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Helicopter Bolt Loosening Monitoring using Vibrations and Machine Learning

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ABSTRACT

The existing helicopter Health and Usage Management Systems (HUMS) collect and process flight operational parameters and sensors data such as vibrations to provide health monitoring of the helicopter dynamic assemblies and engines. So far, structure-related mechanical faults, such as looseness in bolted structures, have not been addressed by vibration-based condition monitoring in existing HUMS systems. Bolt loosening was identified as a potential risk to flight safety demanding periodical visual monitoring, and increased maintenance and repair expenses. Its automatic identification in helicopters by using vibration measurements is challenging due to the limited number of known events and the presence of high-energy vibrations originating in rotating parts, which shadow the low-level signals generated by the bolt loosening.

New developed bolt loosening monitoring approach was tested on HUMS vibrations data recorded from the IAF AH-64 Apache helicopters fleet. ML-based unsupervised anomaly detection was utilized in order to address the limited number of faulty cases. The predictive power of health features was significantly improved by applying the Harmonic filtering differentiating between the high-energy vibrations generated by rotating parts compared with the low-energy structural vibrations. Different unsupervised anomaly detection techniques were examined on the dataset. The experimental results demonstrate that the developed approach enable successful bolt loosening monitoring in helicopters and can potentially be used in other health monitoring applications.

1. INTRODUCTION

Health and Usage Management Systems (HUMS) in helicopters use permanently installed vibration sensors to perform continuous health monitoring and predict failures in dynamic assemblies. Unfortunately, mechanical looseness monitoring is not in scope by vibration monitoring in helicopters (CAP 753, 2018).

IAF's field experience shows that not all bolts in helicopters have secure wiring and existing monitoring solutions like visual inspections including torque checks are not cost effective, performed on ground only and are subject for human errors. The use of vibration sensors appears to be the most cost-effective solution among all the alternatives (including additional sensors installation) given the existence of HUMS vibration sensors kit on the helicopter.

1.1. Mechanical Looseness

The literature divides mechanical looseness into three types (VibrAlign, 2019): A, B and C where each type is characterized by different changes in vibrations spectrum. The spectrum Type A mechanical looseness manifests itself as an increase in the amplitude of shaft's first harmonic (1X), while Type B and C affect the energy of shaft harmonics and subharmonics (e.g. 0.5X) often characterized by a raised vibrations noise floor as a result of changes in system natural frequencies.

Jackson (1996) and Human (2011) suggested that looseness is not a simple phenomenon and undergo certain stages, as the condition of the equipment deteriorates. Initially looseness will manifest itself as Type A, next as B, then as C, and finally only the noise floor will remain in the spectrum. Krot et al. (2020) and He et al. (2014) also found that bolt loosening is best diagnosed by using system natural frequencies.

1.2. Looseness Isolation

Bolt loosening detection by using vibration monitoring has been investigated in previous studies and ML methods were successfully applied (Eraliev et al., 2022). Unfortunately, the separation capability between bolt loosening and other mechanical failures hasn't been addressed. A reliable bolt loosening isolation is required by helicopter operators to reduce false alarms and improve helicopter maintenance.

As mentioned in 1.1 the changes in vibration noise floor, related to system natural frequencies, play a major role in bolt loosening detection. In this study, the vibration noise floor will be isolated from the periodic vibrations related to rotating parts to allow separation between looseness and other mechanical failures.

The methods below enable the separation between vibration background noise and periodical vibration signals. Antoni at al. (2004) and Randall (2004) exploited the periodic nature of the signal in order to build an adaptive filter that rejects uncorrelated noise between time-shifted slices of the signal. Such a filter quickly becomes impractical as it naturally grows with signal's complexity. Another method pioneered by Randall at al. (2011) is cepstrum-based separation of discrete components. Cepstrum is the spectrum of log spectrum. Transform to the cepstrum domain moves all the harmonics of the same shaft to a known place in quefrency (the frequency analog of cepstrum), where these harmonics can be easily removed. Although the method is generic, it is not very accurate, and requires a large number of harmonics per shaft to appear in the spectrum. Groover at al. (2005), Braun (2011), and Peeters at al. (2005 and 2007) remove periodic content by repeatedly resampling the signal to a constant angular basis, removing the bin-centered peaks in the order domain and resampling back to the constant time domain. Groover's method is accurate and better suited for signals with a large number of periodic sources like vibrations, but requires knowledge about system kinematics.

1.3. ML-based Anomaly Detection

In aviation applications, plenty of normal recordings exist with only a small number of abnormal events. Thus, it would be correct to define the bolt loosening detection as an anomaly detection problem. The anomaly detection methods learn the normal data behavior and identify points, sequences or context that deviate from the normal behavior (Goldstein et al., 2016 and Barelli et al., 2021).

In recent years, there has been a rapid growth in application of anomaly detection techniques in aviation (Basora et al., 2019 and Basora et al., 2021) where the unsupervised learning techniques are widely used in analysis of mechanical vibration data. Xu et al. (2019) proposed anomaly detection method in vibration signals collected from a certain type of rolling bearing equipment. Camerini et al. (2018) developed one-class classification SVDD for detection of micro-pitting damage on a helicopter gear. Lee, G.et al. (2020) developed unsupervised anomaly detection method for diagnosis of industrial gas turbines. The authors included in their model different types of data collected from vibration transmitters, temperature and pressure transmitters. Unsupervised anomaly detection models developed by Park et al. (2019) for vibration diagnostics of washing machine and by Oliveira et al. (2019) using 257 attributes, such as real measurements from thermal, acoustic and impact sensors installed in a heavy haul railway line in Brazil. Principi et al. (2019) presented unsupervised method for diagnosing faults of electric motors. Hu et al. (2020) proposed the features extraction method for fault detection based vibration signals of rotating machinery where the features obtained by vibrations FFT from classic rotor and bearing datasets are used as inputs to KCPA and AE models.

There is a wide use of reconstruction-based methods in mechanical fault diagnosis. Liu et al. (2018) and Sun et al. (2019) implemented this approach for the rolling bearing diagnosis and Ma et al. (2020) for damage identification task of a bridge under moving vehicle.

2. Purpose and Problem Definition

The purposes of the current study are as follows:

1. Developing a new methodology for bolt-loosening detection by using vibration sensors already existing in helicopters
2. Enabling reliable bolt loosening isolation from other mechanical problems
3. Testing the methodology by using field data recorded by HUMS

The following challenges were addressed in this research:

1. The helicopter maintenance information in digital form was difficult to access limiting thus the labeling of normal observations.
2. The missing information about the start time of the bolt loosening events makes the abnormal data labeling to be difficult
3. The number of abnormal observations is usually limited in helicopter operations since maintenance actions are scheduled to prevent mechanical failures. As a result, the supervised ML methods requiring significant statistics of abnormal observations cannot be used.
4. Bolt loosening isolation requires separation between vibration noise and shaft-synchronized vibration components (see Section 1.2). However, the background

noise and faulty bearing vibrations cannot be separated since the last are non-synchronized to shaft speeds. On the other hand, given a lack of comprehensive maintenance information, the faulty bearings may be a part of the observations where bolt loosening does not exist.

3. METHODOLOGY

The flowchart in Figure 1 describes the proposed methodology. The feature extraction algorithm generates two datasets (raw and advanced) of the same size: with and without Harmonic filtering to evaluate its influence on the model accuracy. The datasets are divided into training and testing sets where healthy data is divided 50/50 between the sets and the faulty data was fully a part of the test set to enable model performance evaluation. Three unsupervised ML models: Naïve model (less accurate and used as a baseline for models performance evaluation), Isolation Forest and Auto Encoder were built by using the train data and evaluated on the test data. The model evaluation was performed by using AUC criterion given the predicted and expected data labels.

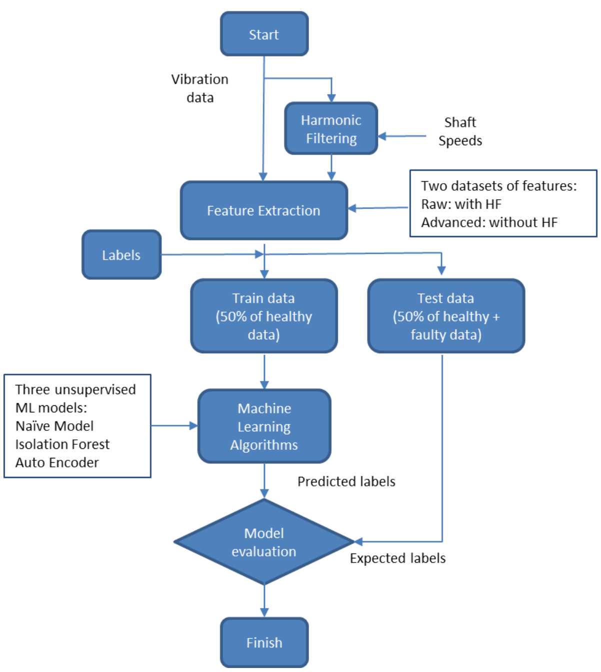

Figure 1. Flowchart demonstrating a proposed methodology

3.1. Harmonic Filtering

The Harmonic filtering (HF) (Groover at al., 2005) was chosen as the best preprocessing improvement to the feature extraction since it provides the best accuracy given the information about system shaft speeds. HF removes the periodic vibration components related to the rotating parts while leaving the background noise related to system natural frequencies (as mentioned in Section 1.2).

The technique consists of the following steps and repeated for each shaft in helicopter drive-train:

1. Times that correspond to the constant angular intervals $\Delta\theta$ are determined from the angular speed of rotating shaft
2. Vibration signal, sampled at constant time intervals Δt, is interpolated into a constant angular basis (cycle domain)
3. The FFT is applied to the interpolated signal
4. All the shaft harmonies, which are now exactly bin centered, are removed from the spectrum
5. The cleaned signal is transformed back to cycle domain via inverse FFT
6. Vibration signal is interpolated back to the time domain, where time intervals Δt are constant

3.2. Order Tracking

Order tracking, as used in the feature extraction, is a method of vibration analysis. The spectral density is calculated in terms of shaft speed (orders) instead of frequency (Hz). Order tracking helps to identify speed-related vibrations such as shaft, gearwheel and bearing defects. The order tracking requires vibration signal to be converted into cycle domain instead of time domain where signal is sampled at constant increments of shaft angle instead of constant increments of time (as described in Section 3.1) and then the spectral density is calculated by using Power Spectral Density (PSD) estimation. More information about the method can be found in Fyfe et al. (1997).

3.3. Feature Extraction

Two different features datasets: raw (without HF) and advanced (by using HF prior to feature extraction) were calculated.

The features extraction consisted of the following steps:

- The order tracking was performed (see Section 3.2)
- The order domain was limited between 0 and 160Hz to eliminate the influence of bearing fault frequencies, which expected to appear at higher frequency band (see Section 2) and divided into M equally spaced bands.
- The Root Mean Square (RMS) was calculated for each band in the order domain resulting in M features per sensor. The RMS at band i was calculated as follows:

$$RMSi = \sqrt{\frac{1}{N}\sum_{j=1}^{N} a(j)}\,, i \leq M \qquad (1)$$

where $RMSi$ is RMS of band i, N is a number of bins in band i, and $a(j)$ is a vibrations PSD at bin j of the order domain.

M=20 was chosen to achieve a trade-off between the model flexibility (requiring high M) and model complexity (requiring low M). Each dataset dimension is equal to 60 (3sensors x 20features).

3.4. Data Labeling

The following solutions of data labeling are proposed to solve the challenges as described in Section 2:

1. Assuming the significant majority of healthy observations in data, all the observations except the known bolt loosening events were labeled as "normal". However, the accuracy of the False Positive (FP) rate estimation is expected to be limited since other mechanical failures may generate FP alerts.
2. Given lack of information about bolt loosening start, the abnormal data period was labeled roughly by using a visual inspection. Thus, the estimation of model True Positive (TP) rate is limited when using this type of labeling.

3.5. ML Approach

The use of anomaly detection techniques is chosen as a best way to detect the problems since the abnormal data amount is limited as mentioned in Section 2. The anomaly detection allows learning from healthy observations only and detecting abnormal observations as anomalies.

Two advanced unsupervised ML techniques were chosen for comparison: Isolation Forest (IF) and Auto-Encoder (AE). The IF algorithm was developed specifically for the purpose of anomaly detection and works on the principle of isolating anomalies. AE allows learning a low-dimensional feature representation on which the given data instances can be well reconstructed. The reason for using AE in anomaly detection is that the learned feature representations are enforced to learn complex relations of the data to minimize reconstruction errors; anomalies are difficult to be reconstructed from the resulting representations and thus have large reconstruction errors. Both methods are widely used in conditional monitoring.

3.5.1. Isolation Forest (IF)

IF is based on an ensemble of random binary trees that compute paths to isolate observations. Each tree of the ensemble is known as an isolation tree, to partition observations until they are isolated. The identifying of a normal observation and abnormal observation by IF can be observed in Figure 2. A normal point (on the left) requires more partitions to be identified rather than an abnormal point (right). Therefore, the key idea is that anomalies are easier to isolate since they require shorter paths or fewer conditions in comparison with normal observations.

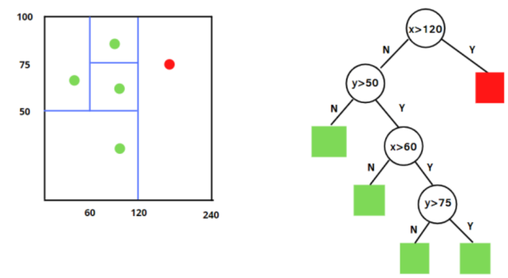

Figure 2. Identifying normal vs. abnormal observations with iForset

The algorithm determines limit values per node based on the feature values chosen randomly. At each step, the limits are split into 2 parts and being checked whether or not the sample observation is within the boundaries. IF determines anomalies scores by the following equation:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{2}$$

where $h(x)$ is the path length of observation x, $c(n)$ is the average path length of search in a Binary Search Tree and n is the number of external nodes. $E(h(x))$ is the mean value of $h(x)$ in the isolation tree. IF can be configured as a binary classifier or regression to weight the observation between normal (0) and anomalous (1). When configured as a classifier, it is possible to define the contamination proportion of outliers in the dataset used as a threshold to round the value to 0 or 1. Therefore, when s is close to 1, it is quite possible to be an outlier. Similarly, a number close to 0 might also be normal. If all observations are close to 0.5, no anomaly is identified (very similar observations).

More details about anomaly detection by IF can be found in Liu, F. T. et al. (2008).

3.5.2. Auto-Encoder (AE)

An auto-encoder is a type of neural network used to encode the data in efficient unsupervised manner. AE is trained to generate the target values equal to the input data through a combination of encoder and decoder networks. These networks have a bottleneck hidden layer of few neurons in the middle, forcing them to generate valid representations that compress the input data into a lower-dimensional code called a latent vector, which used by the decoder to reproduce the original information. AE is trained to minimize reconstruction errors

$$\min_{E,D} \left\| x - D\left(E\left(x\right)\right) \right\| \tag{3}$$

where x is the input data, E is an encoder network, and D is a decoder network. The training of an auto-encoder is performed through backpropagation of the error, just like a regular feedforward neural network.

A typical auto-encoder architecture consists of three main components, as shown in Figure 3.

1. Encoder network: An encoder network is comprised of series of layers with a decreasing number of nodes and ultimately reduces input data into a latent vector. This process is also called dimensionality reduction, and the convolution layers are used for encoding.
2. Latent vector: The latent vector represents the lowest level space in which the inputs are reduced, with essential information preserved with the strong correlation between input features.
3. Decoder network: A decoder network acts as the mirror image of the encoder network. The number of nodes in every layer increases and reconstructs the latent vector to output as a similar input via transposed convolution. As a particular portion of the information is lost during reconstruction, the output data always have lower quality than the input data.

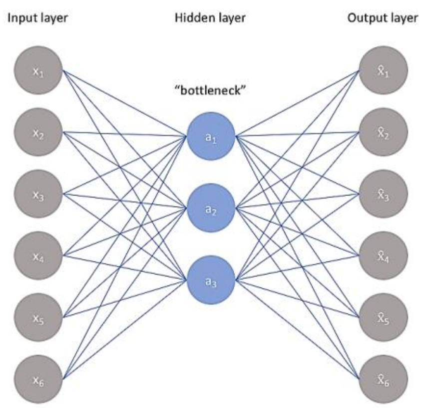

Figure 3. The typical AE configuration

The efficiency of AE in anomaly detection is strongly related to a proper selection of dimension size of hidden layers where anomalies are detected by calculating the residual error in the reconstruction of the input by the decoder. Since anomalies are "few and different", AE tends to achieve lower error for normal observations and abnormal higher residuals for outliers. Similar to IF models, the contamination hyper parameter defines the percentage cut between normal and faults. The records with the highest residual errors are classified as abnormal. More detail about AE as an anomaly detection technique can be found in Chalapathy, R., & Chawla, S. et al. (2019).

3.6. Model Performance Evaluation

Technically, there is no way to measure the performance of unsupervised learning models, since there are no labels available to compare the ground truth. In this regard, we used abnormal signals as labels solely for model's performance evaluation purposes. During the training process, labeled datasets are not provided to the models. The validation dataset contained both normal and abnormal observations to use classification performance metrics.

Classification performance can be measured independently from threshold setting by introducing the receiver operating characteristic (ROC) curves. Such curves represent the fraction of target objects accepted by the model (i.e. normal observations classified as normal) against the fraction of outliers accepted (i.e. abnormal observations classified as normal). The area under the ROC curve (AUC) gives a scalar measure of the achieved separability between states.

4. Dataset and Experiment Description

Intermediate Gearbox (IGB) represents one of the drive-train assemblies in AH-64 helicopters responsible for transfer of rotational moment from the main gearbox to the tail gearbox. The IGB is attached to the airframe by 4 bolts as shown in the Figure 4 and Figure 5.

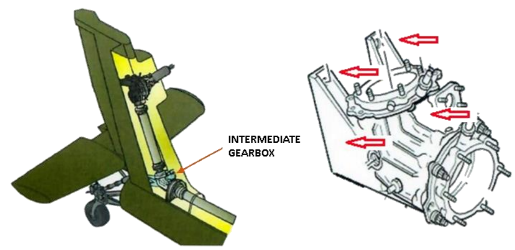

Figure 4. Intermediate Gearbox (IGB) of AH-64 and the corresponding locations of 4 bolts attaching the assembly to the airframe

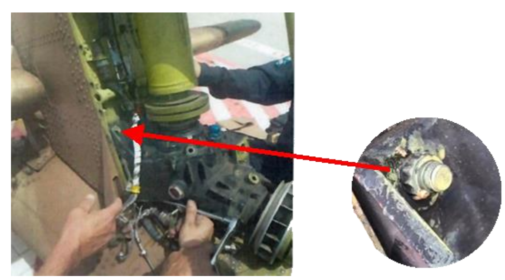

Figure 5. Intermediate Gearbox of AH-64 and the upper left bolt example

Bolt loosening is manually checked before each flight as well as during weekly inspections. The vibrations levels of the IGB input shaft harmonies 1X and 2X are being monitored by HUMS continuously during flight accompanied by periodic manual measurements on-ground. Unfortunately, the existing IGB vibration monitoring does not provide a solution.

The bolt loosening events were detected indirectly by visual inspection of the bolt holes during IGB overalls. The oval form of the holes and signs of corrosion represent the result of bolt loosening needed to be monitored automatically and in advance. See Figure 6 below for example.

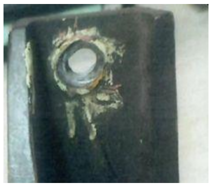

Figure 6. The oval form detected in one of four holes points to bolt loosening

The historical data provided for this research was recorded by the T-HUMS of RSL Electronics Ltd. between 2014 and 2020 from the entire IAF AH64 helicopters fleet. Unfortunately, the data set cannot be published due to confidentiality limitations.

There are 3 vibration sensors in close proximity to IGB as summarized in Table 1.

Table 1. Vibration sensors in IGB proximity

Sensor Code	Sensor Description	Sensor Location	Samp Rate, kHz	Recording Duration
IGB	Intermediate Gearbox	IGB assembly, on IGB	48	10 sec
HBA	Aft Hanger Bearing	IGB input shaft, 0.5m from IGB	12	10 sec
HBF	Fwd Hanger Bearing	IGB input shaft, 1.5m from IGB	12	10 sec

There are four known cases of IGB bolt loosening in AH-64 where T-HUMS data exist, each with slightly different findings (see Table 2).

Table 2. IAF Findings of Bolt Loosening in IGB between 2014-2020

Case #	IGB Installation	IGB Removal	#Oval Holes Detected/ #Total Holes
1	10/07/18	19/12/19	4/4
2	13/11/18	22/10/19	3/4
No data	13/03/14	20/07/14	No data
3	25/12/17	06/05/18	3/4
4	26/03/19	09/03/20	0/4

The problem severity defined as a number of oval holes detected after IGB removal. For example, 4 oval holes in case #1 points to the higher problem severity vs. 0 holes as in case #4 where only low mounting torque was identified. Cases #2 and #3 are of similar severity with 3 oval holes each.

4.1. Data Preprocessing: HF

Figure 7 shows how the high-energy vibrations related to rotating parts are being removed with HF approach (Section 3.1).

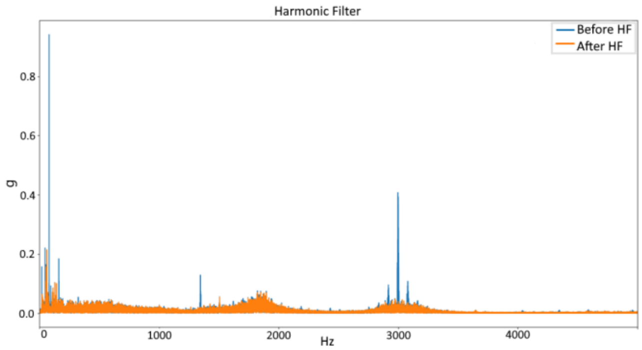

Figure 7. Example of IGB sensor vibrations spectrum before (blue) and after (orange) HF.

The noise floor difference between the normal and abnormal FFT of case#1 (see Table 2) is presented in Figure 8- where a minor noise floor increase can be visually identified.

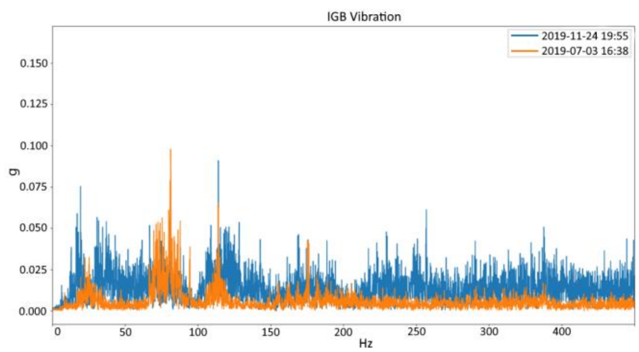

Figure 8. IGB sensor vibrations after applying HF: just after healthy IGB installation (orange) and before bolt loosening is detected (blue)

4.2. Data Statistics and Partition

The calculated features statistics after preprocessing is summarized in Table 3:

Table 3. Available Feature Dataset

Flight Regime	Description	Normal Observations	Abnormal Observations	Total Observations
1	Level Flight High Speed	44828	675	45503
2	Level Flight Low Speed	26371	371	26742
3	Hover	2714	39	2753

The only flight regime #1 with the largest number of observations (45,503 observations in total) was chosen to avoid influence of the helicopter operational conditions.

Further research is required to estimate the possibility of data aggregation from different flight regimes.

4.3. Benchmark Framework Definition

In order to perform ML model evaluation, the Naïve model was chosen as a baseline where other ML methods were evaluated by comparison to this baseline model. The model uses a probabilistic model assuming multivariate Gaussian statistics of the healthy data, estimates parameters of its probability distribution and assigns a log-likelihood to any observation during inference. The squared Mahalanobis distance is proportional to the log-likelihood and serves as an anomaly score for Naïve model, where large score values indicate a novelty in the data. To improve the model's robustness, the score was calculated after the features are divided into 4 groups 5 features each assuming there is no dependency between the groups.

ROC curve (Receiver Operating Characteristic curve) was chosen to define the models performance and benchmarking. The ROC was calculated on the whole range of the model thresholds where True Positive Rate and False Positive Rate represented its axes. The ROC was built by using the test data including 50% of the healthy and all the faulty observations.

Area under the ROC Curve (AUC) was chosen to provide an indication of the model performance across all possible thresholds. Generally, a higher AUC points to a potentially better model performance. In our case, the area of interest is mainly in the region corresponding to a low FP rate (lower than 0.1) which is more practical for helicopter operators. The AUC of the Naïve model was equal to 0.8 as presented in Figure 6, where the model was built using all the 3 sensors and 20 features each (input dimension = 60).

Two different cases are presented in Figure 9: where the basic and advanced features datasets are used. The AUC in both cases for Naïve model is equal to 0.8. The AUC improvement is not significant while the low FP area was improved significantly by using HF pointing to its importance: 26% improvement in TP rate was found for a chosen 0.1 FP rate. Further model benchmarking results will be presented for HF only due to its significant improvement of the ROC for the low FP rate values.

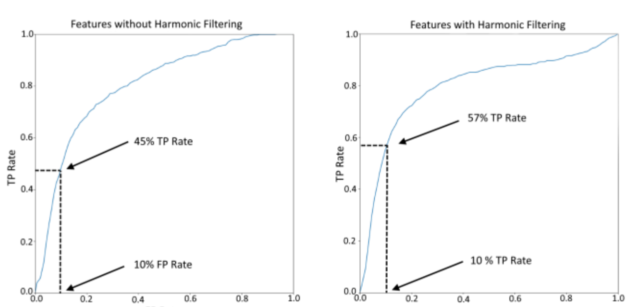

Figure 9. The ROC of Naïve model applied to basic features dataset (left) and advanced features dataset (right)

4.4. Advanced Models Settings

The performance of two advanced models: Isolation Forest and Auto-Encoder were compared to the baseline Naïve model.

The models were trained on the 50% of the healthy data (22,414 healthy observations) and the AUC was calculated by using the test data including other 22,414 healthy and 675 faulty observations.

IF algorithm, implemented on scikit learn library, used the default parameters except the contamination = 0.1 allowing the proportion of outliers in the dataset. Since its initialization is random, the AUC results were generated by averaging 100 runs.

Auto-Encoder algorithm was used with the default parameters except the contamination = 0.1 and hidden_neurons = [10, 4, 4, 10] where the parameter defines a number of neurons per hidden layer whose number is lower compared with the number of input features (60 in our case).

5. Results Summary

Table 4 below summarizes the results. As mentioned above, visual data investigation showed significant difference in the capability of the healthy-faulty data separation between different sensors. It was therefore decided to present the model benchmarking for each sensor separately. Table 4 summarizes the benchmarking and shows significant performance improvement when the IGB sensor only is used – 0.87 vs. 0.80 when all three sensors are used. All models performance on HBA and HBF sensors are poor compared to the IGB sensor. Further investigation is required to deeply understand the reason for the difference.

The stability of the model performance was estimated by randomly choosing subsets from the training set to generate AUC. Both Naïve and AE models were stable while IF model performance was different for different data sets. Given a similar performance between the models, the Naïve or AE model are preferred options for use in production. AUC values presented in Table 4 show that AUC for IF and AE models show no improvement vs. baseline Naïve model. The main reason for the models inaccuracy is the inaccuracy in dataset labeling due to lack of information about the bolt loosening beginning and info about mechanical failures in the healthy dataset. The best results are obtained when the IGB sensor only is being used.

Table 4. AI models benchmarking

Model	AUC – all sensors	AUC – HBA	AUC - HBF	AUC-IGB
Naïve model (Baseline)	0.80	0.61	0.66	0.86
Isolation Forest	0.79	0.51	0.64	0.87
Auto-Encoder	0.77	0.50	0.63	0.86

The IF ROC of IGB sensor is demonstrated in Figure 10. AUC of the IF model built on IGB sensor data is equal to maximal 0.87. The maximal TP rate of 0.75 can be obtained for a chosen 0.1 FP rate.

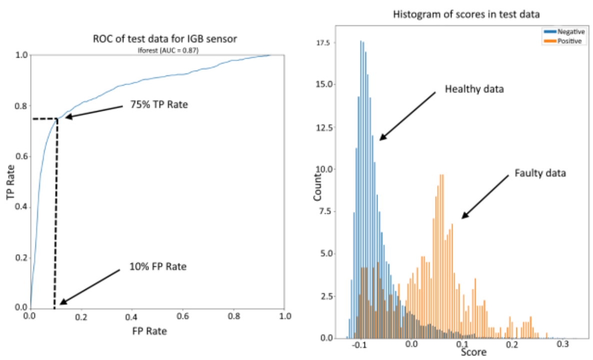

Figure 10. The best ROC of IGB sensor (left image) and histogram of anomaly scores (right image)

The difference in models performance between different sensors required additional data analysis. The histograms of the healthy and faulty data were analyzed in order to understand the difference in data statistics between the sensors. The difference in faulty and healthy data stats is more significant in IGB sensor. See example in one of the inputs in Figure 11.

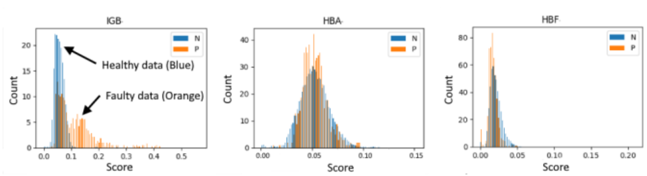

Figure 11. Comparison between the healthy and faulty data statistics for IGB (left), HBA (middle) and HBF (right) sensors

The best difference between the healthy and faulty data is visually recognized mainly in IGB sensor (Figure 11, left image) vs. HBA, HBF. The results fit also physical intuition since only IGB is located on the faulty assembly. As a comparison, the HBA and HBF data statistics are presented (Figure 11, center and right images).

The output of the models represents an anomaly score corresponding to a distance measure between each test observation and the training dataset.

The anomaly score can be used as a Condition Indicator in detecting bolt loosening. All the known bolt loosening cases were successfully detected by the Condition Indicator. Figure 12 shows an example of the Condition Indicator performance of AE model applied to all the data of the helicopter where the case #1 bolt loosening was found. The red line on the Figure 12 helps to identify the healthy and faulty data and is set to zero when no bolt loosening exists and equal to a high value in the period of IGB installation and removal when the problem appeared.

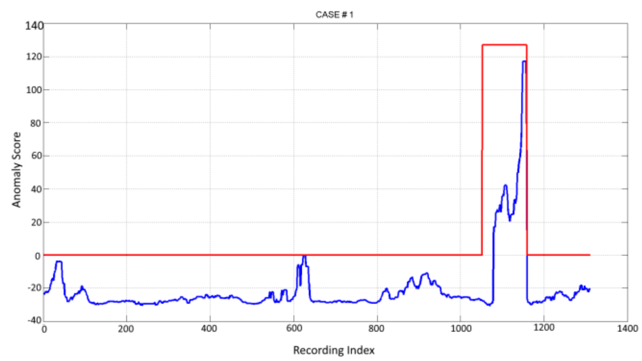

Figure 12. Example of Case #1 loosening detection by new Condition Indicator (blue)

6. Conclusions and Recommendations

A new algorithm of bolt loosening detection by using vibrations and ML is developed and tested on field data recorded by IAF HUMS.

No significant difference in model performance was found between three ML models: Naïve model, Isolation Forest and Auto-Encoder. The models performance evaluation was limited due to dataset challenges as explained in Section 2.

The use of data from IGB sensor only outperforms the models using data from all three sensors. The actual reason is not clear yet and future research is required.

The use of HF as a preprocessing stage improves model TP rate especially for low FP rates where the model is of main interest for operators.

Recommendations for future research

The use of sequence-based anomaly detection instead of point-based may decrease FP rate where anomaly is detected if the samples neighborhood is considered.

Since data is time-based, the use of serial data structure may help to improve model performance. The use of time-based LSTM AE vs. AE as in our case may improve both FP and TP rates.

The use of more information about maintenance actions performed as well as the mechanical failures detected during the helicopters operations may improve significantly data labeling accuracy and improve models performance.

Further investigation of the difference in model performance between different sensors is required for deeper understanding the directions of model improvements.

Contribution

The new developed methodology allows bolt loosening detection and isolation from other mechanical failures. The methodology will improve helicopter maintenance activity by replacing non-reliable human factor used in periodical visual inspections and will expand monitoring scope also to flight conditions vs. existing manual ground-based inspections.

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