Data-Driven Wide-Area Situation Analyzer for Power System Event Detection and Severity Assessment

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Abstract Real-time power system monitoring and assessment leads to two major concern, prediction and evaluation of security and stability of power system. This assists in determination of in-time probable anomaly of the system. However, at the same time it requires real—time technological applications to measure network data at all strategic geographical locations. Synchrophasor technology based wide-area situational awareness ensures power system real—time monitoring and assessment. The chapter proposes real—time data driven Wide-area Situation Analyzer (WASA). WASA first detects an event in the system using synchrophasor measurements and then assesses its vulnerability posed to power network. The vulnerability is measured as severity in terms of first swing transient instability. Level of severity index is developed in terms of generator going out of step. The bus voltage trajectories going away with rest of the system due to generator(s) transient instability are considered. The proposed new approach is based on Center of Frequency (COF) formulated from limited Phasor Measurement Unit measurements. To check for an event existence in the system, a new decision based COF concept is defined. In order to determine the severity of the identified event, a new Predictor Indices (PI) is proposed using COF and PMU measurements. These predictor indices are used in assessment methodology, based on Adaptive Boosting (AdaBoost) of decision estimators. Furthermore, comparative results of proposed wide-area situational analyzer with other machine learning algorithms are also shown. The proposed WASA is instigated on IEEE New England 39 Bus system, successfully validating analyzer performance. The different type of events considered are generation outage, bus outage, load outage and line

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events. Additionally, if any bus outage occurs due to line faults then it is considered as single severity. The results reflects the efficacy of the proposed analyzer in event detection and its assessment efficiently and effectively with very less computational burden. The ability of the proposed analyzer to identify events quickly and correctly makes it appropriate for real—time applications.

Keywords Event detection · Severity assessment · Data-driven method · Wide-area situation analyzer · Predictor indices · WAMS · Power system security

1 Introduction

Modern power system is highly dynamic in nature, is continuously subjected to varied operating conditions. These varying operating conditions may cause failure in the power system. Hence, control center are required to make use of state –of –art tools to timely detect probable failures and increase reliability of electric grids. A secure power system operation thus safeguards continuous monitoring and assessment. With implementation of synchrophasor technology, the real time disturbance monitoring and assessment is adapted [1]. This assessment requires mathematical modelling of the network that can incorporate network changes. This model are to be capable enough for timely say of 'events occurrence' and assess the reach of event in terms of 'severity'. This capability of timely event detection and its assessment is suitable to develop a mechanism for real-time applications. These mechanisms using synchronized measurements are classified in data driven based and physics based approach [2]. Measurements like bus frequency, rate of change of frequency, bus voltage magnitude, rate of change of voltage magnitude, and angles are available from synchrophasor measurements. These measurements either directly or derived quantities of these fundamental signals can be utilized to assess the real-time situation of the power network. Results from [3–13] presents power system event detection diagnostics and their assessment in terms of either classification or localization. These results are formulated by making use of machine learning techniques, statistical tests, signal processing techniques, data transformation techniques, energy methods and combinations of these methods. In majority of these techniques timely detection is achieved, however assessment of such events in terms of their effect on, 'systems health' is not show cased. Transient instability is one of the major aspect that leads the system to collapse. Therefore, transient stability assessment is crucial and has to be continuously evaluated real-time to ensure system remains in safe limits. In [14–31], various methods are proposed to identify and assess transient stability status of power system. In these methods different tools like machine learning, statistical, pattern recognition, energy methods and/or their combinations with synchronized measurements are also applied.

Largely, event detection methods proposed in literature are evaluated in terms of their response time and accuracy. On detection of events, control centers are interested in such events that can cause system to go in 'un-safe limits'. Hence, it is paramount that severity should be determined once the system is detected to have event. The severity assessment help the system operator to develop robust remedial measure if the system is moving towards insecure operation. In general, system inertia is used to assess transient instability status of power system. Assessment of real-time inertia is not easy and a small variation in inertia value may alter transient stability results [32, 33]. To overcome problem of real-time inertia assessment, Centre of Power (COP) is proposed in [27]. Power is not directly available through phasor estimates and has to be additionally calculated. This additional calculation is not easy as due to any event, power network changes and a small variation in calculation due to change in data may lead to different power calculation. This may result in inaccurate transient stability results. Hence, calculation of such indices with minimum additional computation efforts is more feasible.

Therefore, it can be imperative to develop a composite methodology for detecting event timely and assess its severity on power system. The develop method should have a good success rate and minimum response time such that, if required control or remedial actions may be initiated timely. This chapter proposes Wide Area Situation Analyzer (WASA), it utilizes PMU measurements to determine event detection and its severity assessment within first few cycles of event occurrence. A new notion of Center of Frequency (COF) to detect event and using this new notion novel indices, used as predictor indices for severity assessment are proposed. These predictors are statistical measures and hence are very effective and easily computed. The proposed WASA uses Adaptive Boosting of Decision Trees (AdaBoost) regression to amount of severity an event hold in the power network. To calculate the level of severity for an event, a methodology based on probable bus voltage trajectories that move away with rest of the system due to generator(s) transient instability, is proposed. The analyzer takes synchronized bus frequency and voltage magnitude as input and first detects event followed by severity assessment for occurred event, as its assessment is paramount to maintain system intact following event. In this work, events like short circuit, double line outage leading to bus outage, generator outage and load outage are used. These events poses major challenge to system in maintaining stability. Additionally, if any bus outage occurs due to double line faults then it is considered as single severity. The proposed analyzer is data driven and requires less computational effort, can be easily implemented on any test power system. This chapter investigates proposed WASA on IEEE 39 bus power system to predict severity within ~300 ms and ~0.08 root mean square error.

2 Proposed Wide Area Situation Analyzer (WASA)

Power System equipped with PMU infrastructure can capture real-time networks pre, during and post event dynamics [32]. The time tagged network data are stored in data concentrators and retrieved as need arises. In general, bus voltage magnitude and frequency measurements available from PMU are used to monitor real-time power system dynamics [31].

A. *Concept of Center of Frequency-Voltage*

This sub-section describes a new concept of Center of Frequency (COF). The concept is to highlight the combined impact of frequency and voltage variation on the system operation. In general, power system severity assessment utilizes bus voltage angles measurements. Algorithms based on bus voltage magnitudes for severity assessment are simpler and faster [25]. Therefore, in the presented work synchronized bus voltage magnitudes and bus frequency are considered to be input quantities for event detection and its severity assessment. In order to define the concept of method, let assume bus frequency f and voltage magnitude $|v|$ are available from PMUs and represented as given by (1). First and last elements for each column in two matrices is length of synchronized data sample from bus 1 to n$^{\text{th}}$ bus. Bus measurements recorded are with respect to reference bus of the power system.

$$f = \begin{pmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots \\ f_{m1} & \cdots & f_{mn} \end{pmatrix}; |\mathrm{v}| = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{pmatrix} \tag{1}$$

Unlike [27] where concept of center of power used for system vulnerability assessment. The concept of center of frequency do not require additional calculation, instead it uses bus frequency measurements available from PMUs. The objective of the chapter is to develop a situation analyzer that analyzes power system event and its severity in minimum time and with least error. This concept presents real-time system's overall status in terms of frequency and voltage as in (2),

$$COFV = \frac{\sum_{i=1}^{n} f_i |v|_i}{\sum_{i=1}^{n} f_i} \text{ p.u.} \tag{2}$$

where, n is total bus in power network. Equation (2) gives time-stamped Center of Frequency-Voltage (*COFV*) for any system. When we calculate *COFV*, as event occurs pre event values prior to an event is changed, and may take *COFV* to either lie around pre fault value or it may lie far from pre fault values during post fault conditions.

B. *Algorithm for Event Detection*

Corresponding to any load event there will be variation in *COFV*. This variation is shown in (3) as event detection that is used to detect event in power system. This change in (3) is shown as Event Detection (*ED*) index and is used for detect event detection in power system.

$$ED = \frac{\Delta COFV|_{(i-(i-1))}}{COFV_i} \tag{3}$$

where, i is *ith* time-stamp, (*i-1*) is previous time-stamp and *ED* is event detection index. In order to distinguish between random load perturbation and events, a threshold (ε) is defined in (4). If index $ED > |\varepsilon|$, there is an event and if $ED \leq |\varepsilon|$ there is either no event or it's a case of random load perturbation.

$$\varepsilon = \frac{l}{n}(|\Delta V_l|) \text{ p.u.} \tag{4}$$

In (4) l is number of load bus, n is total bus in power network and $|\Delta V_l|$ is per unit change in voltage at load buses at any instant. For any power system, the event detection criteria is calculated by using network bus topology in terms of load bus and total buses in power system.

C. *Severity Calculation using COF and Voltage magnitudes*

After event detection, the next crucial step is to assess its effect on system health. The system may behave abnormally due to one of the following instabilities viz: rotor angle, voltage or frequency instability. Rotor angle instability may be first swing or multi swing transient instability problem. This chapter focuses severity assessment based on first swing transient instability problem. The system health depends on severity level, i.e. if event is more severe it may lead to system collapse rapidly. In this context, first swing transient instability is significant and its timely and fast assessment can prevent the system from catastrophic failure. The bus voltage trajectories going away with rest of the system due to generator(s) transient instability are considered. In this chapter, only generator bus and load bus are considered (zero power bus are not considered) as important nodes. That is due to generator(s) transient instability, generator bus and load bus voltage trajectory are taken as important buses. Relative bus voltage magnitude w.r.t center of frequency-voltage for these important nodes is measured and noted as given by (5)

$$SA_b = |v|_b - COFV \tag{5}$$

where b is (load bus + generator buses) and *SA* is severity assessment for important nodes. The value of SA for each b is calculated and compared with pre-defined threshold (μ). If SA for any bus is greater than μ, then bus is 'critical'. For such cases Severity Matrix (*SM*) is calculated and is mathematically shown as:

$$\begin{aligned} &If\ SA_b > |\mu| \rightarrow SM_b = 1 \\ &else \qquad\quad\ \rightarrow SM_b = 0 \end{aligned} \tag{6}$$

For SM = '1' signifies 'critical bus', is counted and weighted for all total important nodes giving overall Severity Index (*SI*) by (7).

$$SI = \frac{\sum SA_b}{N_b} \tag{7}$$

A pseudo code for severity index calculation below elaborates systematic computation. Severity computed is in terms of first swing transient stability. The value of *SI* lies in range [0,1]. In the range '0' indicates no severity whereas '1' indicates maximum severity as if all important nodes are transient unstable.

```
Pseudocode: Calculation of Severity Index
Initialize: Call |v| and COFV
  for each  monitored bus
     | Calculate |v| - COFV
     | If  (Calculate |v| - COFV) > absolute(μ)
     |    | Severity Count = 1
     | else
     |    | Severity Count = 0
     | end
  end
```

$$\text{Severity Index} = \frac{\text{count(severity Count=1)}}{\text{Total monitored bus}}$$

Record: Severity Index

Pseudocode discussed above is for those buses for which voltage trajectory move away from rest of system due to generator(s) transient instability. Additionally, due to double line faults, bus outage occurs. This single bus outage is also considered as single critical bus and can be considered as minimum severity.

D. *Data mining through Adaptive Boosting of decision trees (AdaBoost)*

AdaBoost [34] is a boosting ensemble of decision trees regressor. Model learns from increasing weights of previous mistakes. It is adaptive as following weak learners stay in favor of the instances that are misclassified by previous classifiers. Root Mean Square error (RMSE) given by (8) is used to evaluate performance of AdaBoost regressor. RMSE is standard deviation of the prediction errors.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{p}\left(\hat{y}_i - y_i\right)}{p}} \tag{8}$$

where, y_i is actual value, $\hat{y}_i$ is predicted value and p is total unseen testing samples. As event is detected and relative bus voltage magnitude is computed using (5), standard deviation of post event data is used as input features for regressor as in (9). These calculated features are taken as Predictor Indices (PI). Standard deviation measures disturbance present in the signal. The features calculated from archived synchronized database is used to train a regressor for associated severity in offline mode. The trained regressor then predicts severity level in real-time for different unseen operating conditions. The feature are given by following relation:

$$feature = S.D(SA_b)\,\forall\, b \in \text{ important bus} \tag{9}$$

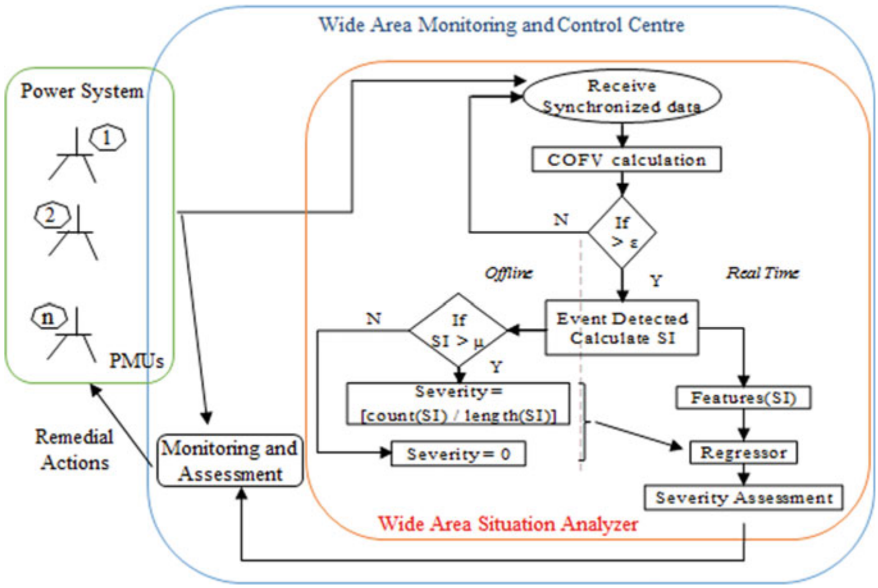

Fig. 1 Proposed Wide Area Situation Analyzer (WASA)

The overall structure of proposed Wide Area Situation Analyzer (WASA) is shown in Fig. 1.

The frequency and voltage magnitude inputs from data center are used to give severity assessment and share with control center for further processing and initiating appropriate measures if required.

3 Performance of WASA: Result and Discussion

The proposed WASA is validated through numerical simulation and analysis on IEEE 39 bus system implemented on DIgSILENT powerfactory. For effective test of proposed analyzer, number of events at different power system loading is used.

A. *Test System Data*

The study is carried for four types of events as short circuit cleared with line outage, double line outage leading to bus outage, generator outage and load outage. Bus voltage magnitude and bus frequency measurements from PMU with 60 samples in 1 s are recorded. As two consecutive value of *COFV* is sufficient to detect any event in the system. Two data samples of bus frequency and bus voltage magnitude are used to detect event. The data window for severity analysis is of post disturbance 18 cycles (300 ms). For events like short circuits, clearance time used in this study is of 6 to 12 cycle. This fault clearance time is sufficient for protection scheme to come into action. Since the test system have 19 load buses and 10 generator buses, while 2 loads are on generator buses, thus in all 27 vital buses are considered that take care of either generator bus, load bus or both.

B. *Event Detection*

The proposed analyzer is implemented on IEEE 39 bus system, having 19 buses with dispatchable loads. At any given instant, random load variation at all the buses is in such a way that voltage variation is $\pm 1\%$. The threshold ε is calculated by substituting these values in (4), with $l = 19$, $n = 39$ and $\Delta V = \pm 1\%$ (here the threshold value of ε is taken as ~0.005 p.u). This threshold value is system dependent. Visualization of event detection is presented graphically in Figs. 2 and 3. The voltage angle-time series is shown for 27 important buses. Figure 2a depicts short circuit case initiated at 0 s at bus 03 and cleared in 6 cycles by opening line 02-03. Time response of bus voltage angle is shown for 3 s. During short circuit events, frequency and voltage value decreases, *COFV* value goes down, and again increases after fault clearance. Event detection index crosses threshold, as at the time of fault inception and at time of fault clearance the ED values is more than threshold. Figure 2b shows double line fault at 0 s making bus 28 outage. Due to this bus outage, network flow changes and accordingly voltage and frequency values changes. The resulting *COFV* and *ED* changes from pre fault values and event is detected at index crosses the threshold. Figure 3a visualizes generator 01 outage connected to bus 30. Due to generator outage, power imbalance takes place and after some time this imbalances minimizes and network functions with decreased generation. As visualized, event detection index identifies the event as soon as generator outage takes place. Figure 3b shows load outage at bus 20. It is visualized that effect of this load outage on bus voltage is less than other events as post event *COFV* value decreases but this decreases is less than other events. Other load outage may have large effects on system voltage and depends on network operating conditions. It is found that Event Detection (*ED*) crosses threshold (ε) for all the four types of events. Similarly, other events are detected and visualized. On detection of event, severity assessment methodology is implemented and is discussed in following sub-section.

C. *Severity Assessment*

Once event is detected, post event data is used to first calculate relative bus voltage magnitude. Relative bus voltage magnitude is used to construct severity index using pseudo code as discussed above. Severity index is then computed that gives level of severity due to event occurred. The level of severity gives number of buses, who's voltage trajectories move away with rest of the system due to generator(s) transient instability. The deviation of bus voltage magnitude from *COFV* shows behavior of bus voltage with rest of the system. With event inception, each bus voltage magnitude will deviate from system *COFV*. The more it deviates, chances of system going towards insecure limits increases. In general, there are difference among stable and unstable faults, post-fault voltage trajectories. For a post-fault stable system, voltage trajectories tends towards flat following a recovery. In case of unstable system, voltage

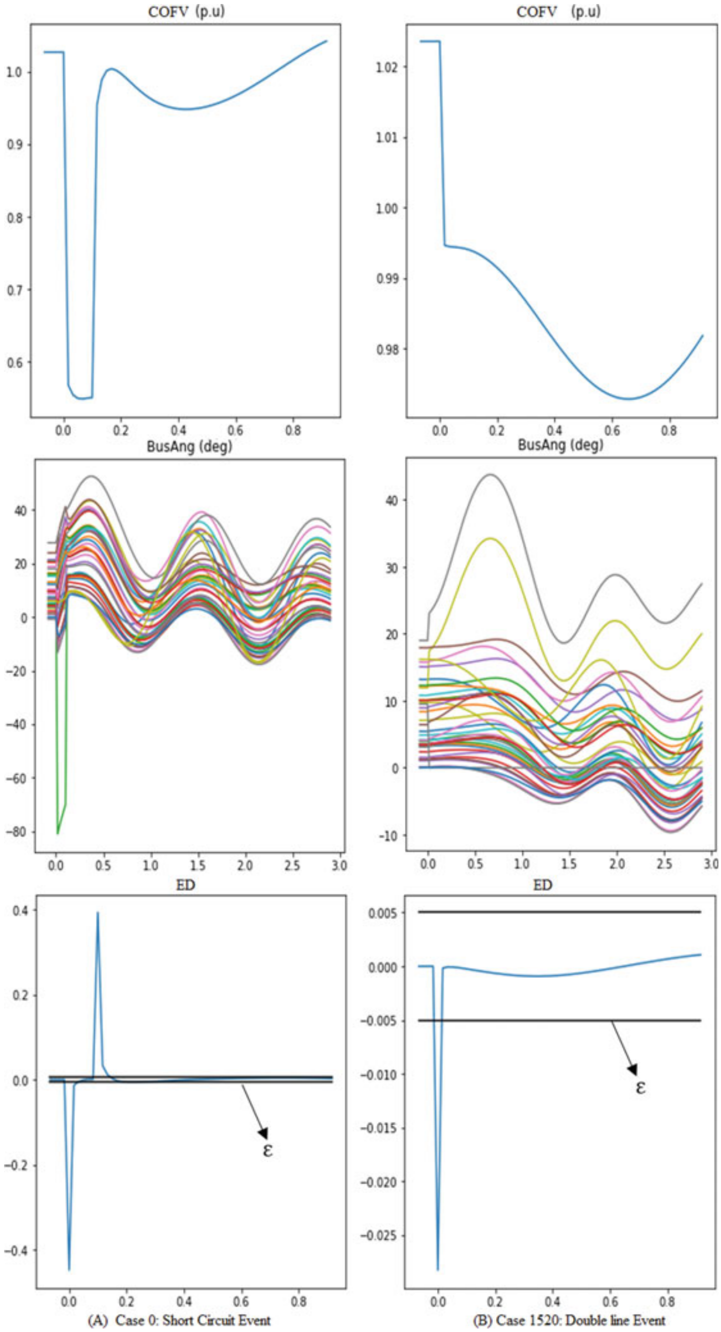

Fig. 2 Visualization of event detection for short circuit and double line faults

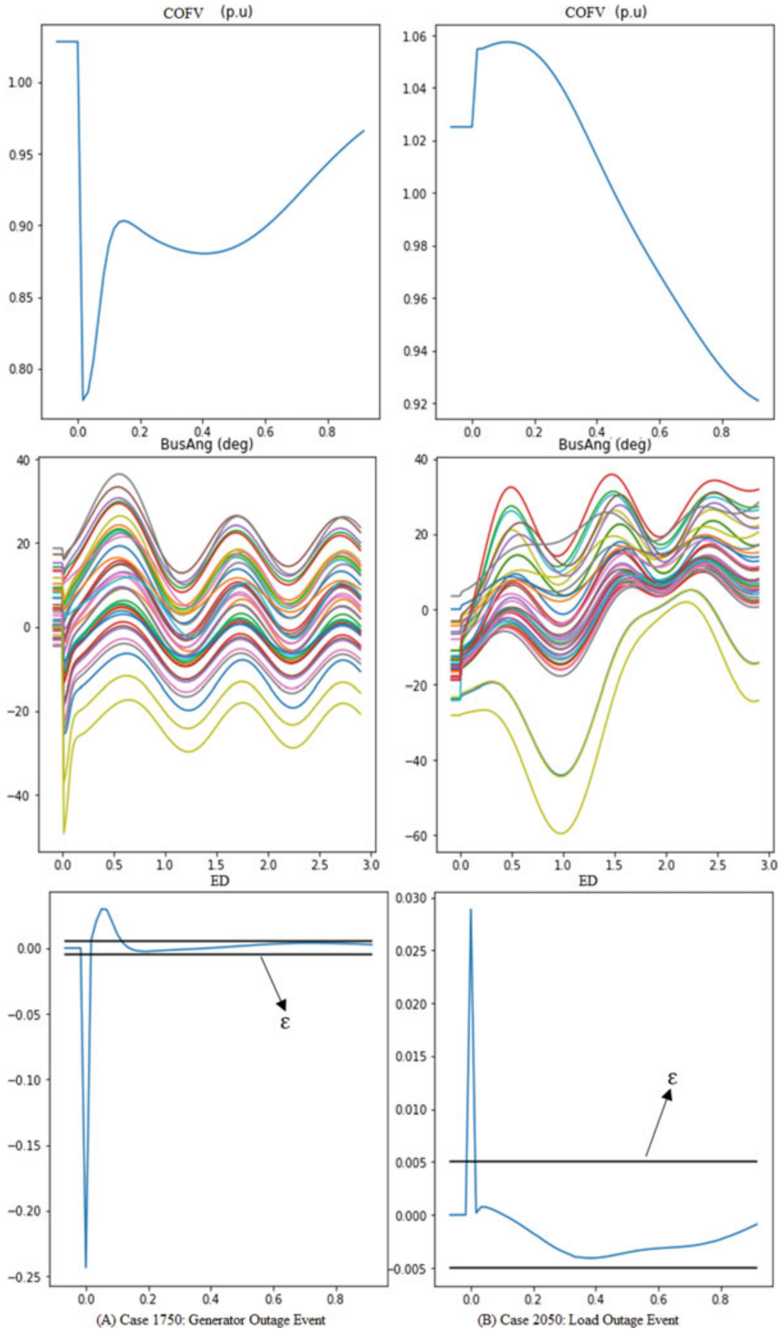

Fig. 3 Visualization of event detection for generator outage and load outage events

trajectories gradually gives rising or falling trend following initial recovery. It is observed during multiple time domain simulation of test power system that at least one bus crosses the threshold (μ greater than 0.2), and simultaneously at least one monitored bus goes transient unstable. Hence, deviation of 0.2 p.u of bus voltage with respect to center of frequency voltage is used as threshold for system qualifying in severity status. In order to understand how event can pose severity to system, Fig. 4 shows an example cases, where event does not affects system operation and can be considered to be less severe event. In Fig. 4, following a short circuit event system remains stable as load and generator bus voltage magnitude do not crosses the threshold. The first row shows generator bus and load bus relative voltage magnitude. While second row shows time series generator bus and load bus voltage angles.

In Fig. 5 double line fault event, which leads to bus outage is shown. In this figure for generator and load bus case, it can be clearly visualized that since generators are transient stable no important bus crosses threshold. Although one load bus do crosses threshold, is due to fact that double line outage event has lead this load bus outage from system. As discussed in section II, sub-section C can be coined minimum severity.

Figure 6 shows case of generator transient unstable case where, occurred event poses severity to the system. In such cases, voltage of critical bus will be most diverged from *COFV*. If for any event, the voltage trajectory of buses diverge from *COFV* and crosses the threshold. The respective bus then enters in 'critical bus' category and is noted in severity index and counted with '1 critical bus' out of total important bus. Figure also shows early detection of critical buses that will move out of step. It can also be shown that the critical load bus move out of threshold before critical generator bus. These critical bus shows instability around 0.8 s whereas bus

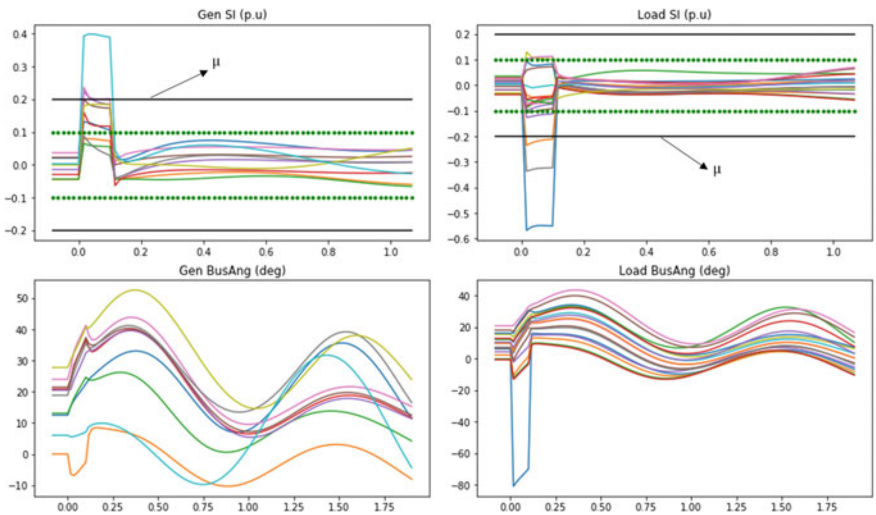

Fig. 4 Visualization of Stable case for short circuit event

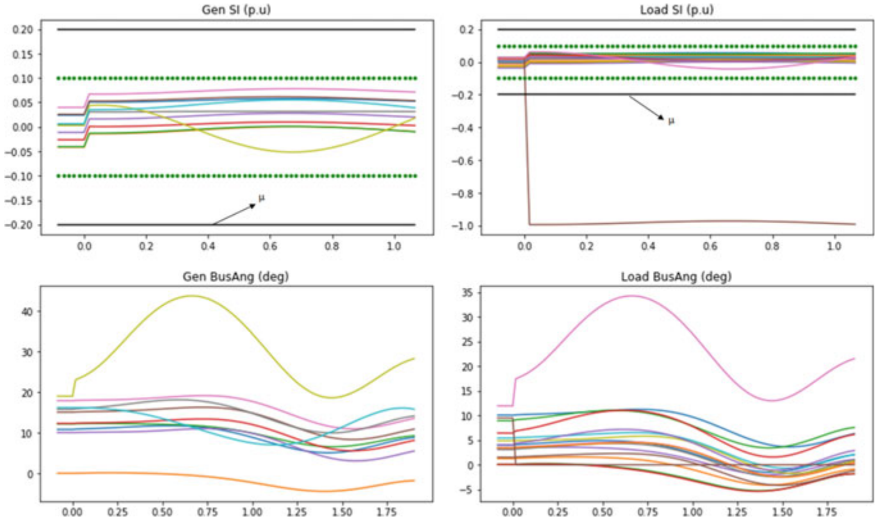

Fig. 5 Visualization of double line event leading to bus outage

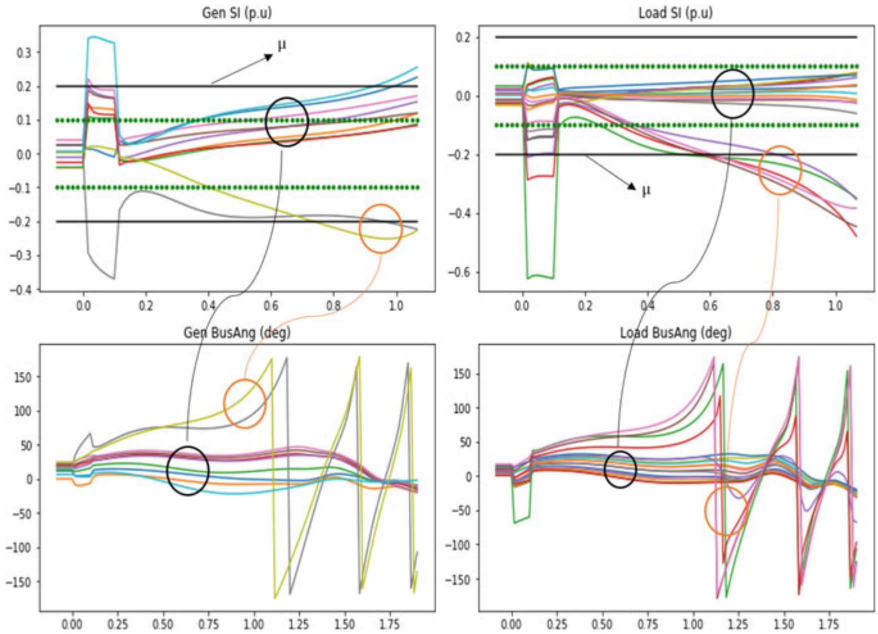

Fig. 6 Visualization of transient unstable case for short circuit event

actually move out of step after 1 s. Thereby giving additional margin for initiating emergency actions.

D. *Results of AdaBoost Regressor*

To calculate the severity of an event in real-time, AdaBoost regressor is implemented. A large dataset of 2221 cases is generated with different operating conditions for modelling and testing unseen cases. Apart from four types of events, no event cases are also incorporated in the study to make the WASA familiar with no event data. These cases overall contribute to zero severity case of 1121 and non-zero severity cases to 1100 as shown in Table 1. For each case, the analyzer takes total 1560 samples out of which 156 for event detection and 1404 for severity assessment. The standard deviation of relative bus voltage magnitude computed using (5) are used as features to the regressor to build and test it for severity ranging between [0, 1]. The overall details are tabulated in Table 2. This data is reduced to 27 Indices as input features. These indices are equal to number of nodes of interest in the system. The AdaBoost Regressor is modeled for various number of trees as shown in Fig. 7 and ensemble of 78 trees is made to build the Regressor to predict severity due to an event. As at this ensemble, RMSE is minimum. Response time taken by proposed WASA for severity assessment is outlined in Table 3. The delay in receiving synchronized data is considered as 0.2 s [13].

Results infers that proposed analyzer computes severity in less than 0.3 s for all the considered cases. This timely detection and assessment of event ensures timely

Table 1 Data Info for operating conditions

S.No	Disturbance type	Total operating conditions	Severity cases	
1	Short circuit cleared with line outage	1499	Zero Severity = 1121	Non-zero Severity = 1100
2	Double line outage leading to bus outage	250		
3	Generator Outage	172		
4	Load outage	280		
5	Normal (no event)	20		
	Total	2221		

Table 2 Details of data from PMU, features and target for Regressor

Synchronized data from PMU	Features	Target
Event detection: Bus voltage magnitude (39×2) + bus frequency (39×2) = 156 Severity assessment: Bus voltage magnitude (39×18) + bus frequency (39×18) = 1404 Total = 1560	Monitored buses = 27	Severity = [0,1]

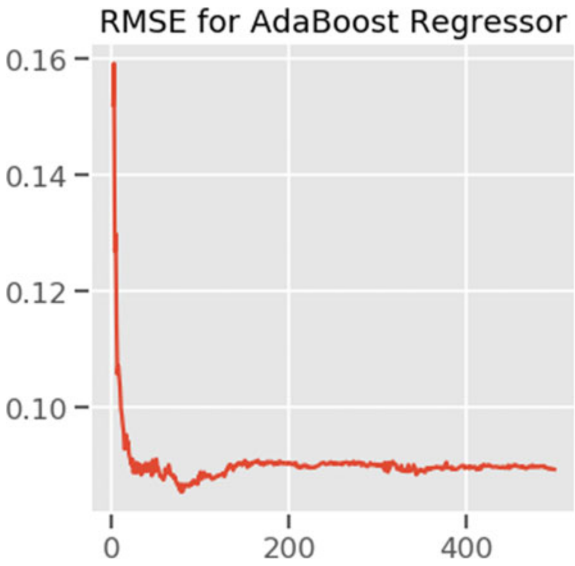

Fig. 7 Root mean square error with different ensemble of trees

Table 3 Response time for severity assessment

Operation	Time (s)
Receiving synchronized data	0.2
COFV calculation	0.003
Event detection	0.0006
SI calculation	0.005
Feature extraction	0.03
Prediction Time (per case)	0.06
Total Time	0.2986

initiation of emergency or remedial actions, if required. The performance of WASA with other Regressor available in literature is also computed and shown in Fig. 8.

The time of action of proposed algorithm with classifiers like Random Forest (RF), Gradient Boosting (GBR), Support Vector Regressor (SVR), Decision Tree Regressor, k-Nearest Neighbor and Multi-Layer Perceptron Regressor is within ~0.35 s. However, the error of these classifiers is more than AdaBoost Regressor. A visualized result for random twenty sample unseen test cases is presented in Fig. 9.

These cases contains both zero and non-zero severity and shows actual and predicted severity for different cases are shown. The analyzer can hence provide probable solution for severity assessment an event contains upon its occurrence and can help control operator to initiate any remedial or control action.

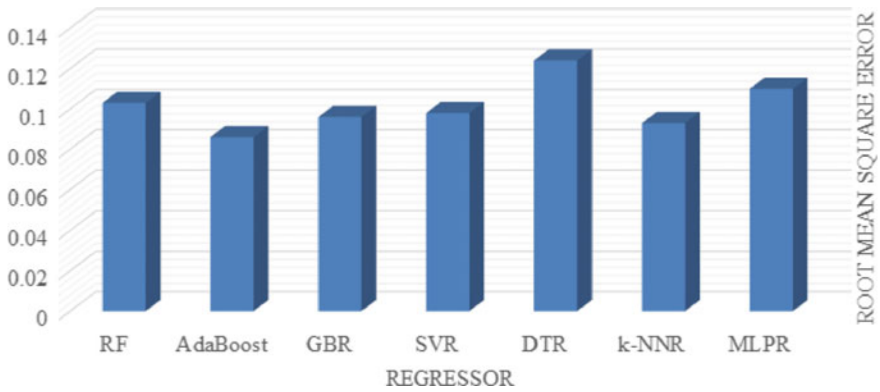

Fig. 8 Proposed WASA performance with Regressors

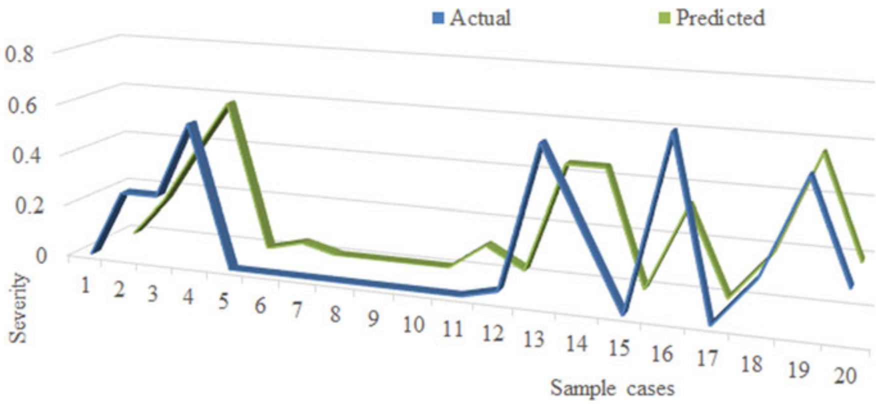

Fig. 9 WASA performance with AdaBoost

4 Conclusions

The real-time situational analyzer WASA is developed to detect and assess the vulnerability of events in terms of severity using synchrophasor data. New concept of Center of Frequency-Voltage (*COFV*) based on real-time bus frequency and voltage measurements is proposed. Successive change in *COFV* detects event. Once event is identified, severity of the event is calculated by formulating new predictor indices. These predictor indices are standard deviation of severity assessment calculated from voltage trajectories and center of frequency based bus voltage magnitude. Level of severity index is also developed in terms of generator going out of step. The bus voltage trajectories going away with rest of the system due to generator(s) transient instability are considered. Due to double line faults, bus outage occurs and is taken as minimum severity. This single bus outage can also be considered as single critical bus These Predictor Indices early detects probable number of generator going out of step. In order to predict probable severity in real-time AdaBoost Regressor is trained using statistical features extracted from these indices. The proposed Wide Area Severity Analyzer is applied on IEEE 39-bus test system. The response time for proposed analyzer is ~ 300 ms and root mean square error of ~ 0.08, which ensures early event detection and severity assessment, and increases real-time power system situational awareness.

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