is a significant gap between the available system model and the physical reality [3], [4]. In this case, data-driven approaches seem to be more suitable, since they are directly based on the measurement data reflecting the actual status of electrical quantities in power grids. Machine learning-based event classification has been proposed and developed in the past two decades exhibiting promising results [2], [5]–[7]. Even regardless of data quality issues, a major hurdle to apply these machine-learning based classifiers is usually a lack of a sufficient data set for training. It is well-known that more eventful data usually lead to a better classification accuracy [5], [6]. However, it is extremely difficult, if not infeasible, to acquire enough eventful data in practice [5]. It is also worth mentioning that simulated data based on system model is always preferred in training as long as the system model is available and accurate. However, as discussed above, an accurate system model in reality is currently not available for most bulk power systems, while this situation will most likely remain unchanged in the foreseeable future [3], [4].

To this end, this article aims at improving the classification accuracy of machine learning-based event classifiers by scaling up the limited available eventful PMU data set. The key idea is to create massive realistic synthetic eventful data from the given limited real data using the proposed two-stage method that leverages GAN and Neural ODEs. Then, given arbitrary common machine learning-based event classification method, the training data set enriched by the synthetic data can contribute to improving the classification accuracy. The key to the success of the proposed idea is to make sure that the synthetic data are realistic and diverse rather than a simple clone of the real data, which is achieved by the proposed two-stage PMU data creation algorithm.

Main contributions of this article are summarized as follows:

1) *Networked PMU Data Generation*: The proposed two-stage networked eventful PMU data creation method can create multiple realistic-looking networked PMU streams that respect the physical constraints and incorporate the ordinary differential equation (ODE) format.
2) *High Computational Efficiency*: Leveraging the insights of the temporal and spatial correlations among PMU streams, the number of synthetic PMUs is determined as the number of generators under the adopted modeling, which is a significant reduction. The two-stage design of the networked PMU data generation algorithm reduces the size of machine learning models and mitigates the computational burden.
3) *Event Classification Improvement*: We show that the created synthetic data can be used to enrich the training data set, thereby improving the event classification accuracy of four popular machine-learning based approaches, especially when the size of the training data set is very limited as is always true in the real practice.

The rest of the paper is structured as follows: Section II introduces the problem of machine-learning based synthetic PMU data creation. Section III briefly reviews the basic ideas of the GAN and Neural ODE models to be adopted in this article. Section IV proposes a two-stage networked eventful PMU data creation algorithm and the associated synthetic data quality check method, and introduces its application on the event classification. Section V presents the case study on the IEEE 39-bus system. Section VI draws conclusions and envisions future works.

II. SYNTHETIC PMU DATA CREATION

To address the shortage of eventful PMU data without relying too heavily on an accurate system dynamic model, we exploit the limited real eventful PMU data by the proposed two-stage GAN-based data creation method to create massive synthetic data. This section introduces the problem statement of machine learning-based synthetic PMU data creation, its associated challenges, and the simplification of the problem by leveraging power system dynamic analysis.

A. PROBLEM STATEMENT

Consider a set of labeled historical PMU measurement obtained covering pre-event, during event and post-event periods, where the label refers to the event type. For PMU i, we denote historical phasor domain voltage and current data by V_i and I_i, which are collected by a time window of T with a time step ΔT. Define one entire sample of an event as $S = [V_1, I_1, \ldots, V_{N_{\mathrm{PMU}}}, I_{N_{\mathrm{PMU}}}]$, where N_{PMU} is the total number of PMUs. The data creation problem tackled by this article is *to develop a data creation algorithm to create synthetic eventful PMU data* $\tilde{S}$ *of certain event type using the corresponding labeled historical samples* $\{S_i\}_{i=1}^{N_S}$ *as the training data, where* N_S *is the number of the historical samples, in such a way that the created synthetic data exhibit relevant properties possessed by the historical data.*

B. CHALLENGES

There are two key challenges for creating synthetic eventful PMU data using any machine-learning based approach: (i) How to make sure that the created PMU data are meaningful, e.g. complying circuit laws for the network and respecting underlying dynamic behavior of dynamic elements? (ii) How to train the neural network in a computationally tractable way? These two challenges are briefly discussed below and will be tackled in the next subsection and two following sections.

1) FIDELITY

Fidelity is a major criteria of the synthetic data quality and also the key for the success of improving event classification. The synthetic PMU data should be physically meaningful, i.e. complying the spatial and temporal correlation in the real data. Here, the spatial correlation is dominated by the Kirchhoff's voltage and current laws which have to be satisfied at each snapshot definitely, and the temporal correlation mainly stems from dynamic elements which are commonly modeled by ODEs. We will show how the spacial and temporal correlations are respected respectively in Section II-C and Section IV-A.

2) COMPUTATIONAL EFFICIENCY

Different from the most popular application field such as image generation, the size of GAN model for time series data is influenced by two key factors: the length of time window and the number of channels. In the context of our problem, both factors are obviously non-trivial, which may lead to an extremely large neural network model and hence render the training process intractable. We will introduce a two-stage GAN-based algorithm in Section IV-A as the solution.

C. PROBLEM SIMPLIFICATION

We first give a brief description about the power systems dynamics. The intuition from this domain knowledge is then used to precisely characterize the spatial and temporal correlation, which are then exploited in developing the GAN-based networked eventful PMU data creation method.

Consider a power system with N_{b} buses and N_{br} branches (including lines and transformers). We denote the actual voltage at bus i by $V_i, i = 1, \ldots, N_{\mathrm{b}}$. We assume all key dynamic elements in power systems are equipped with PMUs, because an NERC Reliability Guideline [8] recommends to place PMUs near significant generating plants, large load buses and grid control devices. For simplicity, this article only considers generators as dynamic elements and also treats all loads as constant impedance.

The dynamic model of a power system contains two parts: differential equations and algebraic equations [9]. Differential equations characterize the temporal dependence through the the dynamics of inner states of generators, while the algebraic equations characterize the spatial dependence though the Kirchhoff's laws. Assume there are N_{g} generator buses in the system and all loads are represented by constant impedance. Let x_i denote the state vector of generator i, usually including rotor angle δ_i, angular speed ω_i and other state variables. The dynamics of ith generator are dominated by

$$\dot{x}_i = f_i(x_i, V_i, I_{dqi}) \tag{1}$$

where I_{dqi} is the dq-axis currents.

The algebraic equations have two parts, stator algebraic equation and network algebraic equation. The stator algebraic equation of the ith generator is given by

$$\begin{aligned} 0 = |V_i|e^{j\theta_i} + (R_{si} + jX'_{di})(I_{di} + jI_{qi})e^{j(\delta_i - \pi/2)} \\ - [E'_{di} + (X'_{qi} - X'_{di})I_{qi} + jE'_{qi}]e^{j(\delta_i - \pi/2)} \end{aligned} \tag{2}$$

where R'_{si}, X'_{di} and X'_{qi} are constant resistance and impedance parameters; $|V_i|$ and θ_i are the magnitude and angle of the terminal voltage V_i; E'_{di} and E'_{qi} are inner voltage state variables included in x_i. This equation can be succinctly written as

$$I_{dqi} = h_i(x_i, V_i). \tag{3}$$

Equations (1) and (3) indicate the temporal correlation among generator buses, echoing the challenges mentioned in Section II-B.

Under the constant impedance load assumption, all loads can be included in the admittance matrix Y. Then, the network equation is given by

$$\begin{bmatrix} I_1^{\mathrm{inj}} \\ \cdots \\ I_{N_{\mathrm{g}}}^{\mathrm{inj}} \\ 0 \\ \cdots \\ 0 \end{bmatrix}_{N_{\mathrm{b}} \times 1} = [Y]_{N_{\mathrm{b}} \times N_{\mathrm{b}}} \begin{bmatrix} V_1 \\ \cdots \\ V_{N_{\mathrm{b}}} \end{bmatrix}_{N_{\mathrm{b}} \times 1} \tag{4}$$

where Y is the admittance matrix containing impedance load and I_i^{inj} is the current injection from generator i.

One can show that, using Kron reduction [9], the network with N_{b} buses can be reduced to a system with only N_{g} generator internal buses. Note that although this article only considers generators as dynamic elements for simplicity, Kron reduction can be extended to reduce the network to a smaller system only containing the buses connected to dynamic elements, e.g. generators, dynamic loads and static VAR compensators.

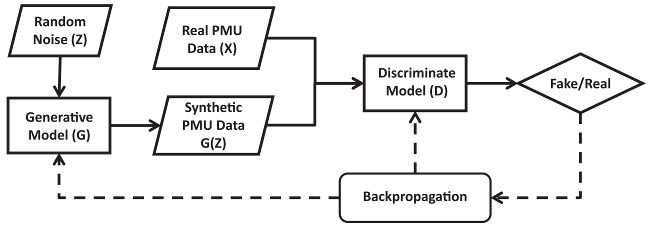


FIGURE 1. The architecture of vanilla GAN [10].

Define $S' = [V_{n_1}, I_{n_1}, \ldots, V_{n_{N_{\mathrm{g}}}}, I_{n_{N_{\mathrm{g}}}}]$, where n_i is the PMU number of the generator bus i. The target problem can be simplified and becomes *to develop a data creation algorithm to create synthetic eventful PMU data $\tilde{S}'$ of certain event type using the corresponding labeled historical samples $\{S'_i\}_{i=1}^{N_S}$ as the training data in such a way that the created synthetic data exhibit relevant properties possessed by the historical data.*

We will achieve it by the GAN-based networked PMU data creation method to be introduced in Section IV-A.

III. REVIEW OF GAN AND NEURAL ODE

This section reviews the basic ideas of the GAN and Neural ODE models that will be adopted in this article to establish the two-stage GAN-based eventful PMU data creation algorithm.

A. GAN

GAN was proposed in [10] which has now arguably became one of the most popular and successful deep generative models. Fig. 1 shows the architecture of vanilla GAN [10].

Both generative model (generator) G and discriminate model (discriminator) D are implemented by neural networks, which are trained by optimizing the following objective function J:

$$\min_G \max_D J = \mathop{\mathbb{E}}_x \log(D(x)) + \mathop{\mathbb{E}}_z \log(1 - D(G(z))) \tag{5}$$

The interpretation is following: (i) The model G is trained to be a function that outputs synthetic data given random noise as its input. Given a batch of noise data as input, a well-trained model G should generate a batch of diverse realistic-looking data. (ii) The model D takes input data sampled from either the real data set or the synthetic data set. Its output, a scalar ranging from 0 to 1, indicates the likelihood that the input data belongs to the real data set. The goal of discriminate model D is to correctly distinguish the real PMU data from the synthetic ones by maximizing the difference between the output scalars of real and synthetic data..

Because of its simple but powerful idea, GAN has achieved a great success in computer vision and a few other fields, of which the representatives are domain transferring of images [11], discrete and continuous time series data creation [12], time series and mixed-type data modeling [13] and etc. There are also a few efforts applying GAN to power systems, including but not limited to renewable scenario generation

[14], local marginal price prediction [15], PMU data creation [16], dynamic security assessment [17] and etc.

However, considering the challenge of temporal correlation, our problem formulation as described in Section II is significantly different from the standard application of GAN for computer vision or renewable energy data creation in power systems [14], where the data can be appropriately characterized by statistical properties. The straightforward application of GAN for generating PMU data independently at each bus [16] obviously cannot yield realistic network-level synthetic PMU data due to the neglect of temporal and spatial correlations. To this end, we will propose a two-stage GAN-based networked eventful PMU data creation algorithm in Section IV-A, which effectively addresses these challenges.

B. NEURAL ODE

Neural ODE [18] was proposed as a new family of deep neural network models in 2018. This model contains two key components: a *neural network* and an *ODE solver*. Instead of specifying a discrete sequence of hidden layers, this model parameterizes the derivative of the state, i.e. a function of state, time and parameters, using a neural network f:

$$\frac{ds(t)}{dt} = f(s(t), t, \theta_f) \tag{6}$$

where θ_f is the parameters of the neural network and $s(t)$ is the state at time t. Given an initial state $s(0)$, the ODE solver can numerically integrate f and generate the system trajectory. Such a feature makes the Neural ODE model inherently suitable for the continuous time series modelling. In the power system literature, a Neural ODE-based approach was proposed for demand forecasting within power grid digital twin framework [19].

In the context of our problem, with the voltage measurements at all generator buses as the state, the corresponding f function of the post-event time series is time-invariant according to the analysis in Section II. In other words, given an initial state, the entire trajectory is uniquely defined. Therefore, we intuitively use the Neural ODE to implement the post-event time series modelling by supervised learning. The Neural ODE model will be another core of the proposed two-stage networked eventful PMU data creation algorithm.

IV. IMPROVEMENT OF MACHINE-LEARNING BASED EVENT CLASSIFICATION BY SYNTHETIC PMU DATA

A. GAN-BASED NETWORKED EVENTFUL PMU DATA CREATION

The temporal and spatial correlations of the real PMU data make our data creation problem fundamentally different from any standard applications of GAN for image generation [10] or for renewable energy data creation in power systems [14]. Although the reduced model in Section II-C can effectively addresses the spatial correlation problem, there are still two problems left unsolved: (i) The temporal correlation that is dominated by ODEs may not be precisely captured by the regular GAN models. (ii) Regular GAN models may induce extremely high computation burden and result in an intractable training process when applied to generating networked eventful PMU data.

To address the aforementioned challenges, a novel two-stage GAN-based algorithm is proposed as shown in Fig. 2, where GAN creates synthetic data including PMU data during the events and initial state of post-event time series, while Neural ODE creates the post-fault time series given the initial state. In the training process, we train the GAN and Neural ODE models separately with the limited real PMU data. In the data creation process, we combine the well-trained G and f models to generate the PMU data of an entire event, where the G model feeds part of its output to the Neural ODE as its initial state.

The above idea is inspired by the work [13]. The difference is that we train the generative models of the discrete and continuous data separately. Specifically, in the training process, we train the GAN model with the objective function in Equation (5) to generate the measurements from t_b^+ to t_e^- and at t_e^+, where t_b and t_e respectively refer to the beginning and end of the event period,[1] and $-/+$ represents the instant before/after the corresponding time. Therefore, the PMU measurements at t_e^+ are the first data point of the post-event time series, which are used as the initial state of the Neural ODE model. On the other hand, the Neural ODE model is trained independently by a supervised learning to minimize the scalar-valued loss function in (7).

$$\min \quad L(s) = \frac{1}{t_1 - t_0} \sum_{t=t_0}^{t_1} ||\bar{s}(t) - s(t)||_2 \tag{7}$$

where $\bar{s}(t) = \int_{x=t_0}^{t} f_{\theta_f}(x)dx|_{\bar{s}(t_0)=s(t_0)}$, $s(t)$ is the post-event measurement at time t, and the function f is a neural network parameterized by θ_f. Note that since we assume the post-event power system model is a time-invariant dynamic system, we can randomly sample arbitrary PMU data segments in the post-event period as the training data of the Neural ODE model.

After the GAN and Neural ODE models are well-trained, they are combined as shown in Fig. 2 as a complete networked PMU data creation model, where the G model generates PMU measurements during the events and initial state of the post-fault time series while the model f generates the whole post-fault time series given the synthetic initial state by G.

The algorithm of detailed training procedures is shown in Algorithm 1, where θ_D, θ_G and θ_f are respectively the parameters of the G, D and Neural ODE f models, N_{GAN} and N_{ODE} are the pre-specified numbers of training epochs respectively for GAN and Neural ODE models, m_b is the minibatch size, ΔT is the time step of real PMU data and $p\Delta T$ is the user-defined time window.

[1] Note that identifying t_b and t_e could be a challenging task when handling real eventful PMU data. However, in this article, it is not our focus to precisely identify these moments. In all tested cases in this article, we assume that these moments are known, e.g. from simulation settings, and we leave the impact study of inaccurate t_b and t_e as our future work.

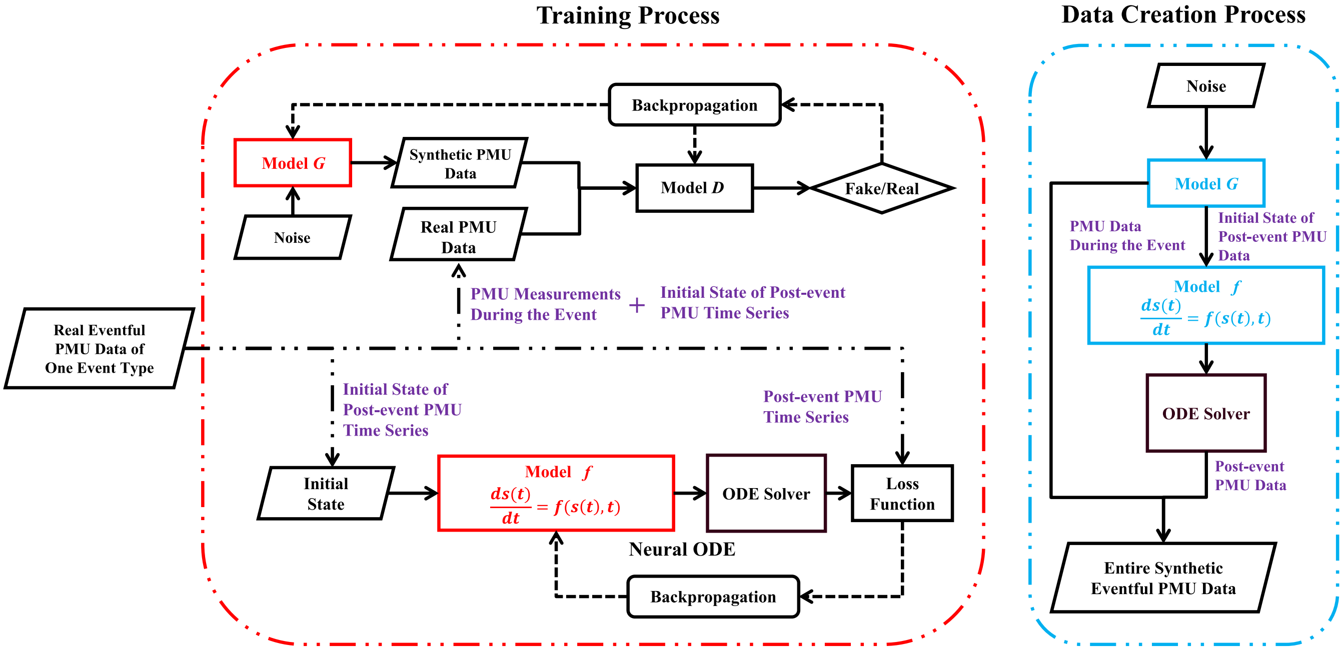


FIGURE 2. The proposed two-stage GAN algorithm incorporating the architecture of GAN and Neural ODE models. In the training process, the *G* model is trained to generate the PMU measurements during the events while the Neural ODE model aims to implement the time series modeling of the post-event data. Note that both GAN and Neural ODE are trained with limited real data set. In the data generation process, we combine the trained *G* and Neural ODE model *f* to generate entire synthetic eventful PMU data, where the *G* model feeds the Neural ODE with part of its output that is the initial state of the post-event PMU data.

Algorithm 1 GAN-Based Networked Eventful PMU Data Creation Algorithm

Initialize θ_D, θ_G and θ_f
for $i = 1$ to N_{GAN} **do**
  for $j = 1$ to k_D **do**
    Sample real data $\{x_k\}_{k=1}^{m_b}$
    Sample latent variables $\{z_k\}_{k=1}^{m_b}$
    $\theta_D \leftarrow \theta_D - RMSProp(J_D(\{x_k\}_{k=1}^{m_b}, \{G(z_k)\}_{k=1}^{m_b}))$
  end for
  Sample latent variables $\{z_k\}_{k=1}^{m_b}$
  $\theta_G \leftarrow \theta_G - RMSProp(J_G(\{G(z_k)\}_{k=1}^{m_b}))$
end for
for $i = 1$ to N_{ODE} **do**
  Sample real post-event data $\{[y_k^0, \ldots, y_k^{p\Delta T}]\}_{k=1}^{m_b}$
  $\theta_f \leftarrow \theta_f - RMSProp(L(\{[y_k^0, \ldots, y_k^{p\Delta T}]\}_{k=1}^{m_b}))$
end for

The proposed two-stage algorithm has two advantages, respectively addressing the two challenges mentioned in Section II-B. On one hand, this two-stage design makes the GAN model create the PMU measurements at only very few special time instants, which significantly reduces the size of the GAN model and improves the computational efficiency. On the other hand, this algorithm embeds the ODE format by incorporating the Neural ODE model, which can effectively learn the temporal correlation of the post-event measurements from different PMUs.

B. SYNTHETIC QUALITY CHECK

Before incorporating the synthetic data to improving event classification, we will verify the physical meaning of the post-event synthetic PMU data. In this article, modal analysis is used to quantitatively show whether synthetic PMU data possess realistic dynamic characteristics of power systems, i.e. modal properties. Specifically, we use Prony analysis [20], a classical ring-down analysis method, to analyze the synthetic data and extract important modal properties including oscillation frequency and damping.

Since modes are the fingerprint of a given linear system (or the linearized part of a nonlinear dynamic system), we can compare the modes of the real data and synthetic data for validating the fidelity of the synthetic data. Without loss of generality, here we select the voltage angle measurements for validation. Details of the validation are summarized below:

1) Modal Property Estimation: Calculate the oscillation frequency (ω_i), damping coefficient (σ_i), amplitude (a_i), and phase (θ_i) of all active modes via Prony analysis for real and synthetic voltage angle profiles.
2) Modes Selection: Only the modes with amplitude greater than a threshold are selected as active modes. The threshold is fixed as the 10% of the maximum value of all mode amplitudes.
3) Validation: For each synthetic profile, modal frequencies and damping ratios of the active modes are compared with those of all real profiles at the same generator bus. We say that the synthetic profile passes the test

if all active modes of the tested synthetic profile appear in the real data. We declare a pair of modes as the same mode if their relative error is less than 5%.

We will show the results of case study in the Section V-C.

C. IMPROVED EVENT CLASSIFICATION

Without loss of generality, we selected several event classification methods from the existing literature [21]–[23] to illustrate the improvement of the event classification accuracy by the synthetic data. It should be noted that other event classification methods can also be potentially improved in a similar way.

Event classification tasks can be separated into two steps: feature extraction and feature classification. Considering the possible impacts brought by choosing different approaches, we select two commonly used methods for each step.

Discrete Wavelet Transform (DWT) [21] and Principle Component Analysis (PCA) [24] as two traditional pattern recognition methods are selected to extract the high-level features. DWT uses the mother wavelet, which is a set of basis functions decomposing the data into several resolution levels. The coefficients, which carry the detailed and approximate information of the data, can be used as features for pattern recognition. PCA projects the data onto the principle subspace such that the variance of the data is maximized. The dynamics of the data can be analyzed by transforming the data into a combination of principle component.

Traditional classifier models Support Vector Machine (SVM) [21] and ensemble learning model [25] are used to complete the classification task. SVM enables mapping the original feature into a higher dimensional space so that the decision boundary can be identified. Bagging is selected as the ensemble learning model, which bags decision trees on a data set by generating bootstrap replicas of the data and growing decision trees on the replicas. It obtains boostrap replicas by randomly sampling the data set with replacement, and then train the decision tree by the random forest.

We implement all techniques mentioned above by the built-in modules in the Matlab toolbox with the default hyperparameter setting, including *pca*, *modwt*, *fitcecoc* and *fitcensemble*. Then, we make pairwise combinations between feature extraction and classification methods, and create four event classification algorithms to be used in Section V-D.

V. CASE STUDY

In this section, we employ the IEEE 39-bus power system and first validate the quality of the synthetic data and then show that the event classification accuracy can be improved by incorporating the synthetic data. Note that we only consider the generators in the IEEE 39-bus system as dynamic elements. Therefore, we will only generate the PMU measurements at all generator buses according to Section II-C.

TABLE 1. Simulation setting of three event types, including bus fault, line tripping and load shedding. Note that both of bus fault and line tripping events are triggered by solid three phase grounding faults.

Event Type	Parameter	Simulation Setting
Bus fault	Fault duration	0 - 0.1s
	Fault location	Random bus
	Sampling frequency	60 Hz
	Time window	15 s
Line tripping	Fault duration	0 - 0.1s
	Fault location	Random line
	Sampling frequency	60 Hz
	Time window	15 s
Load shedding	Shedding percentage	5 - 50%
	Fault location	Random load bus
	Sampling frequency	60 Hz
	Time window	15 s

A. TEST SYSTEM: IEEE 39-BUS SYSTEM

The IEEE 10-machine 39-bus system [26] is simulated to provide the training and test data sets. Specifically, we focus on three types of event: *bus fault*, *line tripping* and *load shedding*.[2] Table 1 shows the simulation configuration of these three types of event. Note that both of bus fault and line tripping events are triggered by solid three phase grounding faults, and all simulations start from the same steady state. We randomly sample the simulation parameters according to the settings shown in Table 1 and get the simulated eventful data from PowerWorld, which include voltage magnitude and angle profiles at all generator buses covering the pre-event, during event and post-event periods. We randomly collect 20 samples for each event type as the input of training the two-stage GAN-based data creation method, and respectively collect 400 and 800 samples for each event type for the purpose of training and testing the machine learning-based event classifiers.

B. MODEL CONFIGURATION AND TRAINING PROCESS

The hyperparameters in Algorithm 1 take the following values according to our prior experience: For the GAN model, we set the maximum training epochs N_{GAN} as 10000, the minibatch size m_b as 8, and k_D as 1. For the Neural ODE model, we set the number of training epochs N_{ODE} as 5000, the time step ΔT as $1/60s$ and the time window $p\Delta T$ as $2s$. Table 2 shows the detailed neural network configuration of both GAN and Neural ODE models. The number of the input layers represents the input dimension. Each cell for the following layers includes the information of layer type, output dimension and activation function. Both GAN and Neural ODE models are trained by RMSProp with a learning rate 10^{-3}.

In the training process, we train GAN and Neural ODE models for each event type successively, given only 20 real samples. The loss values of G,D and f models during the

[2]The proposed two-stage data creation method can handle the generator tripping events. However, the case study does not include it because we cannot generate enough data in the IEEE 39-bus system for test purpose.

TABLE 2. Configuration of GAN and neural ODE models.

Layer	G model	D model	Neural ODE
Input	20	60	20
Layer1	Dense 100 ReLU	Dense 100 ReLU	Dense 100 Tanh
Layer2	Dense 100 ReLU	Dense 100 ReLU	Dense 100 Tanh
Layer3	Dense 60 Linear	Dense 1 Sigmoid	Dense 20 Linear

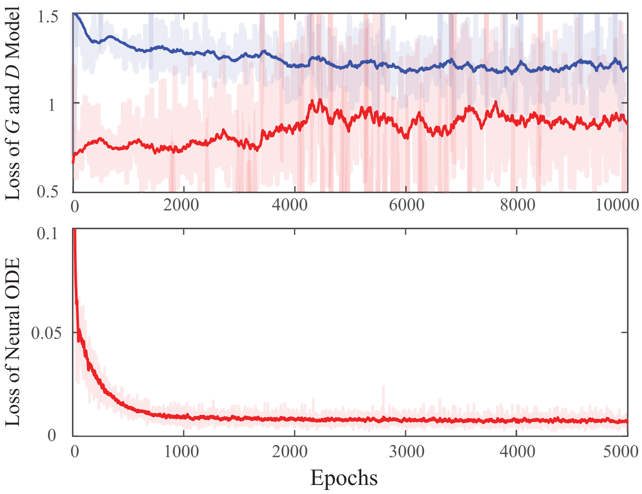


FIGURE 3. Loss curves of *G*, *D* and Neural ODE models during the training process. Here we illustrate the loss curves of *bus fault*. In the top subfigure, the blue curve represents the loss of *D* model while the red one represents that of *G* model.

training process are illustrated in Fig. 3, which shows the success of the training process.

C. QUALITY CHECK OF SYNTHETIC PMU DATA

In this subsection, we will show the fidelity of the synthetic networked eventful PMU data from the perspectives of visual comparison and modal analysis.

1) VISUAL COMPARISON

Fig. 4 illustrates the real (top row) and synthetic (bottom row) eventful voltage angle profiles at all generator buses in a 5s time window which includes the pre-event, during event and post-event periods. Note that we randomly select the synthetic sample for each event type and then determine the real sample by looking for the one that is closest to the synthetic sample. It is observed from the visual comparison that: (i) real and synthetic profiles have similar settling patterns; (ii) the ranges of real and synthetic profiles are nearly the same. These observations imply that the proposed two-stage GAN-based model can generate transient PMU data that capture the inherent temporal correlation.

2) MODAL ANALYSIS

According to the synthetic data quality check method in Section IV-B, we separately test the synthetic data of all event types, with the training and test data sets generated in Section V-A being the benchmark. The modal analysis test result of bus fault, line tripping and load shedding are shown in Table 3. From this table, we can observe that:

TABLE 3. Modal analysis test.

Event Type	Bus fault	Line tripping	Load shedding
Accuracy Train	88.10%	86.60%	80.28%
Accuracy Test	90.23%	87.30%	82.81%

- *Fidelity*: High success rate indicates that the synthetic data approximately capture the dynamic characteristics of the real data;
- *Diversity*: The difference of the success rate between training and test benchmark indicates that the GAN model does not simply memorize the training data but also it creates new and meaningful modes that exist in the test data set.

D. EVENT CLASSIFICATION ACCURACY WITH/WITHout SYNTHETIC DATA

This subsection will firstly show that the number of samples in the training data set has a significant impact on the event classification accuracy, and then show the improvement of the event classification accuracy by incorporating the synthetic PMU data.

From the simulation in Section V-A, we have a training data pool and a test data set for the event classifiers that respectively have 400 and 800 samples for each event type. We will randomly sample a number of training data from the training data pool and test the trained event classifiers on the whole test data set.

Firstly we show the impact of the number of samples in the training data set on the event classification accuracy in Table 4. The first row of the table represents the number of samples in the training data set for each event type. The notation in the first column means the classification methods. For example, PCA-SVM refers to a classification method that extracts the features by PCA and classifies the features by SVM. We randomly pick the given number of samples in the training data set, and then train all four event classification methods. To mitigate the randomness, we repeat this procedure 10 times and calculate the mean and standard deviation of the event classification accuracy as shown in each cell of Table 4. The following can be observed from this table: although these four classification methods have distinct performances, the increasing number of training data always benefits their classification accuracy in the sense of mean value and the standard deviation. Given the fact that there are always only a limited number of real events, the accuracy of these classification methods is expected to be low in the practical application. It also shows the need for more data to improve the event classification accuracy.

Next we show the improvement of the event classification accuracy by incorporating the synthetic PMU data as shown

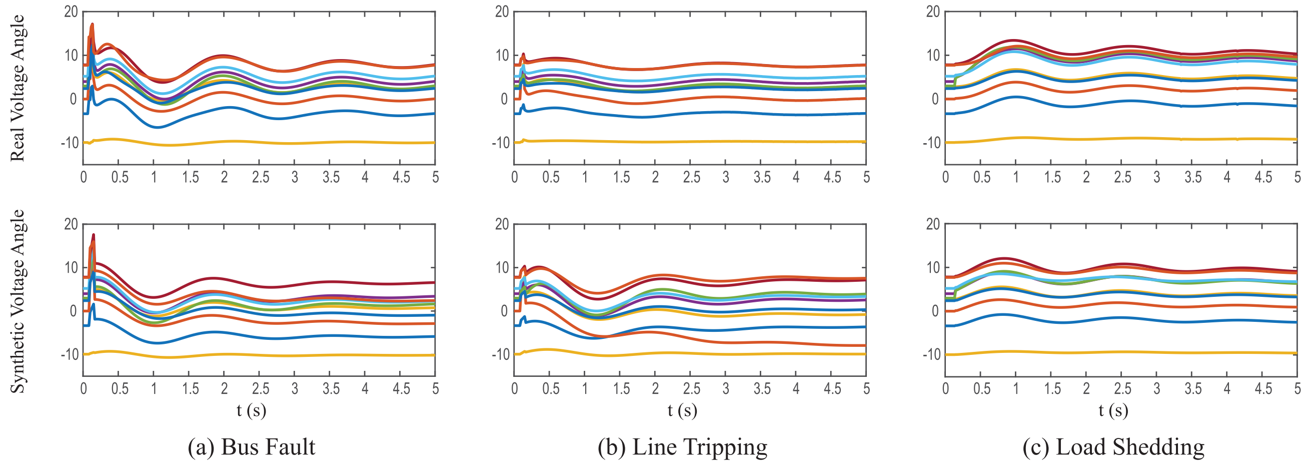


FIGURE 4. Visual comparison between real and synthetic eventful voltage angle profiles at generator buses. The examples of bus fault, line tripping and load shedding are respectively shown in the subfigure (a), (b) and (c). In each subfigure, the top and bottom rows respectively show the real and synthetic voltage angle profiles at all generator buses in a 5*s* time window which includes the pre-event, during event and post-event periods. Note that we randomly select the synthetic sample for each event type and then determine the real sample by looking for the one that is closest to the synthetic sample.

TABLE 4. Impacts of the number of training data on the event classification accuracy.

Real training data	20	40	60	80	100
PCA-SVM	68.97% ±7.79%	72.10% ±2.68%	76.15% ±2.40%	74.80% ±1.64%	76.28% ±1.88%
WT-SVM	80.88% ±3.11%	84.76% ±2.40%	88.24% ±2.29%	90.98% ±1.01%	91.16% ±1.36%
PCA-Ensemble	79.27% ±3.85%	84.72% ±2.19%	89.38% ±1.55%	92.08% ±0.97%	92.93% ±0.76%
WT-Ensemble	82.73% ±3.03%	90.90% ±1.92%	95.71% ±0.82%	96.83% ±0.37%	97.28% ±0.59%

TABLE 5. Improvement of event classification accuracy by incorporating synthetic data.

Synthetic training data	100	200	300	400
PCA-SVM	73.85% ±1.69%	73.77% ±1.27%	73.01% ±2.83%	73.32% ±1.72%
WT-SVM	82.73% ±2.29%	82.69% ±1.27%	81.76% ±2.02%	81.52% ±2.41%
PCA-Ensemble	85.47% ±2.94%	82.32% ±2.23%	82.52% ±2.82%	81.74% ±2.77%
WT-Ensemble	90.05% ±1.42%	88.97% ±2.31%	90.27% ±1.50%	88.16% ±2.18%

in Table 5. Note that the GAN and Neural ODE models used to generate the synthetic data are trained by only 20 real samples for each event type (as described in Section V-A). Since the proposed two-stage GAN-based data creation method has the ability to generate massive synthetic data, we also randomly sample a given number of synthetic data samples and mix them with the real samples for training the event classifiers. Then, we use the created hybrid training data set to train all four event classification methods. To mitigate the randomness, we repeat this procedure 10 times as well and calculate the mean and the standard deviation of the event classification accuracy as shown in Table 5. Comparing Table 5 and 4, we have the following observations:

- Incorporating the synthetic data can effectively and consistently improve the event classification accuracy by 2 to 5 percent, compared to the results based on only 20 real training data for each event type in Table 4.
- When the number of the real data increases from 20 to 100 (shown in Table 4), it always leads to a better classification accuracy than the cases with synthetic PMU data, meaning the synthetic data can aid in the classification accuracy due to the lack of training data but cannot replace the real ones.
- When the synthetic data overwhelms the real training data, the classification accuracy is not negatively affected, implying that the synthetic data are of good quality.

VI. CONCLUDING REMARKS

We propose to create synthetic PMU data via a two-stage GAN method. This approach can scale up the otherwise limited real-world PMU data as follows. First, it leverages the capability of GAN to guarantee the diversity of massive synthetic data. Second, it leverages Neural ODEs to provide meaningful post-fault time-series data. Such synthetic data set can then be fed into subsequent monitoring and decision making processes. As an example, we show that the synthetically created PMU data improves the performance of data-driven event classification. We validate the fidelity of the synthetic data via visual comparison and modal analysis approaches. We also verify that the synthetic data can effectively improve the accuracy of four selected event classification methods.

While the development of GAN and its application in power systems is still at its infancy, this article sheds lights on some great potential in the future. As our ongoing and future works, we will (i) investigate the sensitivity of the two-stage GAN method with respect to the sample window size; (ii) explore other subsequent value-added applications enabled by a massive amount of synthetic PMU data; and (iii) validate and test the proposed idea in real-world-scale systems.

REFERENCES

[1] *Final Report on the August 14, 2003 Blackout in the United States and Canada*, U.S.-Canada Power Syst. Outage Task Force, Ottawa, ON, Canada, 2004.

[2] D.-I. Kim, L. Wang, and Y.-J. Shin, "Data driven method for event classification via regional segmentation of power systems," *IEEE Access*, vol. 8, pp. 48195–48204, 2020.

[3] *NERC Modeling Improvements Initiative Update*, NERC, Atlanta, GA, USA, 2018.

[4] R. D. Quint, "Modeling an dverification for BPS-connected inverterbased resources," in *Proc. ESIG Webinar*, 2019, pp. 1–8.

[5] Z.-L. Gaing, "Wavelet-based neural network for power disturbance recognition and classification," *IEEE Trans. Power Del.*, vol. 19, no. 4, pp. 1560–1568, Oct. 2004.

[6] H. Okumus and F. M. Nuroglu, "Power system event classification based on machine learning," in *Proc. 3rd Int. Conf. Comput. Sci. Eng. (UBMK)*, Sep. 2018, pp. 1–4.

[7] S. Mukherjee, A. Darvishi, A. Chakrabortty, and B. Fardanesh, "Learning power system dynamic signatures using LSTM-based deep neural network: A prototype study on the New York state grid," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2019, pp. 1–5.

[8] *PMU Placement and Installation Update*, NERC Rel. Guideline, Atlanta, GA, USA, 2016.

[9] P. W. Sauer, M. A. Pai, and J. H. Chow, *Power System Dynamics and Stability: With Synchrophasor Measurement and Power System Toolbox*. Hoboken, NJ, USA: Wiley, 2017.

[10] I. Goodfellow *et al.*, "Generative adversarial nets," in *Proc. Adv. Neural Inf. Process. Syst.*, 2014, pp. 2672–2680.

[11] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 2223–2232.

[12] L. Yu, W. Zhang, J. Wang, and Y. Yu, "SeqGan: Sequence generative adversarial nets with policy gradient," in *Proc. 31st AAAI Conf. Artif. Intell.*, 2017, pp. 1–7.

[13] Z. Lin, A. Jain, C. Wang, G. Fanti, and V. Sekar, "Using GANs for sharing networked time series data: Challenges, initial promise, and open questions," 2019, *arXiv:1909.13403*. [Online]. Available: http://arxiv.org/abs/1909.13403

[14] Y. Chen, Y. Wang, D. Kirschen, and B. Zhang, "Model-free renewable scenario generation using generative adversarial networks," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3265–3275, May 2018.

[15] Z. Zhang and M. Wu, "Predicting real-time locational marginal prices: A GAN-based video prediction approach," 2020, *arXiv:2003.09527*. [Online]. Available: https://arxiv.org/abs/2003.09527

[16] X. Zheng, B. Wang, and L. Xie, "Synthetic dynamic PMU data generation: A generative adversarial network approach," in *Proc. Int. Conf. Smart Grid Synchronized Meas. Anal. (SGSMA)*, May 2019, pp. 1–6.

[17] C. Ren and Y. Xu, "A fully data-driven method based on generative adversarial networks for power system dynamic security assessment with missing data," *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 5044–5052, Nov. 2019.

[18] R. T. Chen, Y. Rubanova, J. Bettencourt, and D. K. Duvenaud, "Neural ordinary differential equations," in *Proc. Adv. Neural Inf. Process. Syst.*, 2018, pp. 6571–6583.

[19] X. Xie, A. K. Parlikad, and R. S. Puri, "A neural ordinary differential equations based approach for demand forecasting within power grid digital twins," in *Proc. IEEE Int. Conf. Commun., Control, Comput. Technol. Smart Grids (SmartGridComm)*, Oct. 2019, pp. 1–6.

[20] *Identification of Electromechanical Modes in Power Systems*, document F. TP462, IEEE Task Force Report, 2012.

[21] S. Ekici, "Classification of power system disturbances using support vector machines," *Expert Syst. Appl.*, vol. 36, no. 6, pp. 9859–9868, Aug. 2009.

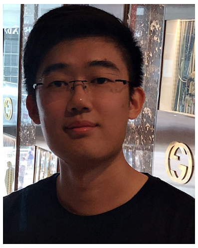
[22] A. A. Abdelsalam, A. A. Eldesouky, and A. A. Sallam, "Classification of power system disturbances using linear Kalman filter and fuzzy-expert system," *Int. J. Electr. Power Energy Syst.*, vol. 43, no. 1, pp. 688–695, Dec. 2012.

[23] R. Ma, S. Basumallik, and S. Eftekharnejad, "A PMU-based multivariate model for classifying power system events," 2018, *arXiv:1812.00246*. [Online]. Available: https://arxiv.org/abs/1812.00246

[24] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality reduction of synchrophasor data for early event detection: Linearized analysis," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2784–2794, Nov. 2014.

[25] L. Breiman, "Bagging predictors," *Mach. Learn.*, vol. 24, no. 2, pp. 123–140, Aug. 1996.

[26] T. Athay, R. Podmore, and S. Virmani, "A practical method for the direct analysis of transient stability," *IEEE Trans. Power App. Syst*, vol. PAS-98, no. 2, pp. 573–584, Mar. 1979.



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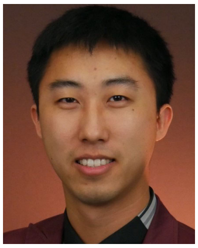

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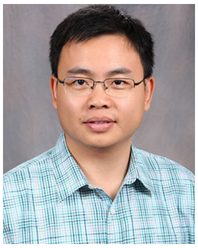

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