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Estimating Level Sea Ice Loads on Sloping Structures Using Machine Learning-Derived Flexural Strength

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ABSTRACT

Global level ice loads on an offshore structure can be reduced through the introduction of sloping elements at the waterline which encourage the incoming sea ice to break in flexure. Ice loads associated with flexural failure are parameterized using flexural strength which, in the case of sea ice, is dependent on scale, ice temperature and brine volume. Numerous studies have been conducted on the flexural strength of ice ranging from in situ tests on natural occurring ice to laboratory tests on artificial ice in a controlled environment. A comprehensive database of flexural strength measurements for sea ice beams was acquired, consisting of more than 2700 records. In this work, machine learning (ML) regression algorithms are employed to predict the flexural strength of sea ice. Ensemble modeling, i.e. the combination of two or more individual models, was also employed during model development in an effort to balance out individual weaknesses and produce more favorable results compared to the individual models. An investigation into level ice loads on a single pier of the Confederation Bridge was conducted using deterministic design load calculations, and based on flexural strength estimates derived from both conventional methods and ML models. In particular, the breaking term in the load calculation has been considered in relation to temperature, ice thickness and brine volume.

KEY WORDS: Sea Ice; Flexural Strength; Machine Learning; Level Ice Loads

INTRODUCTION

The work presented here is a continuation of the authors work on machine learning (ML) and the flexural strength of freshwater ice (Burton et al., 2022). In this previous study ML models were derived, using the same database discussed in the current work, for the purpose of estimating the flexural strength of freshwater ice. The ML models developed were not only able to demonstrate scale-effect trends but also provided evidence to a link between flexural strength and ice temperature, a relationship not included in traditional freshwater ice flexural strength models.

For structures operating in ice-prone waters, ice loading is one of the key environmental factors contributing to the overall design and operation of the structure. When ice interacts with a structure it can fail in several primary modes including crushing, buckling, flexure or a combination of modes. The dominant failure mode of an ice sheet will have a direct impact on the load transmitted to the structure. Timco and O'Brien (1994) found that for arctic structures exposed to transient ice sheets compressive strength was upwards of seven times higher than flexural strength. The design of many offshore structures use this relationship to their advantage employing sloping elements at the waterline to promote ice failure in flexure. Taking this into consideration, the importance of accurate estimations of flexural strength cannot be understated.

The flexural strength of ice has been shown to be sensitive to not only the physical properties of the material, but to the conditions under which the tests are conducted (Timco & O'Brien, 1994). Physical properties such as temperature, porosity, specimen size, grain size and crystal orientation; in addition to loading rate, loading direction and test type (cantilever or simple beam) all contribute to the flexural strength of the specimen. Generally, most publicly available datasets on flexural strength are limited to test type, specimen size, temperature and brine volume (or salinity).

Conventionally, the flexural strength is assumed constant in calculations. It can also be approximated using a single-parameter (Timco and O'Brien (1994) and Ji et al. (2011)) or two-parameter (Aly et. al, 2019) empirical relationship. In this work, ML algorithms have been employed to interpret the relationship between flexural strength, beam volume, brine volume and ice temperature. Models generated using traditional empirical methods have been compared to models developed using ML algorithms to determine if ML can offer improvements over existing methods. Additionally, this work investigates the impact of various empirical relationships on the breaking term of design load equations for a bridge pier. As with any empirical approach, the accuracy of ML methods is dependent upon the quality and quantity of data available, and additional data would benefit this analysis.

DATA SOURCES

The primary source of data for this work was acquired from a freshwater and sea ice flexural strength database developed by Aly et al. (2019). The database contains a compilation of test results as presented in technical publications and contains results from over 2000 freshwater and 2800 sea ice beam tests. Additional data from Karulina et al. (2019) pertaining to a series of field programs conducted between 2010 and 2018 were appended to the Aly et al. (2019) database.

The database includes flexural strength values obtained from three testing approaches: 3-point bending, 4-point bending and cantilever. For the work presented herein each test entry in the database must contain flexural strength, beam volume, brine volume and temperature. Brine volume (v_b) is generally quoted in terms of volume parts per thousand (ppt). It can also be represented as a volume fraction, for instance, 40 ppt = 0.040. For database entries in which brine volume was not available but temperature (T) and salinity (S) were provided, brine volume was estimated using (1) as derived by Frankenstein and Garner (1967).

$$v_b = \mathrm{S}\left(\frac{49.185}{T} + 0.532\right) \qquad (1)$$

The database contains tests conducted on beams extracted from naturally occurring ice sheets as well as laboratory grown ice. The strength of natural ice can be compromised by the inclusion of naturally occurring flaws and/or debris, while laboratory grown ice is generally prepared to limit the formation of such flaws. As a result, laboratory grown ice generally exhibit higher strength properties than naturally occurring ice. As this work is primarily interested in the strength of naturally occurring ice, tests conducted on laboratory grown ice have been omitted.

MODEL COMPARISON METRICS

Multiple machine learning models were generated for the prediction of flexural strength; therefore, a set of comparison metrics were required in order to rank the performance of each model. Firstly, two statistical metrics were generated for each model including the root mean square error (RMSE) and the coefficient of determination, or R^2 value. Secondly, a more qualitative approach was taken in which the models were compared based on how well they predicted the expected physical behaviors of ice.

The RMSE metric provides an indication of the model accuracy, and the average variance between the observed and predicted values. The RMSE is calculated according to the following:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{2}$$

where y_i is the i[th] observed sample, $\hat{y}_i$ is the i[th] predicted sample and n is the number of samples. The R^2 of each model provides an indication of how well the independent variables (beam volume, brine volume and ice temperature) can explain the variances observed in the dependent variable (flexural strength). The R^2 for each model was calculated according to the following:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

where y_i is the i[th] observed sample, $\hat{y}_i$ is the i[th] predicted sample, $\bar{y}_i$ is the mean of the observed samples, and n is the number of samples.

The modeled flexural strength of sea ice is expected to follow an inverse relationship to beam volume, brine volume and temperature. When observing strength vs beam volume, the presence of scale effects trends should be evident as discussed by Aly et al. (2019) and Williams and Parsons (1994), as larger beams include more internal flaws resulting in lower flexural strength. Similarly, the porosity of a sample increases with brine volume resulting in a loss of flexural strength (Timco and O'Brien, 1994). The effect of ice temperatures on flexural strength is a coupled effect, as the temperature affects both the ice lattice itself as well as the brine volume (Timco and O'Brien, 1994), resulting in higher strength at lower temperatures.

BASIC EMPIRICAL MODELS

Within the technical literature there are a number of exponential empirical models which estimate the flexural strength of sea ice based on the physical properties of the sample, including beam volume, brine volume and temperature. In this work several exponential empirical models were used as a benchmark for the machine learning models.

The single most important factor in the strength of sea ice is that of brine volume. In this work, two single-parameter exponential models based on brine volume (v_b) were employed including a model developed by Ji et al. (2011) as shown in (4), and Timco and O'Brien (1994) as shown in (5).

$$\sigma_f = 2.41 \cdot e^{-4.29\sqrt{v_b}} \tag{4}$$

$$\sigma_f = 1.76 \cdot e^{-5.88\sqrt{v_b}} \tag{5}$$

A third model was developed for this paper based on the same model format, and fitting the model to the current database, the resultant model is provided in (6). A comparison between the new model and the models developed by Ji et al. (2011) and Timco and O'Brien (1994) are provided in Figure 1. The new model is very close to Timco and O'Brien's model at lower brine volumes however, it tends to approach Ji's model as brine volume increases.

$$\sigma_f = 1.70 \cdot e^{-4.21\sqrt{v_b}} \tag{6}$$

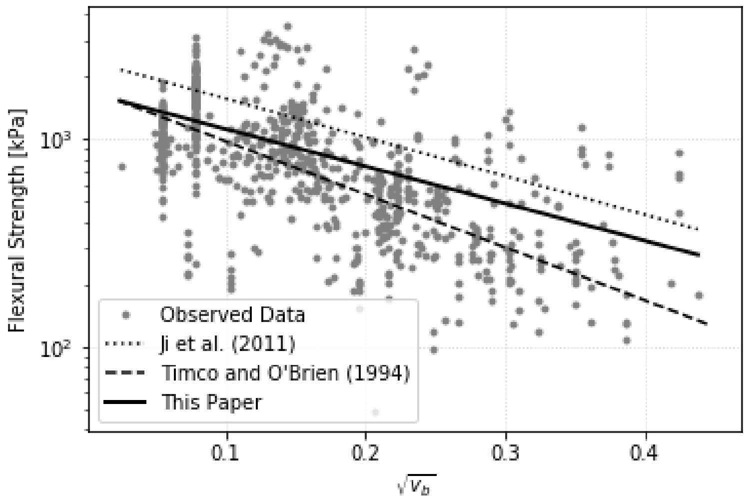

Figure 1. Exponential empirical models – flexural strength as a function of the square root of the brine volume fraction

A relationship between ice temperature and flexural strength was proposed by Ji et al. (2011), in which strength has an inverse linear relationship to temperature as shown in (7). Two additional models were developed using the current database including both linear and a single parameter polynomial regression as presented in Figure 2. The polynomial regression model was considered a better fit to the data and the resulting model is presented in (8).

$$\sigma_f = 0.35 - 0.09T \tag{7}$$

$$\sigma_f = 0.378 \cdot |T|^{0.424} \tag{8}$$

The influence of scale effects on the flexural strength of ice has been debated within technical publications, however, authors such as Butkovich (1959), Williams and Parsons (1994), and Aly et. al (2019) suggest scale effect trends are a contributing component to the flexural strength equation. Two-parameter exponential models which couple the effects of beam volume and brine volume (v_b) were proposed by Williams and Parsons (1994) and Aly et al. (2019) and are shown below in (9) and (10) respectively. Using the same equation format a separate model was fit to the current database resulting in the model presented in (11). A comparison between the three models is provided in Figure 3 and Figure 4.

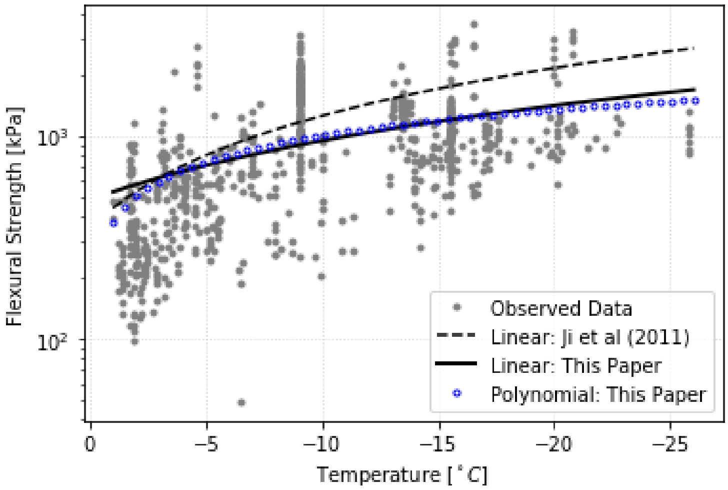

Figure 2. Empirical models – flexural strength as a function of temperature

$$\sigma_f = 1760 \left(\frac{V}{V_1}\right)^{-0.057} e^{-5.395\sqrt{\nu_b}} \tag{9}$$

$$\sigma_f = 1324 \left(\frac{V}{V_1}\right)^{-0.054} e^{-4.969\sqrt{\nu_b}} \tag{10}$$

$$\sigma_f = 559 \left(\frac{V}{V_1}\right)^{-0.128} e^{-1.358\sqrt{\nu_b}} \tag{11}$$

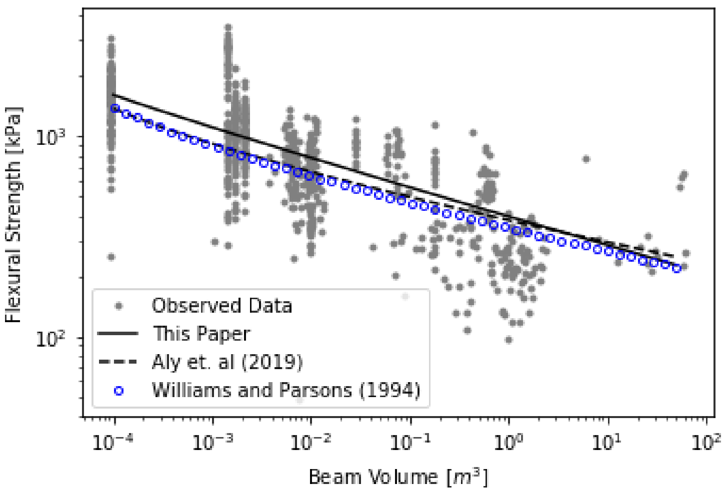

Figure 3. Two-parameter empirical models – flexural strength as a function of beam volume

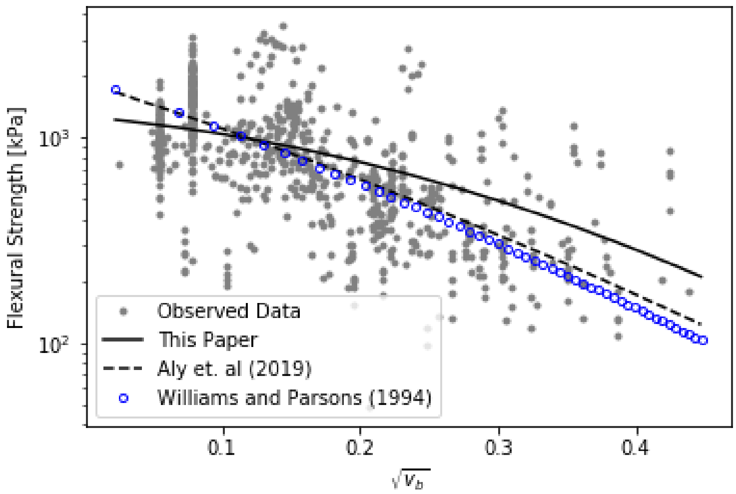

Figure 4. Two-parameter empirical models – flexural strength as a function the square root of the brine volume fraction

MACHINE LEARNING MODELS

Developing an empirical model for a given relationship generally requires the selection of a predefined equation of fit, for instance the linear and exponential models discussed previously. ML regression models are not confined by such initial biases, instead learning algorithms are employed to interpret the relationship between the dependent and independent variables. Four ML regression models were developed based on the multilayer perceptron (MLP), extra trees (ETR), gradient boosted trees (GBR) and k-nearest neighbors (KNR) regression algorithms. Further details on these algorithms can be found in the technical literature, such as Belyadi and Haghighat (2021), Zhou (2021) and Scikit-learn (2021). Ensemble modelling is an approach where two or more models can be combined to help balance out the individual weakness (e.g. variance and bias) of the independent models. Using this approach 6 ensemble models, each composed of a pair of individual models, were generated based on the initial 4 models. All models were generated and tuned using a Python ML library developed by Scikit-learn (2021). Three models were chosen for further investigation in this work including MLP, ETR and the MLP+ETR ensemble. These three models were chosen based on a combination of model accuracy and ability to generalize to new data.

For the presentation of model results, a database of simulated data was developed based upon observed relationships between key ice parameters as presented in the observed data. Three simulated datasets were developed, one corresponding to each of the three independent variables (beam volume, brine volume and ice temperature). Using one of these three independent variables the other two were then derived based on the observed relationships between the variables. These simulated databases help enhance the trendlines resulting from the ML models by reducing some of the variability seen in observed data.

Machine learning model results based on simulated data are shown in comparison to an empirical model in Figure 5, Figure 6 and Figure 7, model accuracies are provided in Table 1. The relationship between flexural strength and each of the three physical ice properties was shown to follow the expected trends for all three models. However, the model of most interest moving forward is the MLP+ETR ensemble, as it draws on the strengths of both the individual models. More details on the other models and the selection of the chosen models will be available in future publications.

While the influence of beam volume, temperature and brine volume on flexural strength can be observed in Figure 5, Figure 6 and Figure 7; the individual influence of these parameters is often hidden as a result of the coupled effects between the parameters. To highlight the influence of an individual parameter the simulated beam volume dataset was modified in which one parameter was systematically changed. The ensemble model was run on two nearly identical datasets, except that the temperature values in one were set to a constant of -1°C, and the other set to -25°C. A similar approach was used for brine volume where the model was run on two modified datasets (5 ppt and 50 ppt), the results are also provided in Figure 8. The data in Figure 8 strengthens the argument that flexural strength is dependent upon temperature, brine volume and beam volume.

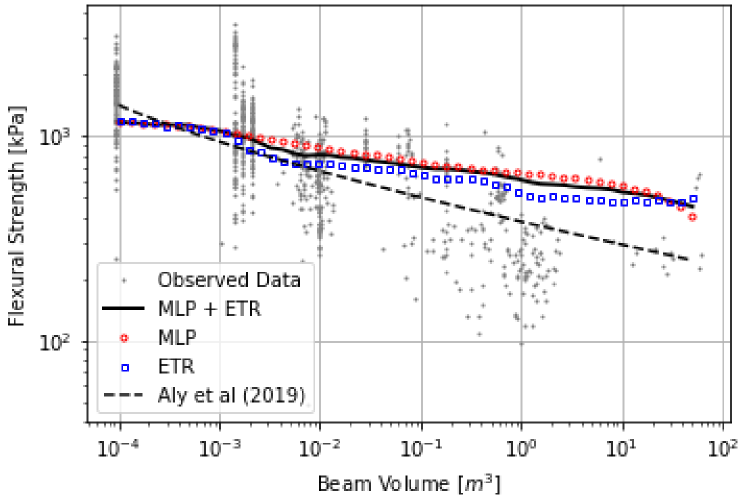

Figure 5. ML models: flexural strength as a function of beam volume

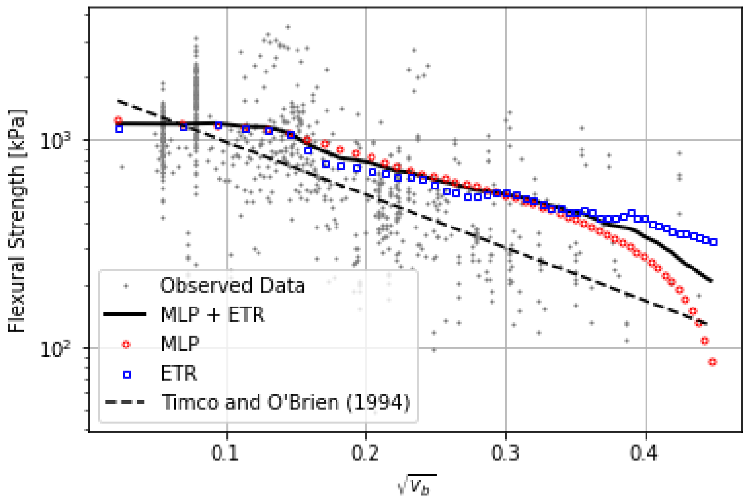

Figure 6. ML models: flexural strength as a function of the square root of the brine volume fraction

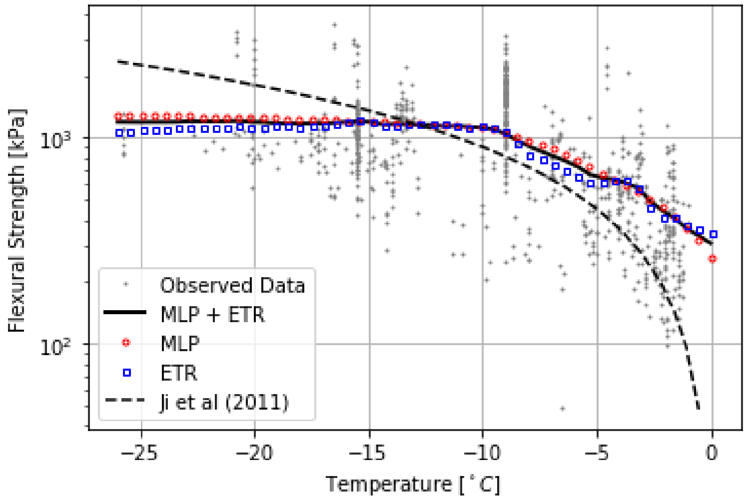

Figure 7. ML models: flexural strength as a function of temperature

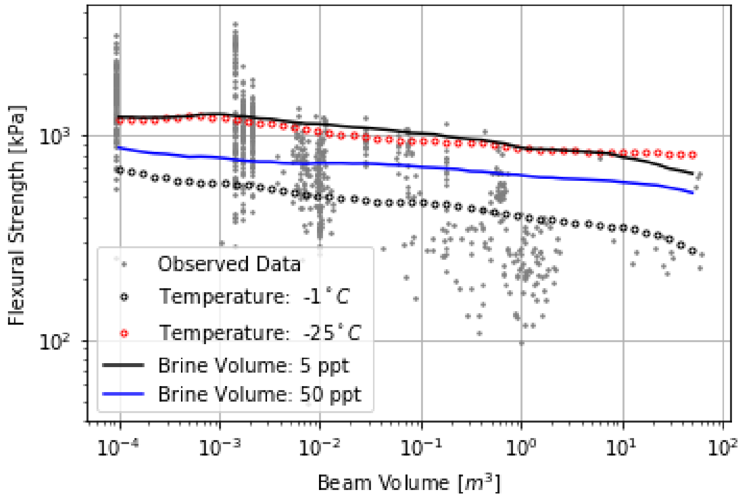

Figure 8. ML ensemble model: flexural strength as a function of temperature and brine volume variations

Table 1. Machine Learning Model Results

Model	R^2 Training Set	R^2 Test Set	RMSE Training Set	RMSE Test Set
MLP	0.35	0.31	0.47	0.53
ETR	0.52	0.48	0.41	0.46
MLP + ETR	0.46	0.42	0.43	0.48

LEVEL ICE LOADS

A comparison study was conducted to determine the impact of flexural strength modeling on level ice loads and how variability in ice parameters can affect these loads. A single pier from the Confederation Bridge was chosen as the test structure for the study. The total horizontal ice load on the pier is a combination of the load to cause flexural failure of the ice sheet and the forces required to push broken ice blocks up the sloped surface. The force to push blocks up the slope is independent of flexural strength and was omitted from this study. The force required to initiate flexural failure, see (12), is based on the method presented in Brown et al. (2001). Here α is the cone angle, μ is the ice-cone coefficient of friction, σ_f the flexural strength, D the diameter of the cone at the waterline, ρ_w the density of water, g the gravitational acceleration, h the ice thickness, E is the Young's modulus of ice and l_c is the critical circumferential crack length as defined in (13). The values for α and μ were set at 52 degrees and 0.2 respectively as described in Brown et. al (2001).

$$F_{Flex} = 0.68\left(\frac{\sin\alpha+\mu\cos\alpha}{\cos\alpha-\mu\sin\alpha}\right)\sigma_f D\left[\frac{\rho_w g h^5}{E}\right]^{0.25}\left[1+\frac{\pi^2 l_c}{4D}\right] \tag{12}$$

$$l_c = \pi\left(\frac{\mathrm{E}h^3}{12\rho_w g(1-v^s)}\right)^{0.25} \tag{13}$$

Deterministic design loads were calculated using the flexural strength outputs from the MLP + ETR ensemble model and select empirical models to determine if any significant differences are present between the different approaches.

A comparison was made between the ML model and the Ji et al. (2011) temperature model (7) for ice temperatures of -1, -5 and -10°C as seen in Figure 9. In this comparison brine volume was held constant at 35ppt and beam volume was estimated at $7h_{\text{ice}}^3$ based on recommendations by Schwarz et at. (1981). The ML and empirical predictions are very similar at warmer temperatures, with the ML loads being slightly lower. As the temperatures decrease the strength values from the Ji et al. (2011) model increase quicker than the ML model resulting in higher loads. A second comparison was conducted in which the Timco and O'Brien (1994) brine volume model (5) and Aly et. al (2019) brine volume and beam volume model (10) were also included as seen in Figure 10. In this comparison temperature was varied from -1°C to -20°C, beam volume was a constant and estimated based on a level ice thickness of 0.4m, and brine volume was estimated based on the observed relationship between temperature and brine volume as seen in the observed data. The Ji et al. (2011) model loads are significantly higher than the other 3 models, and the Ji et al. (2011) model has a steeper load vs temperature trendline compared to the other models. The ML model load is relatively constant for temperatures below -12°C, and at warmer temperatures the ML, Timco and O'Brien (1994) and Aly et. al (2019) models have similar trendlines.

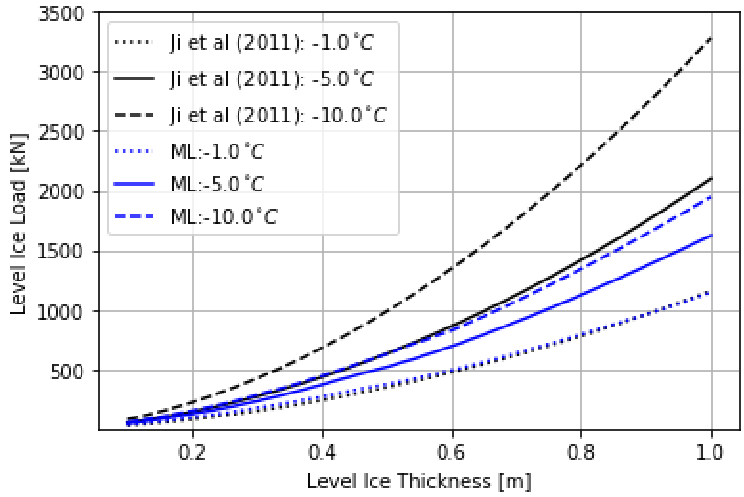

Figure 9. Level ice load as a function of ice thickness and temperature

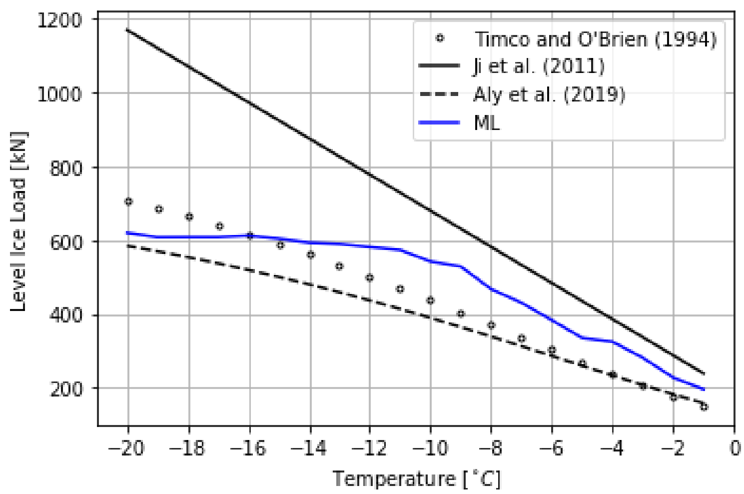

Figure 10. Level ice load as a function of temperature

CONCLUSIONS

The application of machine learning was applied to a comprehensive database of flexural strength ice data. A total of 10 ML models were developed and tested, three models were chosen for discussion in this paper with primary focus being given to the ensemble model composed of multilayer perceptron and extra trees regression algorithms. Additional publications are planned in which the other ML models will be discussed in more detail.

The ML models have shown great promise demonstrating the presence of scale effects trends as well as temperature and brine volume dependencies. The empirical models are more sensitive to input parameters than the ML model, for example in Figure 9 the increase in load resulting from a decrease in temperature was much more substantial for the empirical model. The ML model was on average 20-30% higher than the Timco and O'Brien (1994) and Aly et at. (2019) models, and about 25% lower than the Ji et al (2011) model.

Further work is needed to assess the degree to which inconsistencies in the clustering and ranges of data influence ML models, as compared with “traditional” models. On the one hand, one would expect that the underlying trends in factors influencing strength should be continuous, smooth functions over the entire range reflecting the underpinning physics, and yet the form of such traditional models constrain the fit of the data such that they may not be able capture some of the more subtle effects in the data. This presents analysts with a dilemma, since ML models can potentially capture non-linear effects in the data in ways that are not possible using traditional regression models, but if the data are collected over a broad range of conditions comprised of irregular collection intervals, with highly clustered data in some ranges and sparse data in others, one may question whether the more detailed ML model better captures the underlying physics or whether it better captures anomalies in the types, amounts and clustering of subsets of data that make up the aggregate set. While it is beyond the scope of this paper to reconcile these broader questions, it is clear that the ML models considered here provide a promising tool to aid in the interpretation and modelling of ice strength relationships and which warrants further development.

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