# Evaluation of EMD and SSA sensitivity for efficient detection of aerodynamic instabilities in centrifugal compressors

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# Evaluation of EMD and SSA sensitivity for efficient detection of aerodynamic instabilities in centrifugal compressors

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**Aerodynamic instabilities in centrifugal compressors are dangerous phenomena affecting machines efficiency and in severe cases leading to failures of the compressing system due to high amplitude vibrations. Efficient instabilities detection during compressor operation is a challenge of utmost importance from economical and safety point of view. The most sensitive detection is possible with use of a pressure signal from inside of the compressor because specific pressure patterns are the first symptoms of instabilities. Detection of aerodynamic instabilities results in specific challenges, as the pressure signal is often very noisy and contains high amount of randomness. Surge – most severe instability, can develop very quickly. Therefore, the method of detection should be sensitive but also robust and quick. Another common instability, inlet recirculation is less dangerous, but it results in decrease of efficiency, which is to be avoided. Inlet recirculation often happens before surge, thus its presence can be used for surge proximity detection. The aim of this study is to investigate and compare the performance of two non-linear processing methods - Empirical Mode Decomposition (EMD) and Singular Spectrum Analysis (SSA) in the context of aerodynamic instabilities detection – inlet recirculation and surge. The comparison focuses on the robustness, sensitivity and pace of detection – crucial parameters for a successful detection method. It is shown that both methods perform similarly within the analyzed bounds for both instabilities. A slight advantage of SSA may be noticed for surge due to lower dispersion of the indicator value for the same conditions.**

**Keywords—data-driven techniques, SSA, EMD, surge, compressor, condition monitoring**

## I. Introduction

Centrifugal compressors are machines of great importance for a wide range industries, operating in petrol engines, turboshaft engines and processing plants of various kinds [1]. Compressor operating range is limited by choke for high mass flow rates and the appearance of aerodynamic instabilities at low mass flow rates [2]. For the low mass flow rate centrifugal compressor reaches its peak efficiency, therefore it is not uncommon for instabilities to appear during standard machine operation. There exist a number of well-described instabilities, such as inlet recirculation, stall or surge [3], [4]. Inlet recirculation or rotating stall, being local instabilities are often predecessors of a global instability – surge [5]. The instabilities in centrifugal compressor may vary in effect, ranging from drop in efficiency for inlet recirculation up to abrupt destruction of a compressor in case of surge.

The field of instabilities detection is still in development, focusing more and more on application of data-driven techniques. The most commonly presented methods were based on Wavelet Transform [6], [7] which performed well for selected instabilities, but suffer from lack of universality due to the need of defining a mother wavelet for analysis. Rotating stall can be detected using methods employing bifurcation theory [8], but the method due to its character is limited to rotating stall only.

A promising solution for comprehensive aerodynamic instabilities detection is offered by Empirical Mode Decomposition (EMD) and Singular Spectrum Analysis (SSA). Recently, it was shown that SSA can be used for detection of surge [9] and inlet recirculation [10] which can be regarded a surge predecessor [11]. The same capabilities were demonstrated for a method based on EMD [12]. Neither of those studies considered the influence of length of the input signal for detection as they both used long portions to demonstrate the potential of the methods. The requirement of application to centrifugal compressors instability detection system is that the methods must be quick. Thus, a natural step towards implementation of SSA and EMD into an instabilities detection system is to validate they potential for robust detection of instabilities based on a short signal portions.

The pace of detection may be considered in two aspects. First one – referred hereafter as sensitivity - is the required signal portion length needed for the method to extract features of instabilities in a repeatable and robust manner. The shorter a signal portion allowing for detection, the quicker a method can react to a change in conditions and appearance of instabilities. The other aspect is data processing time. Different methods may have a different computational cost, resulting in a higher or lower time required for obtaining the indication. This second aspect is highly dependent on the implementation of the method, consisting of both software and hardware. The comparison in terms of computational time is done using MATLAB software implementations and a PC computer. It allows benchmarking two methods and provides estimation of timescale needed for applying each of them.

The aim of this study is to evaluate the sensitivity of two data driven methods – EMD and SSA for inlet recirculation and surge signatures identification and eventually detection of those instabilities. The results are used for providing recommendations regarding the potential application of those methods for a real-time aerodynamic instabilities detection system. The computational time for both methods is compared to understand the differences in their performance in the context of quick detection.

This paper presents the outline of EMD and SSA, defines method for processing the results to obtain an indicator, and provides criteria for comparison. Test stand used for obtaining validation data is described along with an experimental procedure. The results are divided into two sections, one for detection of inlet recirculation and the other for detection of surge exploring the differences in methods sensitivity. Finally, recommendations regarding the use of EMD and SSA to instabilities detection are made.

## II. METHODOLOGY

### A. Empirical mode decomposition

EMD is based on the assumption that signal consists of a sum of simple oscillatory modes – intrinsic mode functions (IMFs) and a residue [13] that can be extracted with this method. EMD is able to deal with nonstationary and nonlinear data of different origin. It is direct and adaptive algorithm, with a decomposition base derived from the data. IMFs, due to their derivation, can reflect changes in both amplitude and frequency of phenomena in the analyzed signal. The IMFs are extracted with an empirical method using iterative process making use of the envelope of the signal. The details of the decomposition are described by Huang [13].

There exist several approaches for processing the IMFs, with focus on their energy [12], frequency [14] or amplitude [15] and variation of those values between conditions. It was demonstrated that for detection of instabilities in centrifugal compressors, the approach based on root mean squared values (RMS) of the IMFs can provide insightful results [12]. Thus, this approach is used in this study.

### B. Singular spectrum analysis

SSA is a nonparametric time series analysis method, which extends Principal Component Analysis (PCA) [16]. SSA reduces a signal to a finite number of independent oscillatory components, ordered according to the amount of information contained in each [17]. These components are called Reconstructed Components (RCs). SSA permits to isolate components of the original signal for better understanding of the phenomena and for obtaining characteristic features which may be used for compressor monitoring. The main steps of the conventional SSA are embedding, decomposition and reconstruction grouping and diagonal averaging. Detailed description of SSA process is outlined by Golyandina [17]. The RCs in this study are evaluated by computing their RMS value, which was demonstrated to be applicable when analyzing compressor performance with this method [10].

### C. Compressor test rig

The analysis is based on high-frequency pressure data sampled from several locations inside the centrifugal compressor (Figure 1). The data from this machine was previously analysed and described [7], therefore it can efficiently be used for benchmarking of different methods.

For described investigation, a series of data for different throttle opening areas (TOA) was considered. TOA values ranged from 8.5%, where deep surge was present, to 35%, where the machine was working in a stable regime. In between those values, the flow transformed from stable to unstable. In the process, certain local instabilities could be observed, such as inlet recirculation. The analysis of this phenomenon was done by Garcia et al. [18]. Table 1 summarizes TOA values subjected to analysis in this paper and observed flow conditions. In this study, the focus is on detection of inlet recirculation and unstable conditions, without differentiation between mild and deep surge. Therefore, the conditions for TOA below 18% will be referred to as unstable.

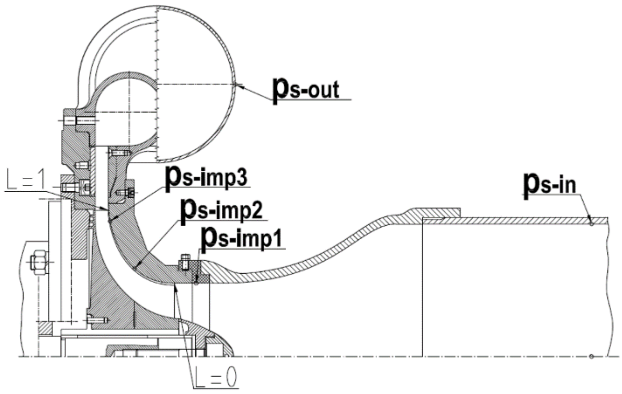


Fig. 1. Experimental stand cross-section with sensors positions [7]

**Table 1. Throttle opening area and observed flow conditions** [19].

| TOA [%] | Flow conditions |
|---|---|
| 8.5 | Unstable - Deep surge |
| 12-18 | Unstable - Mild surge |
| 19-25 | Transient - Inlet recirculation |
| 26 - 35 | Stable |

The data was sampled at 100 kHz, allowing to capture wide range of flow structures. The presence of inlet recirculation was observed for the sensor Ps-imp1 located upstream of the impeller and was not noticed for other sensor locations [7]. Surge was observed for all sensors, with the strongest signature for the Ps-out sensor at the outlet [7]. Therefore, only those two sensors will be used in the study - Ps-imp1 for inlet recirculation and Ps-out for surge.

### D. Approach to decomposition

The decomposition with EMD and SSA is performed on non-overlapping signal portions extracted from a longer signal. The length of the portions varies to evaluate the sensitivity of the methods to instabilities and observe changes in dispersion of the data. For each length, the confidence of prediction is demonstrated to understand the trade-off between the signal portion length and accuracy of prediction. The data used for analysis comes from quasi-dynamic study – where measurements for different conditions were done independently for each TOA.

### E. Indicator of instabilities

Indication of instabilities is based on RMS value of selected components. The indicator is computed using specific signal portions length. When $N$ is the signal length expressed in number of samples, the RMS value can be computed according to equation (1). The same approach is used for IMFs and RCs.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (1)$$

### F. Criteria for comparison

The sensitivity of methods is validated on signal portions $N$=1000, 5000, 10000 and 50000 samples, equivalent to 0.01, 0.05, 0.1 and 0.5 seconds of wall clock time respectively or alternatively to 1, 5, 10 and 50 revolutions of the impeller. Forty windows are used for each operating point to account for stochastic character of pressure signal and understand the dispersion of the data. The outcome is assessed quantitatively using a control line approach. The control line is created based on stable operating conditions and the performance of the method is assessed based on how well the unstable conditions can be differentiated from stable ones.

## III. Results

The results are divided into three sections. First one discusses importance of decomposition parameters and their influence on the decomposition time. Section one summarizes the differences in sensitivity of the methods for detection of inlet recirculation. The last section shows the method sensitivity for surge detection in the compressor.

*Parameters of decomposition*

Both, EMD and SSA are adaptable to the data, without a pre-defined base of decomposition. However, they require a number of decomposition parameters to be set. The choice of those parameters influences the decomposition and its pace.

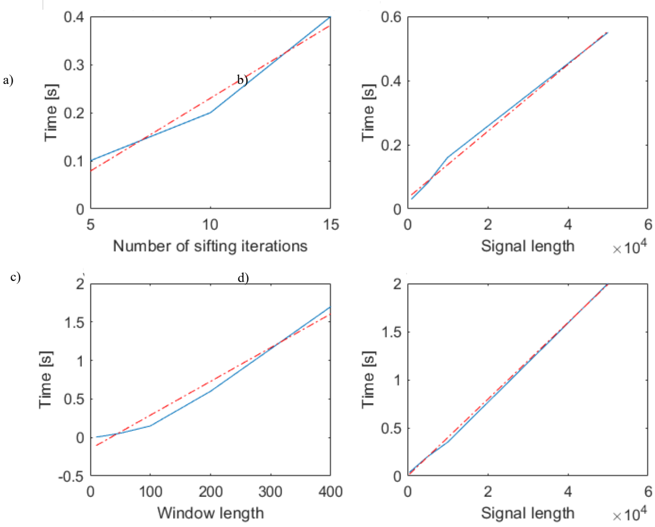


Fig. 2. Influence of SSA and EMD parameters on the pace of decomposition; a) sifting iterations number on EMD decomposition time for N=5000; b) signal length on EMD decomposition time for eight sifting iterations; c) window length on SSA decomposition time for N=5000; d) signal length on SSA decomposition time for L=50; red dash-dot line is a fitted linear trend

SSA is based on singular value decomposition of the signal, which requires a selection of a window length (L) which slides over the signal. There is no consensus about the selection of window length L in reference to signal length N, but certain guidelines were provided in the literature. It was outlined by Golyandina [17] that L should be less than N/2. Some L estimation methods were created, such as that of Wang et al. based on the autocorrelation function [20]. When applying this method for high-frequency signal the window length obtained from the method was very short – several orders of magnitude smaller than the signal length N. In general, the smaller the L value, the worse frequency resolution of the spectrum [17].

Window length affects the pace of the decomposition process, as it results in obtaining more RCs (number equal to L). Thus, the bigger L value, the more time is needed for decomposition. The same applies to the signal length N. Influence of the length of those parameters is summarized in Figure 2 c) and d).

EMD does not require a choice of window length L. However, the procedure of decomposition includes iterative sifting step, where the number of iterations may differ [13]. Similarly, as for SSA, there is no universal approach to defining the right number of iterations. It can be set indirectly through sifting stoppage criterion or directly by setting a specific number of iterations. Stoppage criteria focus on ensuring that the extracted IMFs meet IMF criteria defined by Huang [13] using local or global formulation. It was shown that the criteria are imperfect as well. What is more, too high number of sifting iterations can deplete IMFs of physical meaning [21] and extend the time needed for decomposition. The influence of sifting iterations number on the pace of decomposition is shown in Figure 2 a) and b).

For both decomposition methods, specific components or groups of components have to be chosen for an indicator. In EMD, the first IMF holds the highest frequency components present in the signal and each subsequent IMF holds lower frequency components. RCs from SSA are created in a way that the first RC holds the lowest frequencycomponents and subsequent RCs hold higher frequency components. Therefore, the IMFs and RCs are reversed in order when it comes to their frequency content.

**Inlet recirculation detection**

Inlet recirculation in this machine was manifested by a broadband noise of frequency around 1000 Hz but with no dominating frequency discovered. It was observed the strongest for the sensor $Ps_{imp1}$ located on the shroud before impeller – the area known as inlet recirculation zone .

*EMD-based detection*

For defining the EMD approach, the choice of IMFs was done based on analysis of mean RMS changes for different IMFs, not presented in this study. It was observed that the strongest trace of inlet recirculation was held by IMF 6. Thus, this IMF was chosen as a base of an indicator. To account for stochastic nature of the signal, forty pieces of a signal were used to validate the dispersion of the data and check whether energy of selected IMF can serve as a robust indicator. The variability was investigated for varying signal length N and constant sifting iterations number equal to eight, as suggested by Wang et al. [21].

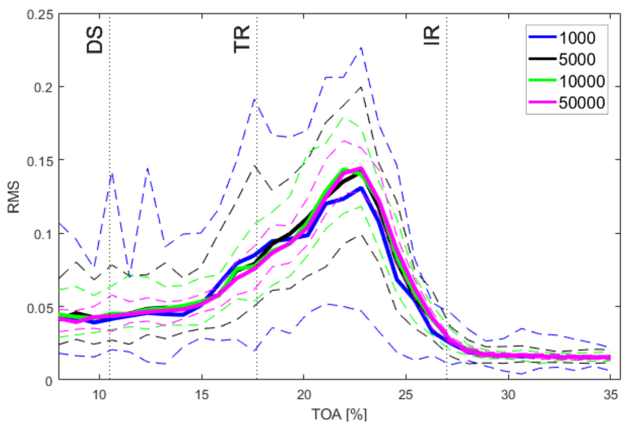


Fig. 3. Comparison of RMS of IMF 6 for different signal lengths N for sensor before impeller; dashed lines are 1st and 99th percentile of distribution for each of the windows

Figure 3 demonstrates changes of IMF 6 energy for different operating conditions. The mean value for all window lengths is similar, but data dispersion differs significantly, decreasing consistently with increasing signal length. The dispersion of RMS values, limits of which are marked with dashed lines, grows visibly for increasing level of instability. Based on visual study, it may be stated that inlet recirculation can be quickly detected when using a window of 5000 samples and above by an increase of RMS value above the reference. Using 1000 samples is not enough to efficiently capture this instability, mainly due to high dispersion of RMS. The RMS level for selected IMF stays above the benchmark as well for surge regime. This might result in problems with differentiating inlet recirculation and surge from each other based on an indicator constructed on IMF 6.

*SSA-based detection*

The inlet recirculation can also be captured through using changes in RMS of RCs produced by SSA. As was shown by Logan et al. [10] RC2 can be used for extraction of inlet recirculation features in centrifugal compressors. An important parameter of the method is window length used for decomposition. Window length choice is regarded case specific, thus the analysis of its influence for compressor data is presented in Figure 4. The window lengths L varied from 15 to 200 signal samples and computations were done for signal length of 5000 samples. Using the shortest window L=15, inlet recirculation is not well distinguished from other operating conditions. For L=30 to L=75, the RC2 energy behaves similarly, increasing in the IR region, which suggests it can be used for indication. The longest windows also allow to distinguish stable conditions from IR, but their RMS changes differ, presenting a drop in the center of IR region. Thus, knowing that increasing window length is expensive in terms of computational time, L=30 was defined to be suitable for the aim defined in this study. The dispersion of the data does not present a consistent dependency on the conditions or window length.

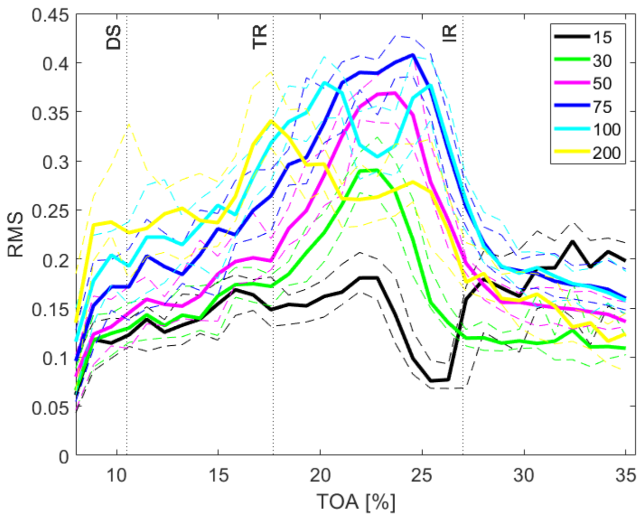


Fig. 4. Influence of window length L on RC2 RMS at different operating conditions for the signal length N=5000; dashed lines mark 1st and 99th percentile of distribution for each TOA

Having defined the window length, the analysis of signal length influence is performed. Figure 5 shows energy of RC2 for different signal portions lengths N with window length L=30. The shape of mean value is very similar in case of all N, suggesting that the signal portion length choice does not have important influence on the energy of RC2 in this case, at least not in the analysed range of lengths. The dispersion of data is importantly higher for L=1000 than for other lengths and seems to decrease for increasing L.

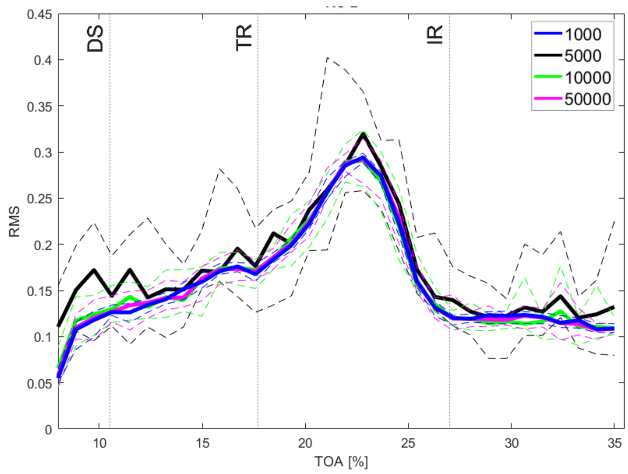


Fig. 5. Influence of signal length N on RC2 RMS at different operating conditions for window length L=30; dashed lines mark 1st and 99th percentile of distribution for each TOA

*Comparison of EMD and SSA performance for inlet recirculation detection*

The comparison of EMD and SSA for inlet recirculation detection done for N=1000 and 5000 is shown in Figure 6. For the shorter signal length, both methods provide good indication of instability using a mean value. However, the dispersion of data is high and prohibits a robust detection based on a single signal portion of this length. When using a longer signal portions N=5000, the dispersion is much smaller and robust identification is possible using a single window for most of the IR region using both EMD and SSA. EMD demonstrates more consistent behaviour for stable conditions, allowing to draw a control line lower than for SSA. Another difference is visible in surge region, where the RMS of IMF 6 remains above control line, while RMS of RC2 falls below.

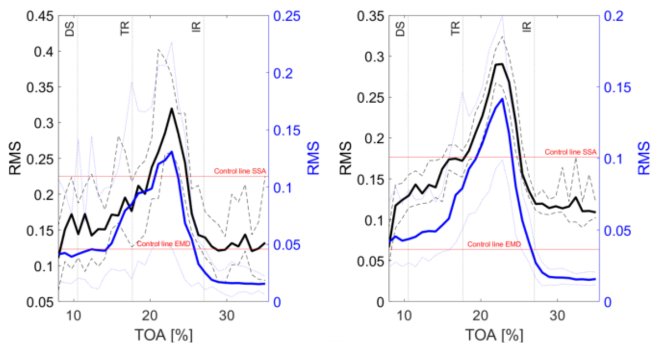


Fig. 6. Influence of window length L on RC2 RMS and IMF 6 RMS at different operating conditions for the signal length N=5000. Black line is plotted for SSA and blue line for EMD. Dashed and dotted lines are 1st and 99th percentile of distribution for each TOA; red lines are control lines for EMD and SSA based on the maximum value in stable conditions

Consequently, a similar signal portion N is needed for both methods to provide a robust indication of inlet recirculation. The estimated time needed for decomposition is 0.06s for SSA and 0.04s for EMD, indicating the advantage of EMD but with both of them being of similar magnitude to each other and clock time needed for collecting this number of signal points.

### Surge detection

Surge detection is of utmost importance for every compressor safety system. The analysis of surge detection potential will be based on differentiating this region from stable operation region.

*EMD-based detection*

The analysis of EMD behavior indicated that high IMFs hold surge information. The IMF chosen to represent this instability is IMF 8. Figure 7 shows mean IMF 8 RMS along with its variation for different signal lengths considered. The mean value of RMS changes steadily as compressor approaches surge. Similarly to IMF 6, the dispersion increases with increasing instability. It is also notable that dispersion decreases with increasing window length. Mean value of the IMF 8 provides clear indication of conditions, but the detection based on the RMS value from a single signal portion is not robust due to high dispersion of RMS values.

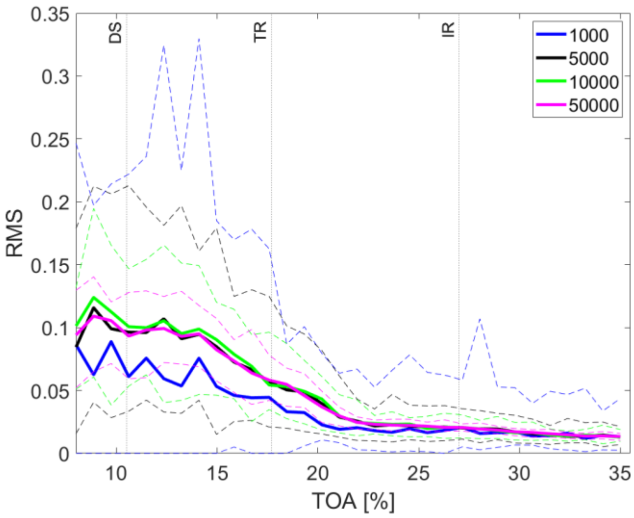


Fig. 7. Comparison of RMS of IMF 8 for different signal lengths N for sensor $Ps_{out}$ at the outlet; dashed lines mark 1st and 99th percentile of distribution for each TOA

Therefore, despite very clear and consistent indication coming from mean value, the RMS of selected IMF requires either longer signal length or obtaining a mean value from several windows. This fact is probably caused by mode mixing, a phenomenon common for EMD [13]. The transfer of instabilities energy from one IMF to another lead to high variation of energy. It is especially evidenced through presence of very low RMS values in some windows in unstable region. Non-stationary character of the pressure signal can also contribute to the observed variability, as for longer windows the dispersion decreases which should not happen if solely mode mixing was responsible This makes using a specific IMF problematic in detection of instabilities. On the other hand, standard de-mixing methods like Ensemble Empirical Mode Decomposition (EEMD) [22] severely influence the pace of decomposition, as the standard EMD procedure is repeated a number of times therein.

*SSA-based detection*

Figure 8 presents the window length analysis done for RC1 from $Ps_{out}$ sensor located at the outlet pipe wall. The same set of window lengths L is used for a signal portion N=5000. RC1 is used for detection, as it is sensitive to appearance of low-frequency pressure oscillations characteristic to surge. The mean value of RMS is similar for all windows, decreasing slightly with increasing window length. This is due to RC1 containing narrower range of frequencies for increasing window size. An important increase in energy takes place at the end of IR region and continues in surge region. With extending the window length, the RMS value for stable conditions decreases, moving the potential benchmark value down. The difference in case of surge region is smaller and a significant change can be observed for window L=200. The window length chosen for further analysis is L=30, similarly as in case of RC2 selected for inlet recirculation detection.

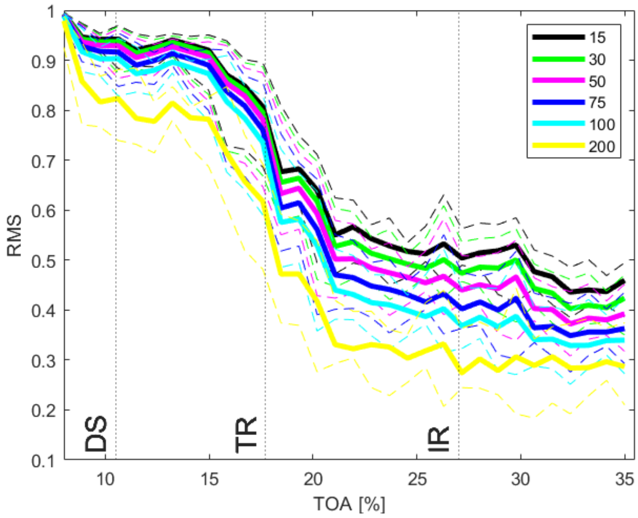


Fig. 8. Influence of window length L on RC1 RMS at different operating conditions for the signal length N=5000; dashed lines mark 1st and 99th percentile of distribution for each TOA

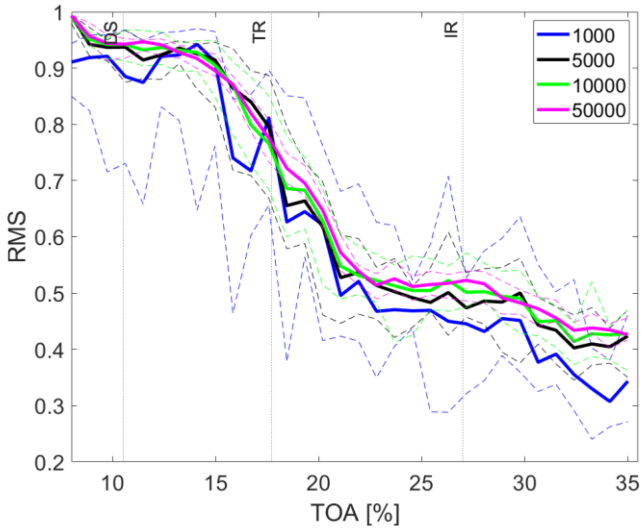


Fig. 9. Comparison of RMS of IMF 8 for different signal lengths N for sensor $Ps_{out}$ at the outlet; dashed lines mark 1st and 99th percentile of distribution for each TOA

Figure 9 presents RMS value of RC1 for varying operating conditions and signal length. It can be noted that the dispersion of the data for signal length N=1000 is much higher than for higher lengths and the mean value experiences more fluctuations. The behaviour of RMS for N=5000, 10000 and 50000 is more consistent and the mean values is almost identical for all those lengths. The data dispersion decreases with increasing N, but the effect is not as striking as for EMD.

*Comparison of EMD and SSA performance for surge detection*

The comparison for surge detection is done with signal length of 5000 and 10000 samples. It can be seen that in case of SSA, the shorter length is sufficient to provide a good distinction of conditions. The increase of energy would start earlier than detected in reference, resulting in producing a number of false alarms happening before the actual surge region. It might be considered a flaw of the method. For the same signal length, EDM fails to produce a robust identification of conditions. It is caused by high dispersion of energy values for the analysed signal portions. Therefore, a longer signal portion is needed for robust identification using the proposed approach. The time needed for decomposition was 0.06s for SSA with L=30 and N=5000. The time needed for EMD with N=10000 was comparable, despite the longer window, being 0.07s. This is of the same order of magnitude as the signal length needed for detection, making these methods potential candidates for real time detection.

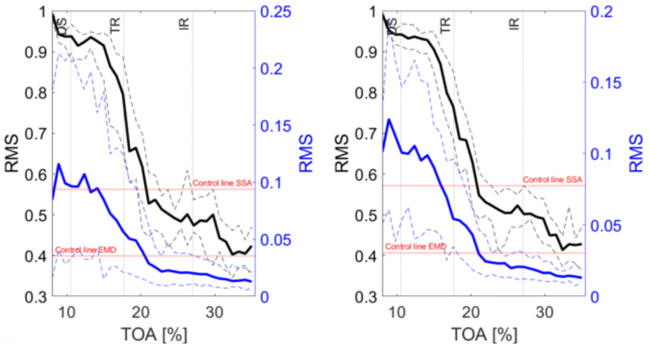


Fig. 10. Comparison of RMS of IMF 8 for different window lengths with data dispersion; data for sensor at the outlet a) N=5000; b) N=10000

## IV. Conclusions

In this paper two non-linear signal processing methods – EMD and SSA were compared in terms of their performance for instabilities detection in centrifugal compressor. Based on RMS of selected decomposition components, the overall detection possibilities and signal length needed for robust identification of inlet recirculation and surge was compared. It was shown that:

- Inlet recirculation can be detected with both methods using a similar signal length and within a comparable time, with a slight pace advantage towards EMD.
- Detection of surge is quicker with SSA, as shorter signal portion (N=5000) is sufficient for robust detection. Similar performance is presented by EMD when using twice as long signal, which transfers into the need of a longer data acquisition. However, the processing time remained similar, making this a viable option.
- Both EMD and SSA can be considered as a base for quick and responsive instabilities detection system as they present similar performance in the presented case study.

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