Ultrasonic Testing and Machine Learning. The Relationship Solving your Bolt Tension Needs.

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ENGINEERING INNOVATION

BACKGROUND

Maintaining the correct bolt tension is essential for ensuring wind turbine integrity and stability. However, current torque- and direct- tensioning techniques are inherently inaccurate and inefficient. While ultrasonic techniques have proven to be a viable solution, their requirement for unstressed length and reference longitudinal time of flight measurements renders them impractical. This presents a need for a nondestructive approach to accurately measure bolt tension.

OBJECTIVE

Develop an ultrasonic test method and tool using machine learning techniques to improve ease of use, enhance accuracy, and overcome the limitations of current technology. The tool should not need unstressed length or bolt reference measurements and should not require highly trained technicians to operate. The tool should be part of a system that is capable of storing and presenting engineers with historical data for trend analysis.

METHODS

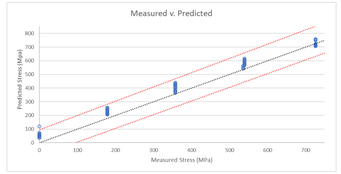
Three Phased Approach

- Phase I: Processing Signals - use advanced signal analysis techniques to process real time data and build a training data set for machine learning based modelling.
  - Feature harvesting, cross-correlation, dynamic processing
- Phase II: Implementing Machine Learning - use machine learning techniques to identify bolt physical features and outliers and predict bolt tension or class.
- Phase III: Reducing User Variability - reduce user variability by developing a solid couplant, magnetic transducer case, and integrated transducer comprising both shear and longitudinal active elements.

RESULTS

Phase I:

Holdout Testing Results

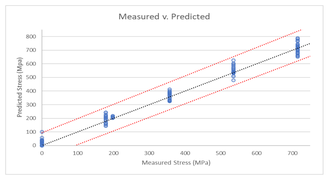


Average Error (Mpa)	Average Error (kN)	Average Error (Kips)
47.47	53.22	11.96

Testing on grade 10.9 HV bolts M42 x 260mm, 265mm, 330mm, 345mm, 355mm, and 425mm

Phase II:

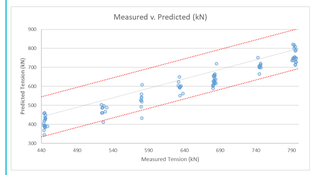
Holdout Testing Results

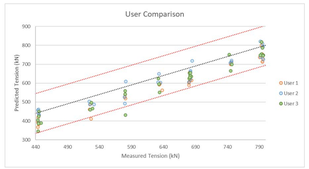


Average Error (Mpa)	Average Error (kN)	Average Error (Kips)
11.90	13.34	2.99

Testing on grade 10.9 HV bolts M42 x 260mm, 265mm, 330mm, 345mm, 355mm, and 425mm

Repeatability and Reproducibility (R&R) Testing





R&R Totals

Average Error (Kips)	Average Error (kN)	Average Absolute Error (Kips)	Average Absolute Error (kN)
-9.127	-40.599	10.285	45.748

R&R User Comparison

Operator	Average Error (Kips)	Average Error (kN)	Average Absolute Error (Kips)	Average Absolute Error (kN)
1	-12.369	-55.02	12.484	55.529
2	-5.196	-23.114	8.005	35.608
3	-9.816	-43.662	10.365	46.107

Testing on grade 10.9 HV bolt M42 x 355mm

Phase II Cont.:

Classification Modelling

Total accuracy ~ 94%
Identified ~95% of loose bolts

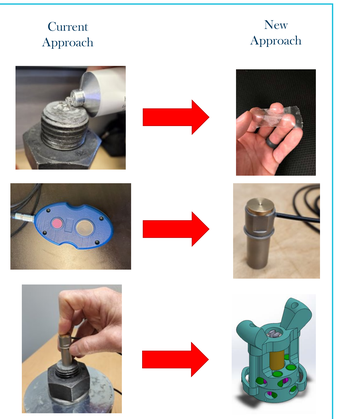
→ Total accuracy ~ 93%
Identified ~ 96% of loose bolts

→ Total accuracy ~ 92%
Identified ~ 98% of loose bolts

Testing on grade 10.9 HV bolts M42 x 260mm, 265mm, 330mm, 345mm, 355mm, and 425mm

Phase III:

- Sources of Variability
  - Liquid couplant exchange
  - Transducer exchange
  - Applied pressure
- Solutions (In Progress)
  - Solid couplant
  - Integrated transducer
  - Magnetic jig



CONCLUSIONS

- Approach performs well on a wide range of bolt lengths (260mm – 425mm)
- Accurate predictions on previously untested bolts
  - Average error as low as 13 kN (3 Kips)
  - Identified up to 98% of loose bolts
- Tool accuracy is consistent across users
  - Average error < 41 kN (10 Kips)

ACKNOWLEDGEMENTS

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