Enhancement of Power System State Estimation

Bei Gou[1] and Weibiao Wu[2]
[1]Department of Electrical and Computer Engineering, North Dakota State University
[2]Department of Statistics, University of Chicago
USA

1. Introduction

Power Utility companies use the state estimator to provide system operating status to the operators of their control center to allow them to manage and to take appropriate measures to prevent the loss of electricity. The unavailability of state estimation solution may cause the occurrence of cascading failures or blackouts in local and/or regional areas for considerable time periods, if disturbance occurs during the period of unavailability and thus can not be closely monitored. The robustness and reliability of state estimation is a critical issue and concern of power utilities.

The Weighted Least Square (WLS) method is the commonly used state estimation methodological approach in power industry. If one or more gross errors are contained in the measurements the WLS state estimator may not reach a solution and diverge. A well-known example when the WLS did not converge due to the existence of a topology error was a indirect contributing factor to the August Blackout in Northeastern U.S. in 2003. According to the President's Task Force the operator could not determine the status of the system because of a computer program 'glitch'. This 'glitch' was a failure of the WLS method to converge and give a solution to the State Estimation. Task Force comments noted the 'unacceptability' of such computer program errors when the economic impact of the consequential blackout was so dramatic. The economic damage of the 2003 blackout was reported to be in excess of $10 Billion dollars.

The following figure shows the convergence property of WLS state estimation. This figure was obtained on IEEE-118 bus system. WLS state estimation has been simulated on 5000 different patterns of load levels for IEEE 118-bus system. It is clear to see that WLS state estimation will be completely unfunctional after the load level reaches a specific amount. Details of this simulation will be explained later in the chapter.

The need to detect the gross errors is a critical and challenging issue for WLS state estimation. Many researchers have tried to develop algorithms to detect gross errors for WSL state estimation without dramatic success. Most of the detection techniques proposed so far are based on a solution of WLS state estimation. The dilemma is that detecting gross errors requires a solution of state estimation under the presence of gross errors that solution may not occur.

Topology errors are classified in two categories: branch status errors and substation configuration errors (Abur and A.G. Exposito, 2004). The analysis of conditions upon which topology errors can be detected was presented in (K. A. Clements and A. Simoes-Costa, 1988 and F. F. Wu and E. H. E. Liu, 1989). A geometric interpretation of the measurement residuals for topology errors identification was provided in (K. A. Clements and A. Simoes-Costa, 1988) which also proposed a systematic analysis of the normalized residuals to detect the bus configuration errors. Ref. (F. F. Wu and E. H. E. Liu, 1989) presented the effect of measurement equations when including topology errors and proposed a method to detect the topology errors by residual analysis. A method based on the number of measurements labeled as bad data was proposed in (H. J. Koglin et al 1986, H. H. J. Koglin and H. T. Neisius, 1990, and H. J. Koglin and H. T. Neisius, 1993). A robust Huber estimator based on an approximate decoupled model was proposed in (L. Mili et al, 1999) as a means of pre-checking the assumed system topology. Effects of topology errors can be considered explicitly by representing the circuit breakers in terms of the real and reactive power flows (Monticelli and A. Garcia, 1991, Monticelli, 1993, and Monticelli, 1993). Observability of breaker flows and cases of undetectable breaker status errors are identifies by the WLAV estimator (Abur et al, 1995). LAV was also used to detect the topology errors in (H. Singh and F. L. Alvarado, 1995). A generalized state estimation was proposed to identify topology errors in (E. M. Lourenco, et al, 2004, and O. Alsac, et al, 1998).

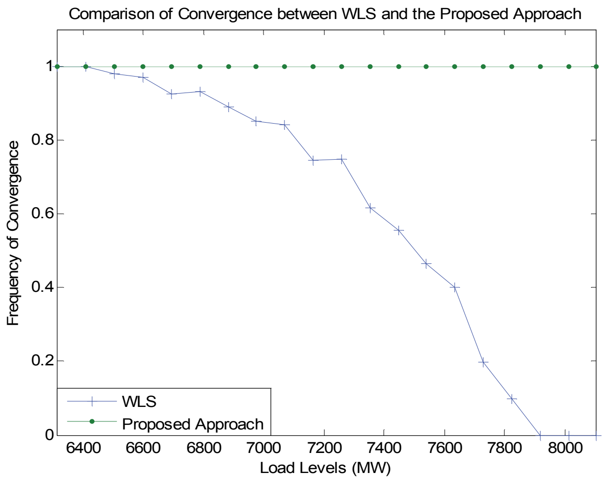

Fig. 1. Divergence rate of WLS state estimator for different load levels in IEEE 118 bus test system.

The newly developed disruptive state estimator is based on a totally different philosophy that does not require a solution of state estimation. As the divergence of the WLS state estimation occurs far too frequently it is to the new approach's merit that a solution of the system is not needed. This new innovative approach also is able to provide a reasonable state estimation solution under any circumstance.

2. Proposed bad data processing algorithm

For a transmission line, if the voltage at one end and parameters of the line are known, then the voltage of the other end can be uniquely calculated from the power flow on this line. The

idea can be applied to the entire system: if a tree formed by branch flow measurements and the root voltage is known, then the voltages of the whole system can be uniquely calculated (P. Bonanomi and G. Gramberg, 1983). The idea is re-studied in this paper.
The proposed algorithms in this paper are totally different from the one in (P. Bonanomi and G. Gramberg, 1983):

1. The tree defined above in (P. Bonanomi and G. Gramberg, 1983) does not always exist and the authors of (P. Bonanomi and G. Gramberg, 1983) did not solve this problem (see discussion in (P. Bonanomi and G. Gramberg, 1983)). This paper solves this problem by introducing an Extended Solving Tree. With suitable adjustment, the PI's proposed algorithms of observability analysis (Bei Gou, 2007, Bei Gou and Ali Abur, 2000, Bei Gou and Ali Abur, 2001, Bei Gou, 2006) can be used to find an extended solving tree and the redundant measurements for all the measurements in the extended solving tree;
2. The bad data detection method is totally different: (P. Bonanomi and G. Gramberg, 1983) made use of KCL and KVL laws and this paper uses the residuals of redundant measurements which is clearer and more efficient in bad data detection;
3. This paper proposes an non-iterative robust state estimation which is equivalent to the weighted least square, and therefore the best estimates of the states can always be obtained under any circumstances.

2.1 Extended solving tree

If there does not exist a tree of measurements to connect all the buses in an island (sub-network), then this island can be processed individually and solved by using WLS. Then the extended solving tree is defined to be a tree that contains not only transmission lines assigned by measurements but also islands whose sizes are minimized.
In the following context, we will still use solving tree for the description, but it should be note that the description is also true for the extended solving tree.

Definitions

Before the description, we give the following definitions:

- *Bus Distance*: the Bus Distance between buses i and j is defined as

$$d_{ij} = |V_i - V_j| = \sqrt{(|V_i| - |V_j|)^2 + (\theta_i - \theta_j)^2} .$$

- *Parent Bus*: bus A is called a parent bus of bus B when bus B can be directly solved from bus A. A bus can only have one parent bus in a solving tree.
- *Children Buses*: Bus A is called a children bus of bus B when bus A can be directly solved from bus B. A bus can have multiple children buses in a solving tree.
- *Ancestor Buses*: ancestor buses of bus A are defined to be all the buses solved before bus A. Ancestor buses also forms an island.
- *Descendent Buses*: descendent buses of bus A are defined to be all the buses that can be solved only after bus A is solved. Descendent buses also forms an island.
- *Recovered Power Flows* of a solving tree: are defined to be the power flows and power injections that are calculated from the solution of the solving tree.

2.2 Error propagation

For a solving tree, it is obvious to see that an error present in any of the measurement in the solving tree will be propagated to its descendent buses. We will show that the following Theorem is true.

Lemma 1: For a given set of redundant measurements, if this set of measurements is perfect, then the solutions of any possible solving trees are identical, and equal to the one when all the measurements are used.
Theorem 2: If a bad data appears in a measurement of a solving tree, then all the recovered power flows corresponding to the redundant measurements of this measurement contain a gross error.

Proof:

Let us assume all the measurements are perfect except a gross error in a flow measurement S_{km} (see Fig. 1 for the explanation) that is included in a solving tree l. S_{km} is a measurement connecting two islands: one is formed by the ancestor buses of S_{km} and the other is formed by the descendent buses of S_{km}. Suppose a gross error appear in S_{km}. So the voltage V_m contains an error. Assume one of the redundant measurements of S_r is recovered and equal to $\tilde{S}_r$. Now we need to prove that $\tilde{S}_r$ is different from S_r which is perfect.
We assume that $\tilde{S}_r$ equals S_r
Now if we form a new solving tree l_1 by including S_r in l and discarding S_{km}. The new solving tree forms a tree and can still solve the whole system. Since $\tilde{S}_r = S_r$, so the solving tree l_1 obtains the same solution as that of l. That means that voltage V_m at bus m solved from l_1 is the same as the voltage solved from the solving tree l. And V_m contains an error due to the error appearing in S_{km} in l.
However, since all the measurements in the solving tree l_1 are perfect, Lemma 1 shows that we should obtain an exact solution. That means that the voltage at bus m should be accurate. We reach a contradiction! Therefore, our assumption is wrong. $\tilde{S}_r$ does not equal to S_r. We conclude the proof. ■

Remarks:

1. Theorem 2 implies that all the voltages at the descendent buses of a measurement S_{km} are pushed in-group to a wrong place by the error in S_{km};
2. Theorem 2 implies that any error including bad data in a measurement of the solving tree, topology error or parameter error in a line of the solving tree, will cause obvious errors in the residuals of the redundant measurements of that measurement.

Examples for theorem 2

A) Gross error in measurement

Let us look at an example. In this example, we introduced a gross error (change the sign) to the real power measurement on branch 4-7. In Fig. 2, we can see that some of the voltages showed by '+' and 'O' are overlapped, while other voltages showed by '+' are moved down, which indicates the approximately same error is attached to all the descendent buses of bus 4.
Detection: The recovered power flows, which correspond to the redundant measurements of this measurement, should have big deviations from the redundant measurements. This feature can be used to detect errors in the measurements.

B) Error in branch parameter

In the same system and measurement configuration, we added an error in the parameter of branch 7-9. The comparison of voltages with and without parameter error is shown in Fig. 3.
Detection: Assume the measurement be perfect on the branch 7-9 that has a parameter error. If the measurement on branch 7-9 is replaced by one of its redundant measurements to form

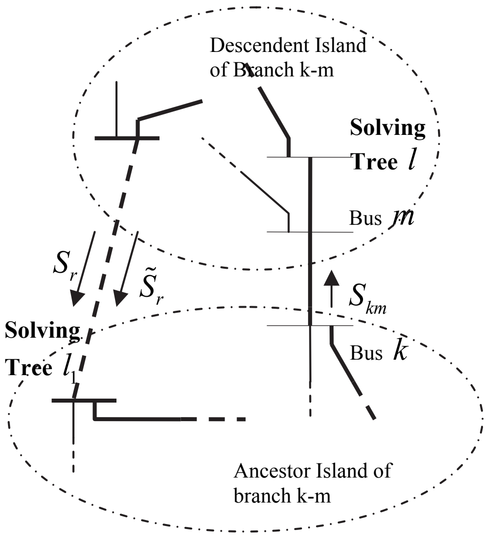

Fig. 2. Explanation of the proof

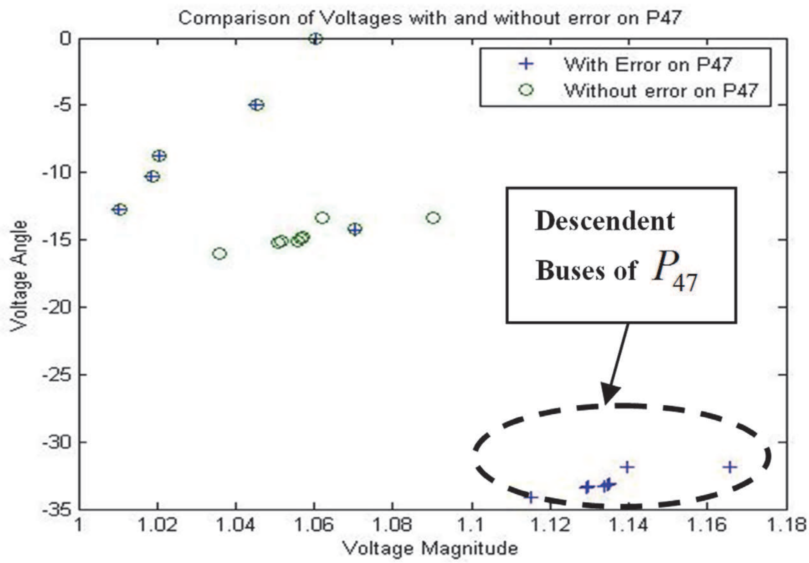

Fig. 3. Comparison of Voltages with and without Errors

a new solving tree, then the recovered power flow of branch 7-9, calculated from the solution of the new solving tree, should be equal to the measurement on branch 7-9. This feature can be used to detect the branch parameter errors.

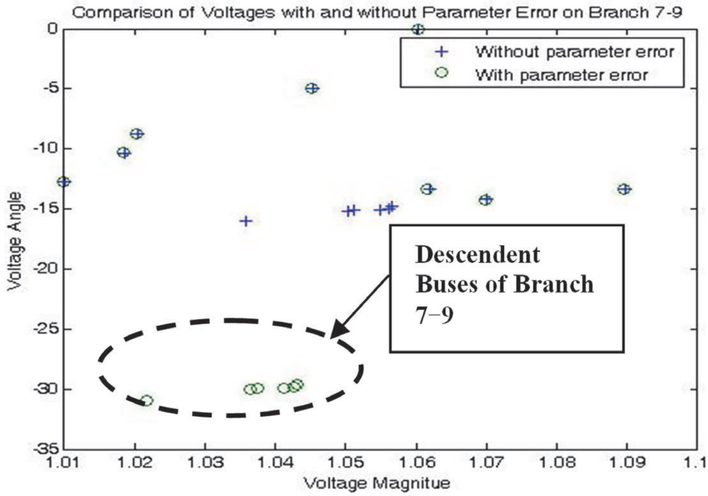

Fig. 4. Comparison of Voltages with and without Parameter Error

C) Topology error

Furthermore, we added a topology error on branch 13-14 that is wrongly considered to be closed while it is actually open. The comparison of voltage with and without topology error shows that only the voltages at the descendent buses of branch 13-14 have errors, which is shown in Fig. 4.

Detection: Assume the injection measurement at bus 14 is error-free. Then the assigned flow measurement on branch 12-13. The voltages between these two buses have very close voltages showing in Fig. 4. This feature can be used to detect the topology error.

Bad data detection

Once the recovered measurements are obtained from the solution of a solving tree, we are able to detect the bad data. The main idea to detect the bad data is to use the redundant measurements. Here we assume that there are no critical measurements and critical pairs. For a solving tree, every measurement (real flow or reactive flow) has at least two redundant measurements that connect the ancestor island and descendent island of this measurement. The residuals of these redundant measurements (the difference between the redundant measurements and their recovered power flows) can be directly used to detect the bad data. Hypothesis Testing Technique (L. Mili, et al 1984) is used to detect the bad data.

The multiple interacting and confirming bad data can be detected by the proposed bad data detection algorithm. We do not need to study it separately.

Critical measurement and critical pairs

Comparing the maximum historical bus distance with the bus distance calculated from the solving tree is possibly able to detect the bad data in the measurements.

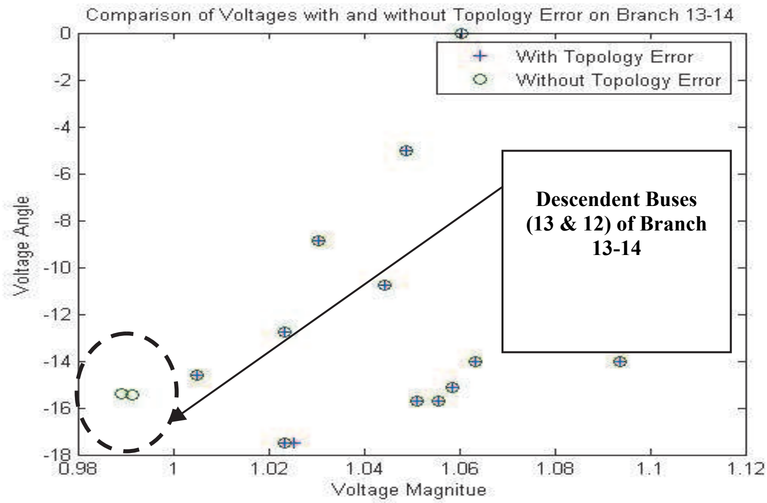

Fig. 5. Comparison of Voltage with and without Topology Error

3. A numerical test example

IEEE 14 bus system is used to test the proposed robust state estimator. A solving tree l is found which is given in Figures 1 and 2.

Three gross errors are added: 1) a topology error on branch 4-7: an open breaker on branch 4-7 is wrongly considered to be closed; 2) a sign change on real power measurement P_{79}; and 3) a sign change on reactive power measurement $Q_{9,10}$. The redundant measurements are flows on branches 2-4, 4-2, 4-5, 5-4, 4-9, 9-4, 6-11, 11-6, 6-12, 12-6, 6-13, 13-6, 9-7; injections at buses

A solution is obtained from the solving tree and power flows are recovered. Comparing the residuals of original measurements and the recovered power flows, we found the following measurements having biggest residuals: real and reactive power flow measurements on branches: 2-4, 4-2, 4-5, 5-4, 4-9, 9-4, 6-11, 11-6, 6-12, 12-6, 6-13, 13-6; and real power flow measurement P_{97} (P_{79} is a measurement in the solving tree).

Big residuals on branches 2-4, 5-4, 6-11, 6-12, 6-13 show that there must be a gross error in the measurement (injection at bus 3) that is assigned to branch 3-4. We removed the injection measurement at bus 3, and add the measurement on branch 2-4 (P_{24} and Q_{24}) to form a new solving tree l_1.

Solve the system by using l_1 and calculate the residuals of original redundant measurements and their recovered power flows. We found the following branches having big residuals: real and reactive power flow measurements on branches 4-9, 6-11, 6-12, 6-13, and the real power flow P_{97} on branch 9-7. It is obvious that those branches indicate a gross error in the measurement on branch 7-9.

We removed P_{79}, Q_{79} and add P_{97}, Q_{97} on the branch 7-9 to form a new solving tree l_2.

Solve the system and calculate the residuals, we found $Q_{11,6}$ and $Q_{10,9}$ have big residuals. Their corresponding measurement in l_2 is $P_{9,10}$ and $Q_{9,10}$. We replaced them with their redundant measurements $P_{6,11}$ and $Q_{6,11}$ to form a new solving tree l_3. The residuals from the solution of solving tree l_3 are all very small.

Then we concert all the redundant measurements to the solving tree, for example, branch flows on 6-12 and 6-13 were converted to measurements on 1-2, injection at bus 10 was converted to flows on 9-10, voltage magnitude measurement at bus 14 was converted to bus 1, etc. After all the redundant measurements were converted, we calculated the voltages at all the buses by using the updated solving tree l_3 and reached the best estimates of IEEE 14-bus system (see Table I). White noises having zero mean and 0.001 standard deviation were added to all the measurements.

Bus	***Solution from Solving Tree***	
	$\lvert V \rvert$	θ
1	1.0610	0.0
2	1.0459	-4.980
3	1.0109	-12.710
4	1.0193	-10.320
5	1.0211	-8.770
6	1.0708	-14.210
7	1.0624	-13.370
8	1.0903	-13.370
9	1.0568	-14.950
10	1.0514	-15.110
11	1.0570	-14.800
12	1.0549	-15.080
13	1.0502	-15.160
14	1.0361	-16.030

Table 1. Estimates of system states from the solving tree

4. Simulation results

The comparison between WLS and our new approach has been performed on IEEE 118 bus system. Three test scenarios that include two random bad data, two random interacting and conforming bad data, and two random topology errors, have been examined. Identical sets of measurements were tested for both approaches. Under light load levels, the new approach is several percent better [99.7%] than the WLS method [97%] in detecting topology errors. Under heavy loads where the WLS method frequently fails to reach a solution and the new approach is very superior.

To validate the new approach we also examined the new approach on a real power system with 5145 buses. A clear delineation between the two methods at a certain load level is apparent, which shows the similar characteristics as IEEE-118 bus system.

A) Comparison-local redundancy method vs. WLS

In this comparison random two bad data were simulated on IEEE-118 bus system with 5000 different load levels.

Random bad data

Method	# of Divergence	# of Bad Data Detected
New Approach	0%	91.2%
WLS	61.5%	36.2%

Table 2. Comparison of convergence of the proposed algorithm with the WLS state estimation

The simulation results are displayed in above table, which shows that the new approach always converges and is able to detect the bad data for most of the cases. Fig. 5 shows the comparison of bad data detection between WLS and the new approach. It is obvious to see that the new approach is much more robust than WLS for all different load levels.

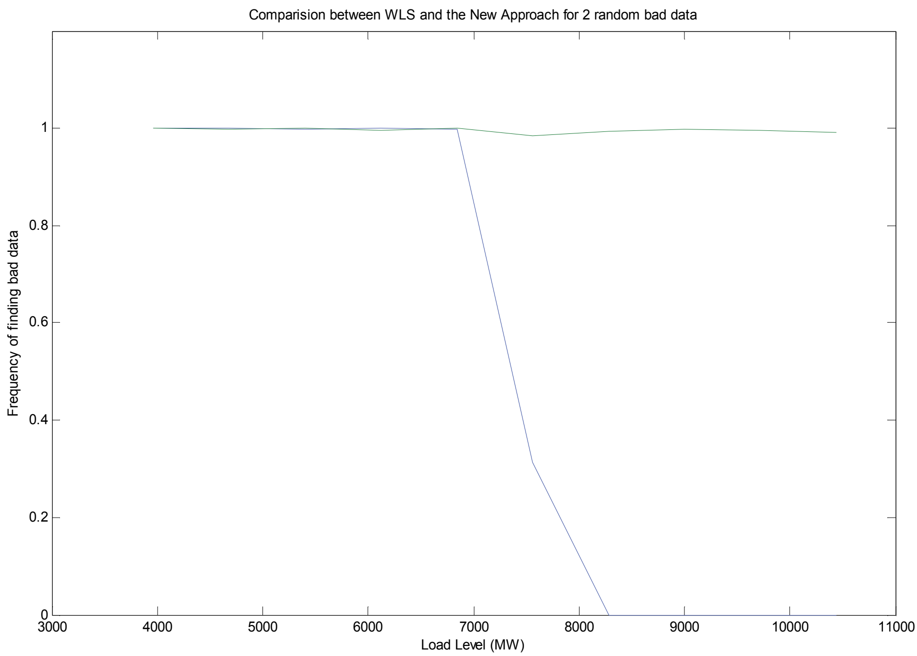

Fig. 6. Comparison of bad data detection between the new approach and WLS

Interacting and conforming bad data

It is known that WLS state estimation has difficulty in detecting the interacting and conforming bad data. This simulation is aimed to test the detection capability of the new approach and its comparison to WLS state estimation. The following table shows the results of comparison. The comparison indicates that the new approach is much more robust than the traditional WLS stat estimation.

Method	# of Divergence	# of Bad Data Detected
New Approach	0%	89.8%
WLS	50.2%	38.1%

Table 3. Comparison of convergence of the proposed algorithm with the WLS state estimation

Fig. 6 shows the comparison of multiple interacting and conforming bad data detection between the new approach and WLS state estimation. The comparison implies that the new approach is much more robust than traditional WLS state estimation and has higher percentage of error detection in light load levels.

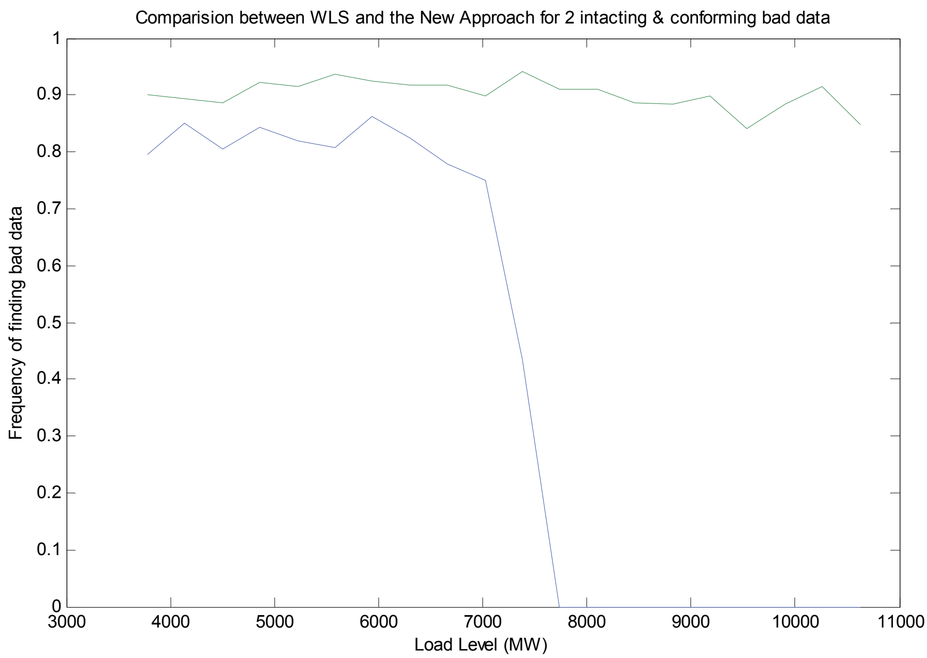

Fig. 7. Comparison of interacting and conforming bad data detection between the new approach and WLS

Topology errors

Topology error is currently the biggest concern of power system operators, especially after the occurrence of North American Blackout in August 2003. Topology errors are severe gross errors, which can make the state estimation fail to converge. This simulation is to test the capability of the new approach in detecting topology errors. The following table shows the comparison of topology error detection between traditional WLS state estimation and the new approach. It is obvious to see that the new approach is much more robust.
Fig. 7 shows the comparison of topology error detection between traditional WLS state estimation and the new approach, under different load levels. The results indicates that WLS state estimation has good detection capability only when the system load is light; the topology error detection capability of WLS drops very fast if the load level reaches a certain amount. On the other hand, the new approach has a very stable capability of topology error detection. It is obvious that the new approach is much more robust than traditional WLS state estimation.

Method	# of Divergence	# of Bad Data Detected
New Approach	0%	99.5%
WLS	53%	46.7%

Table 4. Comparison of convergence of the proposed algorithm with the WLS state estimation

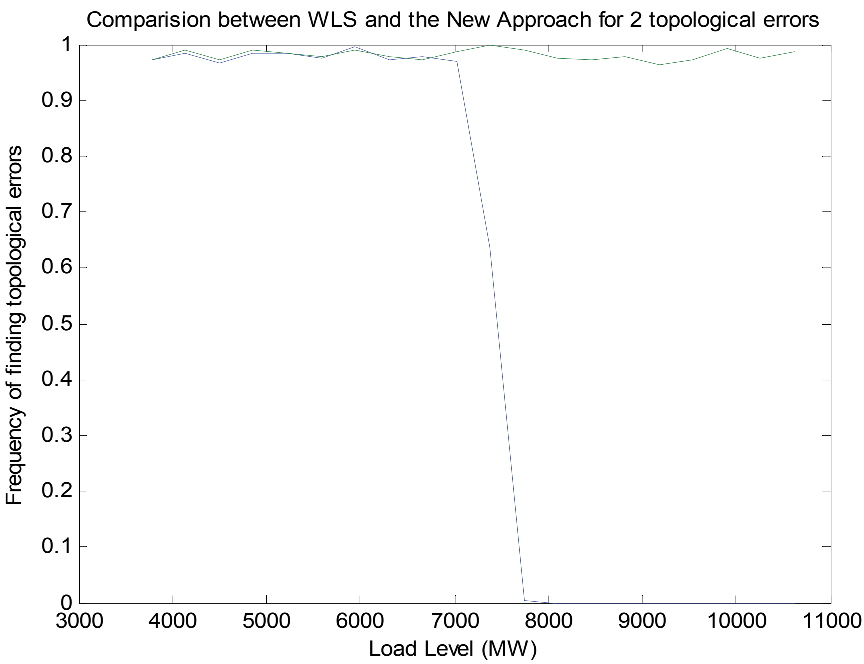

Fig. 8. Comparison of topology error detection between the new approach and WLS

Comparison on a real system with 5145 buses

A real power system with 5145 buses was used to test the new approach. Because from the above tests we found that the divergence of WLS state estimation is the main reason of non-robustness of WLS state estimation, we only compare the convergence ability of the new approach and WLS state estimation on this real system. In this test 6658 branch flow measurements, 1000 injection measurements and 500 voltage measurements are used. 500 sets of measurements were generated by randomly selecting the locations of all the measurements. Here are the results of this test.

The new approach

The new approach was able to get convergent and accurate solutions for these 500 sets of measurements.

WLS state estimation

WLS state estimation failed to get solutions for 169 sets of measurements, and converged to unacceptable solution for 165 sets of measurements, and only converged to accurate solutions for 165 sets of measurements.

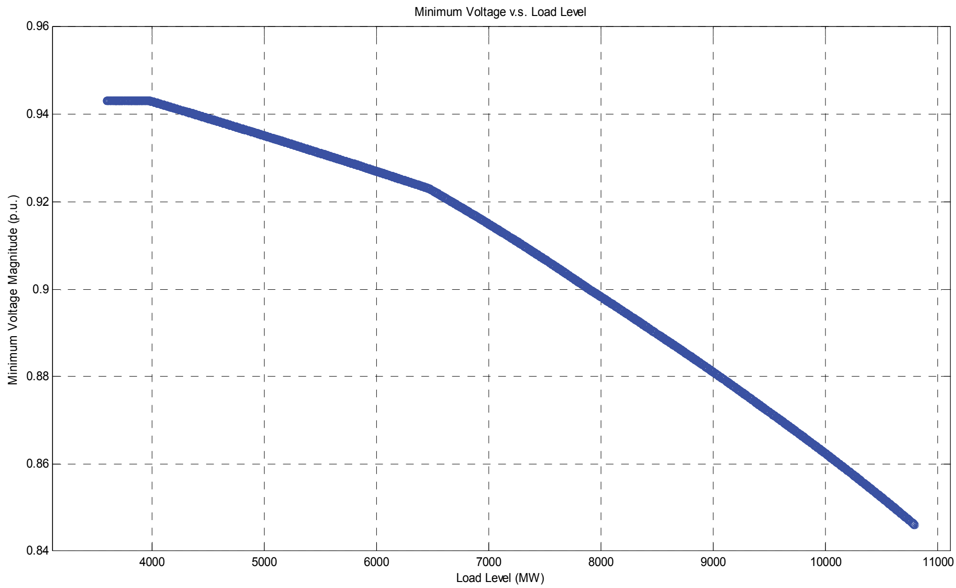

Fig. 9. Minimum voltage magnitudes for 500 sets of measurements.

5. Conclusion

Since topology error is currently the main concern of power system operators, it is very important to develop a robust state estimation that is robust and not dependent on a solution of state estimation. A new approach of topology error detection has been proposed in this paper. The newly developed disruptive state estimator is based on a totally different philosophy that does not require a solution of state estimation. As the divergence of the WLS state estimation occurs far too frequently it is to the new approach's merit that a solution of the system is not needed. Various tests have been conducted on IEEE 118-bus system and a real system with 5145 buses. The results show that the new approach is much more robust than traditional WLS state estimation, and it is ready to be applied in power industry.

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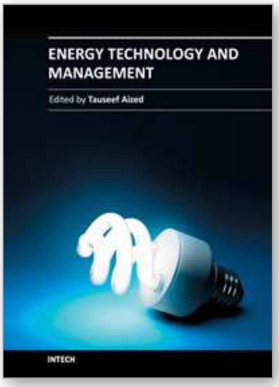

Energy Technology and Management
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The civilization of present age is predominantly dependent on energy resources and their utilization. Almost every human activity in todayâ€™s life needs one or other form of energy. As worldâ€™s energy resources are not unlimited, it is extremely important to use energy efficiently. Both energy related technological issues and policy and planning paradigms are highly needed to effectively exploit and utilize energy resources. This book covers topics, ranging from technology to policy, relevant to efficient energy utilization. Those academic and practitioners who have background knowledge of energy issues can take benefit from this book.

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