‘In Silico’ Testing of a Real-Time PMU-Based Tool for Power System Mode Estimation

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***Abstract*—This paper presents an overview of the software implementation of a real-time mode estimator application and its testing. The application was developed to estimate inter-area modes from both ambient and ring-down synchrophasor data from multiple phasor measurement units (PMU). The software application was implemented in LabVIEW using Statnett’s synchrophasor software development kit (S^3DK), to receive real-time synchrophasor measurements. The different features of the application were tested using two types of experiments presented herein. The first experiment is performed using emulated signals from a simple linear model. The second experiment was designed to use a linearized representation of the KTH-Nordic32 power system model. These experiments are used to carry out quantitative analyses of the tool’s performance.**

***Index Terms*—Mode estimation, inter-area oscillations, phasor measurement units, synchrophasors.**

I. Introduction

Inter-area oscillations are inherent to large power grids and their monitoring is important for safe operation. Synchrophasors can aid in monitoring these oscillations [1]. Continuous monitoring can be performed by applying signal processing algorithms on real-time PMU data to identify critical system modes (including frequency and damping ratio).

The development of new tools for Wide Area Monitoring System (WAMS) should consider thorough testing procedures before their implementation in a control center. Such testing processes should show that the tool provides a reliable monitoring function, while withstanding the constraints of handling real-time PMU measurements. Rigorous testing procedures can be established by defining the requirements to fulfill and combining different kinds of experiments. Experiments can be classified into three main categories, in silico (computer based), ex situ (in a lab environment), and in situ (in native environment) [2].

This paper presents testing methodologies of a newly developed real-time mode estimator that combines two estimation algorithms, one for ambient data and one for ring-down data. The testing procedure chosen involves a group of in silico experiments that serve to quantify the tool’s results.

This tool processes real-time PMU data by using Statnett’s Synchrophasor Software Development Kit (S^3DK) [3]. It is built in LabVIEW using a modular architecture for further refinements of the data handling routines, the estimation algorithms and the graphical user interface.

The paper is organized as follows: Section II presents a brief overview of the measurement-based estimation methods implemented in the tool, while Section III introduces the tool developed. The ‘in silico’ testings are presented in Section IV. Finally conclusions are drawn in Section V.

II. Measurement-based Mode Estimation

In power systems where synchrophasor technology has been deployed, PMU devices are placed in numerous buses of the system. Synchrophasor measurements are streamed continuously and provide two types of data. During the normal operation of the grid, the system is mainly disturbed by small random load variations, which excite the system’s dynamics. In this case, the measurements are referred to as “ambient” measurements. In the case of large disturbances, such as faults, the system’s modes are excited and oscillatory content will be present in the measurements in the form of ring-downs, provided that the modes are damped and the system is stable.

The methods for estimating the modes of the system differ depending of the kind of measurements encountered. Extensive documentation on these methods can be found in [4].

A. Ambient Measurements Analysis

Methods for ambient measurement analysis assume a system disturbed by small random load variations. Here, the system can be viewed as a transfer function, for which inputs are the load variations and outputs the PMU measurements. Because the load variations are of small and random amplitudes, they can be viewed as white noise. Thus, such measurements include the modal response of inter-area oscillations.

Numerous signal processing techniques have been investigated for the extraction of the modes from ambient measurements, most of which are presented in the second Chapter of [4]. In this work, the method implemented is called stochastic state-space subspace identification (SSSID) [5].

These methods usually use large parcels of PMU data to improve estimation accuracy, but are executed continuously.

B. Ring-down Data Analysis

The methods for ring-down data analysis assume a linear model of the system. They differ from the aforementioned ones in that the input excitation is an impulse. The response fitting process is therefore different depending on the selected method. Details on these methods can be found in the first

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Chapter of [4]. In this work, the Eigensystem Realization Algorithm (ERA) [6] is implemented.

These methods also differ in that they require that the measurement data contains ring-down profiles. As a consequence, the processed data parcels are much shorter and should be selected carefully to only contain ring-down profiles. This results in data parcels that are usually around two to four times the period of the inter-area oscillations of interest.

III. Synchrophasor-based Real-Time Mode Estimator

A mode estimator application has been developed to take advantage of both types of mode estimation methods. As PMUs can be placed throughout an entire power system, preliminary studies can help to select the measurement signal types and location with high observability for each of the modes of interest [7]. It was decided to adopt methods that support multiple measurement sources to increase the estimation accuracy.

The application adopts a modular architecture that fully decouples the data acquisition process from the signal processing algorithms. This is achieved by using a buffer of data that supports asynchronous data processing, and can deliver data parcels of different size through a buffer handler. The complete architecture is shown in Fig. 1.

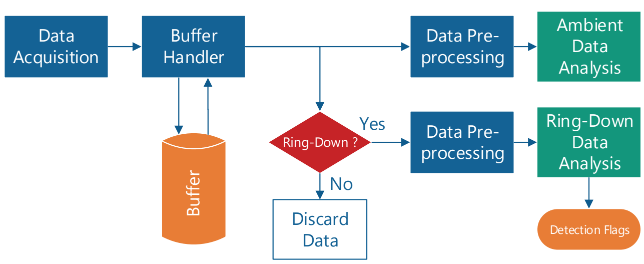

Fig. 1. Modular architecture of the mode estimation application

A. Synchrophasor Data Acquisition and Pre-processing

The synchrophasor data acquisition is built using S^{3}DK [3], which provides LabVIEW tools for utilizing PMU measurements in real-time. It implements the IEEE C37.118.2 standard for synchrophasor data communication. This enables the integration with standard WAMS equipment, such as commercial PMU devices and phasor data concentrators.

The SDK connects to a stream of data and lets the user pick signals to be delivered in LabVIEW for further processing. Using these tools, the developed application includes new code to refine signal selection and let the user define more complex signals, such as angle difference signals or other combinations.

The application also features code to pre-process PMU measurements, which may contain bad data. The pre-processing is carried out in three stages [8]; firstly the data is detrended with a highpass filter set at $0.05\ Hz$, secondly the data is filtered with a lowpass filter set at $2.45\ Hz$ (anti-aliasing,) and finally the data is down-sampled. It is implemented in two parallel instances, one for each mode estimation algorithm to allow different down-sampling factor for each algorithm.

B. 'In Silico' Testing: Emulation for Statistical Testing

The application was originally developed for handling real-time PMU measurements. It was modified to perform studies using emulated signals by changing the data acquisition module, taking advantage of the application's modular architecture.

In this specific case, an additional module was developed to include the simulation of a state-space system, with variable inputs. The state-space system is to be discretized using a time step $T_s = 20$ ms. to emulate a synchrophasor with a reporting rate of 50 samples per second.

The input can be configured to periodically alternate between white noise signals and step signals. Hence, the outputs fed to the buffer contain a controlled amount of ring-downs. These modifications were introduced to carry out statistical testing as described below.

C. Combined Approach for Mode Estimation

The application includes a ring-down detection algorithm. It works on fixed-size data parcels and computes the oscillatory energy of the signal in the [0.1 - 2] Hz frequency range using a method originally proposed by Hauer [9], previously implemented by the authors in [10], and currently being implemented by U.S.A researches [11].

The method requires predetermined thresholds that are set with respect to the value obtained with ambient measurements, to minimize the false positives. In this work, the calibration is performed by computing the mean and standard deviation of the energy calculated by analyzing ambient data during 10 minutes. The threshold was computed as the sum of the mean and 10 standard deviations.

IV. Testing Methods using Emulated Signals

The experiments were performed using synthetic data generated from simulating two different state-space models by exciting the inputs with either white noise or an impulse. The purpose was to systematically study the functional performance of the two algorithms, as well as the detection of ring-down signals. The application is configured to buffer 10 minutes of data (30000 samples) for the ambient algorithm and 16 seconds of data (800 samples) for the ring-down algorithm. For the purpose of this study, both test models are discretized with a time step of 0.02 s. corresponding to the reporting rate for PMUs. First, a study is performed on a fully known simple state-space system. Then a study is performed on a linearized model of the KTH Nordic 32 model [7].

Each experiment is performed in two steps, aimed at testing each of the estimation algorithms. In the first step, the ambient data algorithm is tested, therefore the input signals for the model are set to continuous white noise with specified standard deviation. This ensures the synthesized measurement data is ambient. In the second step, only the ring-down data algorithm is tested, the inputs are alternated regularly between white noise and a step to generate ring-down data periodically. The

TABLE I
MODAL CONTENT OF THE TEST SYSTEM

Mode	Eigenvalue	Frequency (Hz)	Damping (%)
I	$a = 0.985 \pm j0.0988$	0.8	10
II	$b = 0.977 \pm j0.110$	0.9	15
III	$c = 0.973 \pm j0.185$	1.5	5

data synthesizer is configured as such that only one ring-down is present in the data buffer, and to allow for a sufficiently large settling time for the system to return to a steady state before applying the next perturbation.

The experiments produced a large number of estimates that are analyzed in MATLAB, in a similar manner for all tests described in this Section. First, the estimates must be sorted into the expected modes range, this is done by measuring the distance between the estimated and the expected frequency, and sorting according to the smallest distances. The estimates corresponding to each expected mode are placed in a vector of estimates. Second, the number of zeros in each vector of estimates is computed and the zeros are removed from the distribution fitting process (the count of zeros is used to check the efficiency of the estimation). Finally, statistical metrics are computed from the distribution best fitting the empirical data, and also from the empirical data itself.

The performance of the ring-down detection is also assessed by computing the delay between two triggers. Because the step perturbations are periodically applied, this delay can be compared to the period of the perturbations. In this paper, ring-down detection is considered successful if the delay is kept under one and a half period (to take into account the buffering between acquisition and processing of the data).

A. Simple State-Space Model

The first experiment considers a linear time-invariant state-space model ($\dot{x} = Ax + Bu, y = Cx + Du$), where $eig(A) = \{a, b, c\}$ as shown in Table I with the corresponding modes. Note that B and C have $rank(B) = rank(C) = 2$ and their elements are non-zero. The model also includes a non zero feed-through matrix ($D \neq 0$), to model measurement noise in the output. Note that this system is purely synthetic, it was built to have the specified modal content, without representing any specific physical system. Thus, the perturbations applied were arbitrarily chosen to have an amplitude ratio of 500.

For the first run, the input is configured as white noise with standard deviation of 1, and the acquisition is set to gather about 5000 estimates. The resulting estimates are shown on Fig. 2. The results have been analyzed as described above and statistical metrics are presented in Table II, the data presented was taken from the distribution with best fit.

The results presented are globally of good performance, it should also be noted that after the mode sorting, there was less than 1 % of missing estimates, except for Mode II for which that number was 5.4 %. It can also be noticed that the estimation performances for Mode II are of lower precision, this can be explained because Mode I and II are very close in

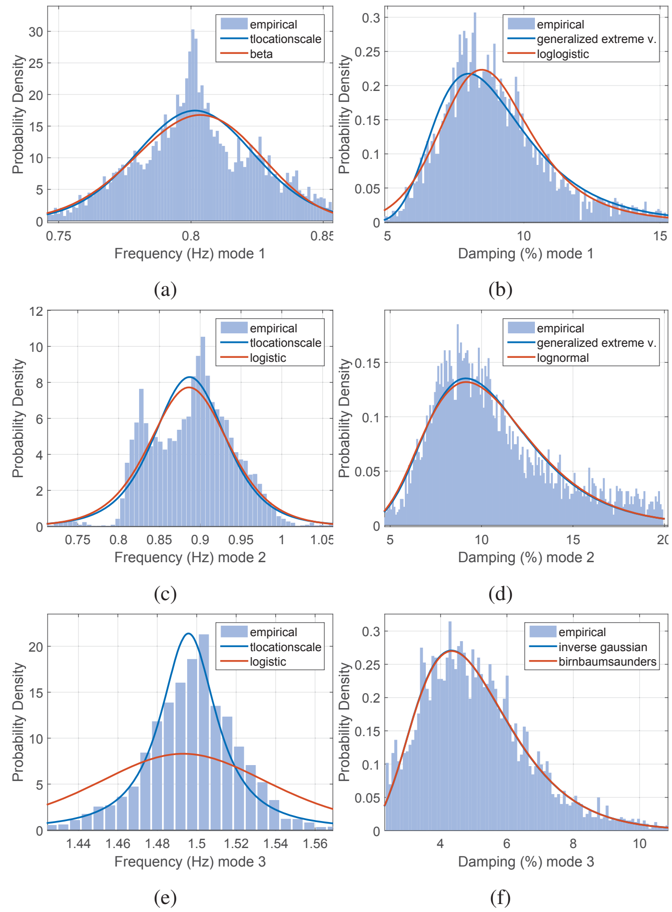

Fig. 2. Frequency and damping estimation from the ambient data algorithm for mode I, respectively (a) and (b), mode II, respectively (c) and (d), and mode III, respectively (e) and (f)

TABLE II
STATISTICAL METRICS FROM AMBIENT DATA ESTIMATES

Mode	Frequency (Hz)		Damping (%)	
	μ^a	σ^b	μ	σ
I	0.80 Hz	0.024 Hz	9.14 %	2.35 %
II	0.89 Hz	0.060 Hz	10.62 %	3.40 %
III	1.49 Hz	0.055 Hz	5.08 %	1.66 %

[a] μ: mean
[b] σ: Standard deviation

the frequency domain. Therefore, the estimation process can fail to detect that there are two modes when there are close, and also the sorting process performed in the analysis was only based on the frequency, leading to some errors during sorting. This can be observed on Figs. 2a and 2c, where the sorting seems to have swapped estimates. It can also be noticed that using the distribution fit for statistical analysis, the influence of the swapped estimated is contained.

The same process is repeated for the ring-down data algorithm, where the input was repeatedly alternated between a step of amplitude 500 and white noise of standard deviation

TABLE III
STATISTICAL METRICS FROM RING-DOWN DATA ESTIMATES

Mode	Frequency (Hz)		Damping (%)	
	μ	σ	μ	σ
I	0.80 Hz	0.017 Hz	9.77 %	0.72 %
II	0.90 Hz	0.014 Hz	14.19 %	1.99 %
III	1.50 Hz	0.008 Hz	4.87 %	0.24 %

of 1. The experiment was set to produce about 900 estimates. The resulting estimates are shown on Fig. 3, and their metrics presented in Table III, where the data is also taken from the distribution with best fit.

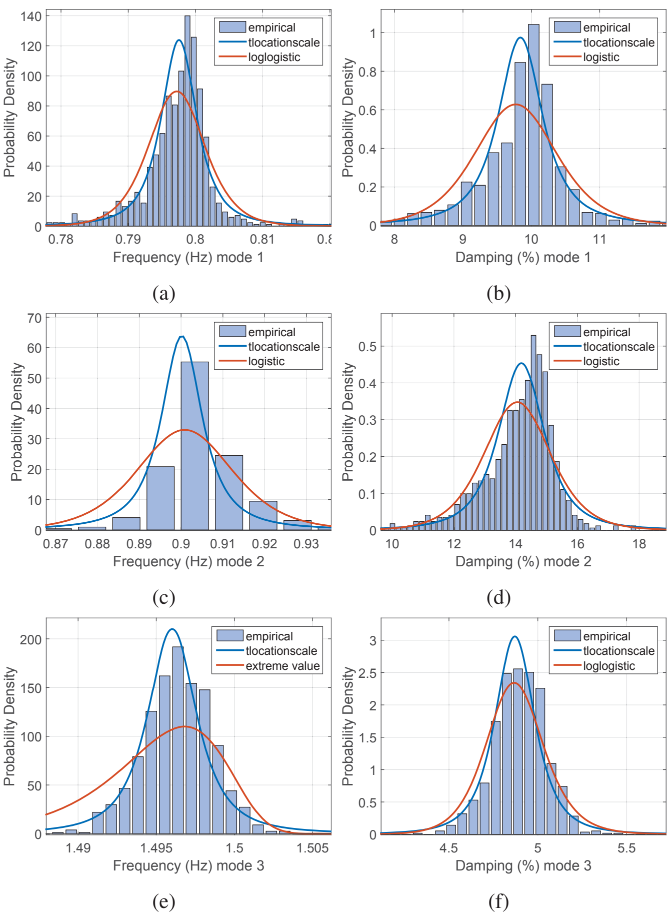

Fig. 3. Frequency and damping estimation from the ring-down data algorithm for mode I, respectively (a) and (b), mode II, respectively (c) and (d), and mode III, respectively (e) and (f)

The results presented are of better performances than the results obtained from the ambient data. In addition, the detection rate is nearly 100 % for all three modes. The performance of the ring-down detection achieves 100 % with the calibration of the threshold as described in Section III-C.

B. Linearized KTH Nordic 32 Model

Following the success of the experiment presented in the previous Section, a second experiment was designed to use

TABLE IV
MODAL CONTENT OF THE NORDIC 32 SYSTEM

Mode	Frequency (Hz)	Damping (%)
I	0.499	3.5
II	0.732	3.18

a power system model. This experiment uses a linearized model of the KTH Nordic 32 power system. In this model, the inputs of the state space system represent the active power and reactive power deviations at each bus, and the outputs are the voltage magnitude and angle deviations at each bus. The knowledge from previous studies on this model [7] was used to choose the output signals that provide the highest observability on the respective dominant path for each of the two most critical modes. For the purpose of this study, the voltage magnitude at buses 38, 40, 44, and 49 were selected as input for the mode estimator application.

The "true modes" of this system were determined from calculating the poles of the state-space description of the system. The two most critical modes are shown in Table IV.

In the first test, the inputs of all 32 buses were set to white noise with standard deviation of 0.2, and the experiment was set to produce about 9000 estimates. The resulting estimates are shown on Fig. 4, and their metrics are presented in Table V, where the data is taken from the distribution with best fit.

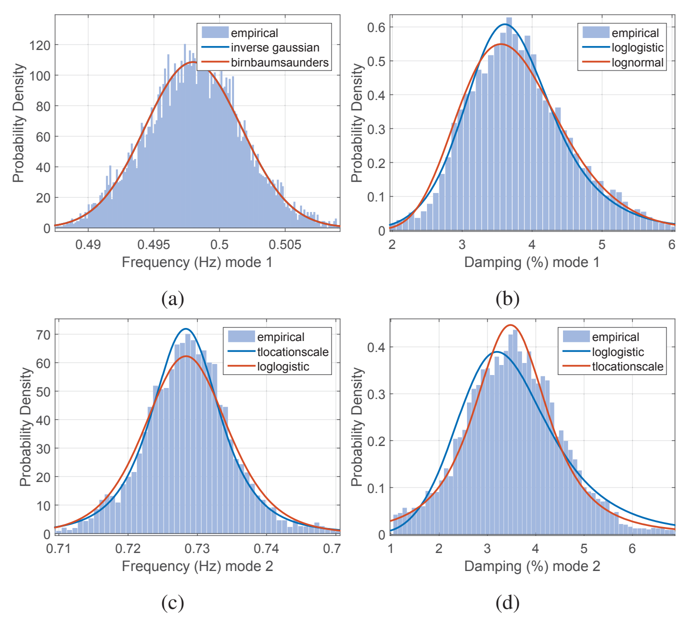

Fig. 4. Frequency and damping estimation from the ambient data algorithm for mode I, respectively (a) and (b), and for mode II, respectively (c) and (d)

The results show excellent performances of the tool, highlighting the importance of the study of dominant paths and observability computations. In addition, the detection rate is nearly 100 % for all three modes.

The same process is repeated for the ring-down data algorithm, where the inputs of all 32 buses were set to white noise

TABLE V
STATISTICAL METRICS FROM AMBIENT DATA ESTIMATES

Mode	Frequency (Hz)		Damping (%)	
	μ	σ	μ	σ
I	0.498 Hz	0.004 Hz	3.78 %	0.79 %
II	0.728 Hz	0.008 Hz	3.67 %	1.39 %

TABLE VI
STATISTICAL METRICS FROM RING-DOWN DATA ESTIMATES

Mode	Frequency (Hz)		Damping (%)	
	μ	σ	μ	σ
I	0.498 Hz	0.0015 Hz	3.43 %	0.37 %
II	0.732 Hz	0.0013 Hz	3.18 %	0.32 %

of standard deviation 0.2, except for bus 40 and 44 where the inputs were repeatedly alternating between a step of amplitude 250 (and length of 2 time-steps) and white noise as in the other inputs. The experiment produced about 1000 estimates, shown on Fig. 5, and their analysis is presented in Table VI.

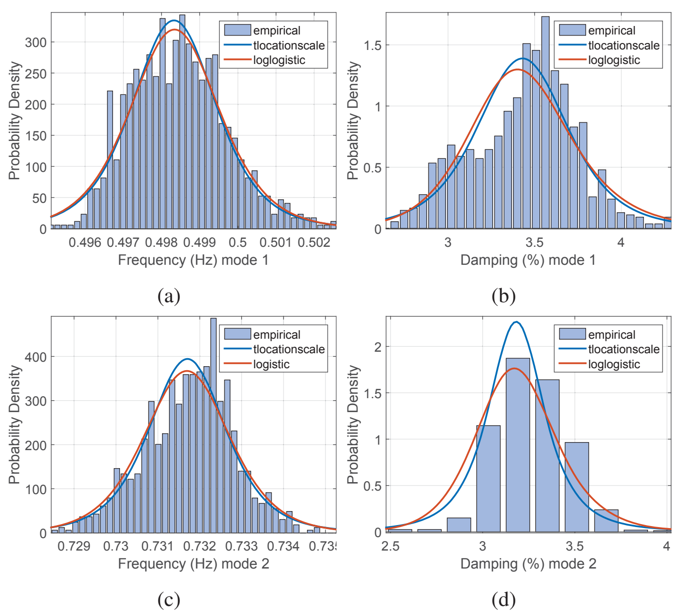

Fig. 5. Frequency and damping estimation from the ring-down data algorithm for mode I, respectively (a) and (b), and for mode II, respectively (c) and (d)

The results presented are of better performances than the results obtained from the ambient data, as for the previous experiment, the ring-down data provides much better damping estimates than the ambient data. Here, again, the ring-down detection rate achieved 100 % thanks to good calibration.

V. CONCLUSIONS

This paper introduces a newly developed tool combining two algorithms for mode estimation, that use different types of signals. Such tool can enhance mode estimation results by providing continuous estimation using ambient data, but at the same time, detect ring-down data and provide more accurate estimation using it. The testing showed that both algorithms perform well, but the ring-down data based algorithm provides better estimation accuracy. An additional component of the experiments was to evaluate the method for determining the detection threshold for the ring-down detection. The current method achieved nearly 100 % of detection rate in both experiments, validating it for further use.

A. Future Work

Considering the results obtained in these ‘in silico’ experiments, it appears natural to continue the testing by building an ‘ex situ’ experiment. This experiment will be part of our future work to test the application in the SmarTS Lab environment [12], where power system models are simulated in a real-time digital simulator that can be connected to PMU devices in a hardware-in-the-loop (HIL) setup.

This allows to go beyond functional testing of the tool, toward end-to-end testing by including the entire mesurement data acquisition chain; thus allowing to evaluate its impact and to compare it with ‘in silico’ results.

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