

Quantifiable Scour Detection for Offshore Wind Turbines Using Resonance Frequency Monitoring and a Digital Twin

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ABSTRACT

This paper presents a methodology for enhancing frequency-based Structural Health Monitoring (SHM) of Offshore Wind Turbines (OWTs) by incorporating digital twin models. The proposed methodology utilizes an automated operational modal analysis to extract modal frequencies from acceleration measurements. The environmental and operational variability is removed through tree-based regression models, which can adequately recognize the different operational states of the OWT. The proposed data-driven approach relies on the detection of the modal frequency changes caused by a damaging scenario in the OWT (e.g. scouring). The digital twin model accounts for the actual properties of the substructure, considering the specific foundation geometry and soil conditions at the monitored OWT location. A statistical control chart is used to identify the possible scour depth by comparing the changes in the normalized modal frequency and the digital-twin calculations. The methodology is demonstrated on 4 months of measurements from a full-scale monitored OWT. The proposed methodology advances the SHM capabilities from damage detection to damage quantification, enabling improved operations & maintenance strategies for OWTs. 

INTRODUCTION

The Structural Health Monitoring (SHM) of structures, such as Offshore Wind Turbines (OWTs), often involves tracking and monitoring the modal frequencies. Structural anomalies that affect the dynamic properties of the structure can be detected through novelty detection of the tracked modal frequencies. These anomalies can indicate damage build-up in the structure and other issues that impact performance or safety.

Scouring is an often occurring structural anomaly for OWTs that consists of erosion around the monopile foundation. In this research, the focus is made on local scouring represented by the depth of the scouring hole around the foundation as shown in Figure  (right). The effects of scouring are affected by the diameter of the foundation, therefore, scour depth is usually normalized by the pile diameter (D). Scouring is a major concern for OWTs as it lowers the resonance frequency and can negatively impact the fatigue lifetime of the structure . If undetected and not remedied, scouring leads to

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premature decommissioning of OWTs, as experienced in the Robin Rigg wind farm [2]. Sedimentation [3], rotor imbalance [4] and icing [5] are examples of other anomalies that affect the modal frequency of an OWT and could be detected and quantified using the proposed methodology.

The current resonance frequency monitoring strategy for scour detection is based on a lower bound threshold based on the original design documents. If the resonance frequency drops below this threshold, an alarm is triggered, signalling a potential issue in the OWT. But the as-design resonance frequency is often lower than the actual, measured resonance frequency, and significant scouring can occur well before the alarm is triggered [6,7]. To address this issue, a data-driven alarm threshold, typically expressed in relation to the variability of the observed resonance frequency, can be set. However, this does not quantify the actual amount of scouring that occurs and can't be compared to design documents to assess the structural impact of the detected scouring. Additionally, the modal frequency resulting from the automated Operational Modal Analysis (OMA) strategy [8], has two main sources of variability; the Environmental and Operational Variability (EOV) and inherent uncertainty from the OMA process [9]. Different strategies exist to normalize for EOV [10,11], but it remains unknown whether the change in frequency (as e.g. caused by a scouring hole) will be hidden by this uncertainty on the tracked modal frequencies.

The digital twin model developed at OWI-LAB, VUB [6] can be used to represent the changes in the dynamic response of the structure due to damage. The model accounts for the actual data and a state-of-the-art soil-structure interaction model (PISA [12]) and is used to compute the modal frequency reduction due to different scouring depths in this research. The frequency drops are calculated for an instrumented monopile-supported OWT with a known soil composition. However, the frequency drops caused by the shallow considered scouring scenarios are smaller than the inherent variability in the first Side-Side (SS1) mode. Therefore, statistical control charts based on confidence intervals are constructed. The more sensitive second order mode (SS2) is not yet considered due to its interaction with harmonics [13] and the larger differences between the predicted frequencies by the digital twin and the measurements [6,14].

INSTRUMENTED OFFSHORE WIND TURBINE

This study focuses on the scouring detection and quantification of a monopile-supported Offshore Wind Turbine (OWT) in the Belgian North Sea. The OWT instrumented with an IoT high-end accelerometer in the Rotor-Nacelle Assembly (RNA) as shown in Figure 1 (left). The ACC enables an accurate calculation of the dynamic response of the OWT through a modal parameter estimation every 10 minutes.

This research focuses on the detection and quantification of scouring but can be extended to the other damage scenarios that impact the modal frequency. In this research, scour is interpreted as local scour along the monopile as shown in Figure 1 (right).

SCOUR QUANTIFICATION METHODOLOGY

This research aims at augmenting the data-driven Structural Health Monitoring (SHM)

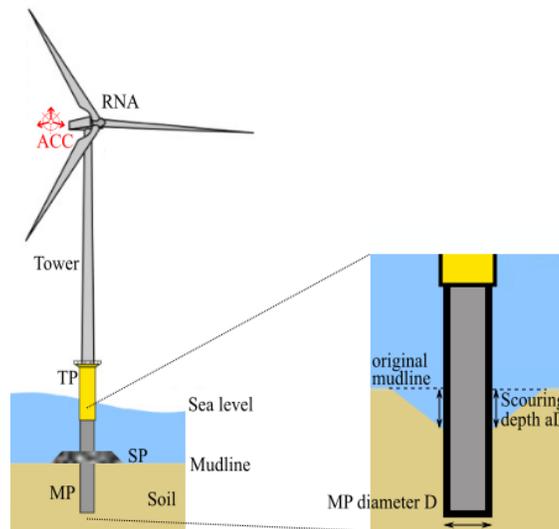


Figure 1. [15] (left) Monopile-supported offshore wind turbine instrumented with a high precision accelerometer (ACC) in the rotor-nacelle assembly (RNA). The foundation is reinforced with a scour protection (SP) layer at the mudline. (right) Illustration of the local scouring depth in terms of monopile diameters (D), shallow scouring depths ($0.05D$ to $0.3D$) are examined in this research.

strategy by combining the traditional Operational Modal Analysis (OMA) with a model-based approach using a digital twin model. The goal is to progress from detection to quantification of anomaly or damage. This process is illustrated in Figure 2.

Data-Driven Approach: Frequency Monitoring

The tracking of the modal frequency is accomplished through an augmented automated OMA methodology. First, modal parameter are estimated for every 10 minutes of the IoT accelerometer data. The least squares complex frequency domain (LSCF) and covariance-driven stochastic subspace identification (SSI-COV) are used to calculate the modal frequencies [16]. The automated OMA results in the modal frequencies, damping ratios and cluster size [8].

After removing the harmonics from the estimated modes, the remaining modal frequencies are fed to a tracking algorithm to automatically detect the physical modes. The DBSCAN algorithm [17] is utilized in a multi-dimensional space that includes the time dimension in addition to cluster size, modal frequency, and modal damping. The multi-dimensional space is transformed through multipliers on the different dimensions to optimize the clustering for the modal frequency tracking problem. The details of this process will be part of a separate future publication. The resulting tracked modal frequencies in the SS direction are shown in Figure 3. The first and second-order modes are clearly tracked. But whilst the first-order mode is almost continuously tracked, the second-order mode shows a lot of missing data, because of the removal of the harmonics. The high availability of data combined with high trust in the tracked frequency and smaller influence due to operational conditions as the Fore-Aft modes leads to the choice of SS1 to quantify scour in the next steps of this research.

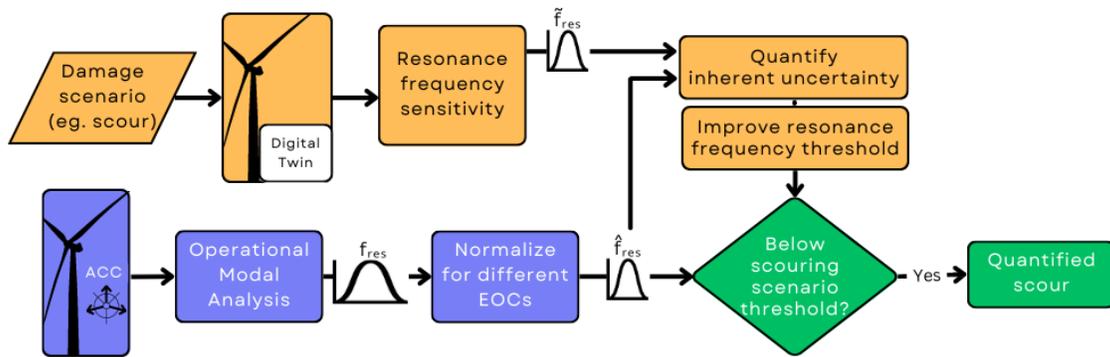


Figure 2. Flow chart for scour quantification (green) through resonance frequency monitoring (blue) and a digital twin (orange).

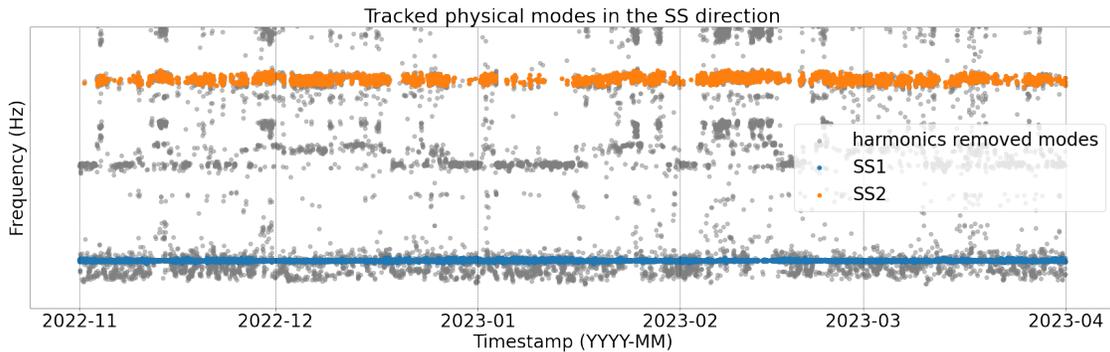


Figure 3. Modes calculated in the Side-Side (SS) direction resulting from the augmented automatic operational modal analysis after removal of harmonics (grey). The physical modes first (SS1, blue) and second (SS2, orange) modes are obtained from the automated tracking. SS1 is used for the scour quantification.

Offshore wind turbines are subjected to many different environmental and operational conditions that can impact the modal frequencies. It is necessary to normalize the modal frequency for the resulting Environmental and Operational Variability (EOV), as it could hide the change caused by damage scenarios. In a previous study, the normalization was done for a monopile-supported Offshore High Voltage Station (OHVS) using a linear regression [14]. However, unlike an OHVS, an offshore wind turbine (OWT) experiences different operational conditions that significantly influence the dynamic response [18]. Additionally, the EOV is driven by some non-linear and discontinuous parameters such as the pitch angle. Therefore, tree-based learners are chosen for the normalization process, as these can differentiate between the different operational conditions (e.g. parked or rated).

To train the normalization model, both the target and input data are required. The target is the SS1 modal frequency. The input data should comprehensively describe the EOV, necessitating the inclusion of weather data and Supervisory Control and Data Acquisition (SCADA) data. The SCADA data is provided by the wind turbine operator and the data from the IoT accelerometer sensor is given by the SHM service provider. The weather data is gathered from the Meetnet Vlaamse Banken, an online database

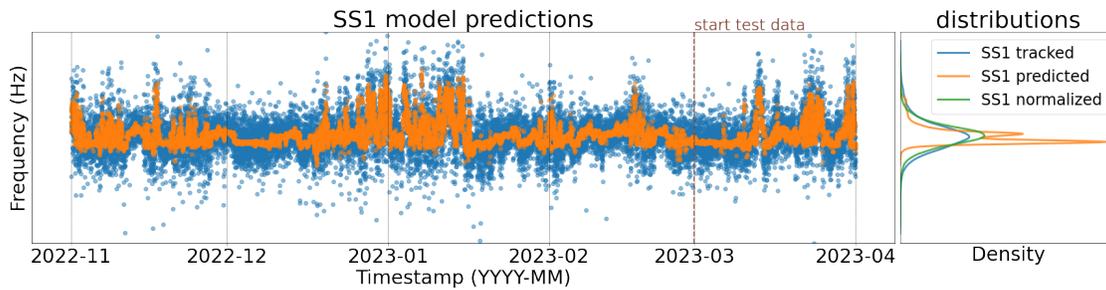


Figure 4. First Side-Side (SS1) mode as resulting from the OMA process (blue) and the prediction resulting from the tree-based EOV normalization model (orange).

containing weather data of the North Sea^[1].

In the next step, a preprocessing step is implemented to encode circular data. Circular data consists of angles with a 360° range, such as yaw and wind direction, as well as temporal data. The challenge with this data is that, for example, an angle of 350° is closer to 10° than to an angle of 300°. To enable machine learning models to understand this, the sine and cosine transformation is applied to encode the circular data^[19].

Following the preprocessing step, the data is divided into a training (80%) and test (20%) data set. The training data is then used to optimize the hyperparameters of the regression models through a Bayesian search and cross-validation using the Hyperopt library in Python^[20]. This optimization process yields a set of optimal hyperparameters for both the Random Forest (RF) regression^[21] and the XGB regression^[22] models. Subsequently, the training data is used to train the models using these optimized hyperparameters. Finally, the models are evaluated on the test data, and the model with the best fit or highest r^2 -score is selected as the normalization model.

The predictions of the normalization model represent the EOV of the modal frequency and can be used to eliminate this variability. The model prediction is shown with the tracked mode in Figure 4. The figure shows that the prediction can follow shifts in the SS1 frequency that are due to EOV but most of the noise remains after the normalization model. The residual is calculated as shown in Equation 1. The residual solely contains the noise or uncertainty of the measurements and OMA, as well as any potential shifts resulting from structural anomalies or damages.

$$f_{res} = f_{meas} - f_{model}(X) \quad (1)$$

The residuals for the SS1 mode are depicted in Figure 5. These residuals exhibit a normal distribution around 0, and any deviation from this distribution can be utilized to detect and quantify scour.

Model-Based Approach: the Digital Twin

The goal of this research is to augment the current SHM strategy from damage detection to damage quantification, through the use of a digital twin. The model is employed to estimate the impact of different scouring depths on the modal frequencies of an OWT.

¹<https://meetnetvlaamsebanken.be/>

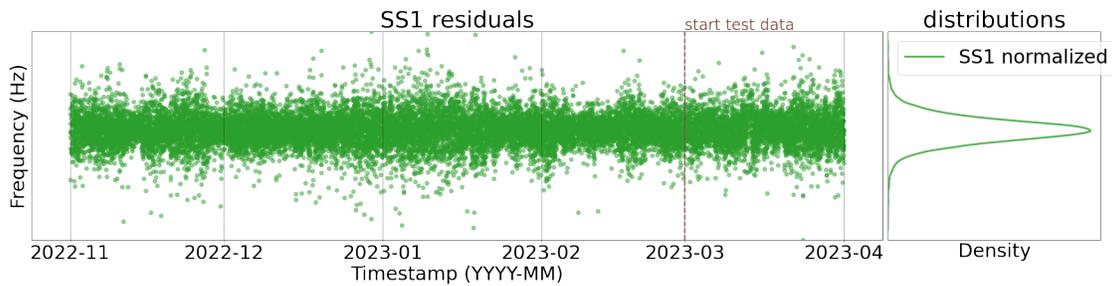


Figure 5. Residuals of the prediction for the first Side-Side (SS1) mode resulting in a normally distributed parameter.

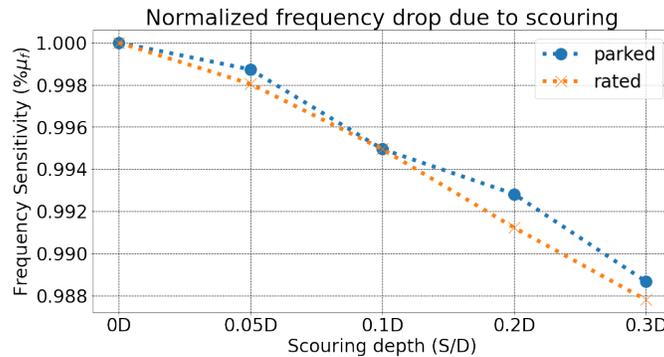


Figure 6. Frequency drops caused by different scouring events for the parked and rated operational conditions.

The digital twin model utilizes a Finite Element model of the OWT, including the monopile foundation, set up through the *OpenSees* simulation platform [23] using the Python interpreter [24]. The soil-structure interaction is represented by the PISA design method [12]. The main modelling hypotheses and assumptions are detailed in a previous publication [6].

The digital twin accounts for the actual properties of the substructure, such as the specific foundation geometry and soil conditions at the monitored OWT location. This allows tailoring the modelled frequency drop due to scouring to the exact OWT location and structure, improving the modal frequency estimation [6]. The retrieval of the substructure properties is integrated with the OWI-metadatabase [25], allowing for seamless retrieval of farm-wide information.

Additionally, the digital twin model accounts for the EOV by incorporating the effects of the tidal levels, hydrodynamic added mass, and rotor loading. The digital twin is used to calculate the sensitivity of the SS1 frequency to varying levels of scouring for the specific location, as shown in Figure 6. The graph illustrates that the frequency drop remains similar for both the rated and parked conditions when the scour depth is smaller than 0.3D. Since this research aims to detect the effects of shallow scouring, the frequency drop is considered comparable across different operational conditions.

Statistical Assessment of the Scour Depth

This subsection discusses the process of detecting and quantifying scour in the foun-

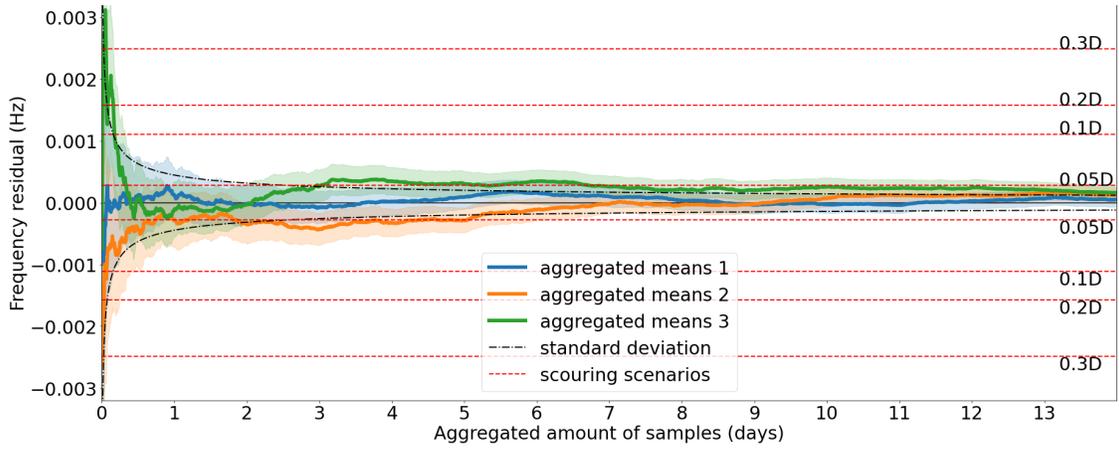


Figure 7. Residuals of SS1 uncertainty evolution with an increased amount of samples. The uncertainty is calculated for 3 different starting points through Confidence Intervals (CI) as given Equation 2 with 99% confidence. The starting point of test 1 is 01/04/2023, test 2 is 08/04/2023 and test 3 is 15/04/2023. The standard deviation shows the width of the uncertainty, whilst the centre is the aggregate of the means.

dation of an OWT using a control chart based on the normalization model residuals and frequency drops calculated by a digital twin. The required number of samples for scour detection is dependent on the standard deviation of the residuals, which is driven by the uncertainty in the normalization model and measurement and OMA noise. Confidence Intervals (CI), as described in Equation 2, are used to determine the number of samples required to detect a shift with a certain confidence [26].

$$CI = \mu_{test} \pm Z_{conf} \frac{\sigma_{tr}}{\sqrt{n_{test}}} \quad (2)$$

In this equation, μ_{test} is the sample mean value of the residuals of monitored data at a given time. The Z_{conf} parameter is the Z-statistic for a given confidence level. In this research, confidence is chosen at 99% for statistical significance. The residuals on the training data follow a normal distribution with a mean of $\mu = 0$ and a σ_{tr} that is used in the CI equation. Finally, n_{test} represents the number of samples considered in the test set. The confidence interval becomes narrower with an increasing number of considered samples (n_{test}).

Figure 7 illustrates the evolution of mean measurements and their CIs with an increasing number of considered signals at three different starting points. The standard deviation of the residuals on the training data (σ_{tr}) is defined in Equation 3.

$$\sigma_{tr} = \sqrt{\frac{\sum_{i=1}^{n_{tr}} (x_i - \mu_{tr})^2}{n_{tr} - 1}} \quad (3)$$

Figure 7 shows the shrinking CIs and thus diminishing uncertainty with the increased number of considered samples. Additionally, the means converge towards zero with an increasing number of considered samples. Both the convergence speed and standard deviation are dependent on the performance of the normalization model.

The uncertainty shown as CIs allows for the determination of the minimum amount of samples required to detect a shift with the confidence used to determine the CI, which is 99% in this case. When the uncertainty in Figure 7 becomes narrower than the frequency shift (red lines) obtained by the digital twin for a specific scouring scenario. This is repeated three times to confirm the trend. In this case, approximately two weeks of data are required to detect a 0.05D scour scenario with 99 % confidence, as the CI becomes narrower than the 0.5D frequency shift obtained from the digital twin. To detect scouring holes deeper than 0.1D, one day of data suffices. These time periods are used to construct the final scour detection control charts shown in Figures 8 for one day (top) and two weeks (bottom).

The control charts, shown in Figures 8, provide a visualization of the scour detection and quantification process. In these charts, all 10-minute tracked SS1 modes are shown in grey, while the aggregated averages are displayed in blue. It is important to note that the aggregated values still exhibit a variability range larger than the scour that needs to be detected due to environmental operating variability (EOV). To address this, the normalized mode is computed. This consists of adding the computed residual, from the normalization tree-based model to the mean model of the training data. The result is the EOV normalized aggregated frequency shown in orange.

The bottom control chart in Figure 8 is capable of detecting and quantifying scour shifts starting at 0.05D. However, the control chart at the top, which calculates daily aggregates, cannot detect the 0.05D scour, as the shift is smaller than the remaining variability caused by process and measurement noise. Nevertheless, it is effective in detecting and quantifying more significant scouring scenarios. This trade-off between detection speed and resolution highlights the importance of choosing an appropriate strategy.

CONCLUDING REMARKS

In this research, a methodology that combines data-driven SHM for damage detection using tracked modal frequencies with a model-based, digital twin model to quantify scouring scenarios based on drops in monitored frequency, is presented. This approach advances the SHM methodology from damage detection to damage quantification for offshore wind turbines.

The proposed methodology utilizes an augmented automated operational modal analysis to extract modal frequencies from acceleration measurements and first removes all harmonic-influenced modes. By normalizing the resulting modes for environmental and operational variability using tree-based learners, a normally distributed residual is obtained, reducing damage detection uncertainty. Modal frequency sensitivity to scouring depth is estimated from a digital-twin model.

Finally, by combining the residuals and the frequency drops predicted by the digital twin model, the presented methodology allows for the quantification of scouring depths. Statistical uncertainties are accounted for through the use of confidence intervals. A demonstration case is presented based on full-scale measurements from a permanently monitored Offshore Wind Turbine (OWT).

The contributions of this research provide insights and practical implications for the monitoring and maintenance of OWTs. By combining data-driven SHM and the digital

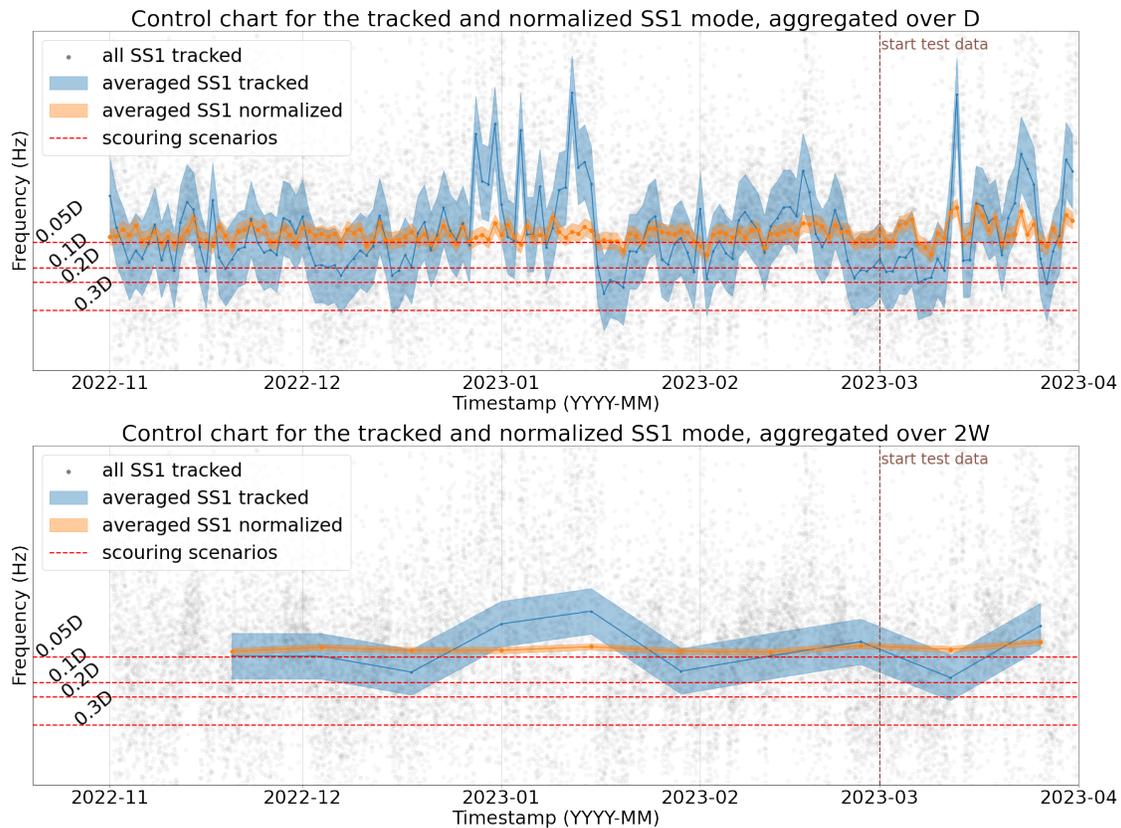


Figure 8. Control charts for scour detection and quantification using the 1 day (top) and 2 weeks (bottom) aggregates of the residuals (orange) and the simulated frequency drops for different scouring scenarios (red). The tracked SS1 data (grey) and the aggregates (blue) are also shown to highlight the importance of normalizing for EOVS and aggregating to ensure the confidence intervals remain below the frequency shifts due to the modelled scouring.

twin model, it is possible to detect and quantify scouring, enabling timely intervention and mitigating potential risks. Furthermore, this methodology paves the way for future research directions, such as the implementation of hypothesis testing for damage detection and the differentiation of scouring from other frequency-impacting failure modes through multi-modal analysis.

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