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Detecting Topological Errors with Pre-Estimation Filtering of Bad Data in Wide-Area Measurements

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Abstract—It is expected that bad data and missing topology information will become an issue of growing concern when power system state estimators are to exploit the high measurement reporting rates from phasor measurement units. This paper suggests to design state estimators with enhanced resilience against those issues. The work presented here include a review of a pre-estimation filter for bad data. A method for detecting branch status errors which may also be applied before the state estimation is then proposed. Both methods are evaluated through simulation on a novel test platform for wide-area measurement applications. It is found that topology errors may be detected even under influence of the large dynamics following the loss of a heavily loaded branch.

Index Terms—Power system State Estimation, Topology Error, Bad Data, PMU, WAMS

I. Introduction

It has been proposed that SCADA systems of the future may incorporate the full potential of PMU technology with direct measurement of all state variables [1]. With reporting rates of PMU data much faster than traditional RTU based measurements it is likely that latencies in data communication and processing become a significant challenge.

Every measurement has some noise component. While PMUs are capable of measuring state variables directly it has been shown that the noise component can reduce the accuracy of system monitoring to undesirable levels [2]. A state estimator may filter the noise component from the measurements. If bad data is fed to a state estimator it might bias the output and produce erroneous estimates of the system state. Thus, a procedure for validating the data must be applied.

Means of data validation can follow either a model free or a model based approach. Approaches for detecting range errors, large noise components, stale data and synchronization errors in PMU data have been suggested without the use of elaborate system models [3]. The model based data validation has predominantly been conducted after a state estimation algorithm has determined a most likely system state. The data validation can then be based on identification of protruding measurement residuals [4]. The hypothesis testing identification method is a better choice in case of multiple bad data [5]. The iterative process of estimating states, identifying and eliminating bad data result in indeterministic execution time. It should therefore be considered to filter at least the simplest identifiable bad measurements before the estimation. Pre-estimation identification of bad data can be done on basis of measurement innovations [6]. Measurement innovations

are differences between a predicted measurement and the actual measurement. To predict a measurement a dynamic state estimator should be applied.

If model based data validation relies on incorrect information about bus configurations or branch statues the results will be unreliable. Commonly a topology processor gathers information such as breaker statues and possibly transformer tap-settings and passes the topology information on to the state estimator [4]. Thus, topology processing must be conducted at rates that match that of the state estimator. Significantly increasing the frequency of the state estimator requires increased frequency of topology processing. The chance of missing topology information or loss of synchronism between topology processing and state estimation is a real issue in PMU based measurement systems [7].

Means of topology error detection have been proposed to exploit normalized residuals in post-estimation identification [8]. This paper proposes a method for pre-estimation detection of branch status errors which can distinguish system dynamics from erroneous branch statuses.

The remainder of the paper is organized as follows: II explains on the pre-estimation filter for bad data and introduces the proposed method for pre-estimation detection of branch status errors. III provides explanations of tests and discusses results hereof. IV concludes the paper.

II. Discriminating bad measurements, topology errors and dynamics in state estimation

Bad measurements, errors in topology information and changes in system state which are not addressed by modelling all cause anomalies in power system state estimation.

A. Pre-estimation filtering of bad data

A bad data filtering process was introduced by Pignati et al in [9]. The algorithm performs a prediction of every set of incoming measurements. The prediction is associated with a confidence bound. Any incoming measurements that lay outside these confidence bounds are flagged as anomalies and processed. Those measurements which fall inside the confidence bounds are fed to a Kalman filter state estimator. The anomalous measurements are treated as either bad data or indicators of an insufficient process model. In the case of detection of bad data the bad measurements are substituted by their predicted values in the state estimator. In cases where anomalies are due to system dynamics the process noise is

updated. A brief description of the algorithm is provided below. The reader is referred to [9] for an in-depth explanation. A system model given by;

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{w}_{k-1} \quad , \tag{1}$$

where $\mathbf{x}_k$ is the state at the kth time-step, $\mathbf{A}$ is the state transition matrix and $\mathbf{w}_{k-1}$ is the process noise at time-step $k-1$. The process model applied is a random walk. This is reflected by assuming the state transition to be a stationary identity matrix and letting the process noise account for the mobility of the state. The process noise is formally given by $p(\mathbf{w}_k) \sim N(0, \mathbf{Q}_k)$ and the process noise covariance matrix $\mathbf{Q}$ reflects the precision of the process model. The measurement equation is given by:

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \tag{2}$$

Here $\mathbf{z}$ is the set of measurements, $\mathbf{H}$ is the measurement Jacobian and $\mathbf{v}$ is the measurement noise. The state vector $\mathbf{x}$ is here composed of bus voltages on rectangular form while the measurement vector $\mathbf{z}$ is composed of bus voltage- and branch current measurements on rectangular form. This yield a linear relation between measurements and state.

The measurement noise is modelled with a zero mean normal distribution; $p(\mathbf{v}_k) \sim N(0, \mathbf{R}_k)$, where $\mathbf{R}$ is the measurement noise covariance matrix. The measurement noise covariance is in [9] assumed uncorrelated.

The Kalman filter state estimator consists of a set of prediction and estimations equations:
Prediction equations:

$$\mathbf{x}_k^- = \hat{\mathbf{x}}_{k-1} \tag{3}$$
$$\mathbf{P}_k^- = \mathbf{P}_{k-1} + \mathbf{Q}_k \tag{4}$$

Estimation equations:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H}\mathbf{P}_k^- \mathbf{H}^T + \mathbf{R}_k)^{-1} \tag{5}$$
$$\hat{\mathbf{x}}_k = \mathbf{x}_k^- + \mathbf{K}_k(z_k - \mathbf{H}\mathbf{x}_k^-) \tag{6}$$
$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H})\mathbf{P}_k^- \tag{7}$$

Here $\mathbf{x}^-$ and $\mathbf{P}^-$ denote the a-priori state and estimation covariance while $\hat{\mathbf{x}}$ and $\mathbf{P}$ are the a-posteriori state and estimation error covariance.

The measurement innovation ν expresses the difference between the predicted set of measurements and the actual incoming measurements:

$$\nu = \mathbf{z} - \mathbf{H}\mathbf{x}^- \tag{8}$$

The measurement innovation covariance $\mathbf{S}$ is given by:

$$\mathbf{S} = \mathbf{H}\mathbf{P}^-\mathbf{H}^T + \mathbf{R} \tag{9}$$

The diagonal elements of $\mathbf{S}$ represent the variance of measurement innovations. A threshold for acceptable measurement innovations is defined on basis of a confidence bound, chosen as a factor γ of the standard deviation of a predicted measurement.

$$|\nu(i)| \leq \gamma\sigma_i \Leftrightarrow |\nu(i)| \leq \gamma\sqrt{\mathbf{S}(i,i)} \tag{10}$$

The state trajectory is not sufficiently represented by a random walk during a dynamic system response. To distinguish bad data from system dynamics Pignati et al. applies a heuristic identification criteria [9]:

> If adjacent measurements are anomalous, then anomalies are due to dynamics rather than bad data.

By verifying that an anomaly occurs on two neighbouring measurements it is inferred that the anomaly is due to a system dynamic and the measurements should not be filtered as bad measurements. On the other hand, if bad data is detected, the suspicious measurement is substituted by the predicted value and the filtered set is fed to the state estimator. This new pseudo-measurement has a measurement noise covariance equal to the corresponding measurement innovation covariance. Tuning of the process noise covariance matrix allow the uncertainty of the state trajectory during dynamics to be accounted for in the process noise. Upon detection of a dynamic state change the process noise of the relevant state variables is penalized by adding to it a large value. The process noise covariance is then permitted to readjust according to the development in the estimation error covariance. Several methods for readjusting the process noise covariance were investigated in [10]. This study uses the computationally lightest of them:

$$\mathbf{Q}_k = \text{diag}(\mathbf{P}_{k-1}) + \text{diag}(\mathbf{P}_{k-2}) \tag{11}$$

B. Topology error detection

The methods of detecting branch status errors is based on the normalized residual test presented in [4]. Though, rather than residuals the inference will be based on innovations.

For any time step the measurement innovation corresponding to a measurement i can be normalized by:

$$\overline{\nu}_i = \frac{\nu_i}{\sigma_i} \quad , \tag{12}$$

where $\overline{\nu}_i$ admits a standard normal distribution $p(\overline{\nu}_i) \sim N(0, \mathbf{I})$.

A branch status error would introduce an error in the measurement Jacobian such that the measurement innovation is given by:

$$\nu = \mathbf{z} - \mathbf{H}_e\mathbf{x}^- = \mathbf{E}\mathbf{x}^- + \mathbf{v} \quad , \tag{13}$$

where $\mathbf{H}_e$ is the erroneous measurement Jacobian and $\mathbf{E} = \mathbf{H} - \mathbf{H}_e$ is the Jacobian error matrix. The statistical features of the measurement innovation show that measurement innovations will be biased by an erroneous measurement Jacobian:

$$\text{E}(\nu) = \mathbf{E}\mathbf{x}^- \tag{14}$$
$$\text{cov}(\nu) = \mathbf{S} \tag{15}$$

A branch-to-measurement incidence matrix $\mathbf{M}$ translates measurement innovations to bias in branch flow:

$$\varphi = \mathbf{M}\mathbf{E}\mathbf{x}^- \tag{16}$$

The bias in branch flow admits the following statistical features:

$$\mathrm{E}(\varphi) = \mathbf{M}\nu \qquad (17)$$

$$\mathrm{cov}(\varphi) = \mathbf{M}\mathbf{S}\mathbf{M}^T \qquad (18)$$

Because the measurement innovations are assumed uncorrelated (i.e. $\mathbf{S}$ is diagonal) the normalized bias in branch flow may be obtained from the normalized measurement innovations:

$$\overline{\varphi} = \mathrm{diag}(\mathbf{M}\mathbf{M}^T)^{-1/2}\mathbf{M}\overline{\nu} \quad , \qquad (19)$$

In the case where correlation between measurement innovations must be considered (18) would have to be evaluated whenever $\mathbf{S}$ changes.

An insufficient process model is likely to impose additional bias on the branch flows during system dynamics. Detection of branch status errors will be based on the assumption that bias in branch flow which is due to dynamics will be more evenly distributed than bias which is due to single branch status errors. On basis of this assumption a criteria has been chosen such that topology errors are detected if the bias in branch flow of any branch significantly exceeds that of other branches:

$$|\overline{\varphi}_{i,k}| < \lambda \cdot \sigma(\overline{\varphi}_k) \quad \forall \quad i \in m \qquad (20)$$

where m is the set of branches and $\sigma(\overline{\varphi}_k)$ is obtained as the standard deviation of the vector of normalized branch flow innovations for each time step. For the cases studied here a factor of $\lambda = 5$ times the standard deviation of branch flow innovations seems to fit the notion of a *significant* difference.

A flow chart of the pre-estimation filter of bad data and branch status errors is found in figure 1. The 'update topology' block has not been implemented for this study. Instead it will be investigated whether the detection of topology errors is possible under dynamic state transitions.

III. EVALUATION OF BAD DATA AND TOPOLOGY ERROR DETECTION AND CORRECTION

The Kalman filter state estimator, the pre-estimation filter for bad data and the proposed method for detecting branch status errors are implemented in Matlab and subjected to three tests; missing data identification during steady state, detection of dynamics following a branch trip and detection of branch status errors following a branch trip. The Cigré Nordic test system shown in figure 2 is used for simulations [11].

Voltage phasors are measured at all buses and branch current phasors are measured at both ends of each branch. The simulations are conducted on a novel software platform for developing PMU applications in a real-time environment [12]. The platform broadcasts snapshots comparable to the output of a phasor data concentrator. The snapshots may be generated by real-time or offline simulations. In this study simulations were produced offline with PSS/E and broadcast at a rate of 10 snapshots per second.

The 'clean' simulation results are scrambled by adding a random noise component according to the measurement
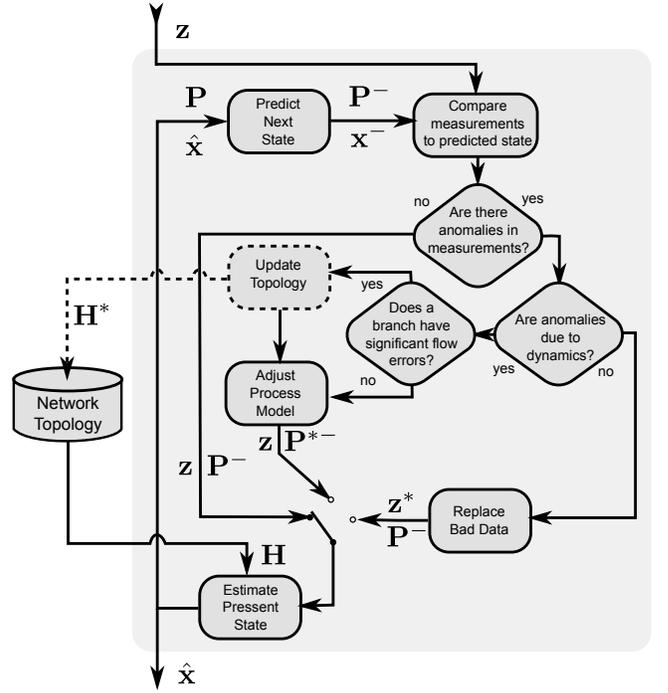

Fig. 1: Proposed flowchart of the pre-estimation filter for bad data and topology errors. $*$ marks quantities which are modified by the filter.

noise model. Measurement errors are assumed uncorrelated and normally distributed with zero mean and variance $\sigma^2 = (1.0\%/3)^2$. The estimation error and process noise covariance matrices are both initialized to: $\mathbf{P}_0 = \mathbf{Q}_0 = 10^{-4} \cdot \mathbf{I}$ The threshold at which anomalies are detected in the measurement innovations are chosen to $\gamma = 4$ times the standard deviation of the respective measurement innovation. A penalty of 10^{-3} is imposed on the process noise covariance which corresponds to state variables that are undergoing dynamics.

A. Bad Data identification in steady-state

The evaluation for bad-data detection and correction which was conducted in [9] is reproduced below. The bad data detection is simulated on a test system in steady state.

The voltage at bus 4032 is replaced by NaN in the interval between 5th and 18th second. This could imitate a local model free data validation procedure which has identified the measurement as bad and replaced the value by NaN [3].

Simulation results are shown in figure 3 where real and imaginary parts of the true (V_{ref}), scrambled (V_{scram}) and estimated (V_{est}) voltage phasors for bus 4032 are plotted against time along with the $\pm\gamma\sigma$ envelope of acceptable measurements.

The pre-estimation filter detects the bad measurement and replaces it with the predicted value. The state estimator uses this pseudo-measurement while the bad data persists. As the pseudo-measurement is based on earlier measurements the confidence in the pseudo-measurement declines as time
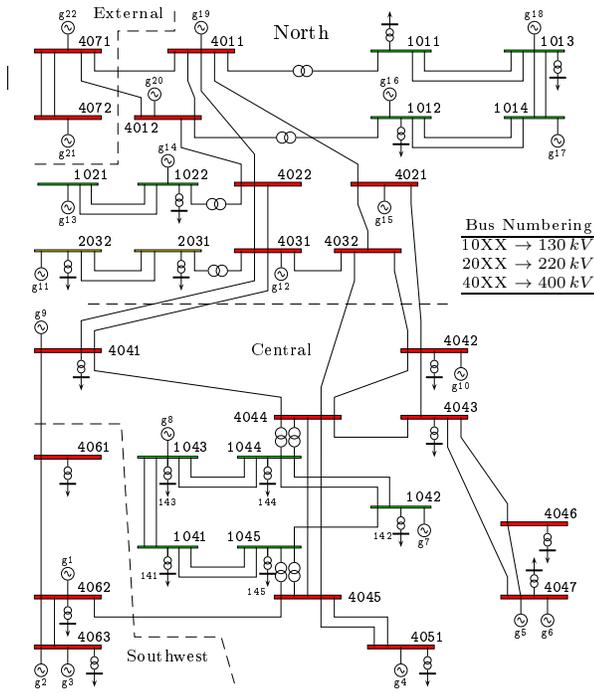
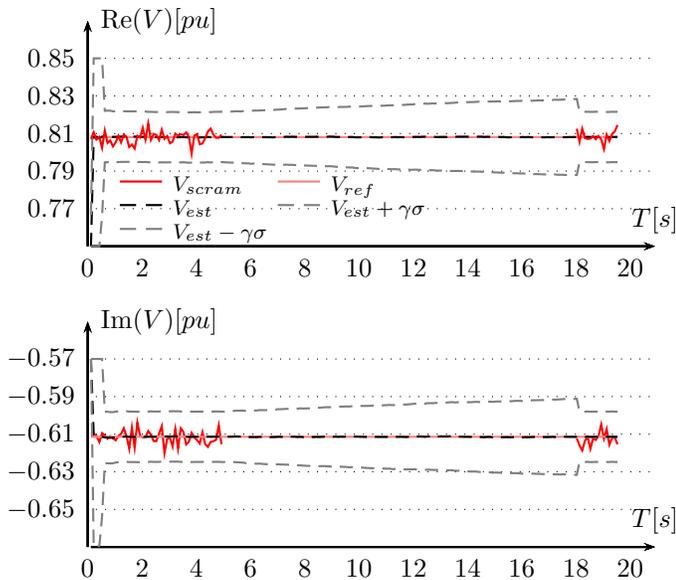Fig. 2: Single line diagram of the Cigré Nordic test system

Fig. 3: Detection and correction of NaN injection on voltage measurement at bus 4032

progresses. The estimated voltage during the NaN injection follows the true value with good precision.

These results support those obtained in [9]. It has further been confirmed that the pre-estimation filter successfully identifies a drifting bus voltage angle and a small magnitude offset during a steady-state simulation.

B. Evaluation of Filter Performance Under Dynamics

Two scenarios are simulated in order to investigate filter performance under both violent and subtle dynamic events.
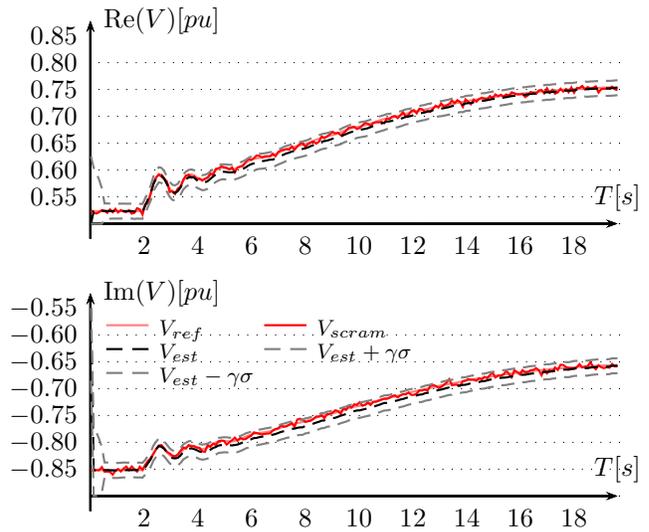

Fig. 4: Voltage at bus 1042 following trip of line 1042-1045

The first scenario is initiated by tripping line 1042-1045. The line caries a steady state current of nearly 90A per phase. The line trips at $t = 2s$. The second scenario begins also at $t = 2s$ with tripping of line 4032-4044 which prior to tripping carries about 550A per phase. Results are presented and discussed below:

*1) Filter performance following trip of line 1042-1045:* Right after this line trips dynamics are detected at 6 nodes. Initially no measurements are identified as bad. During the first 2 seconds after the disturbance the number of measurement locations where dynamics are detected reduces to 2. From the 4th second follows an interval where both the number of detected dynamics and detected bad data fluctuates between 0 and 13. The number of detected dynamics and bad data declines from the 10th second and from the 16th second neither dynamics nor bad data are detected. It should be noted that no bad data were imposed on this simulation. Thus all bad data detected were falsely detected.

The time series in figure 4 show that the estimated voltage at bus 1042 follows the true value somewhat more precisely during the first two seconds after the disturbance than from 4th second till 16th second. The estimated voltage seem to lag behind the true and scrambled values in the interval from 4th to 16th second.

This indicates that the filter performs better under violent dynamics than under subtle dynamics. The slow dynamics later in the simulation poses a greater challenge due to false identification of bad data. Estimation errors for this simulation are provided in figure 5a in form of percent total vector error on selected state variables over time. It is seen that the estimation error reduces towards the end of the simulation where the system approaches a new steady state.

2) Filter performance following trip of line 4032-4044: Tripping the highly loaded line immediately leads to detection of dynamics in measurements at 41 buses. The number grows to 46 after a few snapshots. From the 8th second the number
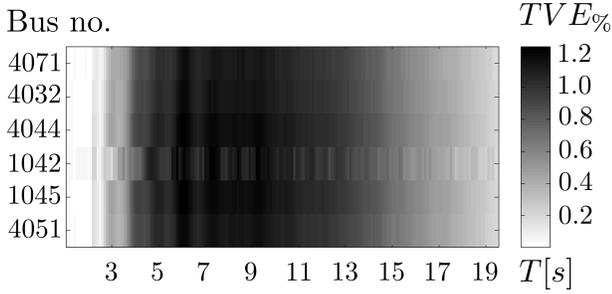
(a) Branch trip: 1042-1045
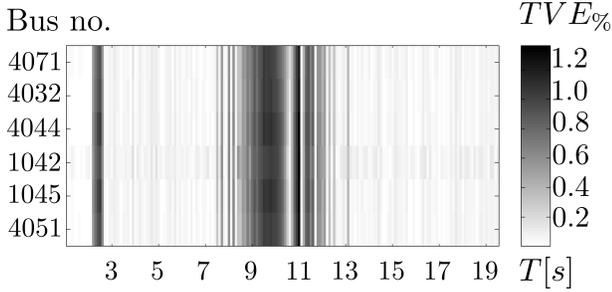
(b) Branch trip: 4032-4044

Fig. 5: Total vector errors of selected bus voltage estimates during dynamic response in two branch trip scenarios

Fig. 6: Voltage at bus 4032 follwoing trip of line 4032-4044

of recorded dynamics start to decrease while a few (1-3) bad data are detected as well. At 10.3s no dynamics are identified. From 10.9s the number of detected dynamics increase and reaches a 46 after 12th second where it remains till end of simulation.

On figure 6 the trajectory of the voltage phasor on bus 4032 travels from the 4th quadrant through the 1st quadrant to the 2nd quadrant from where it swings back through the 1st to the 4th quadrant. The intervals where dynamics were detected on large number of buses coincide with those where the plotted state variable under goes rapid change. The interval where the voltage phasor enters the 2nd quadrant, slows down to a halt, and accelerates back through the 1st quadrant coincides with the interval where a reduced number of state variables were identified as undergoing dynamic change. The plot of total vector errors on figure 5b reveals that the accuracy of the estimator is reduced during the same interval.

C. Evaluation of Topology Error Detection

The branch trip scenarios are run again. Though, this time no external function for validating and updating branch statuses is applied. The method of detecting branch status errors should therefore detect the branch status error after tripping of line 1042-1045.

Tripping of line 1042-1045 leads to immediate detection of the branch status error. Normalized bias in branch flows for selected branches are provided in table I. The bias in several branch flows increase for the snapshot immediately following tripping of branch 1042-1045 at $t = 2.00$s. The bias associated with branch 1042-1045 is distinguishably larger in
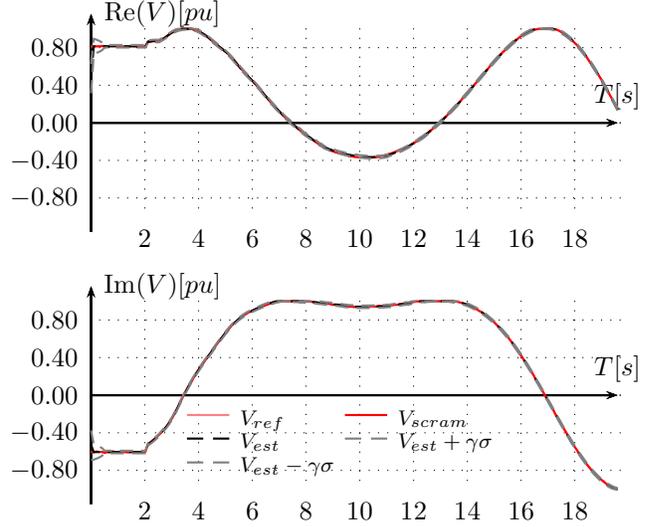
the first snapshot following the disturbance, while the bias in the two adjacent lines 1042-1044:1 and 2 are dominant in later snapshots. A branch status error is on that basis successfully detected. It is further seen that the bias in branch flow is not applicable as a criteria for identifying the erroneous branch.

It takes one additional snapshot before the trip of line 4032-4044 is detected. This is because the large variance in branch flow biases during the first snapshot after tripping the highly loaded line.

When bias in branch flows are obtained from measurement innovations all branches which undergo a change in power flow will be biased by the disturbance. The power in line 1042-1045 is redistributed on adjacent branches which will also be associated with a biased branch flow. Differences in measurement innovation covariances skew the normalized bias in branch flow. The indicator can therefore not be used for identification of the tripped branch. However, it is here shown to work well for detecting that a branch status error is present. Thus, in addition to this a method for identifying the location of the topology error is necessary. For identification of topology errors in static state estimators it has been suggested to augment the state vector by a variable representing the status of suspicious branches and let the estimator perform the identification [4]. It is worthwhile to investigate the suitability of this method in relation to the work presented above.

The methods were tested on an Intel Core i7-3630QM CPU running at 2.40GHz. The time spend on filtering and estimation was found to be on average 16ms during steady state and 23ms during dynamic intervals.

IV. Conclusion

When power system state estimators are to exploit the high measurement reporting rates of PMUs it is likely that updates of network topology information falls behind the state estimator. Detection of topology errors is thus a vital function of robust PMU-only state estimators. This paper has shown

TABLE I: Normalized branch flow innovations of for selected branches. Branch 1042-1045 trips at 2.00s

Time	1.858	1.959	2.060	2.161	2.262	2.363
1041-1045:1	0.179	-0.056	0.210	-0.123	-0.040	-0.073
1041-1045:2	0.113	-0.063	0.018	-0.037	-0.016	-0.173
1042-1044:1	0.085	0.062	0.809	**2.792**	**2.522**	**3.353**
1042-1044:2	0.292	-0.056	0.920	**2.730**	**2.812**	**3.356**
1042-1045	0.220	-0.023	**-3.182**	-1.796	-1.409	-1.227
4044-4045:1	-0.095	0.046	0.225	0.073	0.213	0.186
4044-4045:2	-0.113	0.021	0.223	0.042	0.188	0.158
mean($\overline{\varphi}$)	0.003	0.007	-0.012	0.064	0.057	0.049
st.dev($\overline{\varphi}$)	0.138	0.116	0.439	0.520	0.492	0.591

TABLE II: Normalized branch flow innovations of for selected branches. Branch 4032-4044 trips at 2.00s

Time	1.888	1.989	2.090	2.191	2.292	2.393
4021-4042	0.011	0.089	1.464	-0.738	-0.809	-1.932
4031-4032	0.179	0.000	1.755	-0.530	-0.511	-0.381
4032-4042	-0.105	0.095	-3.700	-3.201	-3.254	-3.685
4032-4044	-0.044	-0.081	4.900	**4.729**	**5.559**	**6.763**
4042-4043	-0.088	-0.040	0.241	-0.172	-0.282	-0.316
4042-4044	0.062	-0.072	2.765	0.486	0.270	0.160
4045-4062	0.166	0.228	-6.539	-2.023	-1.819	-1.380
mean($\overline{\varphi}$)	0.003	-0.003	-0.002	-0.070	-0.163	-0.213
st.dev($\overline{\varphi}$)	0.128	0.127	1.929	0.926	1.047	1.247

how detection of branch status errors can be integrated with identification of bad measurements for a PMU-only state estimator.

A pre-estimation filter for bad data in PMU based state estimators has been evaluated. Simulations showed that the filter successfully identifies and removes single bad data from a measurement set before passing the set to a state estimator. However, it was found that the filter was prone to falsely identifying bad data during dynamic state changes of the system.

The method for detecting branch status errors prior to state estimation has been proposed to use measurement innovations. The method was tested on a simulated system and it was proven capable of detecting a branch trip under both subtle and violent dynamic system conditions.

These findings are valuable for further development of means of identifying and correcting the topology errors.

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