# Implementation of Machine Learning in Bolt Tension Measurements

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# SUMMARY

Implementing ultrasonic elongation techniques in bolt maintenance programs has enabled the direct estimation of bolt tension. However, the limitations of elongation techniques (un-tensioned baseline measurements, complex calibration procedures, and compounding errors from material and environmental variation) make implementation impractical on a large scale for new and in-situ bolts.

The presented work resolves these issues by combining bi-wave ultrasonic technology with machine learning. Bi-wave ultrasonics eliminates the need for un-tensioned baseline measurements and reduces the impact of material and environmental variations. Consequently, a lab-built model translates to bolts in the field enabling large-scale deployment.

To translate a model to the field, the variables that impact the velocity of a wave as it travels through a bolt must be accounted for during the model-building process. Data from the scenarios that a bolt could experience in the field were collected and analyzed. A stacked model, comprising several base models, was used to hone the performance of the tension measurement. Factors such as bolt bending, “cycle-skip,” and signal quality are evaluated.

The model was installed into Predictant’s Bolt iQ device. Holdout testing, witnessed by DNV, was conducted on a variety of bolts across a spectrum of variables. The average error during the testing was -5.51 MPa. The model achieved less than 5% error, relative to yield stress, with 93.32% confidence, and better than 8% error, relative to yield stress, with 99.73% confidence.

# MOTIVATION

Maintaining the correct bolt tension is critical for ensuring the integrity and stability of a wind turbine. Tension is applied to a bolt using a torque wrench or a hydraulic tensioner, and a technician applies a pre-determined torque/pressure value that has been calculated as correlating to the desired bolt tension.

However, the output of these approaches is not the bolt’s tension. It is assumed that the correct tension has been applied based on the conversion calculations. It is well documented that many factors impact these calculations, reducing the accuracy of the conversion to tension in the bolt. These factors include the friction between the bolt threads, nut, and bearing surfaces and the potential for load loss due to nut-tensioner interactions. [1,2,3,4,5,6]

To overcome these limitations, researchers applied ultrasonic (UT) wave techniques to measure the tension in a bolt. These techniques leverage the acoustoelastic effect whereby acoustic waves interacting with elastic deformation in a solid result in the velocity of waves changing with stress. [7] The most common UT technique is the mono-wave elongation method. This method measures the time it takes a wave to travel the length of the bolt and reflect to its source. This time is referred to as the “time-of-flight" (ToF). By comparing un-loaded and loaded ToF measurements on a bolt, the elongation of the bolt is calculated and converted to a tension estimate. [5,8]

Because elongation requires un-loaded baseline measurements for every bolt, it is impractical to implement on a large scale for new and in-situ bolts. Further, elongation tension estimations are sensitive to material and environmental variation. [5] These limitations are overcome, however, by combining bi-wave UT and machine learning (ML), which is the approach taken in this work.

Bi-wave UT operates by transmitting (orthogonally) two waves (longitudinal and shear) into a bolt and measuring the ToF of each. By taking the ToF ratio, baseline measurements of bolts in their unstressed state are unnecessary. [9,10,11]

Though the ToF ratio is less susceptible to material and environmental variation, there are still many variables that impact the velocity and shape of a wave as it travels through a bolt. [12,13] Consequently, data needs to be collected from the many scenarios that a bolt could experience in the field. This results in large datasets (tens of thousands of samples) to analyze. ML excels at detecting patterns in large datasets and can be carefully engineered by humans with deep knowledge of bolt and ultrasonic wave behavior. Therefore, ML is a prime candidate for building a model to measure bolt tension.

# METHODOLOGY

To demonstrate the flexibility of the approach, three different bolt geometries were chosen for testing: 1) M42x235mm, 2) M42x330mm, and 3) M56x400mm. The M42 bolts were grade 10.9 HV tZn coated hex-bolts while the M56 was a grade 10.9 HV tZn coated tower flange stud. Ten samples of each bolt geometry were procured from a bolt manufacturer. Upon arrival, each bolt was catalogued and one bolt from each geometry group was set aside as a holdout bolt to evaluate the performance of the trained model.

The training data collection matrix is depicted in Table 1 below. Data was collected a) from 0-75% of yield stress, b) at temperatures of 0C-40C, c) using a torque wrench, in-line jack, and tensioner, d) from minimum to maximum possible clamp length, e) at head and tail measurement orientations, and f) from no bending to $4^{o}$ bending according to IEC-61400. [14] Approximately 31,000 samples were collected for model training. No surface treatment of the bolt surface was performed.

**Table 1** Data Collection Table.

| Category | Variation 1 | Variation 2 | Variation 3 |
|---|---|---|---|
| Temperature | 0C | 20C | 40C |
| Clamp Length | Minimum | Middle | Maximum |
| Tensioning Method | Hydraulic Jack | Hydraulic Tensioner | Torque Wrench |
| Flange Gap | Zero-degrees | Two-degrees | Four-degrees |
| Orientation | Head | Tail | N/A |

The training data underwent a quality check to ensure it was of the correct schema and met the necessary standards for modelling. For example, the signal-to-noise ratio (SNR), signal amplitude, metadata, and other variables were considered.  To ensure robust model training and generalization, a K-fold cross-validation strategy was employed for both training and hyperparameter tuning. Data was stratified by unique bolt, ensuring all data points from a single bolt were grouped within the same fold, preventing data leakage across folds. At each level, a statistical breakdown of the model performance was output enabling performance to be tracked across groups and relative to performance requirements/goals. For example, the mean, standard deviation, and performance at several confidence intervals were output. Once the model's performance was stable and satisfactory, holdout testing was performed on bolts unknown to the model under the variable conditions outlined in Table 1.

# RESULTS

Following the initial model performance evaluation, two challenges had to be resolved. The first challenge was the presence of flange gaps and bolt bending because these conditions change the dynamics of the wave traveling through the bolt.

**Figure 1** Bolt bending implications.

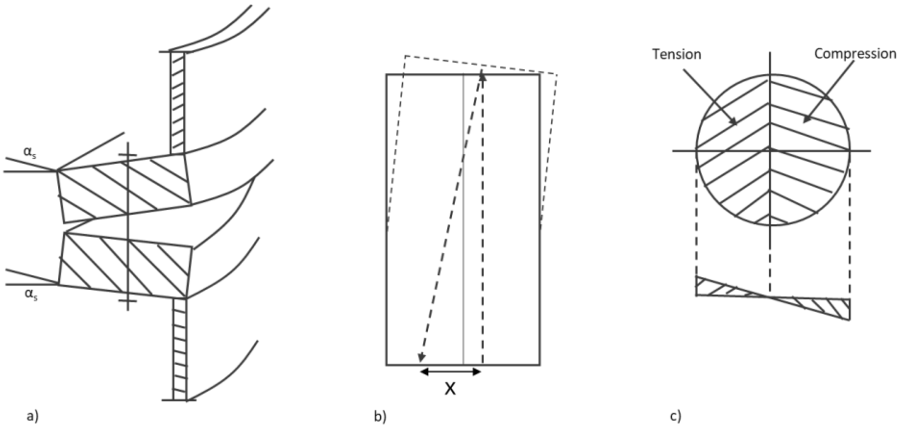
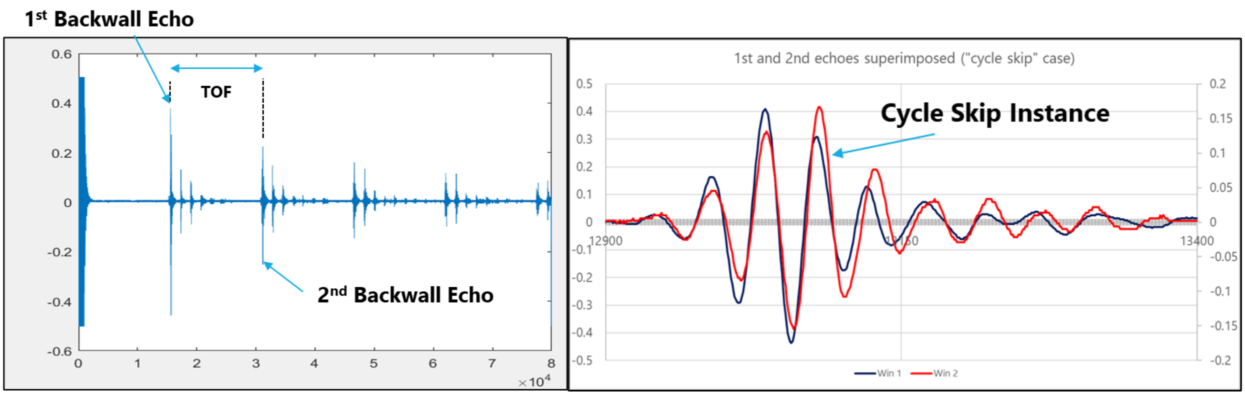



Figure 1a depicts an example L-flange from IEC-61400 where $\alpha_s$ is allowed to vary up to 2 degrees before taper washers must be installed.[14] Such angles cause bending in the bolt and create zones of compression and tension. Figure 1b depicts a simplified wave path of bolt bending. While the wave enters the bolt at a normal incidence to the surface, bolt bending causes the wave to be reflected at an angle. The wave returns on a different path and is received a distance x from its entry point, reducing signal amplitude. Phase shifting of the received wave is also possible. [12]

Differences in the waveforms mean that a model trained on non-bending data does not translate successfully to bent data. It is, therefore, necessary to indicate to the model from which scenario incoming data originated. This is achieved through a classification model implemented as a layer of a stacked model. If the classification deems the bolt as bent, the data is sent to a deep learning (DL) model for tension measurement.

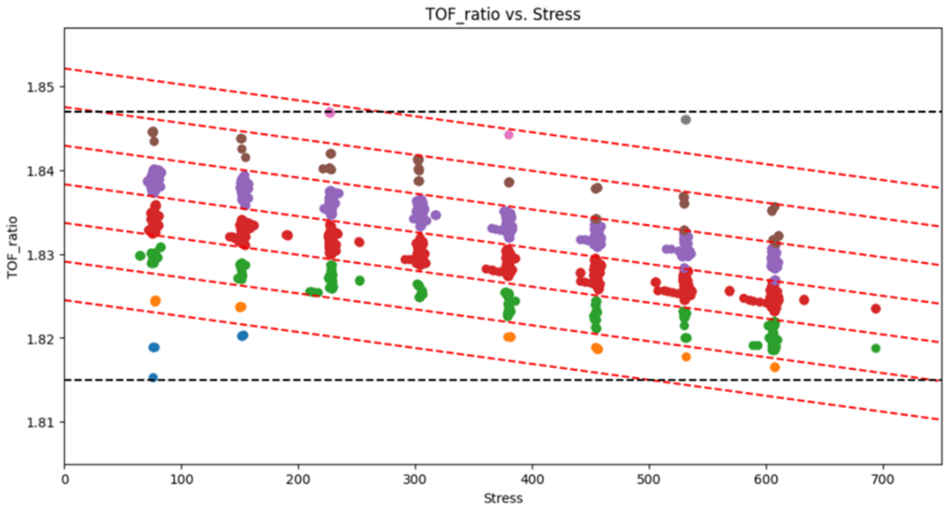
Otherwise, the data passes to a second layer of the stack, which handles the second challenge encountered, "cycle-skip." To determine the shear and longitudinal ToFs, a custom cross-correlation algorithm is used. However, as a wave travels through a bolt it changes shape due to sidewall and bottom surface reflections causing the shape of the first and second echoes to differ. See Figure 2.

**Figure 2** Example of cycle skip.



Typically, the difference is seen as a peak shift, and because cross-correlation functions measure the similarity between two functions, in this case wave echoes, the peak shifts cause error in the ToF estimations, relative to the “true” value. This error is usually in multiples of a wave period and is known as “cycle-skip.” Further, cycle-skip can occur in both longitudinal and shear waves which increases the number of ToF ratio combinations. The result is seen in Figure 3 below, which depicts several “bands” of ToF ratios relative to the stress (MPa) applied to the bolt.

**Figure 3** Example of cycle skip impact.

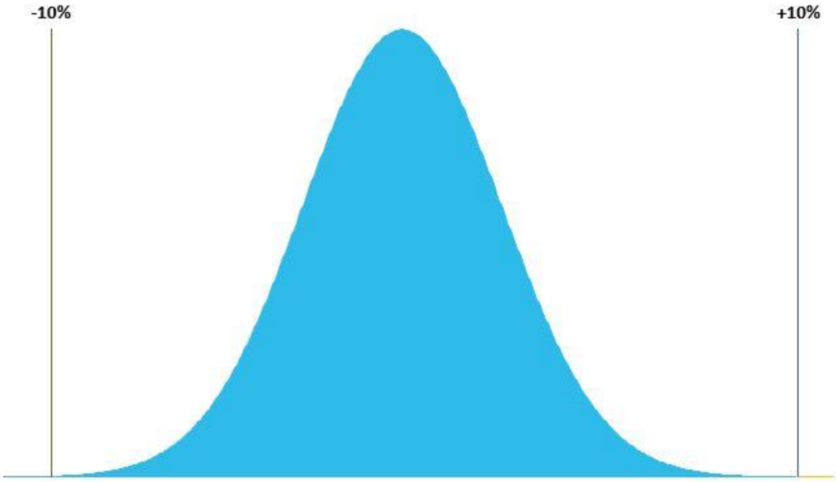



To make an accurate tension measurement, the ratio band of incoming data must be known. The second layer of the stacked model is, consequently, a classification model to identify the ratio band. Once the band is identified the data is passed to a corresponding multi-variable linear regression model that outputs tension. Because the tension model is the last component in the stack, the performance results include any error from the misclassification of bending and/or bands.

The model pipeline was deployed to Predictant’s Bolt iQ$^{TM}$ system.[15] Holdout testing was performed on bolts of each geometry, whose “identity” was unknown to the model. Testing was conducted across the categories identified in Table 1. Measurements, witnessed by DNV, were taken between 15%-75% of yield stress, in 10% increments, and tension/stress was estimated in real-time. The testing comprised 402 measurements.

Figure 4 below depicts the error distribution during testing. The average error during the holdout testing was determined to be -5.51 MPa. The model was able to achieve less than 5% error, relative to yield stress, with 93.32% confidence, 5.5% error, relative to yield stress, with 95% confidence, and better than 8% error, relative to yield stress, with 99.73% confidence.

**Figure 4** Error distribution during testing.




Error of ± 5.00% of Yield Stress (940MPa) with 93.32% CI
Error of ± 8.00% of Yield Stress (940MPa) with 99.73% CI

# CONCLUSIONS

The presented research investigates the efficacy of implementing machine learning techniques to bi-wave UT bolt tension measurements. The research overcame the bending and cycle-skip challenges. This was achieved by implementing a stacked model, which combines several base models to hone the performance of the tension measurements.

Holdout testing, witnessed by DNV, demonstrated the approach was successful. The model's average error was -5.51 MPa and achieved errors less than 5%, relative to yield stress, at a 93.32% confidence interval and less than 8%, relative to yield stress, at a 99.73% confidence interval.

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