POAC'23
Glasgow, United Kingdom

Proceedings of the 27th International Conference on
Port and Ocean Engineering under Arctic Conditions
12-16 June 2023, Glasgow, United Kingdom

Iceberg Drafts Assessment using Decision Tree Regression (DTR), Artificial Neural Network (ANN), and Support Vector Regression (SVR) algorithms

Hamed Azimi[1], Hodjat Shiri[1], and Masoud Mahdianpari[2, 3]

[1]Civil Engineering Department, Faculty of Engineering and Applied Science, Memorial University of Newfoundland, A1B 3X5, St. John's, NL, Canada
[2]Department of Electrical and Computer Engineering, Faculty of Engineering and Applied Science, Memorial University of Newfoundland, A1B 3X5, St. John's, NL, Canada
[3]C-CORE, 1 Morrissey Rd, A1B 3X5, St. John's, NL, Canada

ABSTRACT

Nearly one-fifth of the Earth's undiscovered hydrocarbons are reserved in the Arctic area whereas, the recent offshore oil and gas loading equipment, e.g., subsea pipelines, wellheads, and communication cables, developed in the Arctic waters has led to a considerable awareness of the iceberg draft prediction. The iceberg tip would gouge the ocean floor and the operational integrity of the sea bottom-founded infrastructures may be threatened in the Arctic shallower waters if the ocean depth is smaller than the traveling iceberg draft. Hence, developing an intelligent and cost-effective solution to predict iceberg drafts is necessary to guarantee the operational integrity of the subsea assets. In this study, the iceberg drafts were simulated using three machine learning (ML) algorithms comprising decision tree regression (DTR), artificial neural network (ANN), and support vector regression (SVR). Initially, using the parameters governing the iceberg draft simulation, a set of ML models was defined. By performing several analyses including sensitivity analysis, error analysis, and uncertainty analysis, the premium ML model along with the most significant input parameters was introduced. The obtained outcome can smooth the path to offer alternative techniques to maintain the time and expenditures of the iceberg management projects and subsea structure design, specifically in the primary phases of the construction methodology, corresponding logistics, and the prospective scope of engineering design projects.

KEY WORDS: Iceberg draft simulation; Subsea infrastructures; decision tree regression (DTR); artificial neural network (ANN); support vector regression (SVR).

INTRODUCTION

Every year many icebergs are born out of glaciers in the Arctic area and carried away by the currents and into the North Atlantic. These traveling masses may touch the sea bottom in shallow waters and scratch the seabed, causing "ice gouging" that can endanger the integrity of subsea pipelines and power cables or even directly collide with offshore structures such as ships, platforms, wind turbines, subsea manifolds, etc. Currently, Ice Management such as iceberg towing and re-routing is the most reliable approach to protect the subsea and offshore infrastructures, where the threatening icebergs are hooked and towed in a safe direction. Ice management is generally a costly operation and requires standby marine spread with a range of advanced tools, vessels, and equipment, like subsea survey facilities, to investigate the iceberg draft and determine if it is a threat to infrastructures. Moreover, the Arctic offshore regions with rich wind culture have a high potential for the development of offshore wind farms (Blažauskas et al. 2013). The schematic layout of the iceberg free-floating and iceberg scouring in cold waters is displayed in Figure 1. As shown, the iceberg is in a free-floating circumstance if the ocean depth is greater than the iceberg draft; otherwise, the seafloor is scoured, and the seabed soil shear resistance causes the soil displacement to extend deeper than the iceberg tip threatening the buried subsea assets.

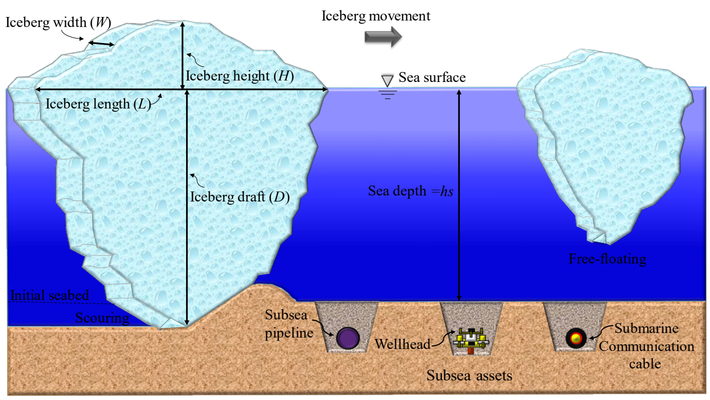

Figure 1: Icebergs in scouring and free-floating circumstances

Owing to the significance of the iceberg draft estimation, extensive experimental, analytical, and numerical studies have been conducted in the domain. For example, McKena (2000) evaluated the threat of ice gouging to offshore petroleum installations serving in the Grand Banks region. The author showed that the iceberg proportions were a function of the iceberg length. Sonnichsen et al. (2003) reported the seafloor surveys and ice gouging on the Grand Bank of Canada in the 2000 iceberg season. The drafts of the iceberg were recorded through a lateral scan sonar tool mounted on the tracking boat. The study demonstrated that there was serious concern about the precision of lateral scans of iceberg draft estimation. Barker et al. (2004) specified the iceberg sails and drafts utilizing the dimensions marked in the field. The investigation revealed that the iceberg draft could be approximated regarding the iceberg waterline length. Dowdeswell and Bamber (2007) scrutinized the draft deepness of traveling icebergs in the Antarctic waters. The authors calculated the draft through the ice thickness, keel depth at the grounding line, and surface elevation. The study ended that a small minority of icebergs in the Antarctica and Greenland waters had drafts deeper than 650 m. Sacchetti et al. (2012) explored the iceberg features and ice scouring in Labrador and Hibernia territories. The characteristics of various icebergs such as wedged, domed, tabular, and pinnacle bergs were considered in this examination. The authors proposed a set of relationships in terms of the iceberg length to predict the iceberg draft. King et al. (2016) completed field experimentation to count the rolling iceberg rate. The iceberg draft was surmised by a calving study, with a computed standard deviation of draft changes from 19% to 34%. The iceberg draft has been approximated using the iceberg mass. Turnbull et al. (2018) suggested an instance of the drift mensuration of shifting icebergs on the Grand Banks of Newfoundland. The study stated that the iceberg draft estimated was roughly 1.3 times deeper than the real iceberg draft. McKenna et al. (2019) modeled the ice gouging on the Grand Banks of Canada adopting the Monte Carlo simulation (MCs). The iceberg draft variations were also employed to reduce the dimension of draft changes in the applied methodology. Stuckey et al. (2021) modeled the 3D iceberg forms through a field survey. The examination exhibited that the iceberg drafts were summed in terms of iceberg length through the power method. They provided two practical instances concerning the information gathered in 2016 and the post-2000 report. Despite the wide applications of machine learning (ML) technology in multifarious fields to simulate different linear and nonlinear problems (Azimi and Shiri 2021a, Azimi et al. 2022, Azimi et al. 2023), the literature indicated that the iceberg draft has not been predicted using ML algorithms so far. Hence, to fill this knowledge gap, the iceberg drafts were simulated through three robust ML algorithms, e.g., artificial neural network (ANN), decision tree regression (DTR), and support vector regression (SVR) models. More information will be presented in the forthcoming sections.

METHODOLOGY

Artificial neural networks (ANN)

ANN is one of the most universally supervised machine learning (ML) algorithms. The main structure of an ANN algorithm consists of at least three distinct layers comprising an input layer, a hidden layer, and an output layer. The input parameters are embedded within the input layer, while the target parameter, e.g., the iceberg draft, is considered in the output layer. The hidden neurons are situated within the hidden layer, where the size of this layer is determined by the problem's complexity and desired accuracy (Azimi and Shiri 2021b). The number of hidden layer neurons was initially set as one and the magnitude of this hyperparameter was increased to 15, where the optimum number of the hidden layer neurons was chosen at 12 for the reason that the proficiency of the ANN algorithm was negligibly altered after this amount. In each hidden neuron, both the input parameters and their weights are calculated using mathematical operations, and the outcome is passed through a transfer function entitled the activation function. The sigmoid function was applied for the current architecture because it had better performance in comparison with other activation functions. Subsequently, the performance of the ANN algorithm was evaluated by the Mean squared error (*MSE*) as the loss function in the present study to measure the difference between the computed outputs and the target outputs.

Decision tree regression (DTR)

A tree data system contains a series of leaves and branches in which each node is regarded as a decision tree (DT). The DT may be used to solve both regression and classification problems. The DT comprises many components, such as a root node, several leaf nodes, internal nodes, and branches. The topmost node in this tree is considered the root node, and the leaf nodes (terminal nodes) end with the titles of types, while the non-leaf nodes are assumed as the internal nodes. Such nodes link to each other through the branches (Pekel 2020). In the present work, the mean squared error (MSE) is involved in maintaining the fitness function in the DT algorithm. In this investigation, the hyperparameters of the DTR algorithms were determined using a trial-and-error strategy. It means that the value of *max_depth*, *max_leaf_nodes*, and *min_weight_fraction_leaf* was primary at 10, 2, and 0.01, and the performance of the DTR algorithm was assessed. The number of hyperparameters was raised in the following stages until the DTR's results reached an adequate level. The DTR model estimated the iceberg drafts with its highest level of precision and correlation as well as its lowest degree of complicatedness until the number of hyperparameters comprising the *max_depth*, *max_features*, *max_leaf_nodes*, *min_samples_leaf*, *min_weight_fraction_leaf*, and *splitter* was, in turn, adapted as 150, *'auto'*, 2, 2, 0.001, and *'random'*.

Support vector regression (SVR)

A support vector machine (SVM) is known as a supervised learning ML algorithm to solve both classification and regression problems. The SVM is based on Vapnik-Chervonenkis (VC) theory, and this algorithm was proposed by Vapnik (1995). To simulate the regression problems, SVR is applied in which the training data is mapped from the input variables (input space) into the objective parameter (feature space) through a function (♀). In the feature space, a separating hyperplane with the highest margin is produced. In a regression problem, a nonlinear transformation from the input space to high-dimensional space is made by using the ♀ function. Regardless of the transformation function (♀), the kernel function can implement the dot product in the multidimensional feature space through the low-dimensional space input variables. In practical applications, several kernel functions comprising the linear, polynomial, and radial basis functions (RBF) are utilized in the SVR algorithm. Moreover, the ε-insensitive loss function is employed as a cost function in this model. To simulate the iceberg drafts in this study, the parameters of the SVM algorithm, such as the penalty parameter (C), the kernel coefficient (gamma), epsilon, verbose, and kernel were respectively tuned as 0.01, 1, 0.5, 1, and linear. The applied parameters of the SVM model in the current study were chosen based on a trial and error method. The Flowchart of the SVR algorithm applied in the current study is shown in Figure 2. Regarding the flowchart, the constructed dataset was initially loaded and it was divided into the training and testing sub-samples. Subsequently, the iceberg drafts were simulated by using the parameters affecting the SVR model. If the performance of the SVR was acceptable, the results were compared with the ANN and DTR algorithms; otherwise, the SVR's hyperparameters were tuned. It is worth mentioning that the definition of acceptable performance for the ML algorithm is determined by the applied indices in equations (8) to (13). These statistical indices assess the accuracy, correlation, and complexity of the ML model at the same time.

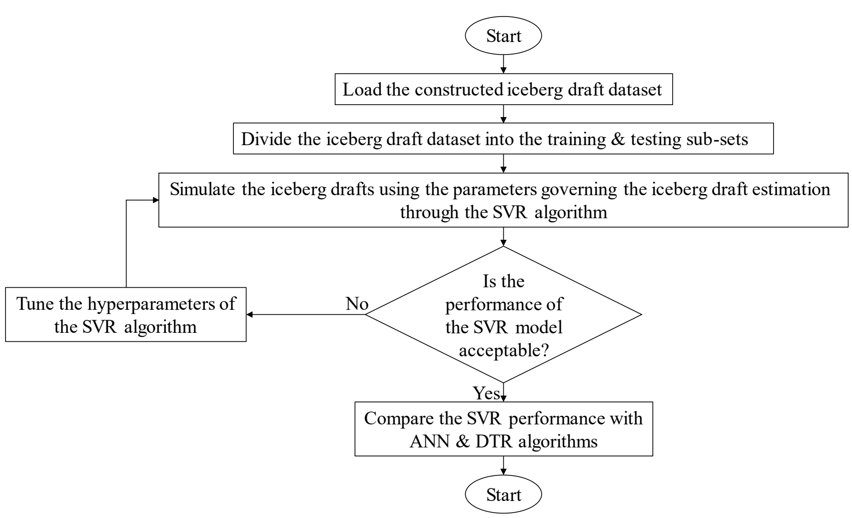

Figure 2. Flowchart of the SVR algorithm applied in the current study

Iceberg drafts

The iceberg draft (*D*) was assumed as a function of the physical characteristics of the iceberg, comprising the iceberg length (*L*), iceberg height (*H*), iceberg width (*W*), iceberg mass (*M*) in several fields, analytical, and numerical studies in the form below (Barker et al. 2004; McKenna et al. 2019; and Stuckey et al. 2021):

$$D = f_1(L, H, W, M). \tag{1}$$

Furthermore, the density of an iceberg (ρ_i), the density of seawater (ρ_{sw}), seawater viscosity (μ_{sw}), and gravitational acceleration (g) may influence the iceberg draft as follows:

$$D = f_2(L, H, W, M, \rho_i, \rho_{sw}, \mu_{sw}, g) \tag{2}$$

The iceberg shape factor (S_f) signifies the global shape of icebergs, which can affect the magnitude of the iceberg draft (Turnbull et al. 2018).

The iceberg shape factor has been already defined. The shape factor of an iceberg describes the estimated fraction filled by the iceberg sail of a rectangle whose dimensions are the length by the height (Turnbull et al. 2015).

The shape factor of the traveling icebergs is considered universally into six categories including Tabular (S_f=0.5), Blocky (S_f=0.5), Domed (S_f=0.41), Dry Dock (S_f=0.15), Pinnacle (S_f=0.25), and Wedge (S_f=0.5) (Rudkin 2005). Hence, equation (2) can be summarized below:

$$D = f_3\left(L, H, W, M, \rho_i, \rho_{sw}, \mu_{sw}, g, S_f\right) \tag{3}$$

It is assumed that the density along with viscosity of the seawater is constant and the value of gravitational acceleration can be regarded as a constant value; as a result, equation (3) is rewritten as follows:

$$D = f_4\left(L, H, W, M, \rho_i, S_f\right). \tag{4}$$

The dimensional form of equation (4) is written below:

$$D = f_5(\Pi_1, \Pi_2, \Pi_3, \Pi_4) \tag{5}$$

here, Π_1, Π_2,…, and Π_4 are dimensionless groups and f_5 is a functional symbol based on the Buckingham-π theorem. Thus, the dimensionless groups below are written:

$$\Pi_1 = \frac{L}{H}, \Pi_2 = \frac{W}{H}, \Pi_3 = \frac{M}{\rho_i . H^3}, \Pi_4 = S_f \tag{6}$$

Equation (5) is then formulated as a function of four dimensionless groups as follows:

$$\frac{D}{H} = f_6\left(\frac{L}{H}, \frac{W}{H}, \frac{M}{\rho_i . H^3}, S_f\right) \tag{7}$$

Therefore, D/H as the iceberg draft ratio is a function of the length ratio (L/H), width ratio (W/H), the mass ratio $(M/\rho_i . H^3)$, and iceberg shape factor $\left(S_f\right)$. Subsequently, the ML models applied in the current investigations were fed with the input parameters in equation (7). Hence, four dimensionless groups, including length ratio (L/H), width ratio (W/H), the mass ratio

($M/\rho_i.H^3$), and iceberg shape factor $\left(S_f\right)$ were applied to estimate the iceberg draft ratio (D/H) through the ML models in the present work. Figure 4 illustrates the combinations of four dimensionless groups introduced to develop the ML models. As seen, to identify the premium ML models, five ML models, e.g., Model 1 to Model 5 were developed, while Model 6 to Model 9 were defined to recognize the most influencing input parameters. Model 1 included all input factors, whilst these dimensionless groups were disregarded one at a time in Model 2 to Model 5. Additionally, models 6 to 9 predicted the iceberg drafts solely one input parameter.

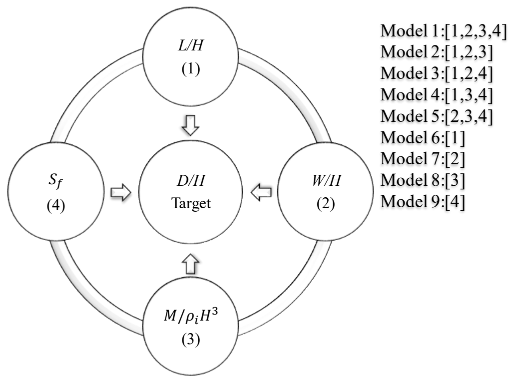

Figure 4. Input combination applied for developing the ML models

Construction of database

Several field observations were adopted to analyze the iceberg draft. The key values of 12 field studies reported by El-Tahan et al. (1985) (38 cases), Woodworth-Lynas et al. (1985) (one case), Løset and Carstens (1996) (52 cases), Barker et al. (2004) (14 cases), McKenna (2004) (two cases), Sonnichsen et al. (2006) (nine cases), Turnbull et al. (2015) (two cases), McGuire et al. (2016) (eight cases), Younan et al. (2016) (29 cases), Talimi et al. (2016) (one case), Zhou (2017) (three cases), Turnbull et al. (2018) (two cases) were used.

It is worth noting that the iceberg drafts in the El-Tahan et al. (1985) study were measured using a set of technices such as submarine cables, exploration vessels, shore-based radar, drill-rig radar, etc. Woodworth-Lynas et al. (1985) utilized acoustic profilers and sextants to measure the iceberg draft. Løset and Carstens (1996) calculated the iceberg draft through the real dimension above the water surface. Barker et al. (2004) employed the sonar profiles of the iceberg draft to document the iceberg draft. McKenna (2004) reported the magnitude of the iceberg draft by analyzing the iceberg profiles obtained from sonar technology. Sonnichsen et al. (2006) asserted that the side scan sonar equipment had been applied to approximate the iceberg draft. Turnbull et al. (2015) estimated iceberg draft regarding the relationships between above-water height and underwater depth. McGuire et al. (2016) applied a multi-beam sonar system for the iceberg draft measurement. Younan et al. (2016) scanned the iceberg drafts by means of a sideway-oriented multi-beam mounted on a remotely operated vehicle (ROV). Talimi et al. (2016) reported that the dimensions of the applied iceberg in this study were obtained from multi-beam sonar profiling. Zhou (2017) used the digital iceberg which was profiled by the National Research Council Canada (NRC). Turnbull et al. (2018) quantified the iceberg draft using a multi-beam profiling system.

The T-test and the P-value for the dataset were calculated, presuming that the P-value of 0.05 or less is statistically significant (Azimi and Shiri 2020), where the likelihood of the relationship between the observed values is influenced by an alternative hypothesis. This P-value for the constructed dataset was estimated as 0.008, representing that the correlations were statistically significant. It is worth mentioning that 60% of the constructed database was utilized for training the ANN, DTR, and SVR models, whereas 40% of the remaining dataset was employed to test these models.

Goodness of fit

To examine the precision, correlation, and complexity of the ML models, several criteria such as correlation coefficient (*R*), root mean square error (*RMSE*), mean absolute percentage error (*MAPE*), Willmott Index (*WI*), coefficient of residual mass (*CRM*), and Akaike Information Criteria (*AIC*) were utilized. The proximity of the *R* and *WI* criteria to one showing the ML model tended to have a high degree of correlation with the values observed. The nearness of the *RMSE*, *MAPE*, and *CRM* indices to zero representing the ML model possessed the lowest degree of impreciseness; however, the complexity of the ML models was not examined through the indices applied. To overcome this restriction, the Akaike Information Criteria (*AIC*) was used. (Azimi et al. 2022).

$$R = \frac{\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (9)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{P_i - O_i}{O_i}\right| \quad (10)$$

$$WI = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (11)$$

$$CRM = \frac{\sum_{i=1}^{n} O_i - \sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} O_i} \quad (12)$$

$$AIC = n \times \log\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}\right) + 2k \quad (13)$$

Here, O_i, P_i, $\bar{O}$, $\bar{P}$, n and k are respectively the observational value, the predicted amount, the average observational values, the average predicted amount, the number of observations, and the number of independent variables in the ML models.

RESULTS AND DISCUSSION

Sensitivity analysis

Figure 5 demonstrates the statistical indices calculated for the ANN, DTR, and SVR models. Model 1 estimated the iceberg drafts using L/H, W/H, $M/\rho_i.H^3$, and S_f parameter. The *RMSE* index for the ANN 1, DTR 1, and SVR 1 models was equal to 0.698, 0.848, and 0.896. The effect of the iceberg shape factor (S_f) was disregarded for model 2, where the value of the *AIC* criterion for the ANN 2, DTR 2, and SVR 2 models were respectively computed to be 132.007, 18.512, and 15.250. The iceberg mass ratio ($M/\rho_i.H^3$) was an eliminated factor for Model 3, e.g., ANN 3, DTR 3, and SVR 3, with a *WI* value of 0.455, 0.785, and 0.870, in turn. The value of the *CRM* statistical index for ANN 4, DTR 4, and SVR 4 was -1.016, 0.025, and 0.104 as the influence of the iceberg width ratio (W/H) was removed for these ML models. The iceberg length ratio (L/H) was ignored for the iceberg draft estimation using the ANN 5, DTR 5, and SVR 5 models when the *RMSE* amount for such models was surmised as 1.598, 2.059, and 1.713. Models 6 to 9 were the function of solely one input parameter, e.g., L/H , W/H , $M/\rho_i.H^3$, and S_f, respectively. The simulation outcomes demonstrated that the ANN 5, DTR 1, and SVR 3 models were detected as the superior models among the ANN, DTR, and SVR models. According to the performed sensitivity analysis, the iceberg length ratio (L/H) and the iceberg width ratio (W/H) had the highest degree of effectiveness to simulate the iceberg drafts, while the iceberg mass ratio ($M/\rho_i.H^3$) possessed an insignificant influence.

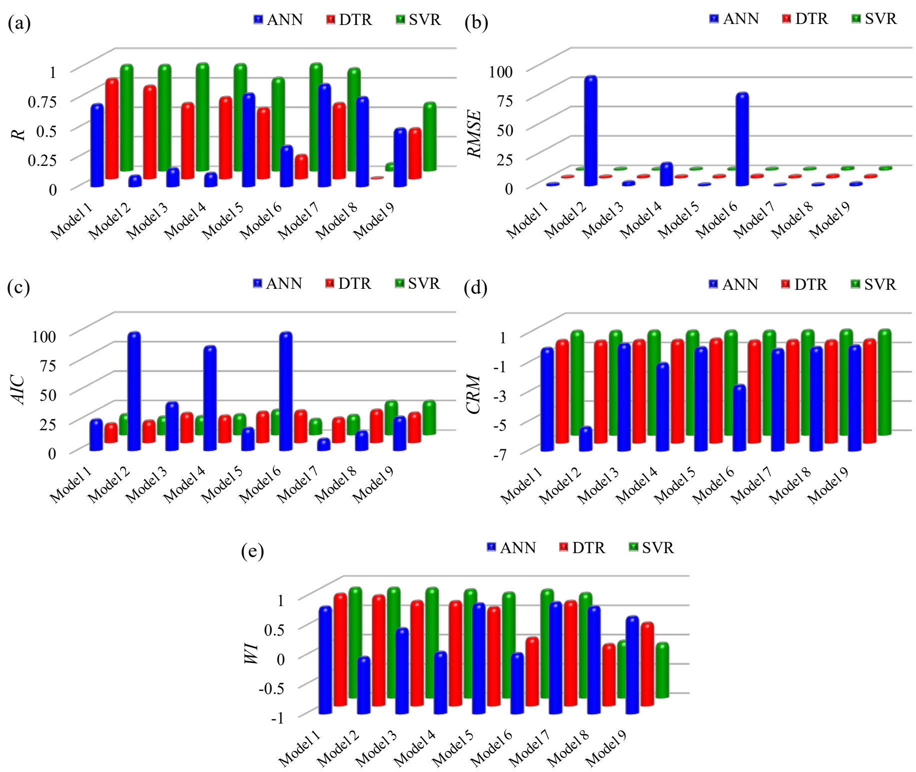

Figure 5. Comparison between the statistical indices calculated for the ANN, DTR, and SVR models

The error analysis showed that roughly one-fourth of iceberg drafts predicted by the ANN 1 model had an error of less than 10%, whereas this amount for the ANN 2, ANN 3, ANN 4, and ANN 5 models was approximately 17%, 23%, 31, and 33%, in turn. Almost 53% of the ANN 5 model's results possessed an error of smaller than 20% but this value for the ANN 6, ANN 7, ANN 8, and ANN 9 models was nearly 40%, 34%, 39%, and 50%, respectively. About one-third of the DTR 1, DTR 2, DTR 3, DTR 4, and DTR 5 models' results had an error of less than 18%; however, this value for the DRE 6, DTR 7, DTR 8, and DTR 9 models was near 21%, 26%, 18%, and 25%. Just about half of the iceberg drafts predicted by the SVR 3 model showed an error of less than 20% and this figure for the SVR 4 and SVR 5 was 42% and 40%. The performed error analysis demonstrated that ANN 5, DTR 1, and SVR 3 had the highest level of accuracy among the ANN, DTR, and SVR models, respectively.

Comparison between the superior models

The performed analysis in the previous section demonstrated that the ANN 5, DTR 1, and SVR 3 models were the superior models to estimate the iceberg drafts. Figure 7 exhibits the scatter plots for these superior models. The value of correlation coefficient (R) for the ANN 5, DTR 1, and SVR 3 models was respectively obtained at 0.789, 0.848, and 0.908. Hence, the SVR 3 predicted the iceberg drafts with the highest level of correlation.

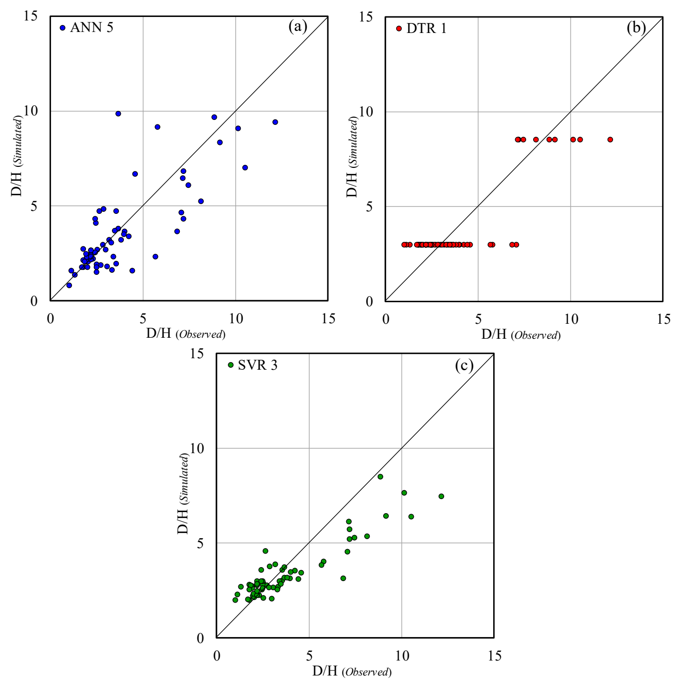

Figure 7. Scatter plots for the superior models (a) ANN 5 (b) DTR 1 (c) SVR 3

The study performed an uncertainty analysis (UA) to further assessment of the ETR models' performance. To do so, the ETR model's error was calculated as the difference between the iceberg drafts predicted through this model and the actual iceberg drafts. The mean (Mean) and the standard deviation (StDev) of such error, values were obtained. An individual ETR model underestimated the iceberg draft if the sign of the Mean value was negative, while the positive sign of the Mean meant that the ML models overestimated the iceberg drafts. Thereon, a confidence interval (CI) was produced near the error counted using the Mean, StDev values, and the "Wilson score technic" by omitting the continuity correction. A normal distribution interval corrected as an asymmetric normal distribution, named the Wilson score interval, was employed to adjust the CI bounds. Subsequently, a $\pm 1.96S_e$ yielded a 95%CI. It should be remarked that the width of the uncertainty bound (WUB) is half of the difference between the lower and upper bound (Azimi et al. 2023). Figure 8 illustrates the binomial and normal error distribution of the ANN 5, DTR 1, and SVR 3 models. Regarding the performed uncertainty analysis, the ANN 5, DTR 1, and SVR 3 models overestimated the iceberg drafts, with a Mean value of 0.252, 0.019, and 0.432. Moreover, the lowest value of StDev was known for the SVR 3 model. Although the widest uncertainty bound was calculated for the ANN 5 (WUB=±0.398), the width of the uncertainty bound for the DTR 1 and SVR 3 was equal to ±0.338. Therefore, the SVR 3 model as a function of L/H, W/H, and S_f was recognized to be the superior ML model to simulate the iceberg drafts in the present study. This model showed the lowest degree of complexity alongside the highest degree of accuracy and correlation with the observational values, where it biased toward the overestimation to predict the target parameter. It is worth noting that the iceberg length ratio (L/H) and the iceberg width ratio (W/H) were known as the most influential inputs in order to model the iceberg drafts.

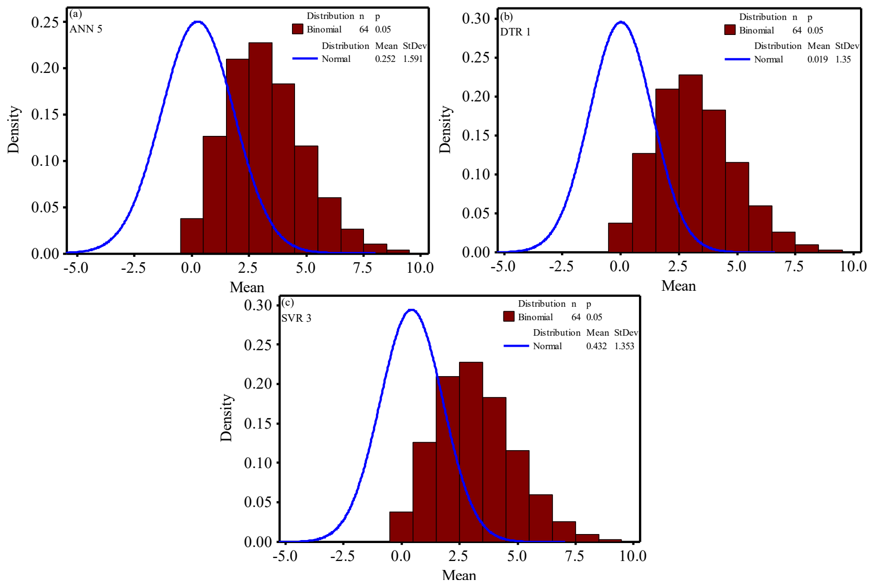

Figure 8. Binomial and normal error distribution of the superior models (a) ANN 5 (b) DTR 1 (c) SVR 3

CONCLUSION

In the present study, three ML algorithms, e.g., ANN, DTR, and SVR, were used to model the iceberg drafts. By performing several analyses including the sensitivity, error, and uncertainty analyses, the superior ML model alongside the most influencing input parameters was distinguished. The SVR algorithm outperformed the ANN and DTR methods in the estimation of the iceberg drafts. The conducted sensitivity analysis proved that the SVR 3 model as a function of L/H, W/H, and S_f was the superior ML model for the simulation of iceberg drafts. The SVR 3 model possessed the highest degree of precision, correlation, and simplicity, meaning that the value of *RMSE*, *R*, and *AIC* for this model was reckoned to be 1.411, 0.908, and 15.562. Regarding the performed error analysis, almost one-fifth of the simulation results of the SVR 3 model had an error of smaller than 12%. The performed uncertainty analysis revealed that the SVR 3 model overestimated the iceberg drafts, with the lowest value of the error standard deviation (StDev) at 1.353. The iceberg length ratio (L/H) and the iceberg width ratio (W/H) were found to be the most effective input parameters to model the iceberg drafts using the SVR algorithm. The obtained results gave a good understanding of the modeling of the iceberg drafts through ML algorithms in order to protect the offshore structures and subsea assets in the Arctic and subarctic areas. These outcomes can facilitate proposing of cost-effective and quick alternatives in the early stages of iceberg management projects and subsea structure designs.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support of "Wood Group," which established a Research Chair program in Arctic and Harsh Environment Engineering at the Memorial University of Newfoundland, the "Natural Science and Engineering Research Council of Canada (NSERC)", and the "Newfoundland Research and Development Corporation (RDC) (now TCII)" through "Collaborative Research and Developments Grants (CRD)". Special thanks are extended to Memorial University for providing excellent resources to conduct this research.

REFERENCES

Azimi, H., & Shiri, H., 2020. Dimensionless groups of parameters governing the ice-seabed interaction process. *Journal of Offshore Mechanics and Arctic Engineering*, 142(5), pp.051601.

Azimi, H., & Shiri, H., 2021a. Assessment of ice-seabed interaction process in clay using extreme learning machine. *International Journal of Offshore and Polar Engineering*, 31(04), pp.411-420.

Azimi, H., & Shiri, H., 2021b. Modeling subgouge sand deformations by using multi-layer perceptron neural network. *31st International Ocean and Polar Engineering Conference*. Rhodes, Greece, ISOPE-I-21-2150.

Azimi, H., Shiri, H., & Mahdianpari, M., 2022. Simulation of Subgouge Sand Deformations Using Robust Machine Learning Algorithms. *Offshore Technology Conference*. Houston, Texas, OTC-31937-MS.

Azimi, H., Shiri, H., & Zendehboudi, S., 2023. Prediction of Ice-Induced Subgouge Soil Deformation in Sand Using Group Method of Data Handling–Based Neural Network. *Journal of Cold Regions Engineering*, 37(2), pp.04023006.

Barker, A., Sayed, M., & Carrieres, T., 2004. Determination of iceberg draft, mass and cross-sectional areas. *14th international offshore and polar engineering conference*. Toulon, France. ISOPE-I-04-116.

Blažauskas, N., Włodarski, M., & Paulauskas, S., 2013. Perspectives for offshore wind energy development in the South-East Baltics. Klaipėda University: Klaipėda, Lithuania. 1-54.

Dowdeswell, J.A., & Bamber, J.L., 2007. Keel depths of modern Antarctic icebergs and implications for sea-floor scouring in the geological record. *Marine Geology*, 243(1-4), pp.120-131.

El-Tahan, M., El-Tahan, H., Courage, D., & Mitten, P., 1985. Documentation of Iceberg Groundings. Environmental Studies Research Funds. Report ESRF Vol. 7.

King, T., Younan, A., Richard, M., Bruce, J., Fuglem, M., & Phillips, R., 2016. Subsea risk update using high resolution iceberg profiles. *Arctic Technology Conference*. St. John's, Newfoundland and Labrador, Canada. OTC-27358-MS.

Løset, S., & Carstens, T., 1996. Sea ice and iceberg observations in the western Barents Sea in 1987. Cold Regions Science and Technology, 24(4), pp.323-340.

McGuire, P., Younan, A., Wang, Y., Bruce, J., Gandi, M., King, T., & Regular, K., 2016. Smart iceberg management system–rapid iceberg profiling system. *Arctic Technology Conference*. St. John's, Newfoundland and Labrador, Canada. OTC-27473-MS.

McKena, R., 2000. Study of iceberg scour & risk in the Grand Banks region. KR Croasdale & Associates Ltd., Ballicater Consulting Ltd., Canadian Seabed Research Ltd., C-CORE, and Ian Jordaan & Associates Inc., PERD/CHC Report, 31-26.

McKenna, R., 2004. Development of iceberg shape characterization for risk to Grand Banks installations. PERD/CHC Report, 20473.

McKenna, R., King, T., Crocker, G., Bruneau, S., & German, P., 2019. Modelling iceberg grounding on the grand banks. *Proceedings of the International Conference on Port and Ocean Engineering under Arctic Conditions*, POAC, Delft, The Netherlands, pp. 9-19.

Pekel, E., 2020. Estimation of soil moisture using decision tree regression. *Theoretical and Applied Climatology*, 139(3), pp.1111-1119.

Rudkin, P., 2005. Comprehensive Iceberg Management Database Report 2005 update. PERD/CHC Report 20-72. National Research Council of Canada (NRC) and Panel on Energy Research and Development (PERD).

Sacchetti, F., Benetti, S., Cofaigh, CÓ., & Georgiopoulou, A., 2012. Geophysical evidence of deep-keeled icebergs on the Rockall Bank, Northeast Atlantic Ocean. *Geomorphology* 159, pp.63-72.

Sonnichsen, G., Myers, R., Simpson, K., Brown, R., McClintock, J., Bullock, T., & Rudkin, P., 2003. Seabed Surveys to Document Groundings from the 2000 Grand Bank Iceberg Season. *Proceedings of the 17th International Conference on Port and Ocean Engineering under Arctic Conditions*. POAC 03, Trondheim, Norway.

Sonnichsen, G., Hundert, T., Myers, R., & Pocklington, P., 2006. Documentation of Recent Iceberg Grounding Evens and a Comparison with Older Events of Know Age. Environmental Studies Research Funds. Report ESRF Vol. 157.

Stuckey, P., Fuglem, M., Younan, A., Shayanfar, H., Huang, Y., Liu, L., & King, T., 2021. Iceberg Load Software Update Using 2019 Iceberg Profile Dataset. *In International Conference on Offshore Mechanics and Arctic Engineering*, 85178, pp.V007T07A018.

Talimi, V., Ni, S., Qiu, W., Fuglem, M., MacNeill, A., & Younan, A., 2016, Investigation of Iceberg Hydrodynamics. *Arctic Technology Conference*. St. John's, Newfoundland and Labrador, Canada. OTC-27493-MS.

Turnbull, I.D., Fournier, N., Stolwijk, M., Fosnaes, T., & McGonigal, D., 2015. Operational iceberg drift forecasting in Northwest Greenland. *Cold Regions Science and Technology*, 110, pp.1-18.

Turnbull, I.D., King, T., & Ralph, F., 2018. Development of a New Operational Iceberg Drift Forecast Model for the Grand Banks of Newfoundland. *Arctic Technology Conference*. Houston, Texas, USA. OTC-29109-MS.

Vapnik, V.N., 1995. The Nature of Statistical Learning Theory, Springer, New York.

Woodworth-Lynas, C.M.T., Simms, A., & Rendell, C.M., 1985, Iceberg grounding and scouring on the Labrador Continental Shelf. *Cold Regions Science and Technology*, 10(2), pp.163-186.

Younan, A., Ralph, F., Ralph, T., & Bruce, J., 2016. Overview of the 2012 iceberg profiling program. *Arctic Technology Conference*. St. John's, Newfoundland and Labrador, Canada. OTC-27469-MS.

Zhou, M., 2017. Underwater iceberg profiling and motion estimation using autonomous underwater vehicles. PhD, Memorial University of Newfoundland: NL, Canada.