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Evaluation of different automated operational modal analysis techniques for the continuous monitoring of offshore wind turbines

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ABSTRACT: This paper will evaluate different automated operational modal analysis techniques for the continuous monitoring of offshore wind turbines. The experimental data has been obtained during a long-term monitoring campaign on an offshore wind turbine in the Belgian North Sea. State-of-the art operational modal analysis techniques and the use of appropriate vibration measurement equipment can provide accurate estimates of natural frequencies, damping ratios and mode shapes of offshore wind turbines. To allow a proper continuous monitoring the methods have been automated and their reliability improved. The advanced modal analysis tools, which will be used, include the poly-reference Least Squares Complex Frequency-domain estimator (pLSCF), commercially known as PolyMAX, the polyreference maximum likelihood estimator (pMLE), and the frequency-domain subspace identification (FSSI) technique. The robustness of these estimators with respect to a possible change in the implementation options that could be defined by the user (e.g. type of polynomial coefficients used, parameter constraint used….) will be investigated. In order to improve the automation of the techniques, an alternative representation for the stabilization charts as well as robust cluster algorithms will be presented.

KEY WORDS: monitoring, offshore wind turbine, operational modal analysis, modal parameters estimators, automated

1 INTRODUCTION

In [5-7], an approach for automatic identification of the different dynamic parameters based on the measurement of the dynamic response of wind turbines during operating conditions has been introduced and validated by performing a long-term monitoring campaign on an offshore wind turbine. The preliminarily results obtained from this long-term validation showed that the proposed approach is sufficiently robust to run online basis where it does not need a user interaction, providing almost real-time parameters that characterize the wind turbine's condition. Since this approach mainly depends on the continuous tracking of the modal parameters of the supporting structures as a tool for the subsequent damage detection, the used modal parameter estimators within this approach plays an important role in the success of the monitoring process. Thus, having an accurate and robust modal parameters estimator in the framework of this monitoring approach is a must. The monitoring results shown in [5, 6] have been obtained by performing the monitoring on data collected during a period of 2 weeks where the OWT was in parked condition. In [5], the modal parameters estimation tools , which have been used, included the polyreference Least Squares Complex Frequency-domain (pLSCF) estimator-commercially known as PolyMAX estimator- and the covariance driven Stochastic Subspace identification method (SSI-COV). In [6], only the pLSCF is used as the modal parameters estimation tool for the monitoring process.

In this paper and in the framework of the automatic monitoring approach presented in [5-7], the state-of-the-art modal parameters estimators will be implemented and applied to a long-term monitoring campaign of an offshore wind turbine. The monitoring considered in this paper has been performed on a subset (i.e. 100 datasets with 10 minutes for each) of data collected during a period of 2 weeks where the OWT was in parked condition [5, 6]. The state-of-the-art modal parameters estimators that will be considered in this paper include the polyreference Maximum Likelihood Estimator (pMLE)[8, 9], the PolyMAX estimator [10, 11], Frequency-domain subspace identification (FSSI) [12]. The applicability of these estimators to identify the modal parameters of the fundamental vibration modes of the supporting structures of the OWT under test over a long-term measurement will be compared and discussed.

2 OFFSHORE MEASUREMENTS

The presented measurement campaign is performed at the Belwind wind farm, which consists of 55 Vestas V90 3MW wind turbines. This wind farm is located in the North Sea on the Bligh Bank, 46 Km off the Belgian coast. The structures instrumented in this campaign are the tower and the transition piece. The measurements are taken at four levels on 9 locations using 10 sensors. The measurement locations are indicated in Figure 1by the red arrows. The chosen sensors levels are at height of 67m, 37m, 23m, 15m above the sea level, respectively 1 to 4. There are two accelerometers mounted at the lower three levels and four at the top level. Figure 1 shows an example of the accelerations measured in the for-aft direction (direction aligned with the nacelle) during 10 minutes of ambient excitation.

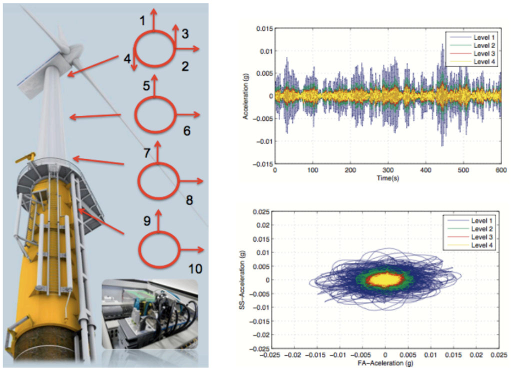

Figure 1: Measurement locations and data acquisition system (left), Example measured accelerations during ambient excitation on 4 levels, with level 1 the highest level, in the fore-aft direction (right-top) movement seen from above (right-bottom)

In order to classify the operating conditions of the wind turbine during the measurements SCADA data (power, rotor speed, pitch angle, nacelle direction) is being collected at 10-minute intervals. In Figure 2, the SCADA data is shown for the selected 100 datasets that will be used in this paper. Most of the times the wind-turbine was idling with a speed lower than 1 rpm and sometimes the wind turbine was in parked conditions. Both conditions allow us to sufficiently comply with the time-invariant OMA assumptions and avoid the presence of harmonic components in the frequency range of interest.

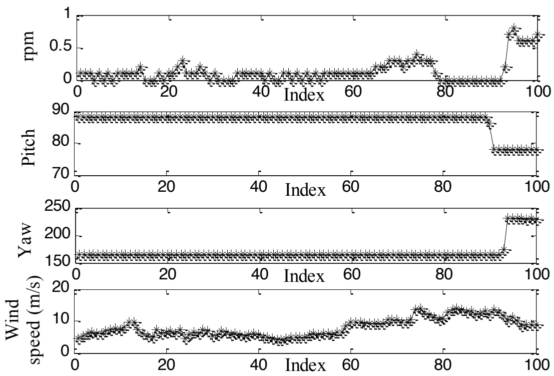

Figure 2: SCADA data for monitoring period from top to bottom: rpm, pitch-angle (deg), Yaw-angle (deg), and wind speed (m/s)

3 FULLY AUTOMATED MONITORING

To allow an accurate continuous monitoring of the dynamic properties a fast and reliable solution that is applicable on industrial scale has been developed. The different steps of the fully automated dynamic monitoring used in this paper are discussd in [5-7]. The following steps are followed:

Step 1: Pre-processing vibration data

1. Creation of a database with the original vibration data collected at 10 minute intervals and sampled at high frequency, together with the ambient data and the SCADA data with corresponding time stamps.
2. Pre-processing the vibration-data to eliminate the offset, reduce the sampling frequency, transform them in the nacelle coordinate system.
3. Calculate the power spectra of the measured acceleration responses using the correlogram approach [7,8].

Step 2: Automated operational modal analysis

1. Applying a modal parameter estimator to the calculated power spectra to extract the modal parameters in an automated way based on a clustering algorithm
2. Calculate statistical parameters (e.g. mean values, standard deviation) of the identified parameters

Step 3: Tracking frequencies, damping values and mode shapes

1. Creation of a database with processed results

The second step (modal parameter estimation step) in this monitoring approach is very crucial step since it will determine the success of the monitoring process. In order to achieve this step with high confidence, several modal parameters estimators have to be tested and compared to each other in terms of the quality of the estimated parameters. In the presented paper, the applicability of three different frequency-domain modal parameters estimators to achieve the second step in the monitoring approach will be tested. These estimators include the polyreference Maximum Likelihood Estimator (pMLE)[8, 9], the PolyMAX estimator [10, 11], Frequency-domain subspace identification (FSSI) technique [17].

Figure 3 shows the five dominant vibration modes in the frequency band of interest that are being tracekd in step 3. These five dominant modes are first Fore-aft bending mode (FA1), first side-side bending mode (SS1), mode with a second Fore-aft bending (FA2) that is coupled mode between the tower and the blades, mode with a second side-side bending mode tower and nacelle component (SS2N), mode with a second Fore-aft bending mode tower and nacelle component (FA2N).

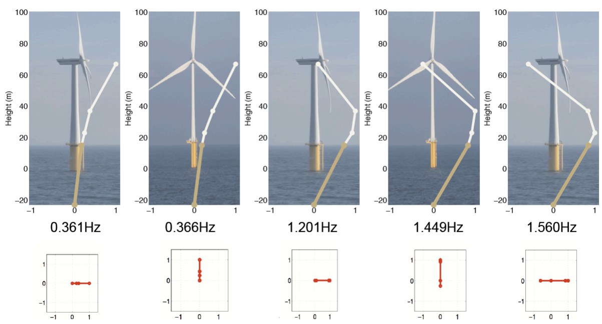

Figure 3: Five dominant mode shapes: from left to right: FA1, SS1, FA2, SS2N, and FA2N

4 CONTINUOUS MONITORING RESULTS

In this section, each modal parameter estimator will be implemented in the second step of the fully automated dynamic monitoring approach shown in Figure 3 and the obtained monitoring results will be discussed. For all the estimators, the maximum number of modes to be identified is set to 32 and for the pMLE, which is an iterative algorithm;vthe number of iterations is set to 20. For the tracking of the five fundamental modes estimated from the different consecutive 10 minutes data sets, the needed MAC criterion between the estimated modes and the reference modes is set to 70% and the allowed frequency difference between the estimates modes and the reference modes value is set to 3%. All the estimators are applied to the analyzed data using different number of modes starting from the maximum settled value (i.e. 32) until two with a step 1. Then, all the estimated modal parameters (i.e. frequencies, damping ratios, and mode shapes) for each mode at each defined number of modes are fed to the hierarchical clustering algorithm to cluster the parameters that correspond to the same physical mode (see Figure 4).

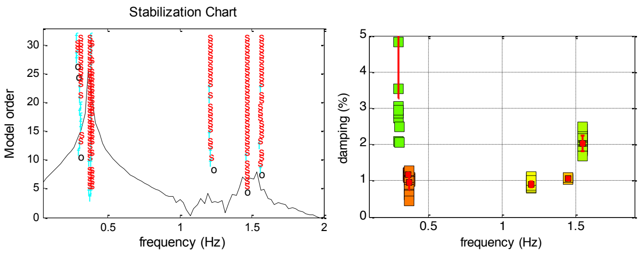

Figure 4: Left: stabilization chart constructed by PolyMAX estimator showing the estimated modes at different model order Right: the clustering results obtained by feeding all the estimated modal parameters ate different model orders to the hierarchical clustering algorithm

In Figure 5 and for each estimator, the evolutions of the natural frequencies and the damping ratios of the identified modes within the analyzed frequency band during the monitoring of 100 consecutive 10 minutes data sets is presented. Figure 6 illustrates the different mode shapes identified in the 100 successive data sets, where it can be seen that the mode shapes from all the estimators are very coherent over the different data sets.

In terms of the damping estimates, it can be seen from Figure 6 that all the estimators show again a similar performance. The damping estimates for the highest 3 modes are reasonably coherent, while the ones associated with the lowest 2 modes present a high scatter. A part of this scatter is attributed to the high dependence of the damping of these modes on the ambient parameters, e.g. wind speed. The damping values of those modes are highly dependent on the aerodynamic damping that resulted from the wind-nacelle interaction and it can be seen from the illustrated mode shapes that those modes are accompanied with high movement at the nacelle position compared with the other modes. This is also explain why those modes have higher damping values compared to the other modes. In addition, this scatter on the damping estimate of the lowest 2 modes can be explained by the fact that the estimation of the very close spaced modes usually faces some difficulties, which increases the uncertainty on their estimates, especially on the damping values.

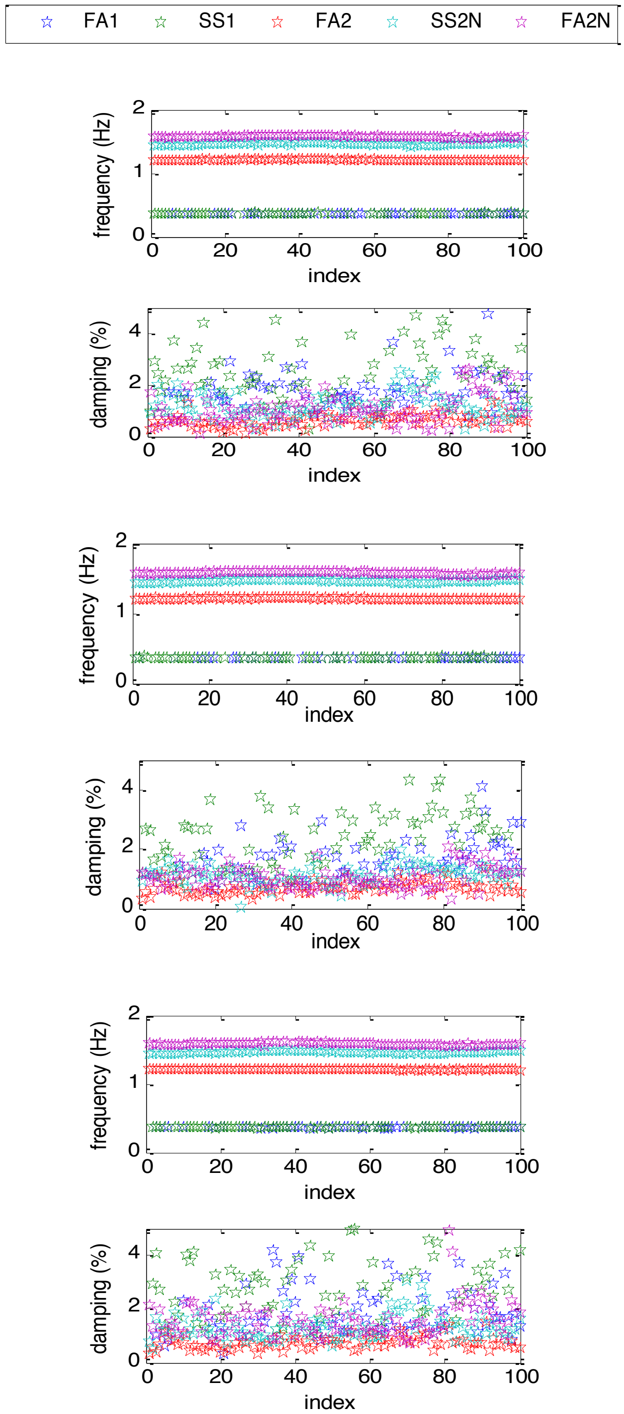

Figure 5: Evolution of frequencies and damping ratios of the 5 dominant modes during the monitoring period using different modal parameters estimators. Top: pMLE, Middle: PolyMAX, Bottom: FSSI

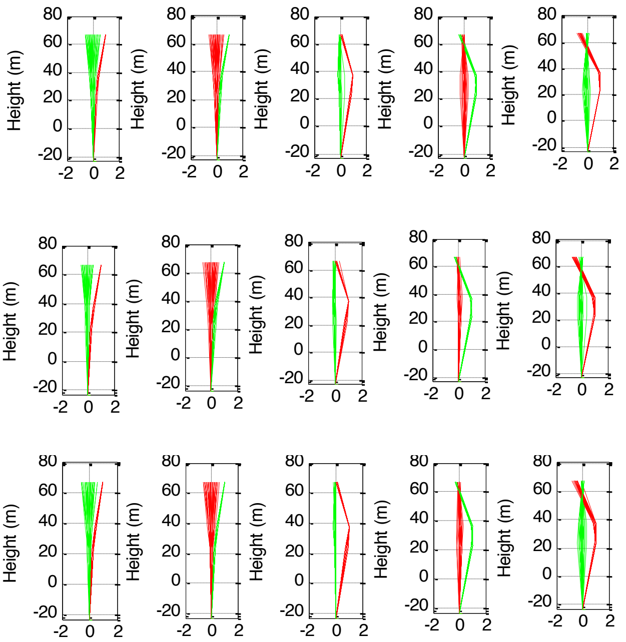

Figure 6: Evolution of the mode shapes of the 5 dominant modes during the monitoring of 100 consecutive 10 minutes data sets: 1st row (pMLE), 2nd row (PolyMAX), 3rd row (FSSI). FA-direction (red lines), SS-direction (green lines). At each row from left to right: FA1, SS1, FA2, SS2N, and FA2N.

4.1 The pMLE results

Table 1 presents the results of the continuous monitoring routines in the analysis of the 100 data sets using the pMLE. In the last column, the success rate of the identification of the 5 dominant modes is quantified. Also presented in this table are the median of the frequency and damping estimates together with their standard deviation. The median and the standard deviation of each mode (frequency and damping) are calculated for the different estimates for that mode over the analyzed 100 datasets. The pMLE is tried four times where the implementation variants have been changed at each time to check the robustness of the estimator with this variation in the implementation options. Different type of polynomial coefficients (real/complex-valued coefficients) and different equation error (linear/ logarithmic equation error presented by equations (2) and (5)) have been tried and the results for each case are presented in Table 1. The results presented in this table show that whatever the implementation options are the pMLE converges to almost the same values and this is for the frequency and damping estimates. The differences between the logarithmic and linear equation error are not remarkable since the analyzed data is not so noisy.

However, it can be seen that the logarithmic implementation gives a bit lower variability (i.e. std) on the estimated parameters over the different analyzed data sets for the 1st mode, especially for the damping estimate. This consistency of the pMLE results is expected since the expected value of the cost function of the pMLE is scale-invariant and hence should converge to the same estimates regardless of the nature of the used coefficients. Since the pMLE is an iterative technique and hence slow, it is found that it needs around 5 minutes to achieve the estimation process for one data set (10 minutes data set) and hence it is slow. This is the only drawback we can mention about this estimator based on the presented results.

Table 1: Results of the continuous monitoring using the pMLE with different implementation variants (**from top to bottom**: Complex coefficients + logarithmic equation error, Complex coefficients + linear equation error, Real coefficients + logarithmic equation error, and Real coefficients + linear equation error.

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.36603	0.003444	1.69866	0.68061	59
2	0.36316	0.005106	2.39327	1.01793	64
3	1.20566	0.005913	0.58861	0.24867	100
4	1.45666	0.015996	1.10231	0.47696	100
5	1.57413	0.017227	0.92266	0.57113	99

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.36497	0.00429	1.70854	0.95741	64
2	0.36375	0.00537	2.21068	1.01024	59
3	1.20600	0.00618	0.66701	0.23009	100
4	1.45718	0.01683	1.11793	0.47897	100
5	1.57684	0.01640	1.00898	0.57642	100

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3653	0.0039	1.7587	0.7456	58
2	0.3636	0.0051	2.3343	1.0163	64
3	1.2059	0.0063	0.5770	0.2395	100
4	1.45691	0.0164	1.0994	0.4682	100
5	1.57386	0.0173	0.9090	0.5423	99

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.36496	0.0044	1.7362	0.9334	55
2	0.36414	0.0058	2.5271	1.1024	62
3	1.20513	0.0070	0.6507	0.2602	97
4	1.45758	0.0158	1.0922	0.5165	98
5	1.57668	0.0166	1.0056	0.5949	98

4.2 The pLSCF (PolyMAX) results

The pLSCF (PolyMAX) estimator is a linear least-squares technique and hence inconsistent (i.e. the expected value of its cost function is dependent on the parameters used). It means that if the parameter constraint used to solve for the numerator and the denominator coefficients changed, the obtained estimates will be also changed. Indeed, the extent of the differences in the final results depends on the level of the noise on the analyzed data [26, 27]. In Table 2 and 3, the results of the continuous monitoring of the pLSCF estimator are shown in terms of the median, std, and success rate of the frequency and damping estimates of the 5 dominant modes within the frequency-band of interest. Please note that the shown median and std values for each mode are calculated over the different 100 estimates of each parameter (i.e. frequency and damping) obtained from applying the pLSCF estimator on the consecutive 100 data sets.

Table 2 shows the results when real-valued coefficients are used with three different parameter constraint cases used to solve for the numerator and denominator coefficients, while Table 3 shows the results when complex-valued coefficients are used with again three different parameter constraints used. The three different parameter constraints that have been tried are the maximum order coefficient, the lowest order coefficients, and the norm-1 constraint. Before we go to the discussion of the obtained results, the computational time taken by the pLSCF estimator to process one 10 minutes data set is about 1.8 s. It can be seen that the pLSCF is very fast compared to the pMLE and this normal since it is one-step approach.

The results presented in Table 2 and 3 show that the change in the frequency parameter values is very small when either the type of the coefficient or the parameter constraint is changed. The damping estimate, especially for the 2 lowest modes, seems to be influenced by the type of coefficients used in particular when the maximum order coefficient constraint is used. For both the real and complex coefficient cases, it can be noted that the parameter constraint used has an effect on the damping estimate values. However, it can be seen that the complex-valued coefficients are less sensitive to the parameter constraint changing compared to the real-valued coefficients. In addition, the complex-valued coefficients give lower variability (i.e. std) on the damping estimates in particular for the lowest 2 modes, which can be explained by the fact that complex-valued coefficients lead to better conditioning problem in comparison to the real-valued coefficient since the model order is halved for complex-coefficients. From all these remarks about the pLSCF results, it can be seen that the final estimates we obtained is highly dependent on the parameter constraint and the type of coefficients used. This makes the user to feel not confident about what he obtained since there are several possible estimates for the same problem.

One possible solution to get out from this problem when using such type of estimators (i.e. linear least-squares estimator), is to try different model orders and at each model order all the possible parameter constraint will be tried. This means that at each model order we start to constrain the lowest order coefficients and consecutively the same is done for the next order coefficients and so on till we reach the highest order coefficients. Then, the obtained modal parameters estimates are sent to the clustering algorithm to obtain the modal parameters that correspond with the physical modes within the frequency band of interest. A typical stabilization chart, which is obtained from such approach, is shown in Figure 7. In the y-axis of this chart, we have now index that indicates to the model order/parameter constraint combination instead of having only the model order like the one shown in Figure 4. Indeed, this stabilization chart is obviously not clear compared to the one in Figure 5 in particular around the lowest 2 modes. But, this is not a big issue since our monitoring approach does not use the stabilization chart to select the physical modes but it uses a clustering algorithm to automatically select them.

Table 2: Results of the continuous monitoring using the pLSCF (PolyMAX) estimator with **real-valued** coefficients and different parameter constraint: **Top**: maximum order coefficient, **Middle**: lowest order coefficient, **Bottom**: norm-1 constraint

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3657	0.0044	1.3137	0.4593	53
2	0.3662	0.0061	1.4940	0.8937	62
3	1.2073	0.0057	0.6145	0.1834	100
4	1.4591	0.0152	1.0386	0.3096	99
5	1.5749	0.0165	1.0375	0.3518	100

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3653	0.0041	1.6444	1.0224	59
2	0.3644	0.0057	2.4171	1.2613	52
3	1.2066	0.0059	0.6793	0.2319	100
4	1.4550	0.0168	1.0573	0.3840	99
5	1.5779	0.0162	1.0647	0.6071	98

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3651	0.0038	1.6761	0.8519	57
2	0.3652	0.0055	2.3370	1.0844	55
3	1.2069	0.0067	0.6371	0.2218	100
4	1.4542	0.0161	1.0615	0.3854	99
5	1.5745	0.0169	1.0006	0.4108	100

Table 3: Results of the continuous monitoring using the pLSCF (PolyMAX) estimator with **complex-valued** coefficients and different parameter constraint: **Top**: maximum order coefficient, **Middle**: lowest order coefficient, **Bottom**: norm-1 constraint

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3654	0.0032	1.7947	0.6470	51
2	0.3634	0.0054	2.4671	0.8434	65
3	1.2064	0.0058	0.6746	0.2096	100
4	1.4583	0.0155	1.1090	0.2916	99
5	1.5743	0.0181	0.9675	0.3511	100

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3654	0.0043	1.6419	0.7075	38
2	0.3639	0.0058	1.8137	0.9503	28
3	1.2060	0.0061	0.6818	0.2417	100
4	1.4531	0.0165	1.0439	0.4145	97
5	1.5757	0.0161	0.9629	0.4290	91

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3648	0.0031	1.4406	0.7071	32
2	0.3638	0.0054	2.5217	1.0281	41
3	1.2065	0.0062	0.6427	0.2208	100
4	1.4571	0.0153	1.0055	0.3134	94
5	1.5761	0.0164	0.9524	0.3907	95

All the modal parameters estimates obtained by the pLSCF estimator with varying both the model orders and the parameter constraint used are then processed by the implemented clustering algorithm to obtain some clusters which correspond to the physical modes. A typical clustering result is shown in Figure 7. Indeed, as it is shown in Figure 7 the number of clusters we obtained have been increased. Based on the statistical properties of each cluster and the tracking options we defined (e.g. MAC, MPC, frequency difference…), the clusters, which correspond to the physical modes, will be automatically selected. In Table 4, the continuous monitoring results, which are obtained by applying the pLSCF estimator to the 100 datasets using the varying model order and varying parameter constraint approach, are shown. The results are shown for both the real-valued and complex-valued coefficients cases. It can be seen from Table 4 that the consistency of the estimates, especially the damping values, when we change the type of the coefficients is much better than we used only one parameter constraint. Also, it can be noted that the pLSCF estimates now are in a good agreement with the ones obtained from the pMLE (see Table 1) whatever real or complex coefficients are used. Moreover, one can see from the last column in Table 4 that the success rate of the identified modes over the different datasets is increased in particular for the 2 lowest modes, which is something positive for the continuous tracking purpose. Since the size of the data is increased, it can be noted from Table 4 that the variability on the estimates has been also increased and this in particular for the 2 lowest modes. The price has to be paid when applying this approach is that the computational time will be increased a bit compared with the classical approach (i.e. applying the pLSCF with only varying order). In the varying order/ varying parameter constraint approach, the processing of one 10 minutes dataset with the pLSCF estimator takes about 4 s, while with the classical approach (i.e. applying the pLSCF with only varying order) it takes 1.8 s. It can be seen that it is still fast compared with the pMLE, which takes about 5 minutes to process one 10 minutes dataset.

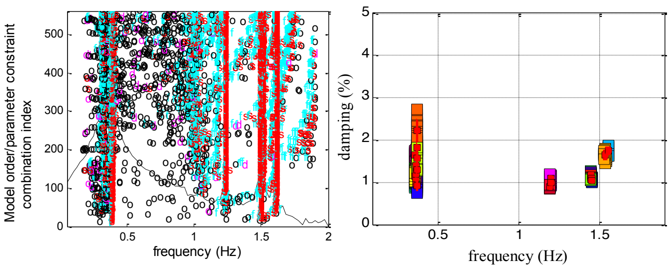

Figure 7: Left: A typical stabilization chart constructed using all the possible parameter constraint at each model order **Right :** The clustering results

Table 4: Results of the continuous monitoring using the pLSCF (PolyMAX) estimator with **real-valued** coefficients (Top) and **complex-valued** coefficients (bottom) when all the possible parameter constraints are used at each model order

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3642	0.0050	1.7135	1.1756	63
2	0.3659	0.0055	2.0737	1.4860	64
3	1.2068	0.0076	0.6696	0.3696	100
4	1.4567	0.0162	0.9957	0.4291	99
5	1.5768	0.0159	0.9266	0.4644	100

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3656	0.0046	1.6630	1.0426	60
2	0.3632	0.0056	2.1433	1.2917	67
3	1.2066	0.0058	0.6627	0.2130	100
4	1.4551	0.0176	1.0298	0.7241	99
5	1.5743	0.0173	0.9384	0.3525	100

4.3 The FSSI results

In the frequency-domain subspace identification (FSSI) technique [12], there are no many implementation variants the user has to tweak. Therefore, we used the technique as it is introduced by the authors in [12]. So, the FSSI technique has been implemented in the framework of the presented fully automated dynamic monitoring approach to process the consecutive 100 data sets and to extract the modal parameters of the 5 dominant modes within the frequency-band of interest. We have set the number of modes to be identified to 32 the same as the one taken for the previous 2 estimators (i.e. pMLE and pLSCF). The obtained results of the continuous monitoring using the FSSI technique in terms of the median, std, and the success rate are presented in Table 5. In general, the computational time taken by the SSI techniques depends on the number of outputs and the way by which the matrices of the state space-mode are generated. Since the analyzed data set has only 6 outputs and the FSSI technique that we are using is optimized with respect to the computational time, the FSSI technique takes about less than 1 s to process one 10 minutes dataset.

Table 5: Results of the continuous monitoring using the frequency-domain subspace identification (FSSI)

mode	Median freq Hz	Freq. std	Median damp %	Damp. std	Success rate (%)
1	0.3654	0.0051	1.6324	1.1947	66
2	0.3641	0.0057	2.7955	1.3468	71
3	1.2073	0.0058	0.7290	0.2854	100
4	1.4589	0.0165	1.1941	0.4942	100
5	1.5749	0.0165	1.3431	0.6973	100

The results show a good agreement with the ones obtained by the pMLE and the pLSCF that uses the varying model order/varying parameter constraint. The FSSI technique identifies slightly higher damping values than the pMLE and the pLSCF estimators for all the modes except for the first one. In [5], a time-domain subspace identification approach called SSI-COV has been used and compared with the pLSCF estimator in performing a continuous monitoring for the OWT under test using two-weeks datasets. The results presented in this reference showed also that the time-domain SSI identifies slightly higher damping values. What can be noticed also from the results presented in Table 4 that the frequency-domain subspace identification (FSSI) technique gives a bit higher success rate compared with the pLSCF and pMLE estimators. This can be attributed to the fact that the mode shapes in the FSSI technique have been estimated directly from the state space model, while for the pMLE and the pLSCF estimators the mode shapes are calculated in a second step using the LSFD estimator.

5 CONCLUSIONS

In this paper, the applicability of three modal parameters estimators namely the pMLE estimator, the pLSCF estimator and frequency-domain subspace identification (FSSI) technique to extract the modal parameters of the tower and the supporting structure of an offshore wind turbine in a continuous monitoring fashion has been investigated. There were two main concerns that motivate the work and the investigations done in this paper. The first concern was the need to check the robustness of these estimators with respect to a possible change in the implementation options (e.g. type of coefficients, parameter constraint…) that could be defined by the user. The second concern was to check if these estimators would converge to the same results, although they are different algorithms. The pMLE seems to be very robust with respect to the implementations variants that can be used where it always converge to the same results. This was expected since the asymptotic properties of the pMLE say that it is consistent estimator. On one hand, this puts more confidence in the pMLE results we got. On the other hand, the investigations done in this paper showed that the pMLE is the slowest estimator compared with the other two estimators (i.e. pLSCF and FSSI). The pLSCF is found to be very fast in comparison with the pMLE, but it is found that it is inconsistent with respect to any possible change in the implementation options (e.g. type of coefficients, parameter constraint…). To avoid or decrease the risk of this inconsistency problem of the linear least-squares estimators, e. g. the pLSCF estimator, we proposed a global estimation approach. In this global approach, we proposed to try the different model orders and at each model order, we apply all the possible parameter constraint that might be used. Then, all the modal parameters estimated over all these modal orders and all these parameter constraint are sent to a clustering algorithm. The results showed that the proposed approach helps to improve the consistency of the pLSCF estimator when the implementation options changed and also the success rate of the 5-dominant modes has been increased. The investigation done for the FSSI technique using the analyzed data sets showed that this technique is the fastest one compared with the pMLE and the pLSCF estimators taking into account that the computational time of the SSI techniques is highly dependent on the number of output that is only 6 in our case. The SSFI technique identifies slightly higher damping values compared with the pMLE and the pLSCF estimator. The reason behind that is still needed to be fully understood. In addition, the FSSI technique showed a bit higher success rate compared with the pMLE and the pLSCF estimator. We can attribute that to the fact that the mode shapes of the FSSI technique are estimated directly from the state-space model while for the pMLE and the pLSCF the mode shapes are estimated in a least-squares sense in a second step using the LSFD estimator. Therefore, for the pMLE and the pLSCF estimator we suggest to estimate directly the mode shapes from the used model. It means that the mode shapes will be estimated directly from the numerator and the denominator coefficients of the right matrix fraction description model that is being used to parameterize the measured data. This direct estimation of the mode shapes from the used model could help to improve the quality of the estimated mode shapes and hence the tracking process. The effects of the out-of-band model are better modeled in the polynomial model than they are in the modal model, which could help to improve the quality of the estimated mode shapes. The modal model uses only two terms to model the effects.

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