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ANALYSING BWR INSTABILITY WITH VARIATIONAL MODE DECOMPOSITON (VMD) AND COMPARISION WITH EEMD AND FFT.

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ABSTRACT

In dynamic, complex and non-linear systems, the analysis of transients, instabilities or unusual events is fundamental, as well as the knowledge of the system's behaviour in the frequency space. What is usual in this type of study is to have discrete and digitally acquired data, due to a sampling process with a determined period or frequency. Extracting information from this data set is done by numerical methods, such as the Fourier Transform (FFT), the Hilbert-Huang Transform (HHT) or techniques from chaos mathematics (Attractors). In this way we have scarce data, with some loss of information, analyzed with numerical techniques that introduce, also, some dilution of the information. In particular, the techniques of analysis in the frequency space, by their very nature, blur, frequencies and bandwidths. This leads in some cases to the identification of unsuitable or very wide frequencies or intervals, which make the extracted information unusable. To this effect, we have studied the VMD technique that provides more real and representative frequencies of the system as well as narrower bandwidths that make possible better identification of phenomena and influences. This technique has been applied to the analysis of thermohydraulic instabilities in nuclear boiling water reactors (BWR). The cases had already been analyzed with traditional FFT and HHT techniques. The results of the application of the VMD are very good, improving over the previous ones the identification of main frequencies and their bandwidths. In this way, cleaner frequencies are obtained. So the VMD technique has better characteristics and improves the results of the previous techniques, posing as a very good tool for the analysis of transients or instabilities.

KEYWORDS: HHT, VMD, transient, instability.

1. INTRODUCTION

The analysis of thermohydraulic instabilities in boiling water reactors has given rise to many studies and techniques, as well as indicators and announcers [1-5]. In recent times, several techniques derived from signal analysis such as Fourier transform, Hilbert transform, Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) have been used [6-8] to monitor and characterize BWR instabilities. Other techniques based on the characteristics of non-linear systems have been also applied for that purpose [9-11] though it seems that most of the literature on this field of research is based on Hilbert-Huang Transform (HHT) [12] and its modifications.

In this work, we propose to use a recent developed signal processing methodology called Variational Mode Decomposition (VMD) [13] for improving the disadvantages present in HHT such as mode-mixing [14,15]. The goal is enhancing the determination of the critical frequencies of instability and their association to the oscillation modes of the power profile of the core. In this case, the application is not direct, since the VMD method needs adjustments depending on the signal, so an important part of this work is to determine the internal parameters for the method to be efficient and effective in this field of application. In other fields, it has been successfully used as can be seen in numerous research articles [13,15,16]

In addition, a comparison of the results of the previously mentioned methods (FFT, EEMD) is included in this work in order to show the benefits of the methodology used.

In the decomposition methods based on the HHT, the modes in which the primitive signal is decomposed are not mono frequency [3,8], and therefore the important frequencies of the processes studied have dilution between several of the modes, that is, mode mixing problem is not avoided [14] . In such a case it is difficult to identify which harmonics are most relevant in the instability process as they are diluted between the different intrinsic mode functions.

The fundamental advantage of the methodology chosen for this work is that the modes tend to be mono-frequency, so it is very interesting since the modes have all the information of the selected frequency. One of the important points of the methodology is to determine some internal parameters of the decomposition process, so that the frequency intervals are as narrow as possible and mono-frequency is guaranteed. When this is achieved it is possible to use backbone plots (instantaneous amplitude vs instantaneous frequency)[17,18] to identify which modes are most connected to the instability phenomenon.

Using this methodology, the analysis is more efficient, since an exhaustive decomposition of the main signal is no longer needed, operation that consumes resources. Nor is it necessary to recombine modes in order to group all the information of a given frequency, which is spread over several modes. Besides, the backbone plots can be also used to organize the modes according to their relevance. With all this, the technique presented has advantages of efficiency of calculation and integrity of the information contained in a mode, since it is monofrequency.

The methodology, once adjusted, will be applied to some of the cases known in the literature of nuclear instabilities (Cofrentes, Laguna Verde, and Ringhals) and which establish the basis of comparison for the results.

The expectation of this methodology is not to determine new modes of instability in existing signals, but rather to establish an efficiency of calculation and identification of instabilities using less computational and analytical resources.

2. HILBERT-HUANG TRANSFORM AND ITS MODIFICATIONS

Hilbert-Huang transform is a signal processing methodology developed by Huang [12] for non-linear and non-stationary data. It is based on decomposing the signal through EMD in a series of intrinsic mode functions (IMF) which have the following characteristics [19]:

- Each mode is centered in a frequency band
- The number of extrema and the number of zero crossing must be either equal or differ by one (at most)
- At any point, the mean value of the envelope defined by the local maxima and local minima must be zero.

The EMD algorithm, in contrast to all previous existing methods, is adaptive, with a posteriori-defined basis, based on and data driven [19]. The algorithm behind it is iterative and it consists of finding local extrema and building with them an envelope whose mean will be subtracted from the signal. With this new data series, the algorithm verifies if the IMF characteristics are fulfilled and if it is so, this is the first IMF and the decomposition will follow on the rest of the signal. When the criteria is not fulfilled, the process of finding extrema begins again until an IMF is found.

Therefore, the signal is eventually divided into n IMFs and a residual $r(t)$or mean trend as:

$$x(t) = \sum_{i=1}^{n} IMF_i + r(t)$$

Once the original signal is divided into these IMFs, the Hilbert transform can be applied to all of them. As compared to traditional Fourier analysis, Hilbert approach is local and it is defined as follows:

$$H\left[h(t)\right] = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{h(\tau)}{t-\tau} d\tau$$

where P is the Cauchy principal value and *h(t)* is a certain IMF. The kernel $\frac{1}{t-\tau}$ confers to the Transform a local character as opposed to the Fourier analysis. Practical applications come from the analytical signal $g(t)$ defined as the complex function:

$$g(t) = h(t) + iH\left[h(t)\right]$$

The instantaneous amplitude and phase are:

$$a(t) = \sqrt{h^2 + H^2[h]}$$
$$\phi(t) = \tan^{-1}\left(\frac{H[h]}{h}\right)$$

So that the instantaneous frequency is the time derivative of the phase divided by 2π:

$$f = \frac{1}{2\pi}\frac{d\phi}{dt}$$

Instantaneous frequency, instantaneous amplitude and time can be plotted in a 3D colour map in order to see both the frequency content and the energy of the signal along the time span considered which is referred as Hilbert spectrum.

HHT has been widely used in many fields [17,18,20-22] but it has some drawbacks regarding the frequency content of each IMF. When a certain harmonic disappear, it is no longer possible to find it in the EMD phase and this will lead to a certain IMF_j with several harmonics (wider frequency band), that is, mode mixing problem[8,14]. Since the algorithm finds first the high frequency IMFs, the mode mixing will be present in all the IMFs found after IMF_j. In order to avoid this, the EMD was modified into EEMD (Ensemble Empirical Mode Decomposition).

The EEMD consists of adding Gaussian white to the original signal, then calculate and average multiple EMDs. It should be noted that the intermittent phenomenon of original signal can be eliminated through white noise frequency evenly distributed statistical characteristics and mode aliasing of EMD is restrained [23]. This procedure has several disadvantages; on one hand the number of decompositions increase considerably and on the other hand, the standard deviation of the added white noise needs to be previously determined in order to avoid the mode mixing problem. This last task is not straightforward and it is very dependent on the case of study. In BWR instabilities it was tested in [8] with successful results but it could only be applied on Cofrentes Nuclear Plant instability due to the time consuming task of determining the standard deviation of the white noise. So, though EEMD method works, a more efficient and operative methodology would be of great interest for BWR instabilities analysis.

3. VARIATIONAL MODE DECOMPOSITION

In this section, the decomposition method called VMD will be explained as well as how to determine its internal parameters. This last part is important for the method to be fully functional, and useful for the analysis of thermohydraulic instabilities in BWR reactors. It is important not only to determine when the instability takes place but also the relative importance of the modes between each other, so that it is possible to identify the mode or modes which are most related to the instability phenomenon.

The variational mode decomposition is an entirely non-recursive methodology to decompose a signal into different modes, which are extracted concurrently. The model looks for an ensemble of modes and their respective center frequencies, such that the modes collectively reproduce the input signal, while each being smooth after demodulation into baseband [13]. According to the definition of Intrinsic Mode Function or mode [18], each of them should be centered around a certain frequency band which is obtained adaptively based on the concept of center of frequency, that is the center of gravity of the mode's power spectrum.

In order to assess the bandwidth of a mode, the following steps need to be followed in the VMD methodology:

1) for each mode , compute the associated analytic signal by means of the Hilbert transform in order to obtain a unilateral frequency spectrum.

2) for each mode, shift the mode's frequency spectrum to "baseband", by mixing with an exponential tuned to the respective estimated center frequency.

3) The bandwidth is now estimated through the H^1 Gaussian smoothness of the demodulated signal, i.e. the squared L^2–norm of the gradient. The resulting constrained variational problem is the following:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}$$
$$s.t. \quad \sum_k u_k = f$$

Where u_k are the different modes and ω_k their center of frequencies. This minimization problem is solved through Lagrangian multipliers in a sequence of iterative sub-optimizations called alternate direction method of multipliers (ADMMM) that can be seen in [13,24,25].

3.1 VMD ADJUSTMENT. TUNNING TECHNIQUES

The VMD methodology is based on an optimization which uses the concept of Wiener filter. In this filter the Fourier transform of a denoised signal f can be expressed as:

$$\hat{f}(\omega) = \frac{\hat{f}_0}{1+\alpha\omega^2}$$

Where ^ indicates Fourier transform, f_0 is the real signal affected by additive zero-mean Gaussian noise and α represents the variance of the white noise.
For practical applications of the VMD algorithm, prior to the decomposition, the user needs to indicate the number of modes in which the signal will be divided and the parameter α. The number of modes can be estimated by using the standard EMD which is available already in many software packages for numerical applications such as Matlab. Nevertheless, α needs to be determined for each case as the authors of the algorithm do not specify how to do that.

In this work, two methods have been tested to determine the parameter α. The first one, is based on the Fourier transform of the residual obtained from each decomposition for each α. If the decomposition is achieved properly, the residual should be a mean trend with no harmonic content, that is, the Fourier spectrum should have high amplitudes around zero Hz.

For instance, in the case of an instability, the decomposition can be applied by using different α values. Each decomposition leads to a different residual (see Figure 1). It can be seen that the higher the value of α, the less noisy the residual is. Nevertheless all the residuals obtained are able to reproduce the trend of the time series. In order to choose one, the Fourier transform is applied to all the residuals and the resulting spectra are plotted in Figure 2.

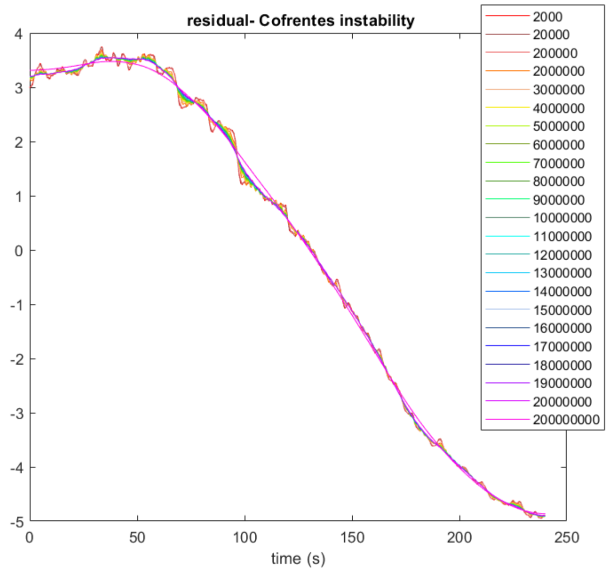

Figure 1: Residuals obtained in VMD decomposition of the instability time series from a LPRM. Legend shows the different values of α parameter used in the VMD algorithm

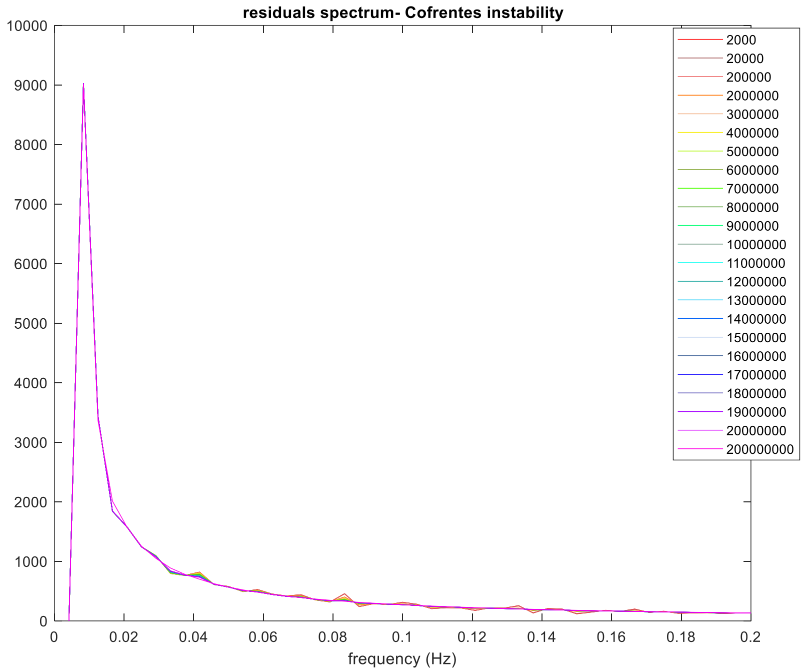

Figure 2: Fourier spectrum of the residuals obtained for different α values (legend) using the VMD decomposition algorithm

As can be seen, the different spectra show practically no differences between the different residuals obtained. This means that another criterion is needed to objectively choose the α parameter.

The instability has been studied in previous work [3] and it is well known which harmonics are dominant along the time span considered. In this case, the harmonic at 0.5 Hz should appear as dominant and it is expected to be present in Mode 1, if not, the decomposition would not be adequate. By examining the spectra of mode 1 for the different α decompositions, it is possible to choose objectively the α value.

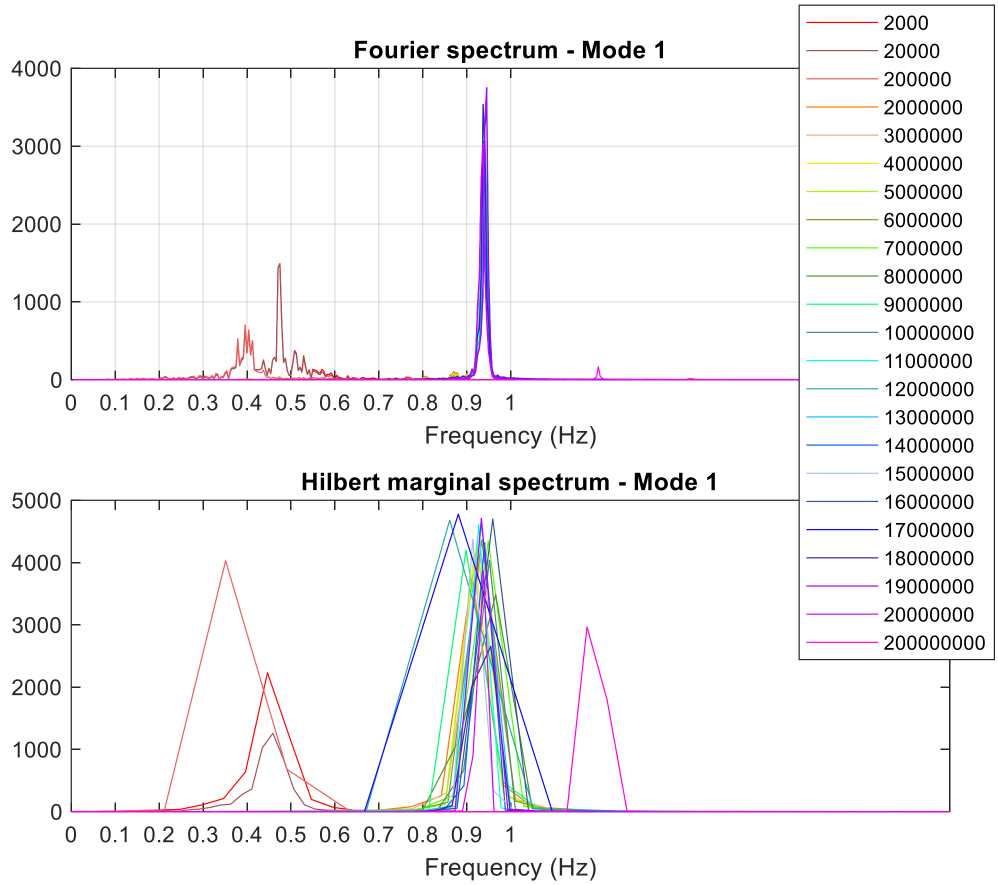

Figure 3: Mode 1 spectrum for the different k values decompositions using VMD algorithm,

As can be seen in Figure 3, when α lies above 200 000, mode 1 no longer presents 0.5 Hz harmonic. Basically only α= 2000 and α=20000 leads to a 0.5 Hz Mode 1. Since the higher α, the less noisy the residual, the value chosen is α=20000.

4- RESULTS

In this section the results from the applications of the VMD decomposition algorithm are detailed as well as a comparison with other methodologies used in previous work [3,8].

4.1 VMD RESULTS

The figures and analysis presented are based on the proper selection of α parameter as explained in section 3.1. The instability cases analyzed are; Cofrentes, Laguna Verde and Ringhals.

4.1.1. Cofrentes

The instability event from Cofrentes can be seen through a Low Power Range Monitor (LPRM) detector time series (Figure 4). The event shown occurred at Cofrentes

Nuclear Power Plant in Valencia (Spain) on January 29th, 1991, during a normal startup sequence, right before the transfer to high speed of the recirculation pumps [1,5]. As can be seen in [5,8], this instability has two main frequencies; one at 0.5 Hz and another one at 1 Hz. These characteristics are associated to out of phase instabilities or mode 2.

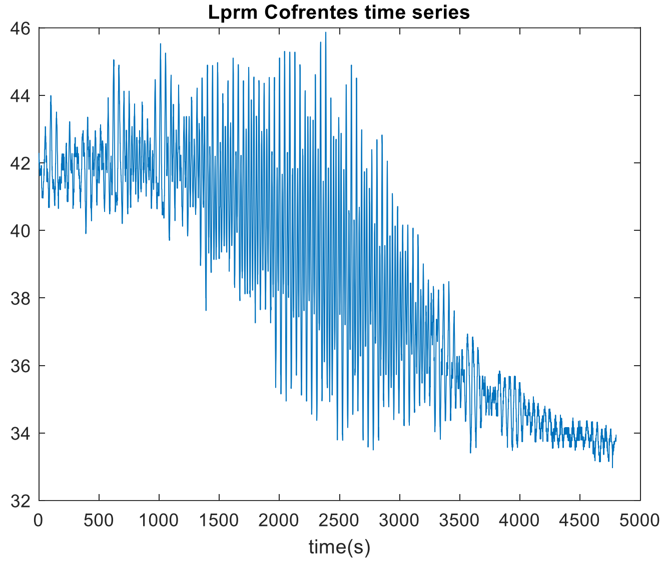

Figure 4: Cofrentes instability time series from a LPRM

For this case, the decomposition using VMD was performed with α=20000 and the resulting Hilbert Spectrum is shown in Figure 5, where the previously mentioned frequencies at 0.5 and 1 Hz show higher instantaneous amplitude. Note also one mode at around 1.5 Hz and another at 2 Hz which are discussed in [5].

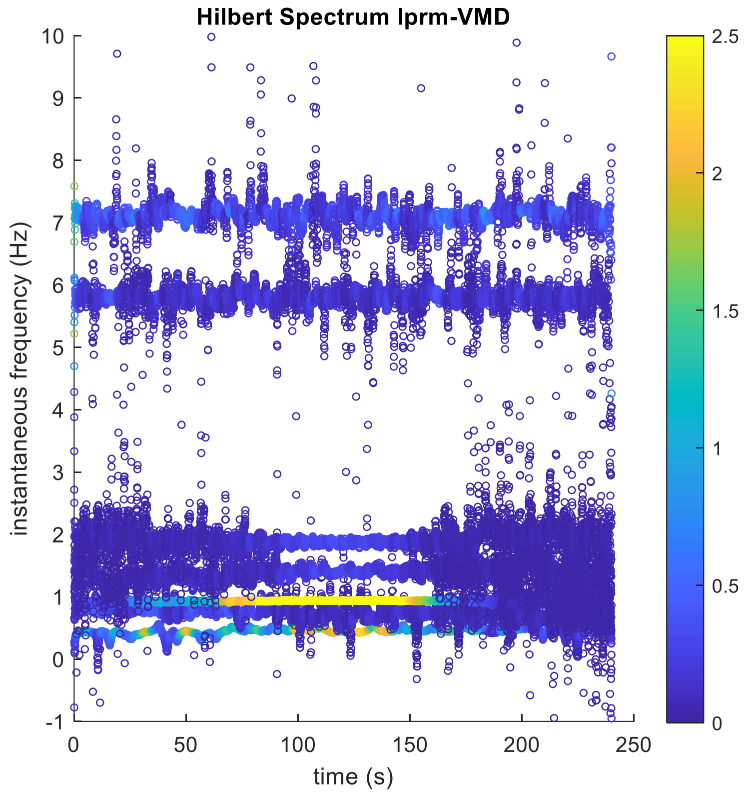

Figure 5: Hilbert spectrum obtained with VMD methodology

The decomposition allows examining in detail every mode. As can be seen in Figure 6, Mode 1 presents 0.5 Hz harmonic and mode 3 lies on 1 Hz. The decomposition shows a clear separation between modes in terms of frequency content, that is, the mode mixing problem is avoided (see reference [8,14]). Besides, mode 3 (1 Hz mode) is the one which presents the highest instantaneous amplitude, followed by Mode 1 (0.5 Hz). This is the reason why the Hilbert Spectrum in Figure 5 shows yellow colour for a certain time span which coincides with the instability.

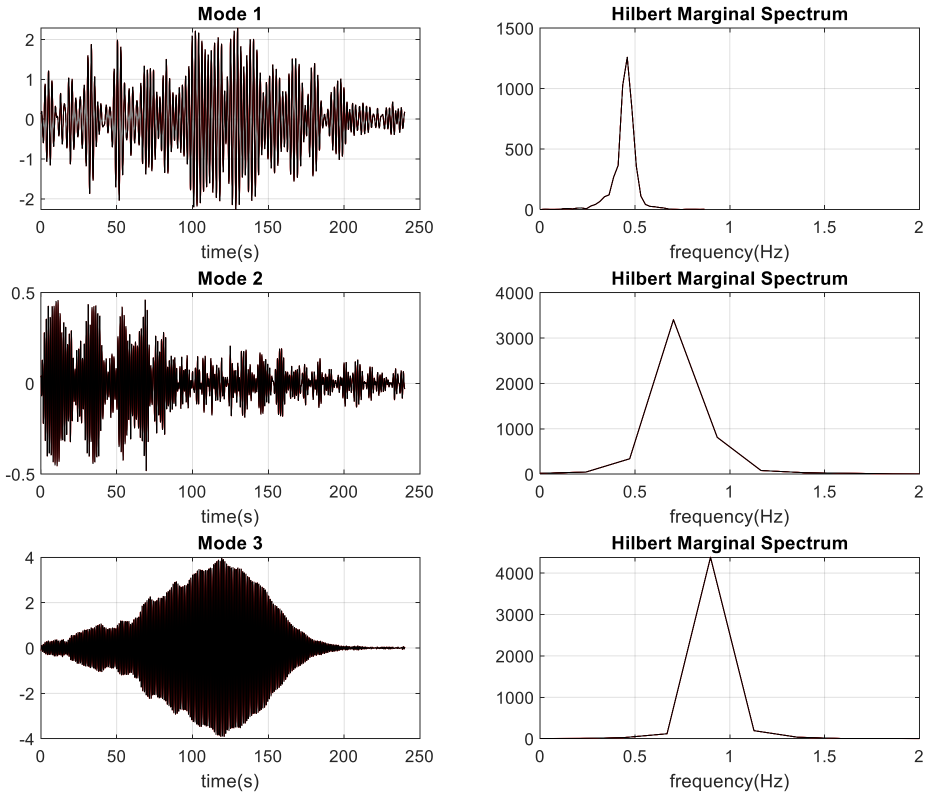

Figure 6: Mode 1-3 and their respective spectra by using VMD methodology

4.1.2. Laguna verde

The Laguna Verde instability time series from a lprm can be seen in Figure 7. It occurred at Laguna Verde Nuclear Power Plant in Veracruz, Mexico[26]. The power began to rise when the operator closed the flow control valves (FCV) during the starting up of Unit 1[5]. The operator decided to scram the reactor at t=715 seconds.

In this instability the main frequency found is 0.5 Hz and it is an in phase type or core wide oscillation [5].

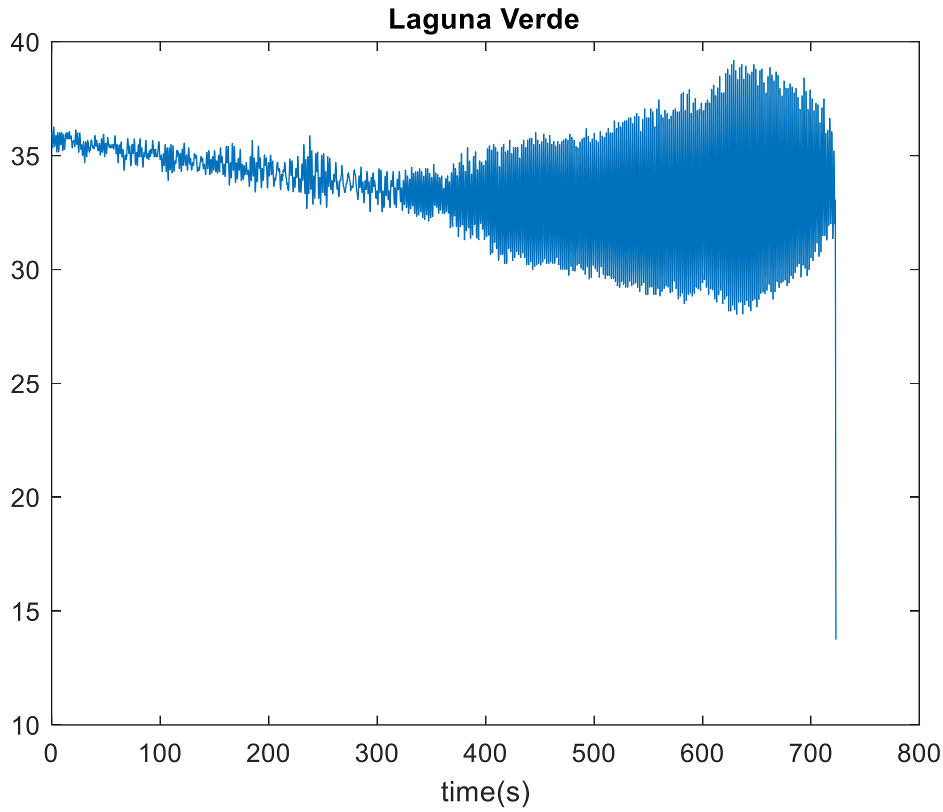

Figure 7: Time series Laguna Verde Instability event

The Hilbert spectrum obtained with VMD is plotted in Figure 8. Note there is an increase in the amplitude at 0.5 Hz and the 1 Hz mode is visible and very well defined after 400 seconds.

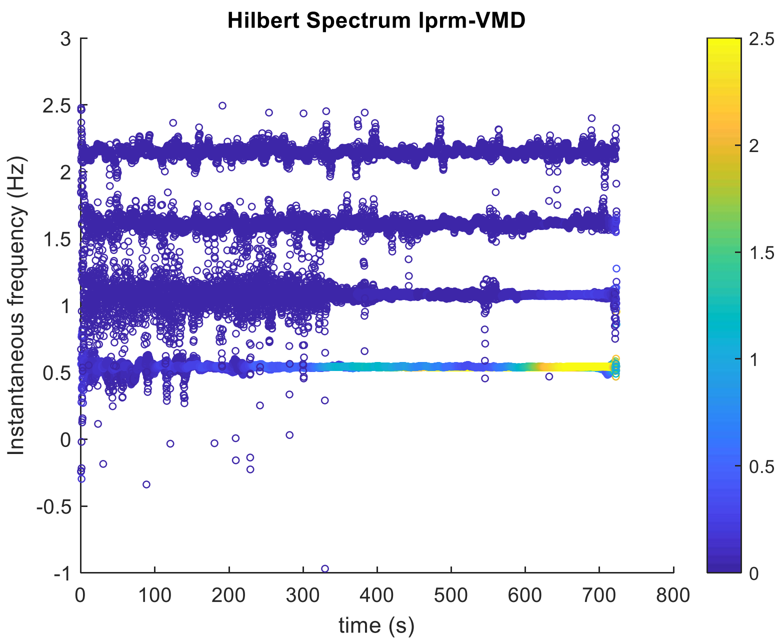

Figure 8: Hilbert Spectrum of a Laguna Verde times series during an instability event,

As can be seen in Figure 9, Mode 1 and 2 present 0.5 Hz harmonic and they have the highest instantaneous amplitude and mode 3 lies on 1 Hz. In this case, the VMD distinguishes two modes in the 0.5 Hz range. In fact, according to [5] the instability began at 320 s with a precursor at 240 s. From Figure 9 it seems that mode 1 gathers the instability begging at 320 s and the precursor seems to be more connected to mode 2.

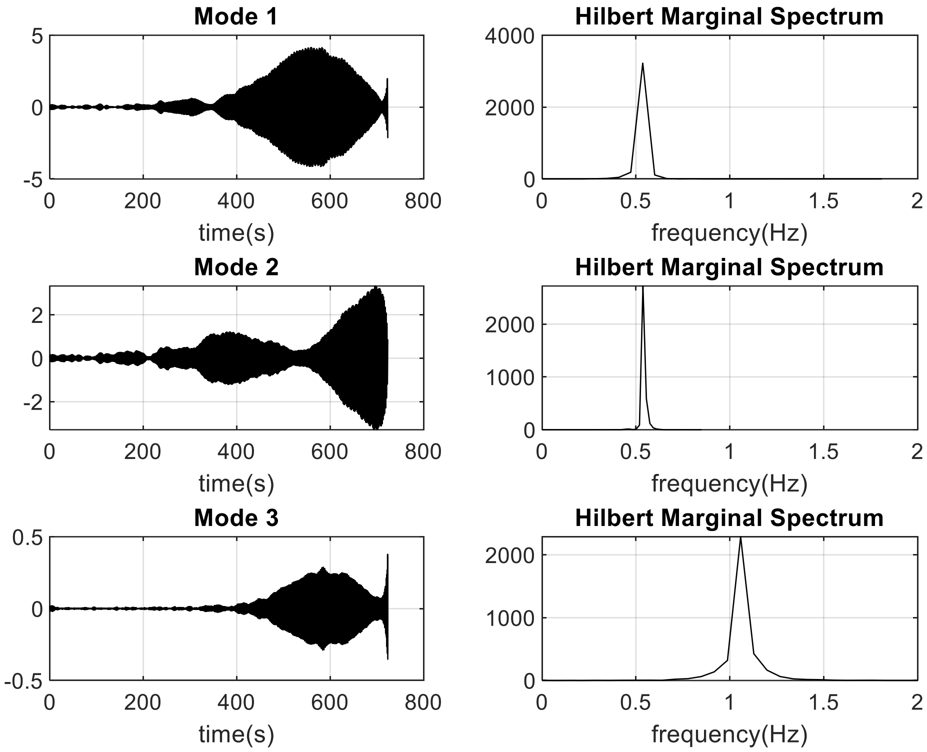

Figure 9: Mode 1-3 and their respective spectra by using VMD methodology

4.1.3. Ringhals

In this subsection the results from Ringhals instability event can be seen. In Figure 10 there is an APRM signal during the instability and as can be seen, an analyst could not clearly establish when the instability began or even if an instability is taking place. According to [5] two main modes at 0.5 Hz and at 1 Hz are found and it corresponds to an in-phase instability, with an incipient overlapping out-of-phase instability.

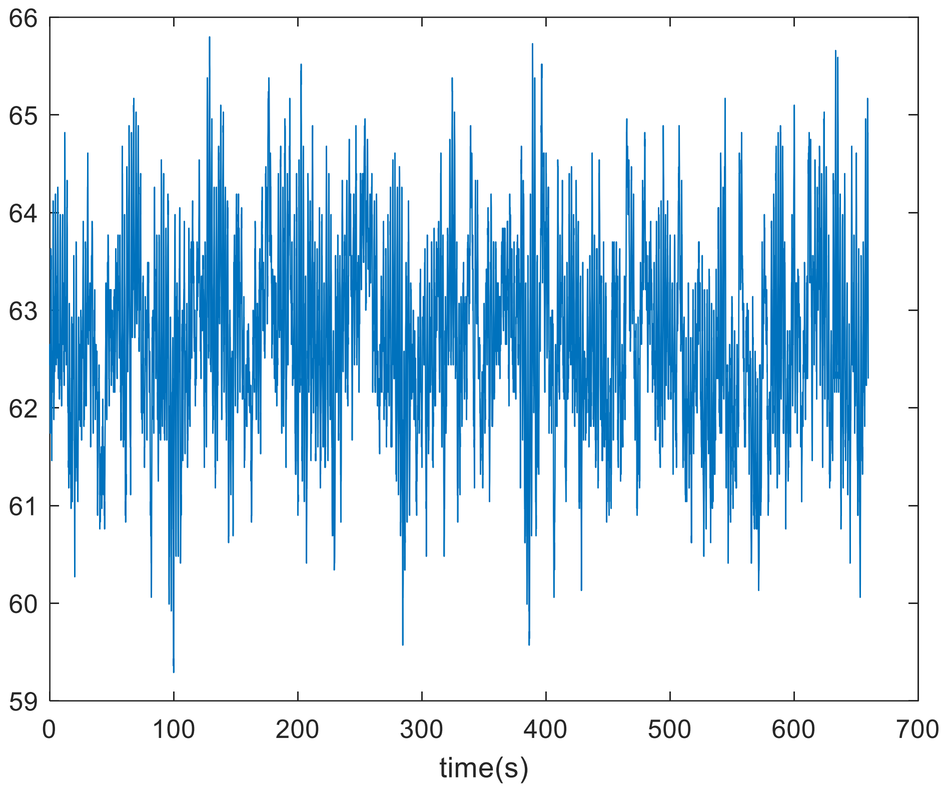

Figure 10: Ringhals instability event

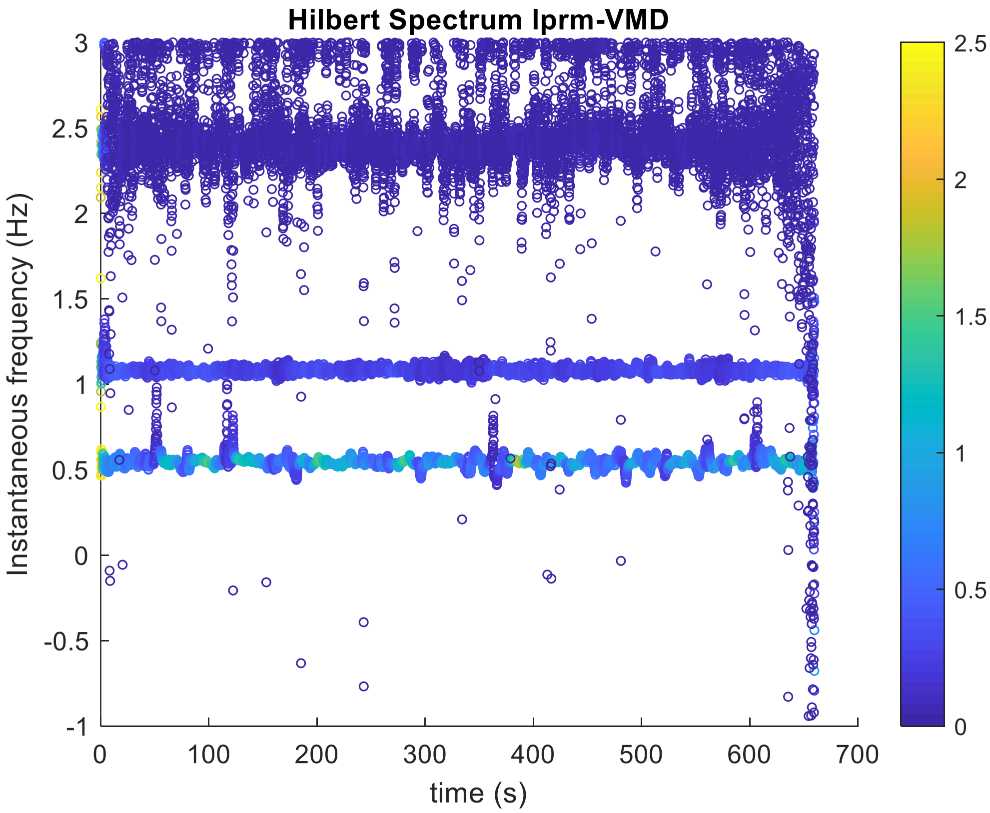

Figure 11: Hilbert spectrum based on VMD methodology for Ringhals instability event

From Figure 11 it is possible to distinguish the 0.5 Hz harmonic among the rest and with a lower amplitude, the 1 Hz frequency. By examining in detail every mode (see Figure 12) it is possible to appreciate that Mode1 has an amplitude which fluctuates along the time span and it does not have a clear increasing tendency like in previous cases. Mode 2, with lower instantaneous amplitude but clearly above Mode 3, is also present during the recorded time.

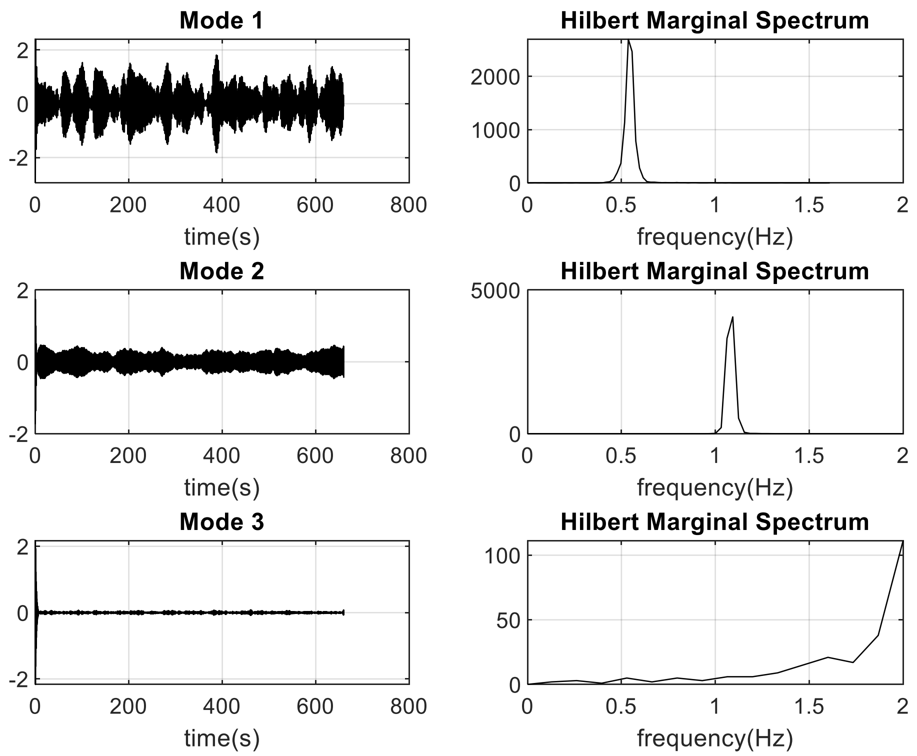

Figure 12: Mode 1-3 and their respective spectra by using VMD methodology in Ringhals data

4.1.4. Stable lprm series from Cofrentes

In order to understand the instability and how it manifests itself in the different methodologies, a stable time series from Cofrentes nuclear Power plant will be analyzed in this subsection. Figure 13 shows the recorded signal with a sampling time of 0.05 s.

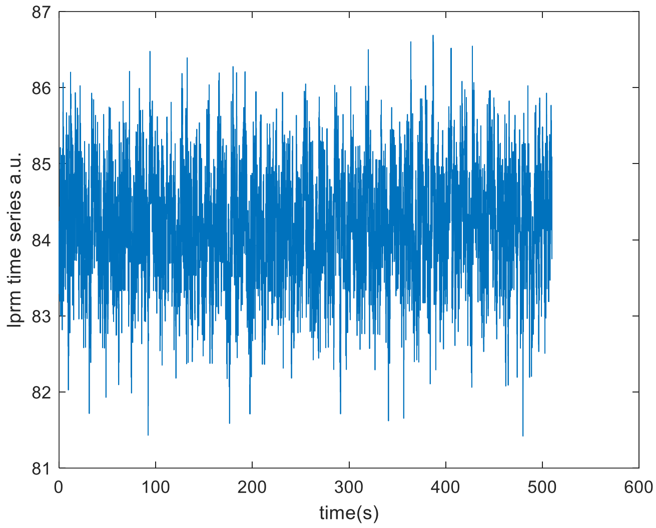

Figure 13: Lprm time series from a stable situation in Cofrentes NPP.

After applying the VMD algorithm, the resulting Hilbert spectrum is shown in Figure 14. As can be seen the 0.5 Hz frequency has higher amplitude than the rest. All frequencies are present in the data though the 0.5 Hz harmonic has more energy.

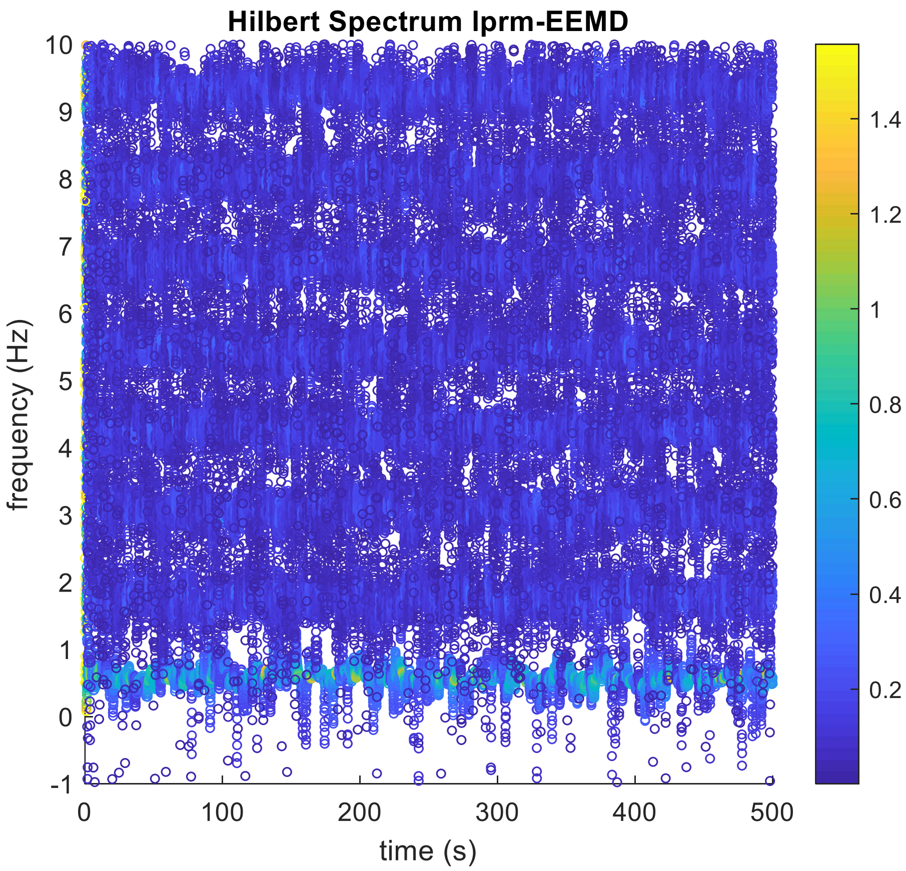

Figure 14: Hilbert spectrum based on VMD methodology for a stable time series from Cofrentes NPP

The modes can be seen in detail in Figure 15 where despite there is no instability the 0.5 Hz mode shows the highest amplitude.

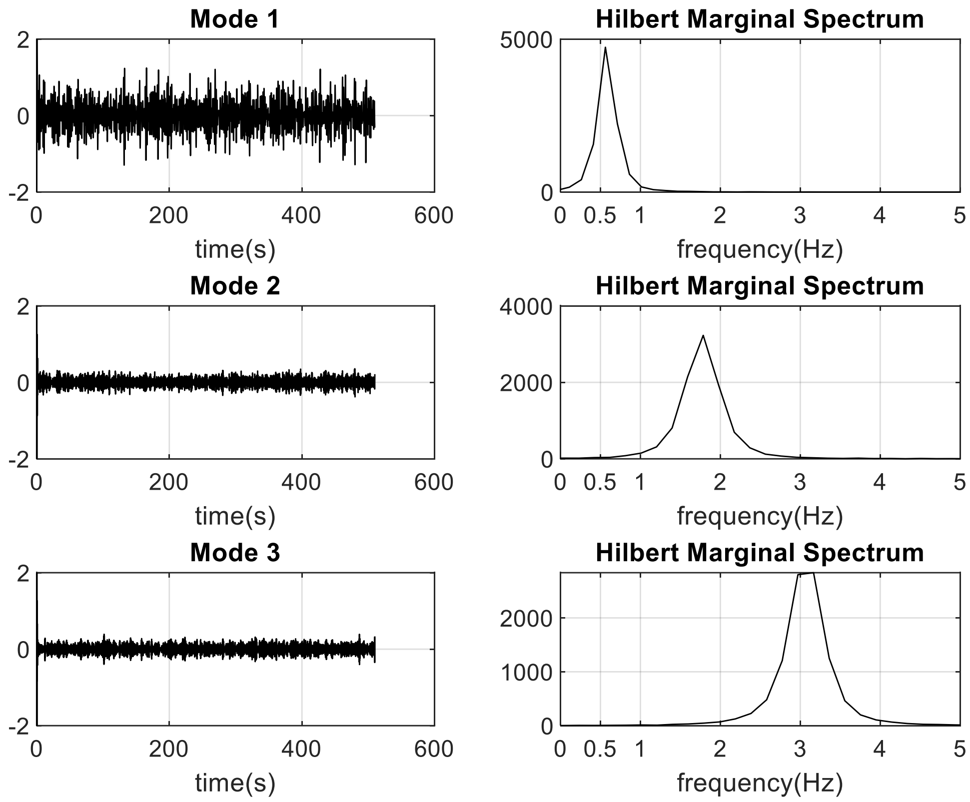

Figure 15: Mode 1-3 and their respective spectra by using VMD methodology for a Cofrentes stable data series

4.2 EEMD vs VMD Results

Ensemble empirical mode decomposition was developed to overcome certain limitations of EMD methodology. Though both are empirical techniques, EEMD implies to add white noise to the original signal several times so that the analysts can create an ensemble of decomposed signals. The modes obtained with every decomposition are averaged. The goal is to avoid the mode mixing problem [18] and obtaining a series of modes with just one frequency each. Since white noise has been added, all frequencies are found, not only the ones from the original signal but also the ones coming from the added white noise. These are supposed to have lower amplitudes so that you can identify the phenomenon the analyst is looking for. This methodology has been used previously with successful results [8] but it has certain disadvantages. Firstly, the decomposition of the ensemble is a time consuming task. If one wants to make a proper averaging of all the IMFs, the decomposition should be performed 300 times at least, that is, 300 ensemble size is needed. However, the standard deviation of the added white noise needs to be determined for every case you analyze. This means that if the analyst tests 10 different standard deviations, the number of decompositions to be performed are 300 times 10. Therefore, although good results, the preliminary analysis to choose proper standard deviation is not straightforward and requires of knowing signal processing tools and the phenomenon itself.

In VMD methodology, the selection of the α parameter is very straightforward and it requires up the most, around 20 to 30 different decompositions. Since α depends on the frequency range of the signal [13], once it is obtained for a certain plant, you can apply it for any signal of the same type from that reactor. In the case of the EEMD methodology, the standard deviation of the added white noise is very dependent on the order of magnitude of the signal [14] and this can change along the cycle, in different cycles, different measurements, etc.

In Figure 16, both methodologies are compared. On the left subfigure, the Hilbert spectrum obtained with VMD decomposition clearly presents a 1 Hz harmonic whose amplitude increases from around 75 seconds to 170 seconds. In the right subfigure, a similar observation can be made but there is a difference. With VMD methodology and during that time span, the instantaneous frequency of the 1 Hz harmonic has a very low dispersion. One of the features of the signals during instability events is that the neutron time series are ordered and they become less noisy. This can be clearly seen in the left subfigure.

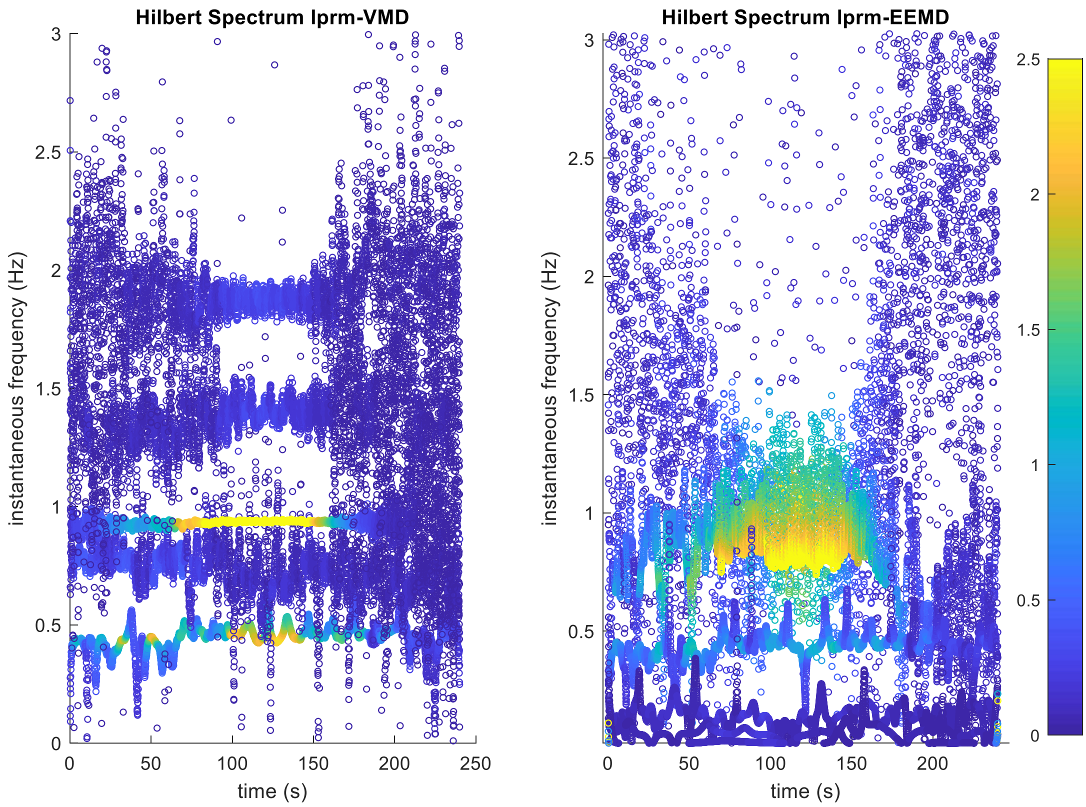

Figure 16: Hilbert spectrum of Cofrentes instability with VMD (left) and EEMD (right) methodologies.

Regarding the modes obtained, we can see in Figure 17 how the first mode is clearly centered at 0.5 Hz in VMD methodology. In the EEMD case the first mode is wide band noise. It is necessary to observe the second mode to appreciate the 0.5 Hz harmonic in the EEMD methodology, but it is also accompanied by the 1 Hz harmonic (see Figure 18). This means that the mode mixing problem has not been completely overcome. The prevalence of one harmonic respect to the other (1 Hz respect to 0.5 Hz) is a good indicator of the type of instability is taking place. So, being able to separate both frequencies in different modes give more information on when the instability began and which type there is at any instant.

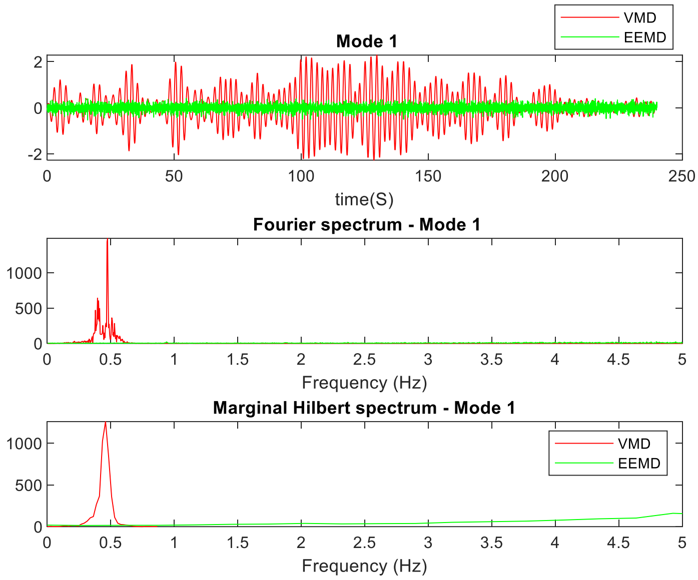

Figure 17: Mode 1 and their Fourier and marginal Hilbert spectra for VMD and EEMD methodologies.

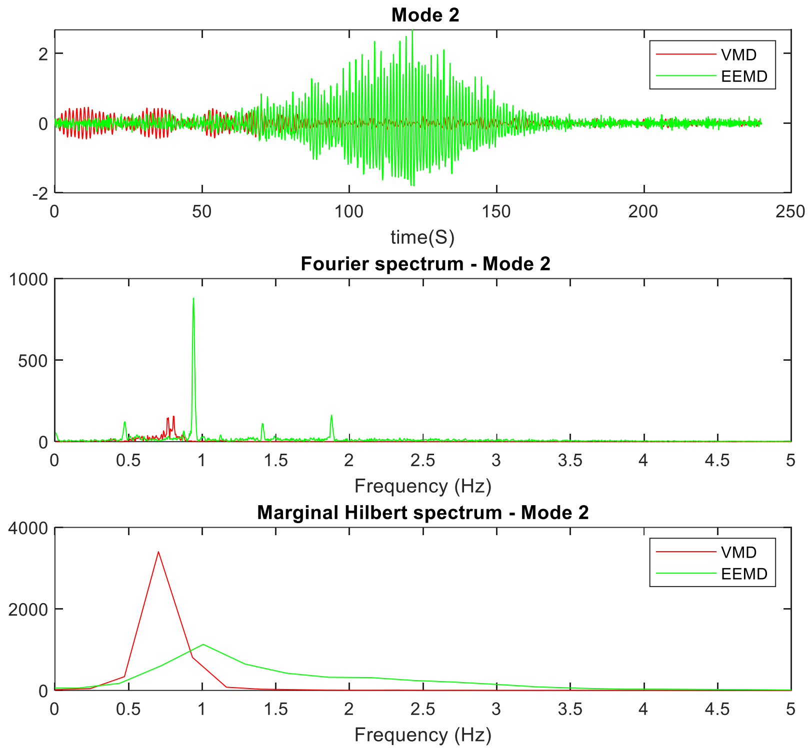

Figure 18: Mode 2 and their Fourier and marginal Hilbert spectra for VMD and EEMD methodologies in Cofrentes instability

At last, mode 3 presents for both methodologies the 1 Hz harmonic but the EEMD still shows mode mixing (see Figure 19) whereas the VMD does not.

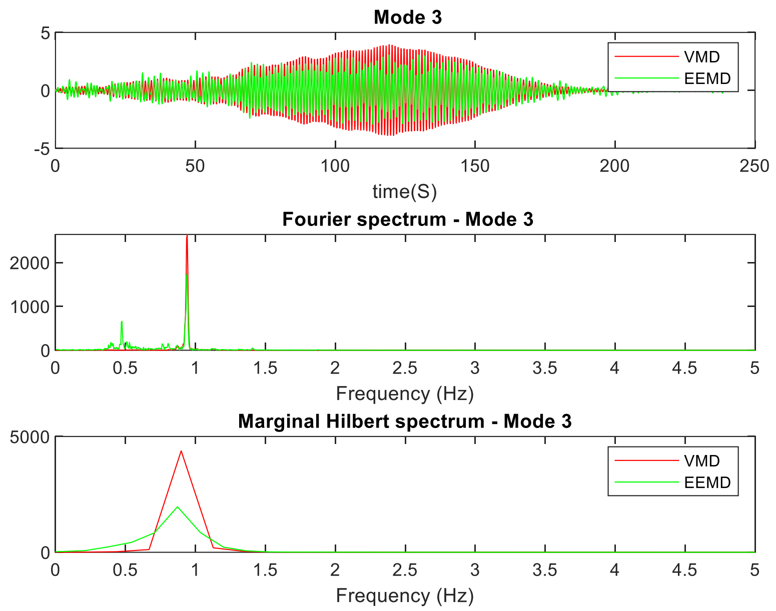

Figure 19: Mode 3 and their Fourier and marginal Hilbert spectra for VMD and EEMD methodologies in Cofrentes instability

In the case for Laguna Verde (see Figure 20) there are several differences in the EEMD and VMD spectra. On one hand, the frequency band of the 0.5 harmonic is wider in the EEMD, that is, there is high dispersion in the instantaneous frequency values given by the Hilbert transform. On the other hand, the 1 Hz harmonic is not even present with EEMD (right subfigure in Figure 20) whereas in VMD corresponds to the third mode as was shown in Figure 9. It is very likely that EEMD did not work fine in this case because the added white noise used has not the proper standard deviation. As was mentioned before, this is not an easy task and it is not required for VMD.

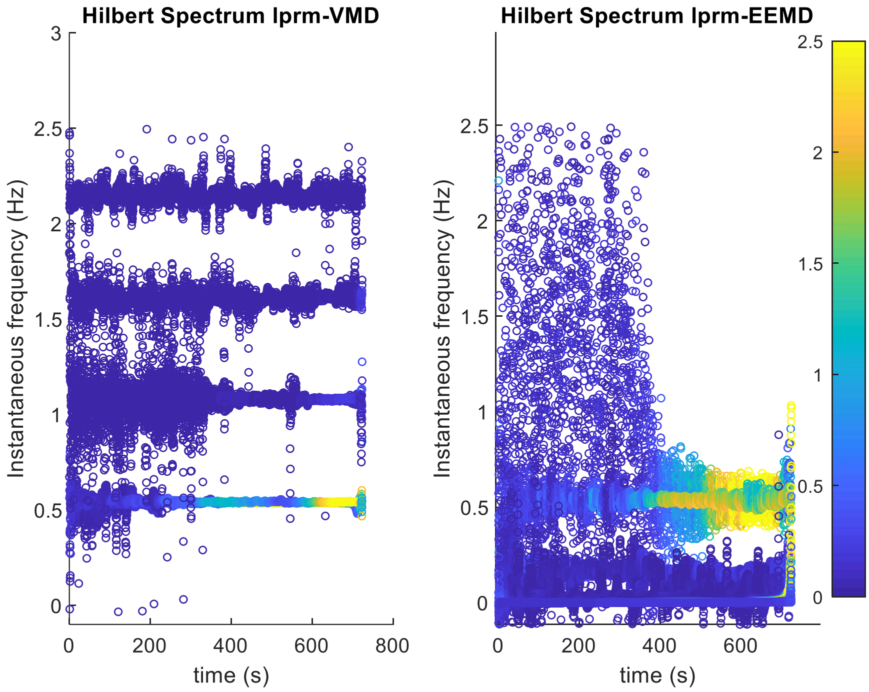

Figure 20: Hilbert spectrum of Laguna Verde instability with VMD (left) and EEMD (right) methodologies.

In the case of Ringhals, the instability is not so easily detected by visual inspection of the time series as in previous cases. After the decomposition, it is possible to see that mode 1 from VMD is centered at 0.5 Hz (see Figure 21) and mode 2 at 1 Hz. EEMD presents mode mixing again since Mode 2 (see Figure 22) is centered at 2 different frequencies, 0.5 and 1 Hz.

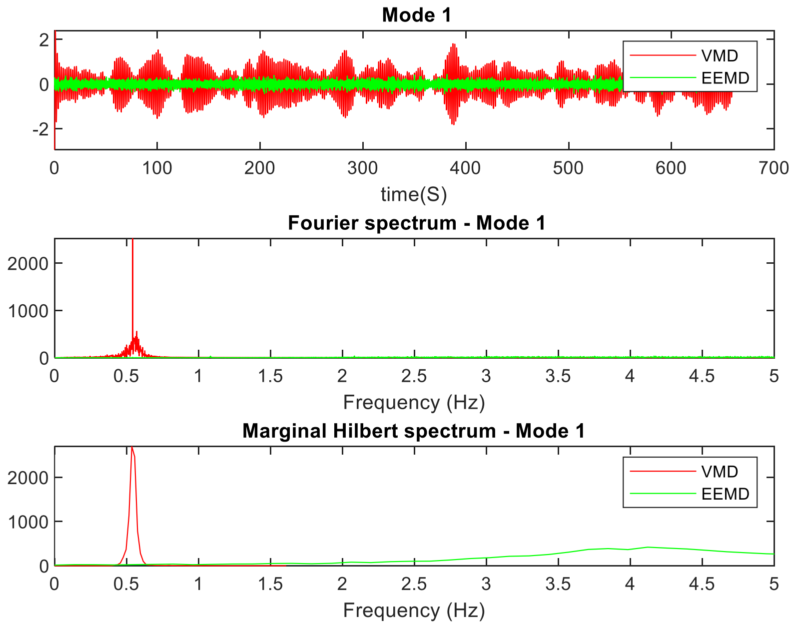

Figure 21: Mode 1 and their Fourier and marginal Hilbert spectra for VMD and EEMD methodologies in Ringhals instability

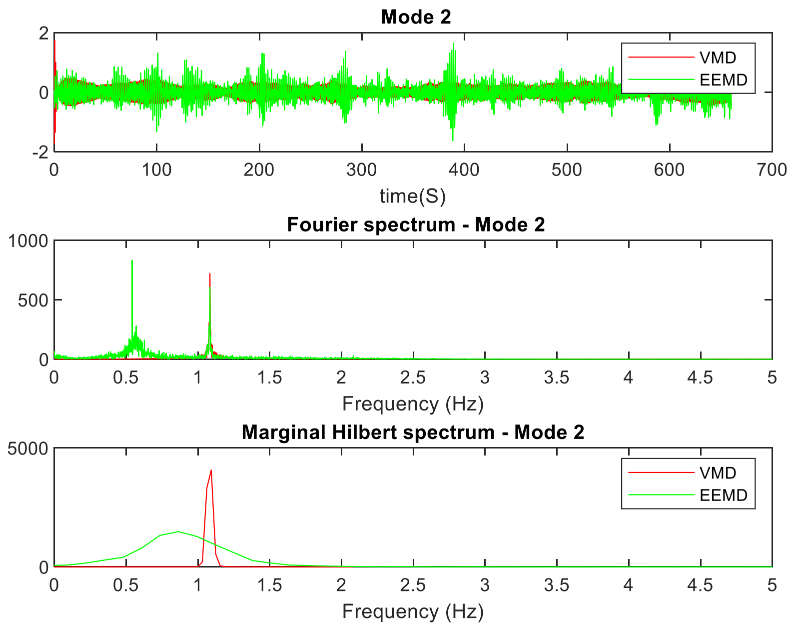

Figure 22: Mode 2 and their Fourier and marginal Hilbert spectra for VMD and EEMD methodologies in Ringhals instability

For the stable case, EEMD and VMD present some differences as can be seen in Figure 23. On the left subfigure, there is only one harmonic (0.5 Hz) which presents higher amplitude than the rest. On the right subfigure, apart from the 0.5 Hz harmonic, frequencies above 5 Hz also present high amplitude. In both methodologies, time series contain all frequencies from 0 Hz up to the Nyquist frequency whereas in an instability case only certain frequencies are excited. Nevertheless, the VMD spectrum shows clearly that the 0.5 Hz frequency is dominant.

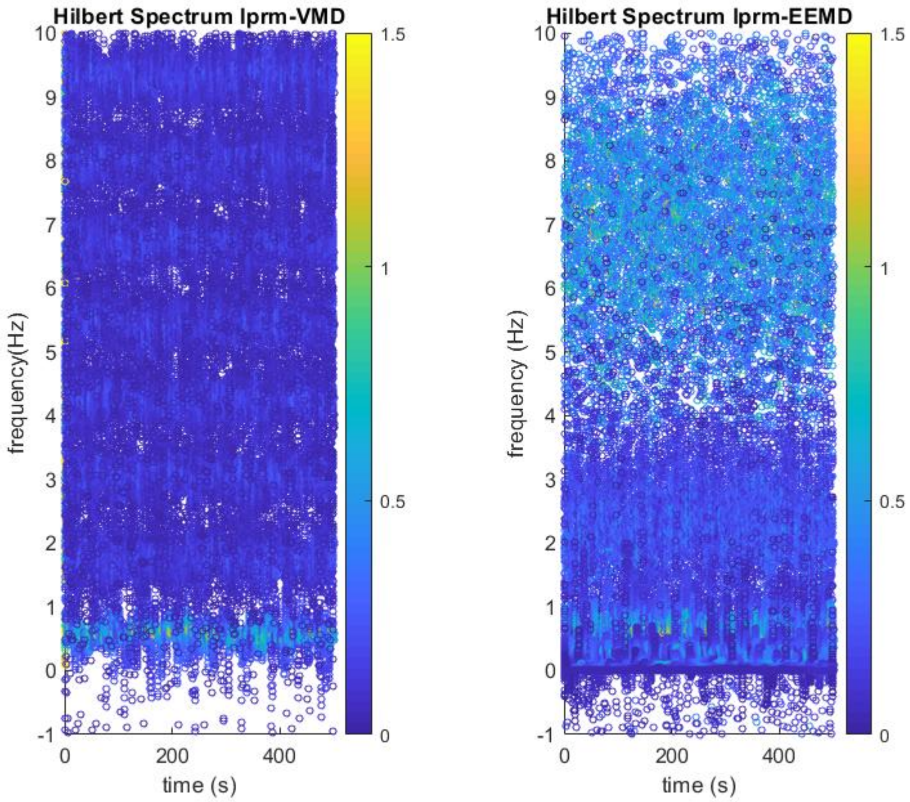

Figure 23: Hilbert spectrum from VMD (left) and EEMD (right) for a stable time series from Cofrentes NPP

4.3 FFT vs VMD Results

FFT is not a local methodology though STFT has been useful for several applications where an amplitude-frequency-time analysis is needed. You can find it in many software packages for signal processing and staff from the plant are more familiar with Fourier transform than any other signal processing method. It can be very useful to apply it before any other methodology is utilized. The analysts can obtain a first approach of the frequency content of the signal. It is limited since it divides the signal in different blocks and the amplitude and frequency obtained is a global result for each block.

In Figure 24 the Hilbert spectrum is compared with a Short time Fourier spectrum. Both are similar since it is possible to identify which harmonics have higher amplitude and when. Nevertheless, the VMD allows to isolate from the original signal in the time domain the mode related to the instability.

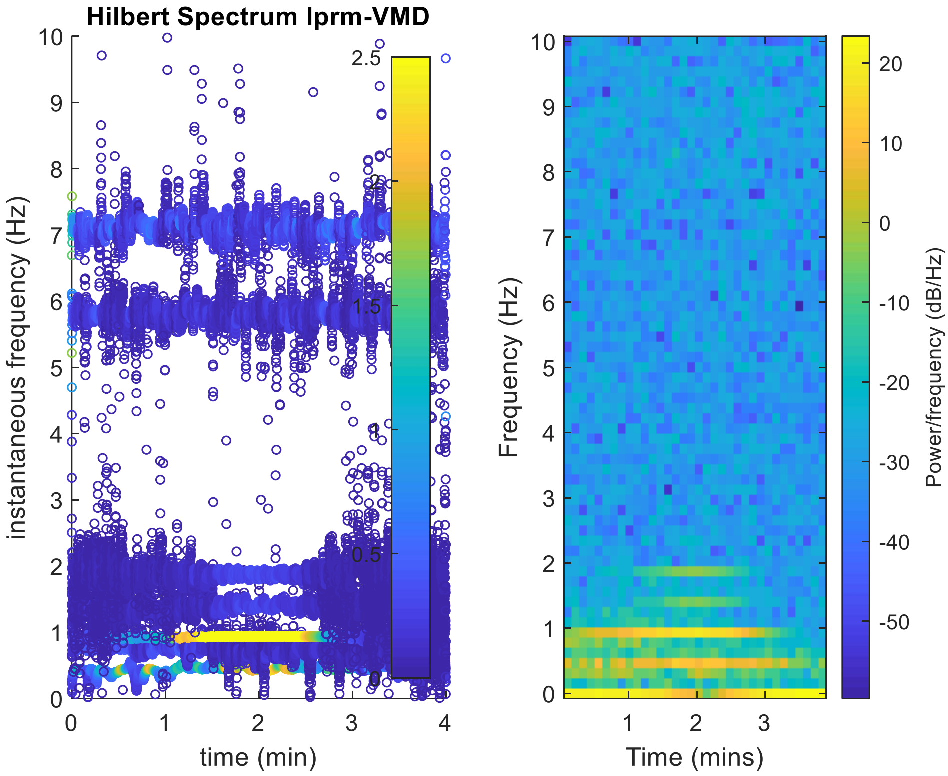

Figure 24: Hilbert spectrum from VMD (left) and STFT (right) of lprm signal at instability event in Cofrentes

Although STFT is limited compared to other advanced methodologies, it is useful for validation when certain adjustments need to be made before a new methodology is applied.

In the case of the stable series from Cofrentes, the STFT and the Hilbert spectrum from VMD is plotted in Figure 25. On the right subfigure, the STFT shows higher amplitude in the low frequency range but it is not possible to distinguish the 0.5 Hz Mode.

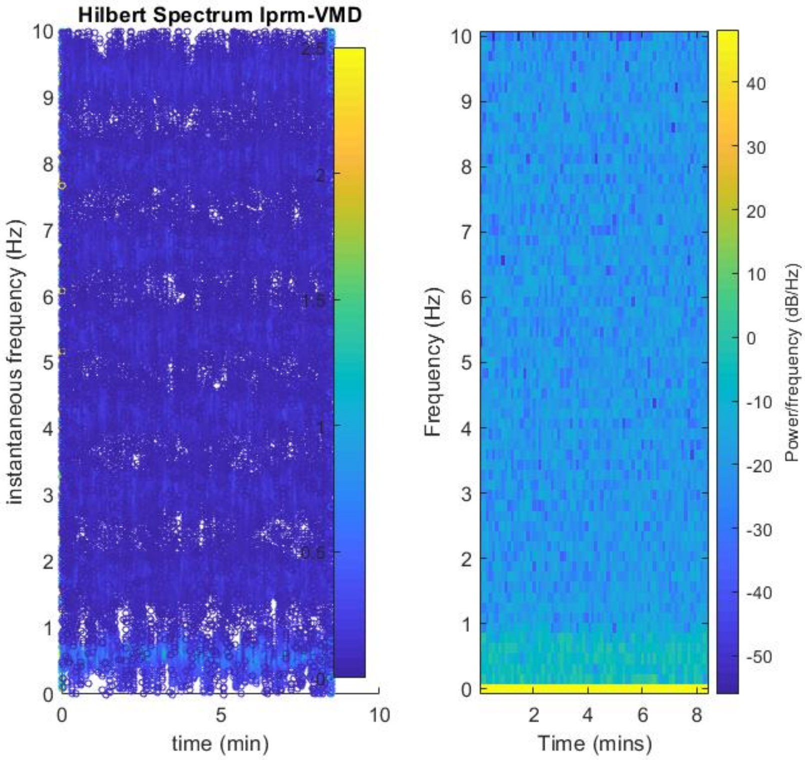

Figure 25: Hilbert spectrum from VMD (left) and STFT (right) of lprm stable signal in Cofrentes

4.4 Backbone plots for discriminating instabilities

Up to now, most of the publications regarding the study of BWR instabilities where focused on its detection [3,5,8,9] and several methodologies have been tested to do that. Nevertheless, not all the instabilities are connected to the same harmonics, that is, there are instabilities where there is a prevalence of the 1 Hz harmonic and in other cases is the 0.5 Hz one. Even, it is possible to find other harmonics at 1.5 Hz or 2 Hz [27]. Therefore, discriminating which harmonics are the most important can help to classify the instabilities. With that purpose the backbone plot will be utilized. In this plot, the instantaneous amplitude of every mode is plotted against the instantaneous frequency. The modes related to the instability are supposed to have the highest amplitude, so this could be used to make a hierarchy of modes.

In Figure 26, there is a representation of the backbones for Cofrentes instability calculated by using VMD (left subfigure) and EEMD (right subfigure). Several observations can be drawn:

- The modes in VMD are clearly centered at one frequency whereas in EEMD the dispersion of the instantaneous frequency is very high.
- In the VMD subfigure the most important mode is the 1 Hz harmonic and in the second place, the 0.5 Hz. In the EEMD, due to mode mixing, there are two modes at 1 Hz and both spread up to 0.5 Hz in the x axis.

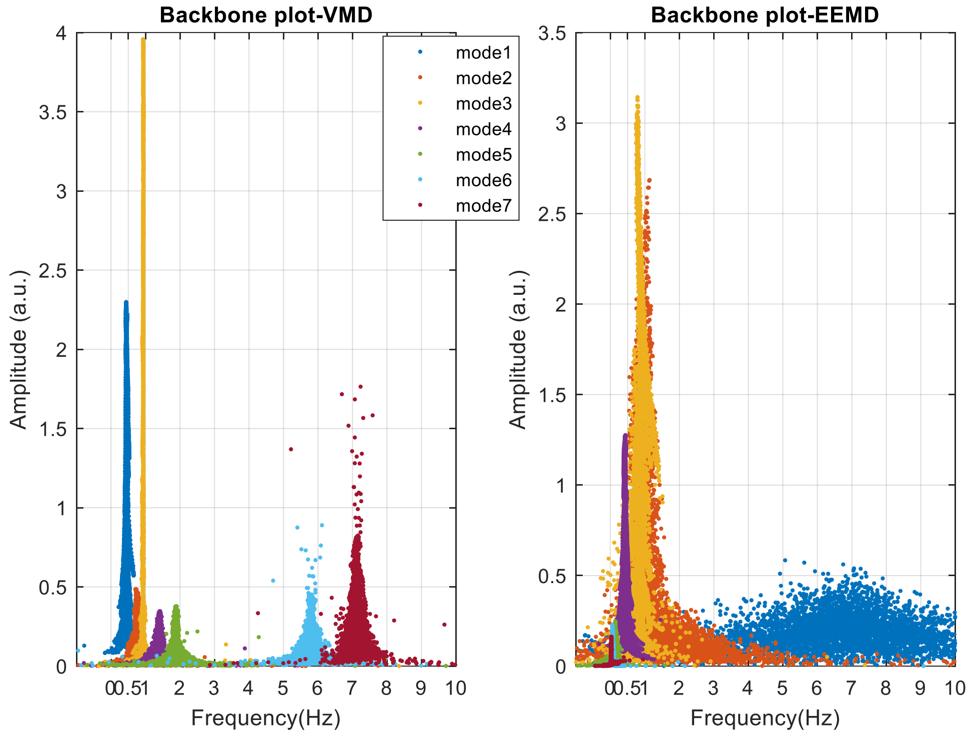

Figure 26: Backbones for Cofrentes instability based on VMD (left) and EEMD (roght) methodologies.

The backbone for Laguna Verde is in Figure 27. Similar observations as in Cofrentes case can be made. Besides, in the case of using EEMD methodology, it is confusing to establish which mode is the dominant one since mode 4, 5 and 6 reach higher amplitudes than mode 2 located at 0. 5 Hz. In the VMD subfigure, it is clear that 0.5 Hz modes are the most relevant in the signal.

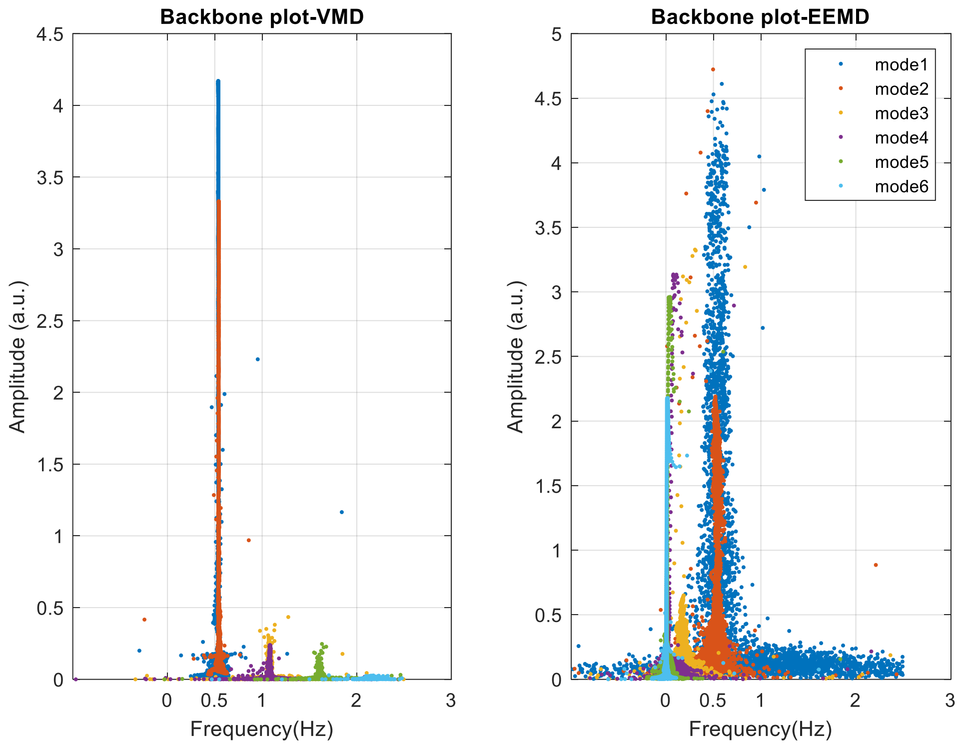

Figure 27: Backbones for Laguna Verde Instability with VMD (left) and EEMD (right) figures

In the Ringhals case, the instability is not as clear as in Cofrentes or Laguna Verde but it is still possible to establish a hierarchy of modes with the backbone plot as can be seen in Figure 28.

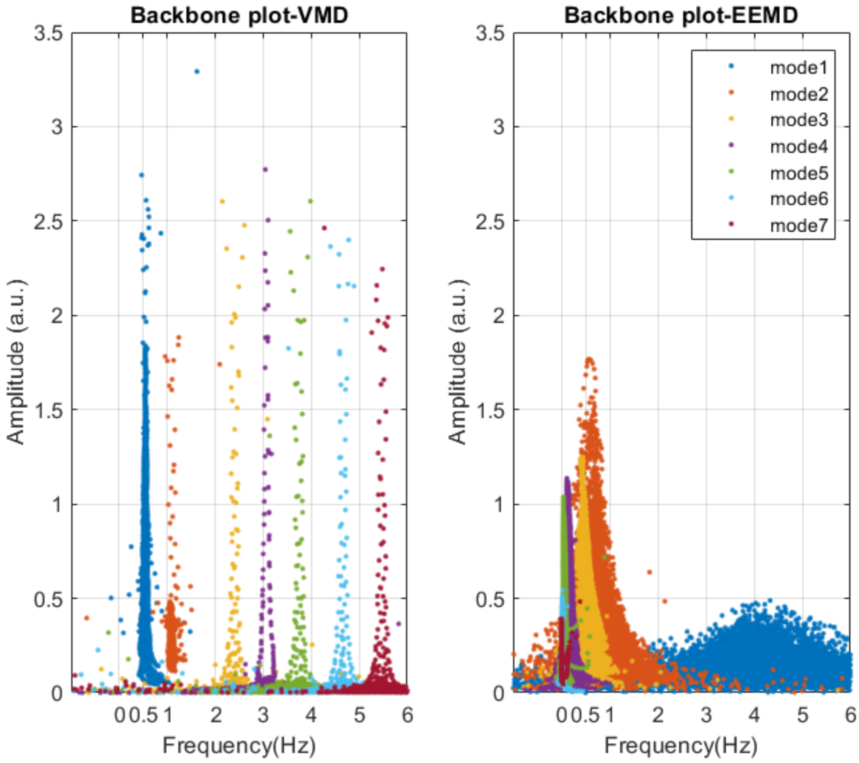

Figure 28: Backbones for Ringhals Instability with VMD (left) and EEMD (right) figures

The 0.5 Hz harmonic in the left subfigure presents more points than the rest, so that it means it is dominant in the signal but it has not reached a very high amplitude yet. This observation cannot be done in the right subfigure for the EEMD methodology. In fact, it is not even possible to organize the modes according to their relevance in the signal.

At last, in

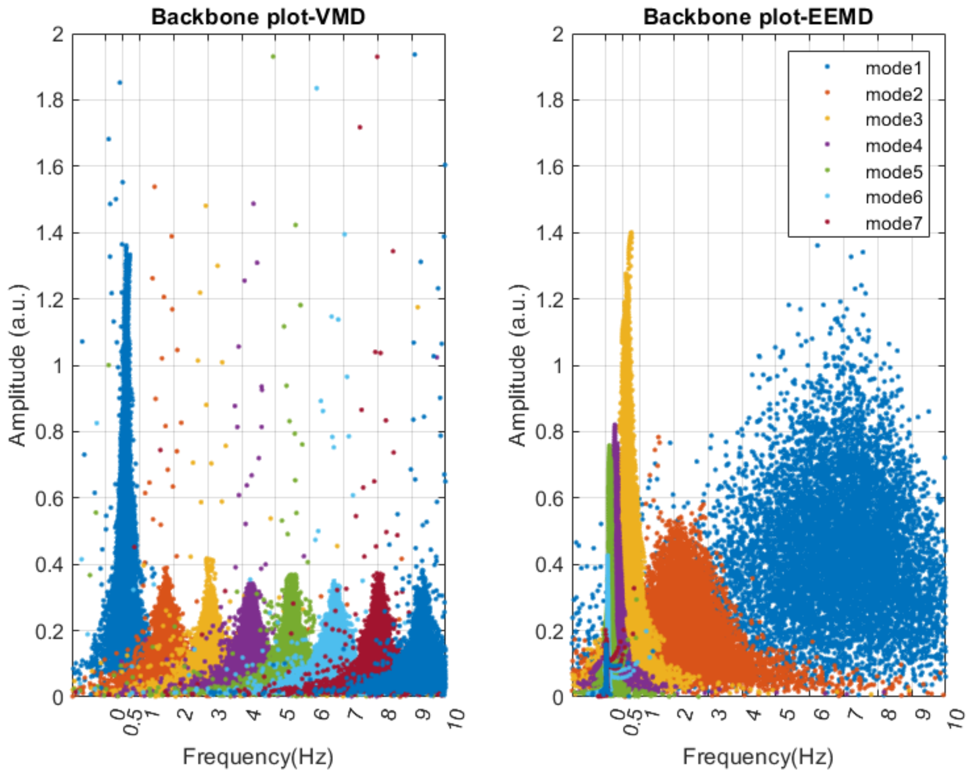

Figure 29 the backbones for the stable Cofrentes case are plotted. On the left subfigure, the VMD methodology is used and as can be seen, each mode covers a certain frequency range. The 0.5 Hz mode is the one with the highest amplitude. In the right subfigure, the 0.5 Hz mode also has the highest amplitude but the frequency range covered by each IMF changes from IMF to IMF. The difference with the instability cases lies on the dispersion of the instantaneous frequency values found on the main modes (0.5 Hz and 1 Hz) specially when the VMD algorithm is used. As for the EEMD algorithm, the difference between an instability case (see Figure 28 on the right) and a stable case is not so evident.

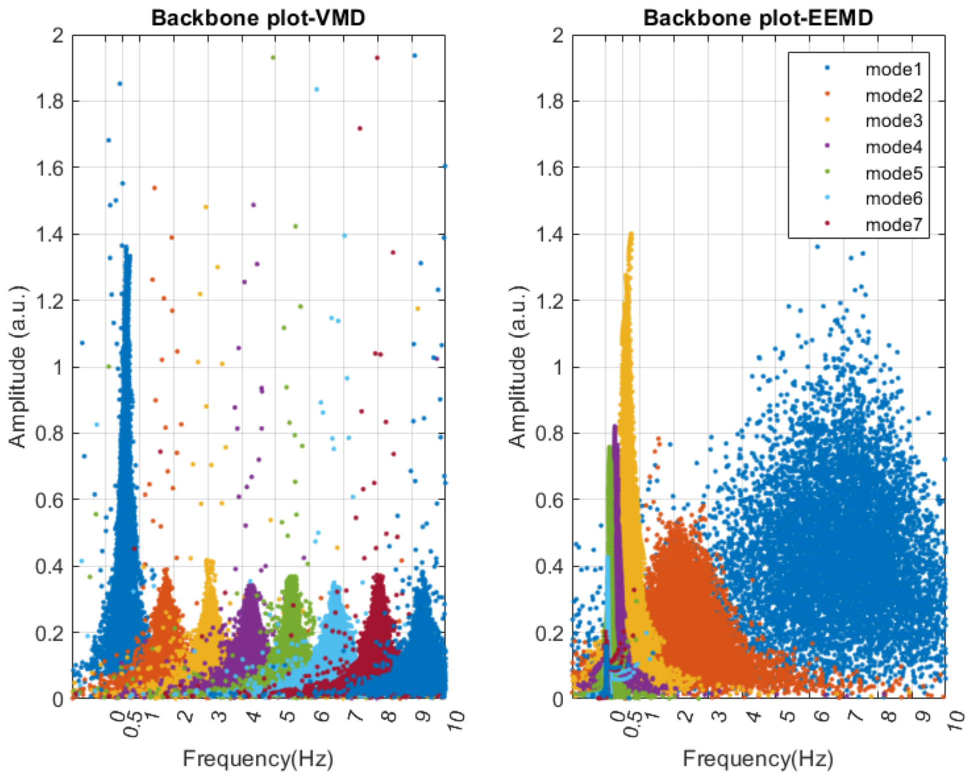

Figure 29: Backbones for a stable Cofrentes series with VMD (left) and EEMD (right) methodologies.

5 CONCLUSIONS

Several conclusions can be drawn from the results obtained in applying the VMD to the instabilities of Cofrentes NPP, Laguna Verde NPP and Ringhals NPP.

5.1 CONCLUSIONS REGARDING THE VMD TOOL.

In section 2.2 it has been determined that the methodology is sensitive to the value of the parameter Alpha. This parameter must be selected to offer clean frequencies and the minimum bandwidths possible, otherwise we will have a mixture of modes and frequencies. The ALPHA parameter must be adjusted in each application as the result of the method is sensitive to its value.

5.2 CONCLUSIONS REGARDING FREQUENCIES AND BANDWIDTHS

The results offered in section 3., show that the frequencies extracted with the VMD are very clean and with a small or narrow bandwidth. Therefore, the VMD has a better resolution and accuracy than the application with EEMD and FFT. Regarding the comparison with the EEMD, another improvement is that the modes are mono-frequency which makes the analysis more efficient.

The modes in VMD are clearly centered at one frequency whereas in EEMD the dispersion of the instantaneous frequency is very high.

5.3 CONCLUSIONS REGARDING INSTABILITY.

The improvement in the modes, focused on the frequencies, makes it much easier to identify the modes of oscillation of instability, since there is no dilution with other nearby frequencies.

In the case of Cofrentes NPP, the 1Hz and 0.5Hz modes are clearly separated. The dominance of the 1Hz mode (Figure 20) confirms the out-of-phase instability. There are 2 other modes at 1.5 and 2 Hz that have low energy and therefore the corresponding oscillation modes are not excited.

In the case of Laguna Verde NPP the main mode of oscillation of the core power is 0.5 Hz, which falls one oscillation in phase. The frequency of 1HZ or the out-of-phase or half-core oscillation, is not activated since it presents a low energy. The same applies to the 1.5 Hz or quarter-core oscillation mode.

In the case of Ringhals NPP, as with the green lagoon NPP, the 0.5 Hz or phase oscillation mode is identified. However, the out-of-phase (1 Hz) or half-core mode is already representative. This case could be the transition between in-phase and out-of-phase instability (cases of Laguna Verde NPP and Cofrentes NPP). There are also other harmonics present, which make it difficult to identify the modes of instability.

The use of backbone plots for discriminating the different type of instabilities is possible if the VMD methodology is applied. Besides, by analyzing a stable case it is possible to see that the time series have all the frequencies and the 0.5 Hz mode has the highest amplitude. When the instability takes place, only certain frequencies are excited.

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