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REVIEW

Adding power of artificial intelligence to situational awareness of large interconnections dominated by inverter-based resources

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Abstract

Large-scale power systems exhibit more complex dynamics due to the increasing integration of inverter-based resources (IBRs). Therefore, there is an urgent need to enhance the situational awareness capability for better monitoring and control of power grids dominated by IBRs. As a pioneering Wide-Area Measurement System, FNET/GridEye has developed and implemented various advanced applications based on the collected synchrophasor measurements to enhance the situational awareness capability of large-scale power grids. This study provides an overview of the latest progress of FNET/GridEye. The sensors, communication, and data servers are upgraded to handle ultra-high density synchrophasor and point-on-wave data to monitor system dynamics with more details. More importantly, several artificial intelligence (AI)-based advanced applications are introduced, including AI-based inertia estimation, AI-based disturbance size and location estimation, AI-based system stability assessment, and AI-based data authentication.

1 | INTRODUCTION

As a critical underpinning of modern society, the electric power grid consisting of hundreds of thousands of components is one of the most complex and man-made dynamic systems in the world. Situational awareness is critical to the operation and control of large-scale power grids. Situational awareness can accurately and timely translate the collected data into useful information or knowledge to allow grid operators to better understand the current situation of a power grid and then make decisions or take actions [1].

With the increasing integration of renewables and the retirement of conventional generators, power grids exhibit more complex dynamics because inverter-based resources (IBRs) have different dynamic characteristics compared to conventional synchronous machines [2]. Moreover, due to the intermittence of renewable resources, power grids will experience more dramatic and frequent operating condition variations. Meanwhile, the integration of distributed energy storage (e.g., electric vehicles) and more dispatchable loads can fundamentally change today's power grid operation paradigm [3, 4]. All of these make it necessary to further enhance today's situational awareness capability to provide better insights into system dynamics.

Currently, numerous real-time data are collected and sent to control centres by conventional Supervisory Control and Data Acquisition (SCADA) or Wide-Area Measurement System (WAMS) [5, 6]. Compared with conventional SCADA, WAMS provides higher resolution, more accurate, and time-synchronized measurements to reflect system dynamics.

Many algorithms are developed and implemented for situational awareness, which can be divided into three major categories as follows: physical model-based approach, data-driven approach, and artificial intelligence (AI)-based approach.

The physical model-based approach relies heavily on the physical model of the power grid. It usually maps the collected measurements to the physical model to reflect the current status of a power grid, for example, state estimation. After that, the critical measurements are compared with predetermined thresholds, or a time-domain simulation of a snapshot model of the large-scale power grid is needed to estimate grid stability [7]. However, this method typically requires significant offline or online simulation time and cannot well accommodate the dramatic and frequent operating condition variations of a power grid dominated by IBRs.

Meanwhile, various data-driven (or measurement-driven) approaches based on synchrophasor measurements have been proposed for power grid situational awareness [8–11]. This method uses the collected measurements to build a simple model online for situational awareness, for example, transfer function model and state-space model. Compared with the physical model-based approach, the computation burden can be significantly reduced by using the developed simple measurement-driven model or reduced model. However, the development of such a measurement-driven model is not trivial. The measurement-driven model also needs to be frequently updated online to reflect the fast operating condition variations.

The aforementioned two approaches are mainly based on the physical model and physical principles. They are insufficient in predicting major risks/threats in large-scale power grids, for example, the California Wildfire Blackouts and 2021 Texas power crisis. Moreover, although massive spatial-temporal data are collected and sent to control centres, the hidden knowledge in the large-volume data has not been fully exploited. Recently, AI had many successful applications in various areas, such as image recognition, language processing, social media, and fraud detection [12]. AI also has great potential to significantly improve power grid situational awareness to overcome the shortcomings of the two approaches above and accommodate fast-changing operating conditions.

Various AI-based methods have been developed to improve power grid situational awareness with promising results [13, 14], including load forecasting [15], wind power forecasting [16, 17], outage prediction [18], stability assessment [19], electrical equipment fault detection [20], grid fault diagnosis [21], and intrusion detection [22]. Note that the AI-based approach also belongs to the data-driven approach. However, since its inputs are usually feature data and it does not directly rely on a physical model, this study treats the AI-based approach as the third approach. AI technologies have also been used in control functions of different timescales, for example, demand response [23], frequency control [24], voltage control [25], and emergency control [26], but they are out of the scope of this study.

As a pioneer in WAMS, FNET/GridEye is a Global Positioning System (GPS)-synchronized power grid dynamic frequency and phase angle monitoring network deployed at the distribution level. It uses single-phase Phasor Measurement Units (PMUs) to measure synchrophasor at the 110 or 220 V distribution level and transport data to application servers via Internet [27, 28]. FNET/GridEye is the only monitoring system that provides real-time insights into the dynamic behaviours of all interconnection grids in North America. About 12 GB of data are collected every day, accumulating a massive and unique spatial-temporal power grid data asset. Various online and offline applications have been implemented on FNET/GridEye to monitor large-scale power grids. It proves to be an effective situational awareness tool for electric utilities, Independent System Operators, and regulatory agencies.

More importantly, thanks to its low-cost, easy deployment, and plug-and-play features, a newly developed application for situation awareness can be quickly implemented on FNET/GridEye and validated using the collected measurements from realistic power grids. After that, this new application can be easily integrated into the existing WAMSs deployed at control centres to enhance the situational awareness of grid operators. Certainly, FNET/GridEye usually has only single-phase synchrophasor measurements, not three-phase. However, this does not impede its application in typically balanced transmission grids.

This study introduces the latest progress on FNET/GridEye development, especially the application of AI technologies in FNET/GridEye to enhance its situational awareness capability. The main contributions of this study are summarised as follows.

- The sensors of FNET/GridEye have been upgraded to support (1) power quality monitoring, (2) ultra-high reporting rate (1500 frames/second), and (3) transportation of point-on-wave (POW) data
- The communication between sensors and FNET/GridEye servers has been upgraded to support ultra-high density (UHD) synchrophasor and POW data communication by using a lossless bit-wise-based compression method
- Several AI-based advanced applications have been developed, including AI-based inertia estimation, AI-based disturbance size and location estimation, AI-based stability assessment, and AI-based data authentication. These new applications are developed using realistic power grid models and actual measurements collected by Frequency Disturbance Recorder (FDRs)/Universal Grid Analyzer (UGAs)

2 | OVERALL ARCHITECTURE OF FNET/GRIDEYE

The overall architecture of FNET/GridEye is illustrated in Figure 1, which consists of three levels: data collection level, data communication level, and data application level.

2.1 | Data collection level

Two types of sensors are deployed at the data collection level, FDR and UGA. FDR is the earlier version of the sensor usually deployed in an office room or at home to collect GPS-synchronized measurements, including frequency, voltage magnitude, and voltage angle, from an ordinary 110 V or 220 V outlet. UGAs are the advanced version of FDRs with higher sampling and reporting rates, and newly added power quality monitoring functions. Currently, more than 200 FDRs/UGAs have been deployed in North America, as shown in Figure 2. Also, there are more than 100 FDRs/UGAs deployed in other countries, including major large interconnections around the world.

The sampling rate of a UGA is usually 96 points per cycle, which means a 5760 Hz sampling rate for 60 Hz power grids and a 4800 Hz sampling rate for 50 Hz power grids. The power quality monitoring functions deployed in UGAs are listed in Table 1. The harmonics and total harmonic distortion are calculated through the 1024-point Fast Fourier transform (FFT) algorithm per second, while the voltage sag and voltage swell are calculated with the voltage magnitude per half cycle [29]. The maximum error rate for the harmonics is about 0.7%. The voltage flicker is calculated through the square-detection method. The estimation

TABLE 1 Power quality monitoring functions of UGAs

NO.	Function name
1	Harmonics (2nd to 15th order)
2	Total harmonic distortion
3	Voltage sag
4	Voltage swell
5	Voltage flicker
6	Signal-to-noise ratio

Abbreviation: UGA, Universal Grid Analyzer.

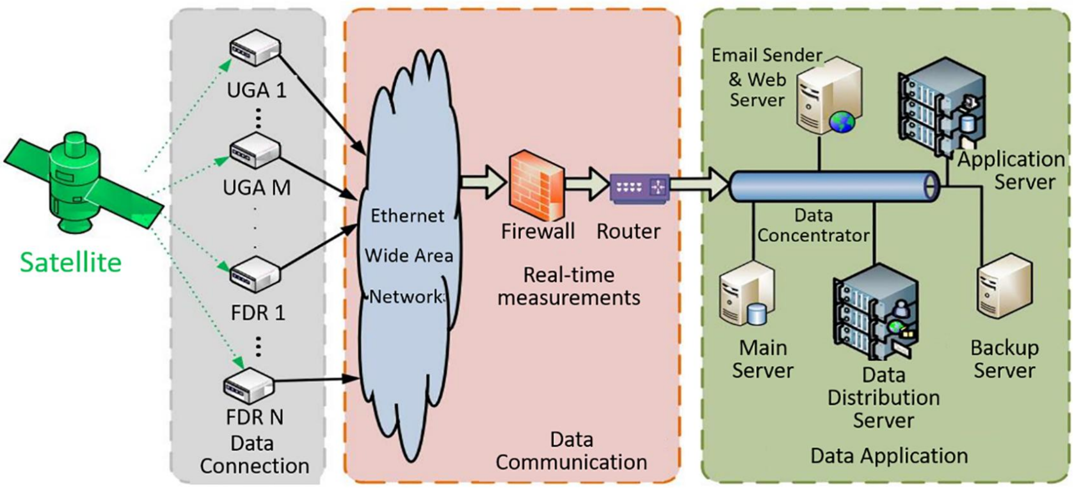

FIGURE 1 Overall architecture of FNET/GridEye. FDR, Frequency Disturbance Recorder; UGA, Universal Grid Analyser

FIGURE 2 Frequency disturbance recorder/universal grid analyser deployment in North America

of signal-to-noise ratio is based on the power density spectrum, which is also calculated through the 1024-point FFT algorithm per second.

Another improvement of UGAs is the higher reporting rate of synchrophasor. Previously, FDRs support only a 10 Hz reporting rate. With the advanced hardware, the UGA reporting rate can reach 120 Hz. As shown in Figure 3, the frequency responses from a 120 Hz UGA and a 10 Hz UGA are compared under a 60 Hz ideal power source. The UGA with 120 Hz reporting rate has a higher resolution and can be utilised in protection and real-time control. Moreover, UGAs can also be treated as an open-source PMU testing platform where synchrophasor algorithms, such as zero crossing and high-speed algorithm, can be tested and validated [30].

2.2 | Data communication level

UGAs utilise the IEEE C37.118.2 protocol over TCP/IP to transfer real-time data to the data centre. Due to the presence of UHD synchrophasor and POW data to monitor power system dynamics with more details, there is an urgent need to develop a data compression method to transfer synchrophasor data in a more efficient and lossless manner [31]. FNET/GridEye uses a lossless bit-wise-based compression method, that is, time-series special compression [32]. Since the difference between every two values is small due to the high sampling rate, the proposed method has a satisfactory compression performance for the high-density synchrophasor data. During daily operation, the average compression ratio reaches 4.9, and that of the POW data is 3.3. Additionally, multiple synchrophasor measurements are integrated into one data frame to further reduce the communication burden [33].

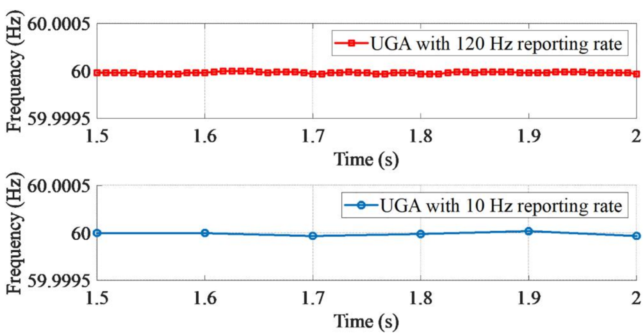

FIGURE 3 Frequency measurement comparison: 120 and 10 Hz reporting rate. UGA, Universal Grid Analyser

2.3 | Data application level

FNET/GridEye servers are used to archive the data received from FDRs and UGAs and detect power system events. The architecture of the FNET/GridEye servers is illustrated in Figure 4. 'FNET Server' programme establishes connections with the sensors and parses the data stream under the IEEE C37.118.2 protocol. The data are then archived to a file-based Microsoft Access database at the local hard drive. The programme is deployed to the 'Main Server' and the 'Backup Server' for redundancy. The data streams are forwarded to a 'Data Distribution Server' and then distributed to the 'Application Server', 'Backup Application Server', and 'Utility/organization Data Subscribers'.

On the application server, OpenHistorian, an open-source software for synchrophasor data concentration and analysis, is deployed to host the application algorithms, such as generator trip/load shedding events detection, oscillation detection, and line trip detection [34]. The detected events or oscillation cases are then analysed, and corresponding reports are generated and sent to FNET industry members via emails. A backup of the application system is also deployed for redundancy.

3 | ADVANCED APPLICATIONS BASED ON AI

There are various online and offline applications deployed on FNET/GridEye. The online applications include real-time monitoring and visualization, generation trip/load shedding alert, line trip alert, islanding alert, oscillation alert, and fault-induced delayed voltage recovery alert. Recently, forced oscillation detection and source location estimation function is added [35]. The offline applications include post-event analysis,

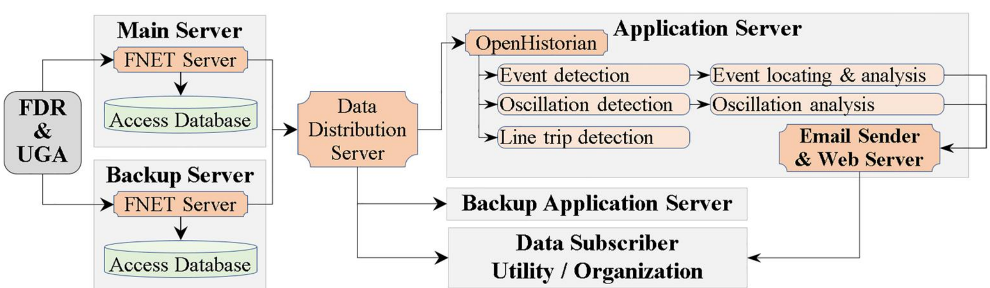

FIGURE 4 Architecture of FNET/GridEye servers. FDR, Frequency Disturbance Recorder; UGA, Universal Grid Analyser

and large-scale power grid model validation. More details can be found in our previous publications [36–39]. This study will introduce several recently developed new applications based on AI on FNET/GridEye.

3.1 | Inertia estimation based on ambient measurements and AI

Power system inertia is the kinetic energy stored in the rotating mass of synchronous generators and some industry motors. When the system is subjected to a disturbance, for example, generation trip, the stored energy can be released to reduce the generation-load imbalance before the mechanical part of synchronous generators can react. Historically, since large-scale power grids are typically dominated by conventional synchronous generators, power system inertia is not a concern. However, due to the increasing integration of IBRs that inherently do not provide inertia, the decreasing system inertia becomes a significant concern in a power grid dominated by IBRs [40]. Due to the insufficient inertia, a power grid can experience larger frequency fluctuation that could trigger generation trips and under-frequency load shedding unnecessarily. Therefore, it is crucial to monitor system inertia under varying operating conditions.

Usually, system inertia is estimated based on the unit commitment, which monitors the on/off status of synchronous generators and aggregates the nameplate inertia of all online units. This method may not be accurate enough since it does not consider the inertia contributed by loads and emulated inertia contributed by IBRs [41]. Also, inertia can be estimated based on the collected measurements during a large disturbance [42]. However, these event data cannot be used to monitor system inertia in real-time because of the randomness of the large disturbances. Additionally, continuous stimulation signal can be injected into the system. The system responses, together with the stimulation signal, are used to estimate system inertia by estimating coefficients of the swing equation [41]. This method requires periodical injection of the stimulation signal, and system responses may be impacted by other natural small perturbations in the system.

The ambient measurements under natural small disturbances can also provide sufficient information for inertia estimation. The variations of system inertia can be identified by relative magnitudes and phases of ambient frequency measurements at different locations. These variations are quantified by the minimum volume enclose ellipsoid (MVEE) method [43, 44], and the extracted features are utilised as inputs to the AI model.

An AI-based inertia estimation approach is developed using the ambient frequency measurements collected by FNET/GridEye [45]. The system dynamics embedded in the ambient frequency measurements are represented by MVEE in its volume, centre vectors' eccentricity, and the projection of its longest semi axes, etc. The extracted features are then fed into the multivariate random forest regression (MRFR) algorithm to learn the underlying relationship between the features and system inertia. MRFR is an ensemble of regression trees trained by bootstrap sampling and random feature selection [46]. It builds a large set of regression trees and averages the output of each tree to improve the performance of the final model.

This inertia estimation approach is validated in the realistic North America Western Electricity Coordinating Council (WECC) system. Figure 5 shows the ambient frequency measurements and the associated MVEE under 100% inertia and 50% inertia. The graphic parameters of MVEE, including the ellipsoid volume, centre vectors, eccentricity, and the projection of the longest semi axes, are used for inertia estimation. Figure 6 shows the estimated inertia and the actual inertia under both heavy load and light load seasons. Mean absolute percentage errors (MAPE) is used to indicate the prediction accuracy. The estimated inertia is very close the actual inertia (MAPE = 1.2% and 0.8% for heavy load and light load seasons, respectively). The actual inertia is obtained by aggregating the inertia of each in-service synchronous generator. This application can be used for other power grids if a sufficient number of FDRs/UGAs are deployed. Typically, the dispatch data are needed to develop the training database to train the AI model.

3.2 | AI-based disturbance size and location estimation

It is critical for system operators to know the location and the size of a disturbance in a timely and accurate manner. Typically, this important information is processed by the disturbance identification function based on system model and received data. AI technologies can also be used to estimate disturbance size and location, which does not require system model information, for example, topology and power flow. This feature is very important for FNET/GridEye, whose sensors are deployed at the distribution level. This method consists of the following steps [47]:

1. Perform a recurrence quantification analysis on the received measurements to identify a predetermined number of FDRs/UGAs that are closest to the disturbance
2. Construct the associated MVEEs based on the data received from the identified FDRs/UGAs
3. Extract one or more parameters from the developed MVEEs
4. Input the one or more parameters into a MRFR algorithm to determine the location of the disturbance and a power mismatch corresponding to the disturbance

As shown in Figure 7, the received frequency measurements after a generation trip disturbance are divided into

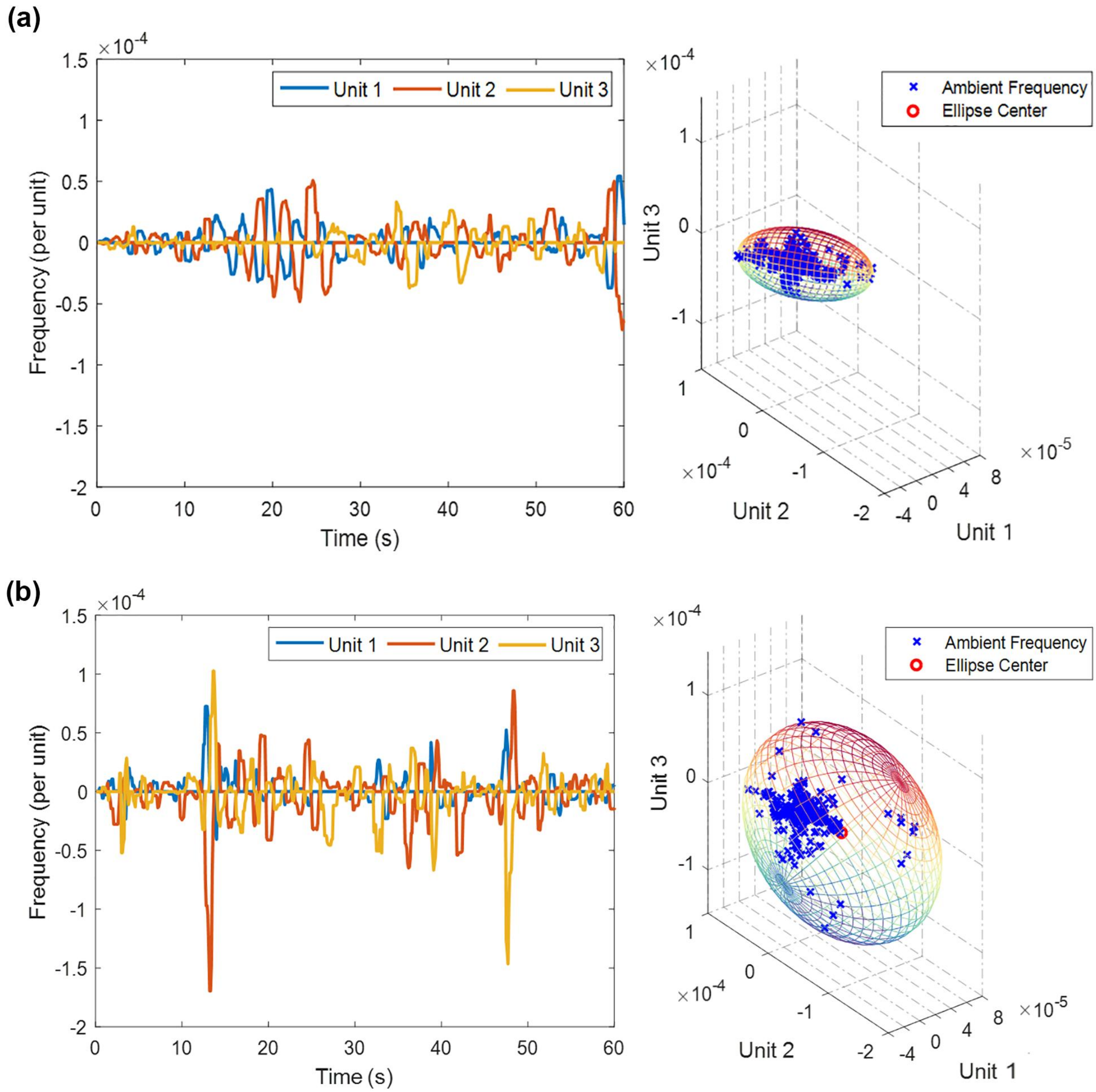

FIGURE 5 Ambient frequency measurements (left) and characteristic ellipsoids (right). (a) 100% inertia. (b) 50% inertia

four data windows: the beginning of the event (W1), initial period of the event (W2), intermediate period of the event (W3), and settling period of the event (W4). MVEEs are applied to frequency measurements to extract features from three FDRs in different data windows. The extracted features are fed into random forests to estimate disturbance size and location.

Tables 2 and 3 show the comparison of the statistic estimation error between the proposed AI-based approach and the traditional method based on Time-Delay-of-Arrival [36]. The AI-based method has higher accuracy in both event location estimation and magnitude estimation. Figure 8 shows two sample disturbances where the AI-based method can estimate more accurate disturbance location than conventional method. Currently, together with the existing event detection and location application in FNET/GridEye, this AI-based new application is generating and sending event reports to various electric utilities, Independent System Operators, and regulatory agencies for real-time event alerts and post-event analysis.

3.3 | AI-based system stability assessment

Traditionally, power system stability assessment is based on the time-domain simulations of a few selected scenarios (e.g., spring, summer, and winter) under N-1 and some selected N-k contingencies [48]. However, due to the intermittence characteristic of the renewable generation and the high renewable penetration, a few selected scenarios cannot cover the daily and hourly variations in operating conditions. More importantly, it requires tremendous time to evaluate system stability using time-domain simulations by screening all possible scenarios. Although the measurement-driven approach with a reduced model or simplified model can reduce the simulation time, the model itself needs to be updated online frequently to accommodate the fast variations in power grid operating conditions.

AI-based system stability assessment is a more efficient approach. A deep learning model can find the hidden relationship between the complex operating conditions and system stability and provide accurate predictions [49]. More importantly, the deep learning model does not require the preselected features by human beings or other algorithms. It can automatically assign low weighting factors to non-critical input features.

The deep learning model is used to predict frequency nadir under the largest generation trip disturbance for frequency stability assessment, oscillation frequency and damping ratio of the dominant oscillation mode for small-signal stability

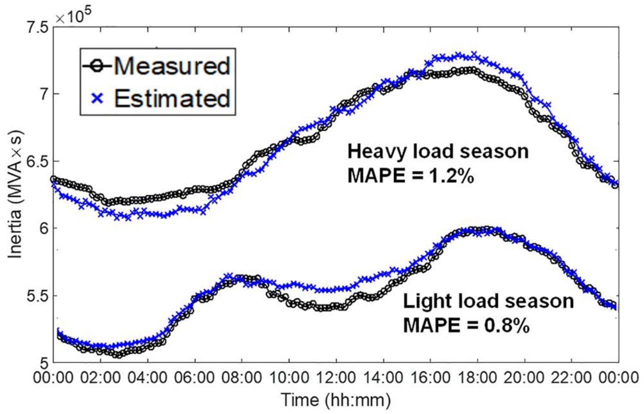

FIGURE 6 Predicted inertia and actual inertia in Western Electricity Coordinating Council system during heavy and light load seasons. MAPE, mean absolute percentage error

TABLE 2 Comparison of disturbance location estimation

	Percentage of events (%)	
Location estimation error (miles)	**TDOA-based method**	**AI-based method**
0	30	70
<50	50	98
<100	65	100

Abbreviations: AI, artificial intelligence; TDOA, Time-Delay-of-Arrival.

TABLE 3 Comparison of power mismatch estimation

	Percentage of events (%)	
Mismatch estimation error (%)	**Beta value-based method**	**AI-based method**
<10	45	80
<20	70	95
<30	95	100

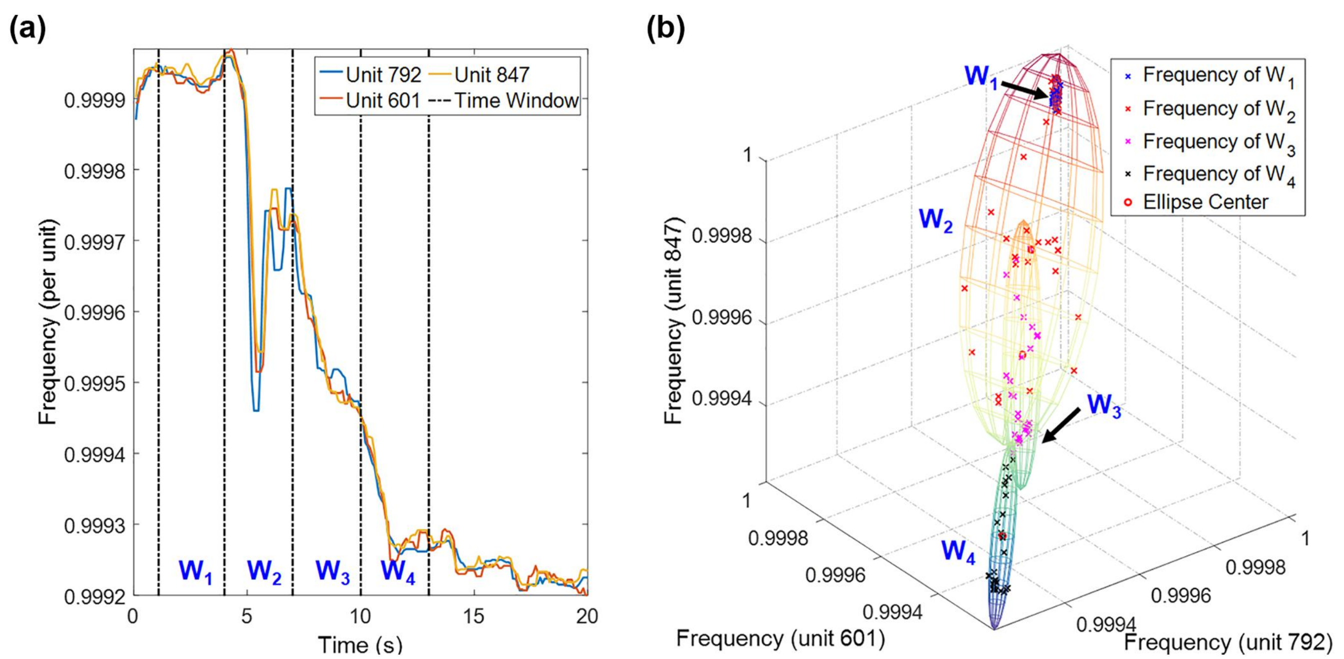

FIGURE 7 Frequency ellipsoids during the generation trip starting at 4 s. (a) Frequency measurements. (b) Frequency ellipsoids

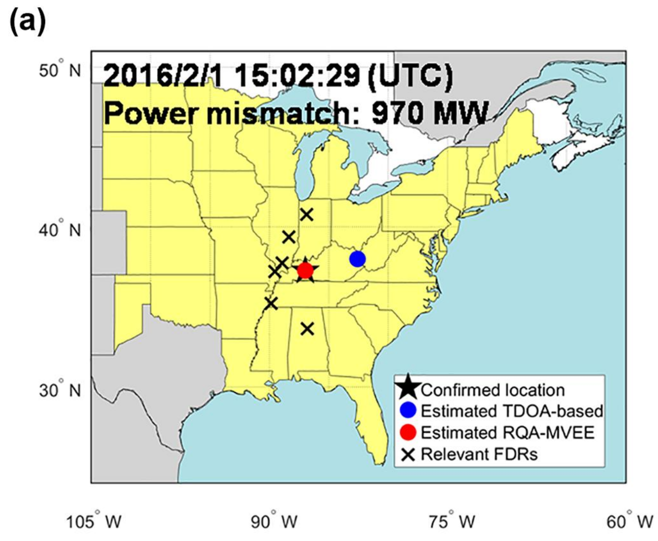

FIGURE 8 Comparison of disturbance locations estimated by TDOA-based and artificial intelligence method. (a) Event 1 on February 1st, 2016. (b) Event 2 on March 12th, 2016. FDR, Frequency Disturbance Recorder; MVEE, minimum volume enclose ellipsoid; TDOA, Time-Delay-of-Arrival

assessment, and minimum critical clearing time (CCT) for transient stability assessment. The reduced 240-bus WECC system model developed by US National Renewable Energy Laboratory is used in this study [50, 51]. The model has 8784 dispatches representing hourly variations in an entire year of 366 days.

3.3.1 | Frequency stability assessment

Figure 9 shows the deep learning neural network-based frequency stability assessment as an example. The deep learning neural network has three layers: input layer, hidden layer, and output layer. The power output of each generator, inertia of each generator, and loads are the inputs of the deep learning model. The output is the predicted frequency nadir. The major steps of this AI-based method are as follows:

1. Clustering to reduce the size of the training database: The purpose of clustering is to ensure that the selected training dataset covers all the clusters. The affinity propagation algorithm is used for clustering, which does not need to assign the number of clusters as traditional clustering methods do, but by manipulating the preference parameter in the algorithm. A total of 8784 dispatches of an entire year are clustered into 494 clusters with default parameters in the affinity algorithm. The clustering results are given in Figure 10
2. Time-domain simulations: The ground truth is obtained by time-domain simulations. A fixed 1, 200 MW generation trip at the same location is used as the disturbance. Thanks to the clustering results, only 10% of the total dataset are used as the training dataset, while the rest 90% are used for testing

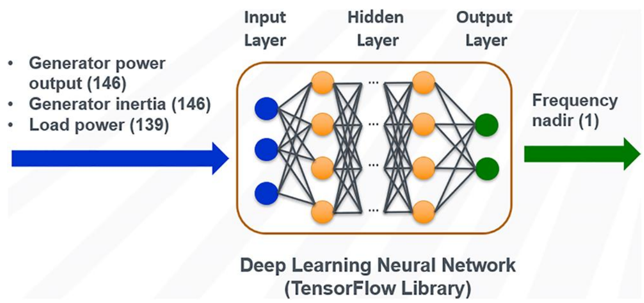

FIGURE 9 Deep learning neural network-based frequency stability assessment

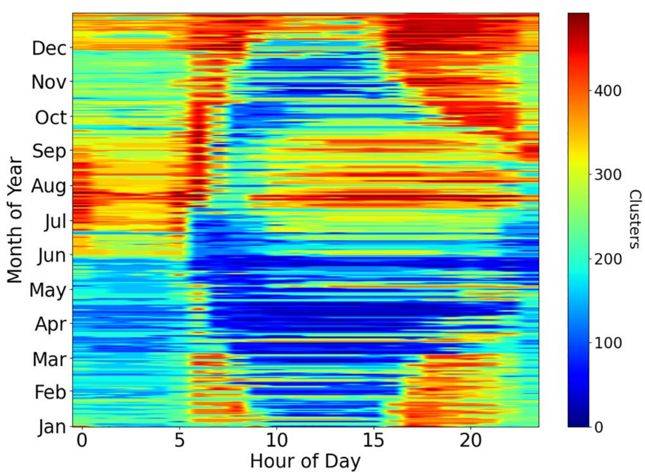

FIGURE 10 Clustering results of 8784 dispatches

3. Train and validate the AI model using the training dataset and testing dataset
4. Apply the trained and validated AI model to online applications

Figure 11 shows the statistic error of frequency nadir prediction. The predicted frequency nadir is close to the simulation results even if the model is trained with only 10% of the total dataset. Figure 11a,b show the prediction value and error histogram on the testing dataset (90% of the total), respectively. Also, if we assume that the error complies with Gaussian distribution, the error probability density function (PDF) is showed in Figure 11c. With 96% probability, the prediction error is smaller than 0.024 Hz. Also, Figure 12 shows the comparison between the predicted and simulated frequency nadir of three selected days. It further demonstrates the high accuracy of the AI-based frequency stability assessment.

3.3.2 | Small-signal stability assessment

Similarly, the deep learning model can be used to predict oscillation frequency and damping ratio of the dominant oscillation mode under different dispatches. The inputs of the deep learning model are the same as shown in Figure 9, while the outputs are the predicted oscillation frequency and damping ratio under each test scenario. The procedure is similar to that introduced in Section 3.3.1. The ground truth is obtained by Prony analysis of the system responses after a large disturbance. Figures 13 and 14 show the statistic errors of the predicted oscillation frequency and damping ratio, respectively. Also, the predicted frequencies and damping ratios are compared with the simulated results in three selected days in Figures 15 and 16. The prediction results are very close to the simulation results.

3.3.3 | Transient stability assessment

The deep learning model can also be used to assess system transient stability. The minimum CCT is selected to represent the system transient stability level when a three-phase fault is applied to each of the high-voltage buses. The inputs of the deep learning model are the same as shown in Figure 9, while the outputs are the predicted minimum CCT. The procedure is similar to that introduced in Section 3.3.1. The ground truth is obtained by time-domain simulations. When the rotor angle between any two generators (capacity larger than 100 MVA) is greater than 180°, the system is considered transiently unstable. Figure 17 shows the statistic errors of the predicted minimum CCT. Also, the predicted results are compared with the simulated results in three selected days in Figure 18. The prediction results are very close to the simulation results.

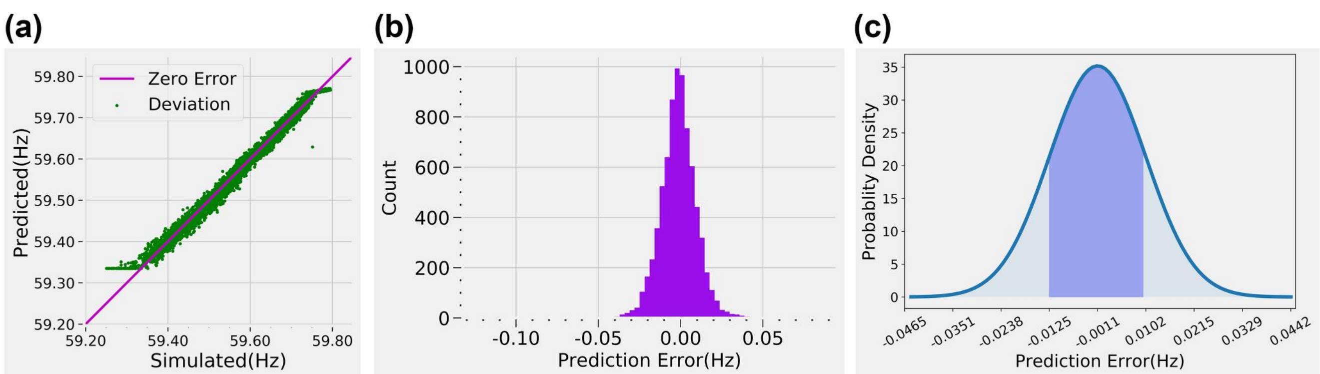

FIGURE 11 Statistic error of frequency nadir prediction. (a) Predictions on testing dataset. (b) Prediction Error histogram. (c) Prediction Error PDF

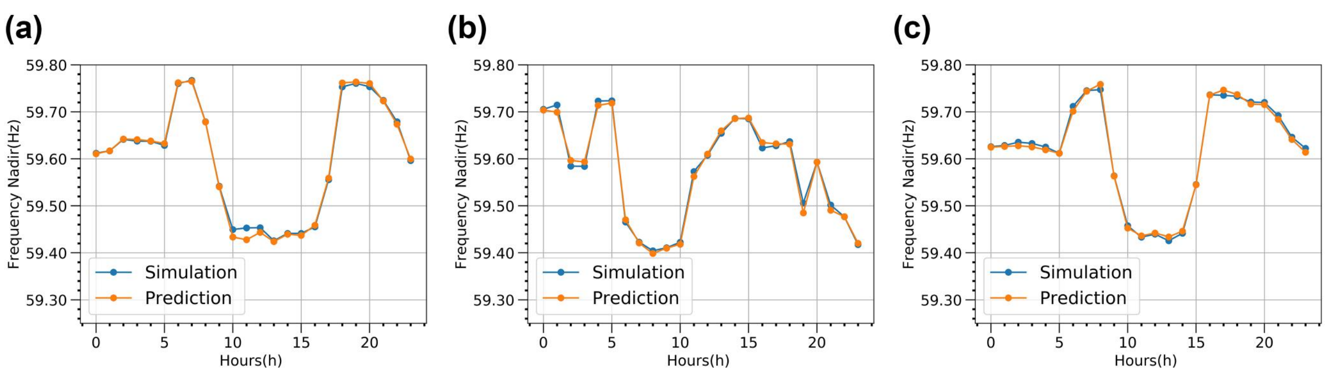

FIGURE 12 Predicted and simulated frequency nadir of three selected days. (a) March 1st. (b) June 4th. (c) January 15th

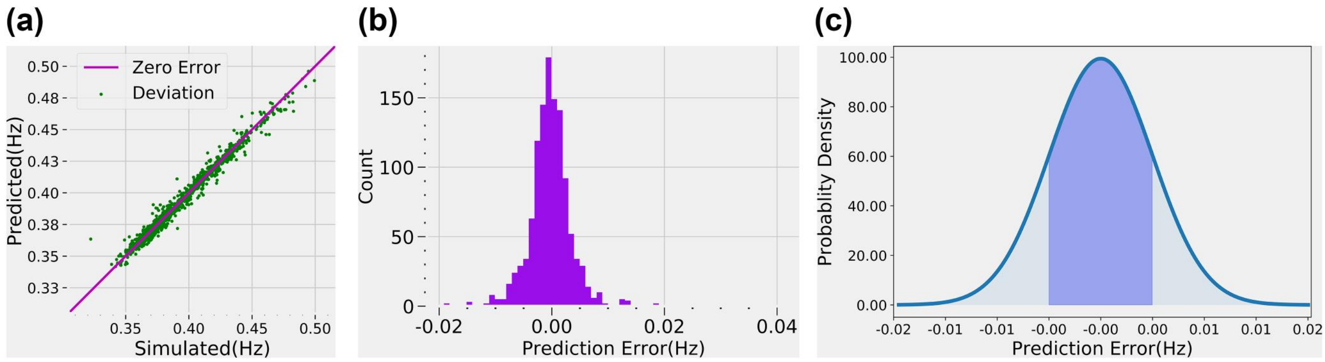

FIGURE 13 Statistic error of predicted oscillation frequency. (a) Predictions on testing dataset. (b) Prediction error histogram. (c) Prediction error PDF

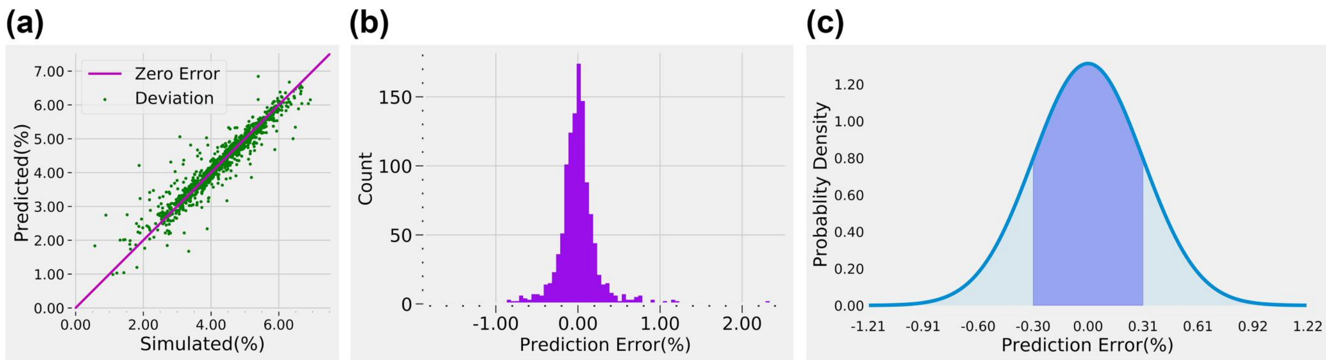

FIGURE 14 Statistic error of predicted damping ratio. (a) Predictions on testing dataset. (b) Prediction error histogram. (c) Prediction error PDF

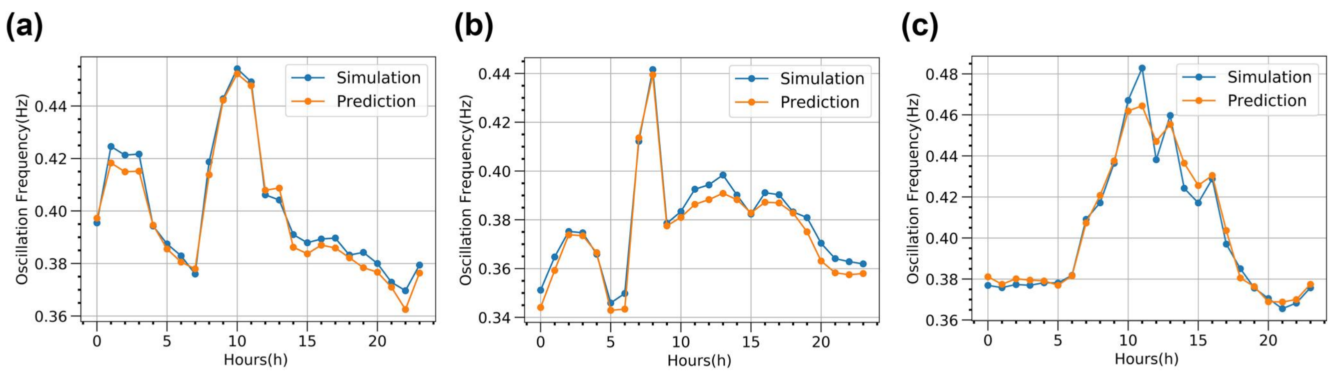

FIGURE 15 Predicted and simulated oscillation frequency of three selected days. (a) March 21st. (b) July 19th. (c) October 10th

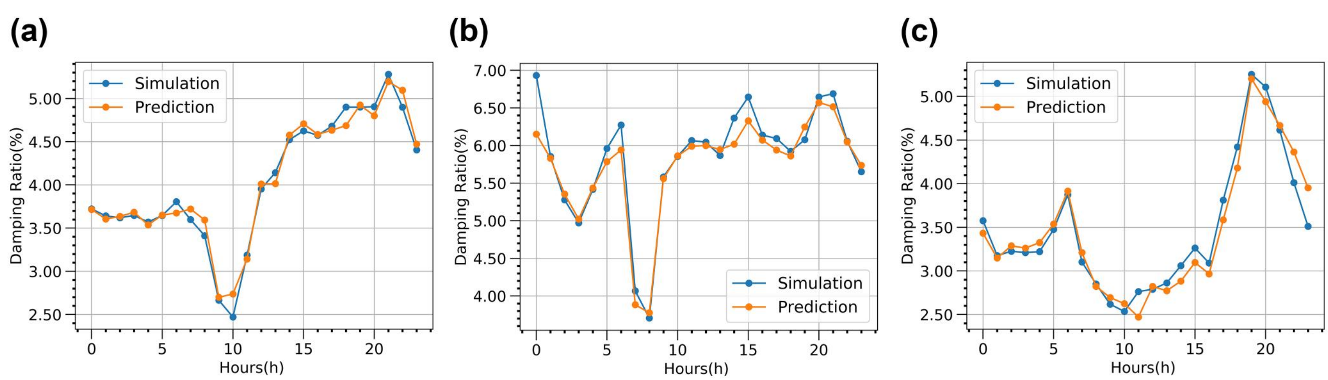

FIGURE 16 The predicted and simulated damping ratio of three selected days. (a) March 21st. (b) July 19th. (c) October 10th

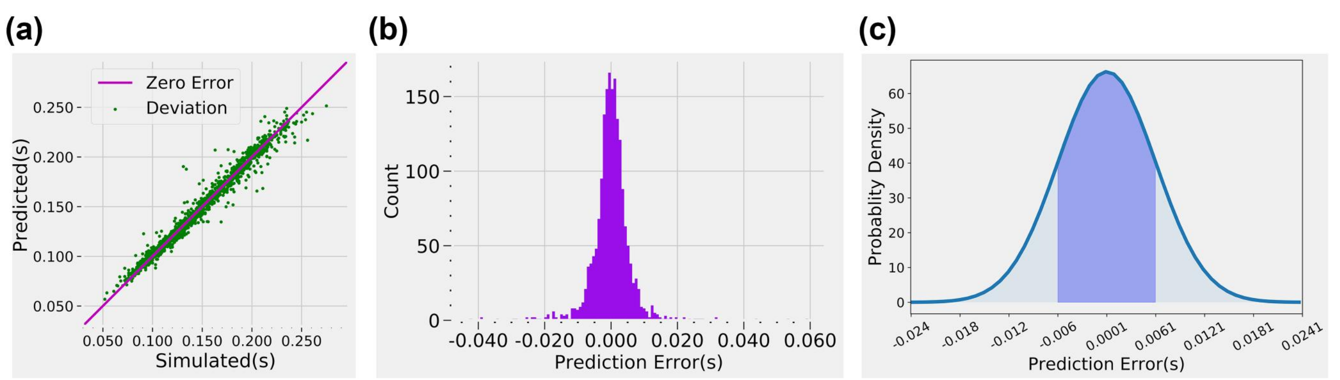

FIGURE 17 Prediction error of minimum critical clearing time. (a) Predictions on testing dataset. (b) Prediction Error histogram. (c) Prediction Error PDF

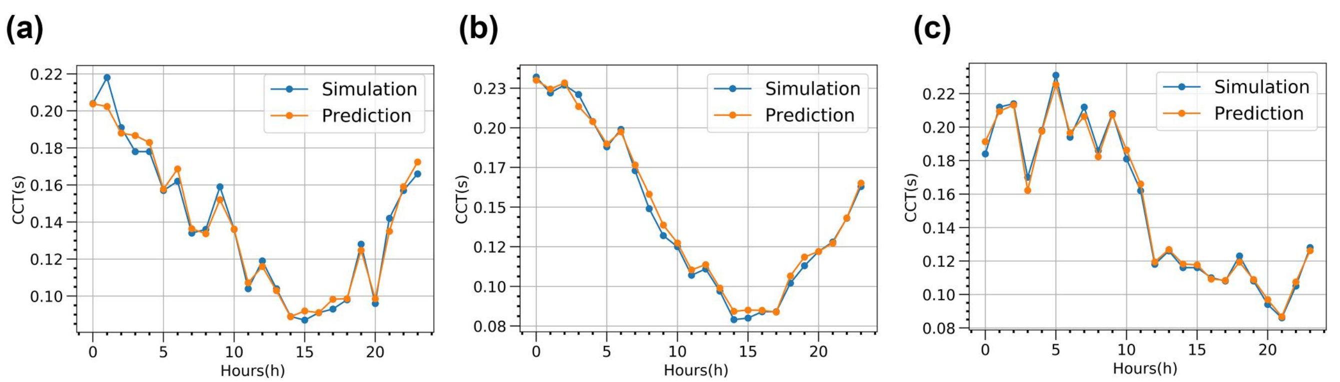

FIGURE 18 Critical clearing time prediction of three selected days. (a) April 27th. (b) September 9th. (c) September 23rd

3.3.4 | Performance comparison

The performances of the AI-based stability assessment are given in Tables 4 and 5. Its accuracy is compared with the random forest method, while its computation time is compared with the traditional time-domain simulation method. It is evident that the estimation accuracy of the proposed AI-based method is better than that of the classic random forest-based method. Also, the AI-based method can significantly reduce the computation time to perform an accurate and efficient stability assessment in a power grid dominated by IBRs.

Currently, the developed AI-based stability assessment method is being validated on the realistic 20k-bus WECC system model. A large number of snapshot models are under development to train and validate the proposed AI model for stability assessment.

TABLE 4 Comparison of estimation accuracy

	Random forest-based (%)	AI-based (%)
Frequency	98.30	99.72
Small-signal	98.33	99.18
Transient	98.44	99.29

TABLE 5 Comparison of computation time

	Time-domain simulation (h)	AI-based (ms)
Frequency	~4	~0.18
Small-signal	~1	~0.16
Transient	~24	~0.11

3.4 | AI-based data authentication

With more applications of wide-area measurements in power grid situational awareness and real-time control, cyber-security becomes a big concern. Since the real-time requirements in power grid monitoring and control may prevent the application of conventional encryption technologies, power grids lack security properties in monitoring and control protocols. Moreover, defending against data spoofing attacks is more difficult for power grids compared with other local control systems.

Some potential attacks on WAMS have already been recognized, including communication link damage (CLD), denial of service (DoS), and data spoofing [52]. Though both CLD and DoS may result in significant communication delay or even missing data, existing technologies can detect these attacks with no difficulty. Some data spoofing attacks, such as data injection and replay attacks, are easily detected, and the spoofed data may be corrected if they only account for a small portion of the overall measurements.

However, if malicious intruders are familiar with the power system and WAMS configuration, sophisticated data spoofing attacks may be performed, which have attracted little research attention and cannot be detected by the existing approaches. One example of such sophisticated data spoofing is source identifier mixing. Attackers can mix the source identifiers of measurement data from different PMUs without changing measurement values. In this case, the power system state estimator is deceived into rearranging data to wrong positions in the measurement matrix, producing faulty results.

The wide-area measurement data have spatial and temporal signatures caused by natural responses of each local grid's continuous and random condition changes. These signatures are almost impossible to counterfeit, making them unique resources for data authentication. In this work, spatial and temporal signatures and AI technology are utilised to authenticate measurements in power grids to effectively prevent malicious cyber-attacks from causing catastrophic losses [53]. The architecture of the proposed AI-based data authentication method is illustrated in Figure 19. This method uses ensemble empirical mode decomposition (EEMD) and FFT for data pre-processing and the back propagation (BP) neural network for machine learning. The measurements of different timescales are extracted using EEMD, which is a time-frequency signal processing technology that overcomes the major shortcoming of traditional empirical mode decomposition method—the effect of mode mixing [54]. The frequency spectrum from the FFT analysis is the input of the BP neural network. The BP neural network is a popular neural network model that is trained by the error BP algorithm. The BP neural network can be used to learn a large number of mapping relations of an input-output model without requiring a mathematical description of these mapping relations [55]. The output of the BP neural network is the consistent degree between the measurements and a specific FDR identifier.

The proposed data authentication method is verified using three FDRs that are closely deployed in Knoxville, Tennessee, US, as shown in Figure 20. The average distance of the three FDRs is 7.9 km. Since the frequency measurements collected by the three FDRs are quite similar, it is challenging to authenticate the data from a specified FDR if the three FDRs' IDs are randomly swapped. However, during the test, the proposed AI-based method achieved 80.9% accuracy in authenticating the data source, significantly higher than other methods whose accuracy is around 60%–70%. The developed data authentication method can be easily integrated into other WAMSs, since PMU measurements deployed at the transmission level also have the similar spatial and temporal signatures.

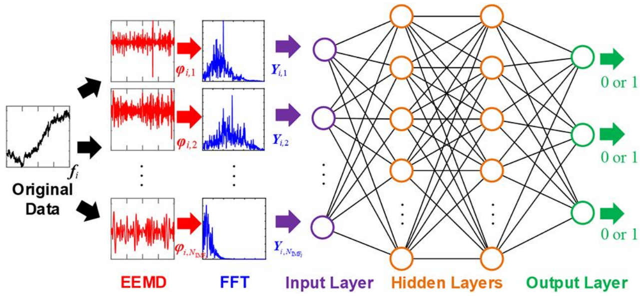

FIGURE 19 Architecture of the proposed back propagation neural network

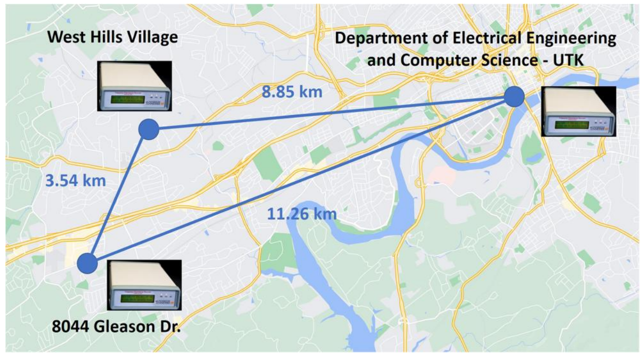

FIGURE 20 Locations of three Universal Grid Analysers

4 | CONCLUSION

This study introduces the latest progress of FNET/GridEye, especially the advanced applications based on AI technologies. At the data collection level, a new version of single-phase PMU called UGA is developed, which can provide more measurement types with a higher sampling rate and reporting rate. At the data communication level, a new data compression method that enables the efficient communication of UHD synchrophasor measurements and POW data is used. At the data server level, several AI-based methods have been proposed to estimate system inertia using ambient frequency measurements, estimate disturbance size and location, assess system stability (frequency stability, small-signal stability, and transient stability) using dispatch data, and authenticate the received data. Compared with traditional methods, these AI-based methods can provide more accurate results and improve efficiency.

However, the major challenge of applying AI technologies to power grids is that the learnt models usually do not consider the intrinsic constraints in the physical models. The learnt models are typically 'black box' models that are difficult to explain or interpret in the sense of physics. Moreover, the existing AI technologies are not robust enough to adapt to systems' time-varying characteristics. Additionally, data privacy and availability are a big concern, which requires the AI-based methods to be functional with partial or limited data.

Therefore, the developed new functions will be improved by addressing aforementioned challenges (e.g., incorporating physical model/laws into the learning process) and further validations on FNET/GridEye. After the 'trial' on FNET/GridEye, these AI-based applications can be easily implemented to other WAMSs to significantly enhance the situational awareness in power grids dominated by IBRs.

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CONFLICT OF INTEREST

The authors declare conflict of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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