



Cavitation nuisance identification through machine learning during propeller optimisation

Downloaded from: <https://research.chalmers.se>, 2025-04-17 16:16 UTC

Citation for the original published paper (version of record):

Gypa, I., Jansson, M., Bensow, R. (2022). Cavitation nuisance identification through machine learning during propeller optimisation. Proceedings of the seventh International Symposium on Marine Propulsors - smp'22: 384-391

N.B. When citing this work, cite the original published paper.

Cavitation nuisance identification through machine learning during propeller optimisation

Ioli Gypa¹, Marcus Jansson², Rickard Bensow¹

¹Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Gothenburg, Sweden

²Kongsberg Maritime Sweden AB, Kristinehamn, Sweden

ABSTRACT

The marine propeller design process runs under strict time limitations and even if it entails contradicting requirements from different stakeholders and complex physical phenomena, the analysis tools must be very fast. Cavitation nuisance is such a complex phenomenon that is hard to predict accurately from these tools and requires additional evaluation by the blade designer. Thus, a good blade design depends on approximate analysis tools and on the expertise of an experienced blade designer. Therefore, we previously developed an interactive optimisation methodology, where interactive genetic algorithms were utilised for blade design optimisation and cavitation was manually evaluated by the blade designer. However, since blade design involves a large design space, the optimisation requires populations of thousands of individuals, something that makes the manual evaluations by the blade designer very laborious. Accordingly in this study, a machine learning pipeline has been developed with the aim to reduce the number of manual evaluations and classify the cavitation nuisance automatically. Nested-cross validation has been used to identify the best classification algorithms combined with the most suitable hyperparameters for three different propellers with both suction and pressure side cavitation. The results have shown that using machine learning can be very beneficial to reduce user fatigue in interactive optimisation processes.

Keywords

Marine propeller design, cavitation nuisance, machine learning, classification algorithms, nested cross-validation

1 INTRODUCTION

The selection and design of a marine propeller is a complex procedure that requires expertise in various scientific fields and involves several stakeholders that set the requirements and constraints of the problem, like propeller efficiency, fuel consumption, overall cost, comfort, cavitation, and propeller-induced pressure pulses among others. Blade design is a multidisciplinary design optimisation process that has several objectives related to those requirements. Although it usually involves a large

design space, since it depends on many design variables, the design process runs under strict time limitations and the optimisation must be performed as efficiently as possible.

Due to the time limitations, high-fidelity simulations and experiments are not feasible, thus fast analysis tools are used during the optimisation for predicting the complex physical phenomena involved. Cavitation is one of the most common constraints in marine propeller design problems, which is hard to predict accurately from these fast analysis tools and requires additional evaluation by the blade designer. Thus, the success of a good blade design depends on approximate analysis tools and on the expertise of an experienced blade designer.

With that in mind, an interactive optimisation methodology was presented by Gypa et al (2021), where interactive genetic algorithms (IGAs) were utilised for blade design optimisation and cavitation was evaluated interactively by the blade designer. In that process, the blade designer manually evaluated and classified designs as “accepted” or “rejected”, according to the shape of the cavitation on the blade at the angle with maximum cavity volume. Then this information was inputted back to the genetic algorithm (Deb et al 2002) and the optimisation was directed towards areas of the design space with designs of high performance and in parallel with acceptable cavitation, according to the preference of the blade designer.

In theory, using only the manual evaluations as an input to the IGA code for the evolution of the optimisation would be sufficient. In practice though, blade design requires very large populations of thousands of individuals during the optimisation of complex problems due to the large design space. Consequently, the blade designer must manually evaluate all these designs, which easily leads to user fatigue. This is a common problem in interactive optimisation procedures (Wahde 2008). This process becomes even more complex and laborious with blade design scenarios that involve several objectives and there is both suction and pressure side cavitation.

Therefore, a prediction model is essential to classify the cavitation nuisance automatically, instead of requiring

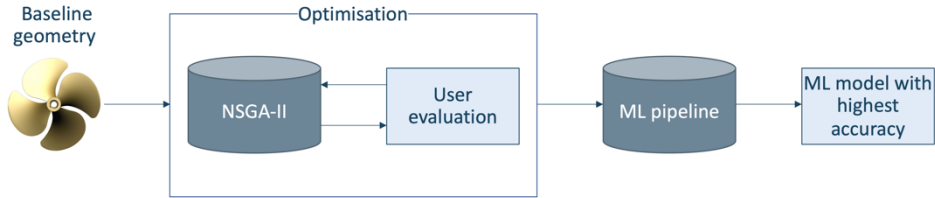


Figure 1: Optimisation and ML pipeline framework

user evaluation of the whole population. In (Gypa et al 2021), this classification was executed with satisfactory predictability by using support-vector machines (SVMs) (Cortes & Vapnik 1995) for a propeller design of a conventional cargo vessel.

The objective of this study is to accelerate and improve the existing interactive optimisation process, by reducing the fatigue due to performing high number of user evaluations. This is done by building a machine learning (ML) pipeline, where the input is a dataset that has been labelled by the blade designer, and five ML classification algorithms and their hyperparameters are investigated and the output is a model that offers the highest predictability. Nested cross-validation (NCV) is utilised as a means towards selecting the best model efficiently. In this study we have investigated three propeller designs, to cover propellers for different types of vessels and for including both suction and pressure side cavitation.

2 METHODOLOGY

The general concept of the methodology is that a dataset is created, which is inputted in the ML pipeline, NCV is used for investigating various hyperparameters of different ML algorithms and finally have the best model for each algorithm as an output. The best model is the one that has the hyperparameters that give the highest accuracy; this is then selected as the final model. When there is a new dataset, this model is used for cavitation nuisance prediction.

2.1 Optimisation and Data Preparation

The first step of the methodology is to create and label the data that will later be inputted into the ML pipeline. As shown in Figure 1, a propeller geometry is created, which is the baseline of the optimisation. When the optimisation is performed, images of the cavitation shapes on the blade of the designs are displayed and the blade designer rejects the designs with non-satisfactory cavitation. This process is referred to as data labelling. Then the most important features (input features) of the dataset together with the binary user evaluation are inputted in the ML pipeline. It should be noted that the dataset does not necessarily have to be the output of the optimisation procedure. For example, if there is a database with different designs and their cavitation, this can be used as an input to the pipeline as well.

2.2. Nested Cross-Validation

The next part of the methodology is the use of NCV (Stone 1974), which is an effective way to incorporate

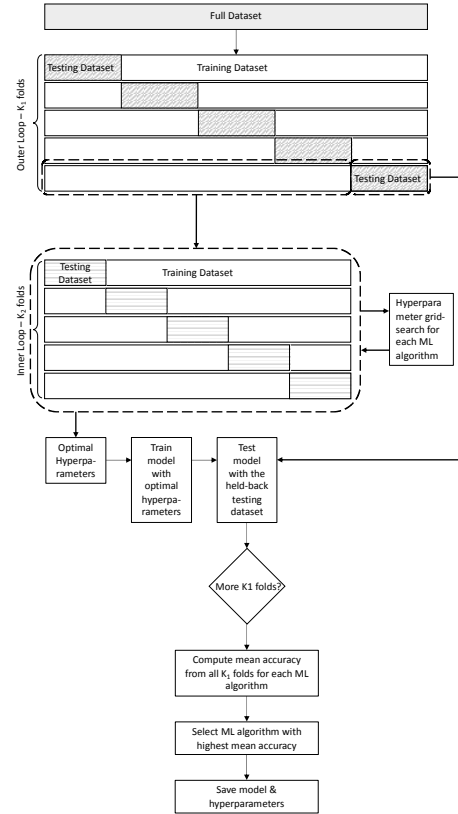


Figure 2: NCV process

hyperparameter tuning of different ML algorithms. The NCV process has two main loops, the outer and the inner, which are shown in Figure 2. K-fold cross-validation (CV) is carried out in both loops. The purpose of the outer loop is to split the dataset into training and testing sets K_1 times, by using K-fold CV, and later input each training set into the inner loop. The testing sets will be used in the end for validation of the best models.

The purpose of the inner loop is to investigate which hyperparameters are the best for the targeted ML algorithm, to achieve the highest accuracy. This is done by first splitting the input dataset (which is the training dataset of the outer algorithm) into training and testing sets K_2 times, again by using K-fold CV. Then the values of the hyperparameters are explored through the grid search method, which is an exhaustive search process that loops through a pre-defined hyperparameter space of the targeted algorithm. Every combination of hyperparameters is fitted to the ML algorithm for each one of the K_2 training sets, and the accuracy is validated through the inner testing sets. The ML algorithm is finally refitted on the whole dataset by using the best found

hyperparameters and the accuracy of the model is computed.

Since we want to compare the performance of different ML algorithms, there is one additional loop in the methodology, where the inner loop of the NCV process is repeated for each one of the algorithms. Note that each algorithm has different hyperparameters, and their ranges must be defined before the NCV process begins.

The output is one model for each ML algorithm by the inner loop, where the best hyperparameters have been selected. In the outer loop, the mean prediction accuracy is computed for each algorithm and the one that offers the highest accuracy is selected. This is considered the best model of the pipeline and is saved. When there is a new dataset, it is inputted in the best model and a prediction is done for the cavitation of the designs of the new dataset.

3 RESULTS AND DISCUSSION

3.1 User Scenario

Three different propellers are being used in this study. Propellers I and II are two different twin controllable pitch propellers for two ROPAX vessels and propeller III is a single fixed-pitch propeller for a car-carrier. Propellers I and II have both suction and pressure side cavitation, whereas propeller III has only suction side cavitation. Since a different model is built for each combination of propeller and cavitation type, there are in total five propeller cases, the I-SS, I-PS, II-SS, II-PS and III-SS, where SS and PS are the suction and pressure sides respectively.

Figures 3~7 show examples of the images of the cavity shapes of the five cases that are displayed to the blade designer for manual evaluation. The goal in every case is of course to eliminate the cavitation, but since this is not always possible, cavity shapes that are smooth, without much thickness at the tip and without growth at the root of the blade, are generally preferred. However, the user evaluation is dependent on the complexity of the project and the experience of the blade designer.

Two different sets of input have been used as input features for the ML pipeline separately, the design variables and the cavitation parameters. This means that two different models are built, based on the two different input sets. The design variables (there are different variables for each propeller case), such as pitch over propeller diameter, camber, chord length, skew etc. define the design space, where the optimisation algorithm searches for the optimal solutions. The cavitation parameters, here given by maximum cavity volume, cavity centroid harmfactor, cavity length, cavity closure line harmfactor, cavitation thickness at the blade tip, and non-dimensional cavity change (see further (Vesting et al 2016)), are the output of the hydrodynamic analysis tool MPUF-3A (He et al 2010) that is used during the optimisation, and they describe the cavity shape of each design. The reason that both sets of input features are being used is that the different cavitation shapes of the designs might be produced by other means, except through optimisation.

For each case, an optimisation run of 1000 designs has

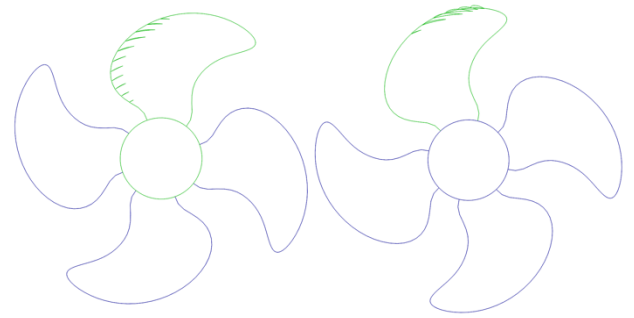


Figure 3: Case I - SS

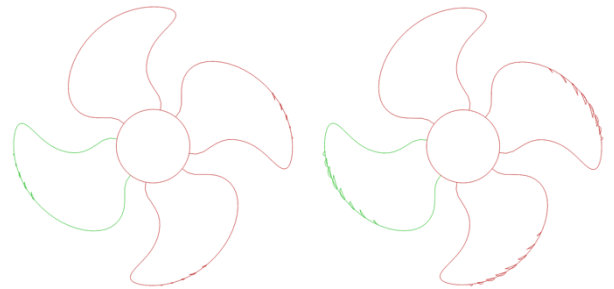


Figure 4: Case I - PS

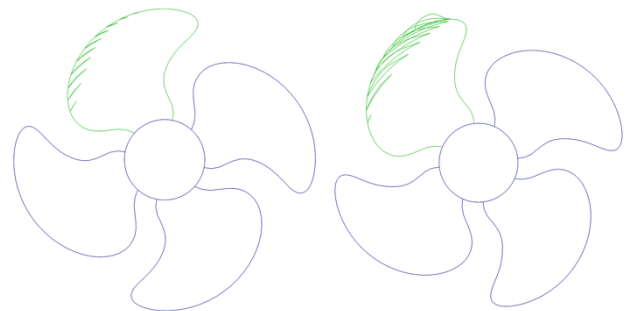


Figure 5: Case II - SS

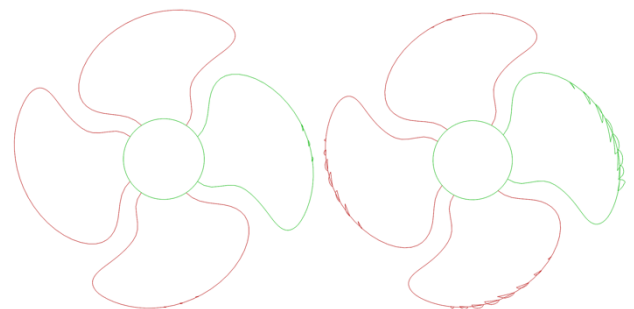


Figure 6: Case II - PS

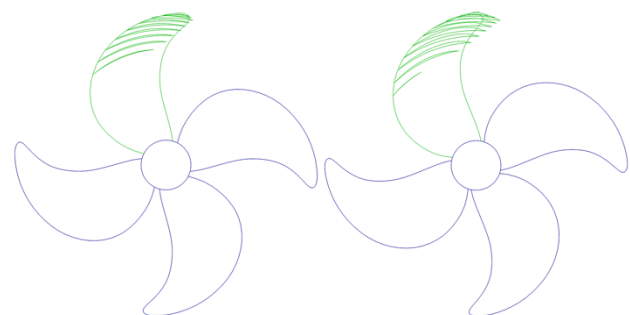


Figure 7: Case III - SS

been performed, out of which approximately the half are unique designs, and the blade designer evaluates their cavitation. Then the input features of the dataset together with the user evaluation are inputted in the ML pipeline and the output is one unique ML model for each propeller case. Then another run of 500 designs is performed and the cavitation evaluation is predicted by the ML model. In order to compute the accuracy of the prediction, it is compared to a new manual assessment. The prediction is done twice for each one of the input feature sets. The following five ML algorithms have been tested: k-nearest neighbours (KN) (Fix & Hodges 1989), neural networks (NN) (Hopfield 1982), decision trees (DT) (Quinlan 1986), SVMs and XGBoost (XGB) (Chen & Guestrin 2016).

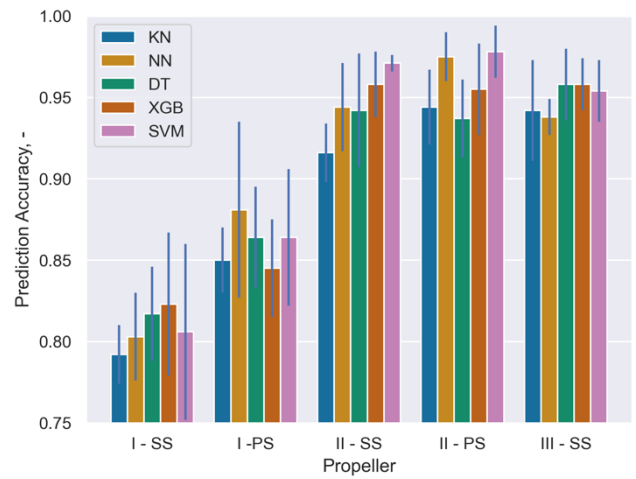
3.2 Results

During the NCV, the five ML algorithms are being tested with different hyperparameters for every propeller case. In order to find the best model (ML algorithm & suitable hyperparameters) that offers the highest prediction accuracy, the mean accuracy for each ML algorithm and for its different hyperparameters is computed. This is presented in Figure 8, where the prediction accuracy results of the models that have as input the design variables and the cavitation parameters, are shown in Figures 8a and 8b respectively. The x-axis of each bar plot shows the five different propeller cases and each one of the bars for every case represents one ML algorithm. On the y-axis the mean prediction accuracy is shown.

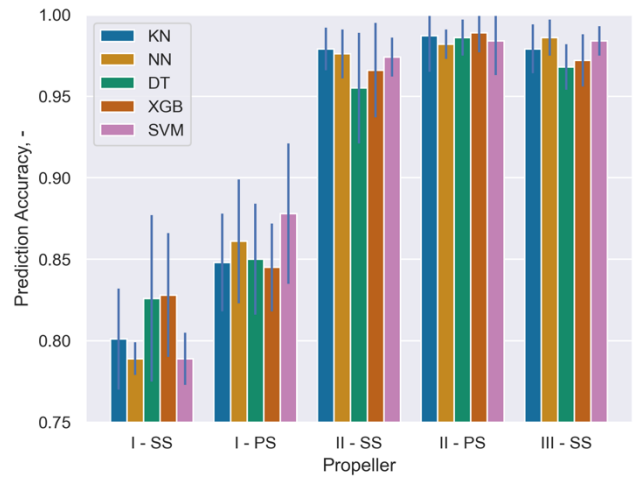
As depicted from the plot 8a for the cases I-SS and III-SS, the algorithm that offers the highest mean prediction accuracy is the XGB, for cases II-SS and II-PS the SVM and for the I-PS is the NN. In plot 8b, it is shown that the propeller cases I-SS and II-PS have the highest mean accuracy with the XGB algorithm, the case I-PS with the SVM, the case II-SS with the KN and finally the III-SS with the NN. By comparing the two input feature sets, it is observed that the cases I-SS and I-PS have approximately the same prediction with both sets, but the propeller cases II-SS, II-PS and III-SS had better predictability with the cavitation parameters as input features.

The best model for each propeller case is considered the one that combines the algorithm that had the highest mean accuracy with the values of the hyperparameters that gave the highest accuracy. Then the model of each propeller case is saved and when new data are inputted, the model is trained with the whole old dataset and a prediction is done for the new dataset.

The next step is the prediction of the new datasets for every case. In Tables 1~2 the maximum prediction accuracy computed during the NCV and the prediction accuracy of the cavitation evaluation of the new datasets for the design variables and the cavitation parameters are presented respectively. In both tables, the prediction accuracy for the new dataset is very close to the maximum prediction accuracy computed during the NCV.



(a) Design variables



(b) Cavitation parameters

Figure 8: Mean prediction accuracy for five ML algorithms and five propeller cases

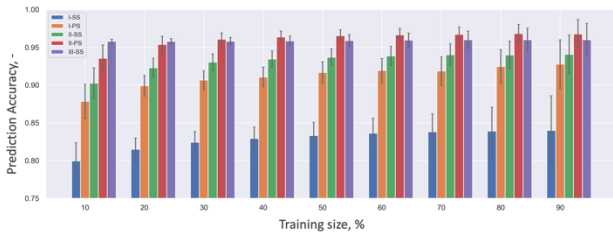
Table 1: Prediction accuracy – Design variables

Propeller Case	ML Algorithm	Maximum Prediction Accuracy	Prediction Accuracy New Dataset
I-SS	XGB	0.86	0.87
I-PS	NN	0.93	0.94
II-SS	SVM	0.97	0.92
II-PS	SVM	1.00	0.94
III-SS	XGB	0.98	0.98

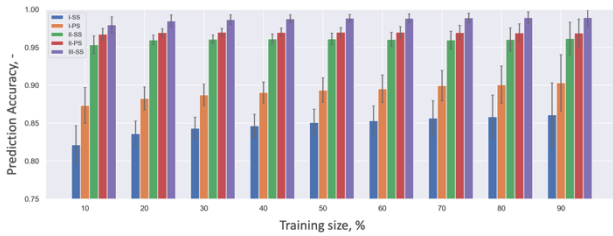
Table 2: Prediction accuracy – Cavitation parameters

Propeller Case	ML Algorithm	Maximum Prediction Accuracy	Prediction Accuracy New Dataset
I-SS	XGB	0.89	0.87
I-PS	SVM	0.90	0.92
II-SS	KN	1.00	0.95
II-PS	XGB	1.00	0.95
III-SS	NN	0.99	0.99

An investigation on the training size of the datasets is done for the best model of each propeller case, with the aim to reduce the manual evaluations by the blade designer and in parallel maintain a satisfactory prediction accuracy. This is shown in Figure 9, where for every propeller case, the best model has been trained with nine different training sizes and the model has been trained and done prediction 2000 times. On the x-axis the training size is presented and on the y-axis, there is the mean prediction accuracy (from the 2000 repetitions). The colour of each bar represents one propeller case, and the error (standard deviation) is shown with grey colour.



(a) Design variables



(b) Cavitation parameters

Figure 9: Training size investigation

In Figure 9a, where the input features are the design variables, it is observed that the models of the cases II-SS, II-PS and III-SS have a mean prediction accuracy of above 90%, by including the error, with a training size of 20%. The model I-PS has satisfactory predictability of above 90% with training size of 30-40%. The model I-SS has a lower predictability with all training sizes, thus it depends on the blade designer and on the project, which prediction accuracy that is considered acceptable. Note that it is not crucial for the ML pipeline to have an extremely high accuracy, since we use it as part of the optimisation process and the accepted designs will be re-evaluated in later generations.

Similar outcome is shown in Figure 9b, where the input features are the cavitation parameters. The models II-SS, II-PS and III-SS have a mean predictability of above 95% with 10-20% training size. For models I-SS and I-PS the predictability is generally lower, but an increase is observed for training sizes of 40-50%.

By comparing the two plots, it is evident that for the models of the propeller cases II-SS, II-PS and III-SS the input features of the cavitation parameters give better results. For the case I-PS the design variables are more beneficial as input and for the case I-SS, both models give approximately the same prediction accuracy.

Although the prediction accuracy of a model is very important, understanding and explaining the output of the model is equally important. We are doing this by using and presenting the SHAP (SHapley Additive exPlanations) values (Lundberg & Lee 2017) of the best model of each propeller case. The SHAP values show how much a predictor contributes either positively or negatively to the target variable. The SHAP values are investigated in this study for the initial datasets of 1000 designs, for a training size of 80% and a testing size of 20%. The models that are investigated are the best models from the NCV that were presented in Tables 1~2.

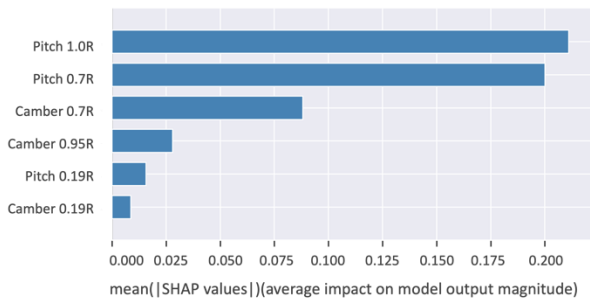
In Figures 10 and 12 the variable importance plot is presented for all five propeller cases and for the design variables and cavitation parameters as input respectively. The purpose of this plot is to show which variables contribute the most to the model, which means that they have the highest predictive power. The x-axis presents the average of the absolute SHAP value for each feature and the y-axis presents the input features. The features are presented on descending order, based on the significance of their contribution.

Interestingly, the Figures 10a~e that have the design variables as input features, all have the pitch at 1.0R as the most significant feature. Especially, in cases II-SS and II-PS, it seems that the pitch at 1.0R is the only important feature. In I-SS also the pitch and camber at 0.70R are important and in case III-SS, all other features seem to contribute to the prediction of the model almost equally.

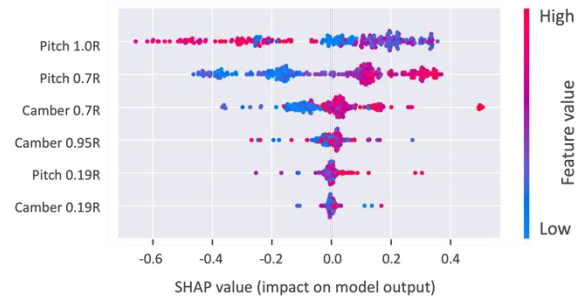
The cavitation parameters that were mentioned earlier are the output of the analysis tool MPUF-3A for suction side cavitation. For pressure side cavitation, only the parameters maximum cavity volume, cavity centroid harmfactor and cavity changed are defined by the software. This is shown in plots 12b and 12d, where the cavity volume (cav_vol) and the cavity change (cav_chg) are the most important features. On the contrary, Figures 12a, 12c and 12e that represent the cases with suction side cavitation, show that the most significant feature was the cavity centroid harmfactor (cav_cnt). For case II-SS also the cavitation thickness at the blade tips (cav_tip) and the cavity length (cav_len) were important as well.

A similar type of plot is presented in Figures 11 and 13 and is used to visualise the directionality impact of the features, where the positive or negative relationships of the predictors with the target variable are shown. The variables are presented again here on the y-axis in descending order, based on the feature importance and the x-axis represents the SHAP value, where a positive or negative SHAP value shows positive or negative impact on the model respectively. Each point on the chart is one SHAP value for a prediction and a feature. The colour scale shows whether the actual value of the feature is low (blue) or high (red).

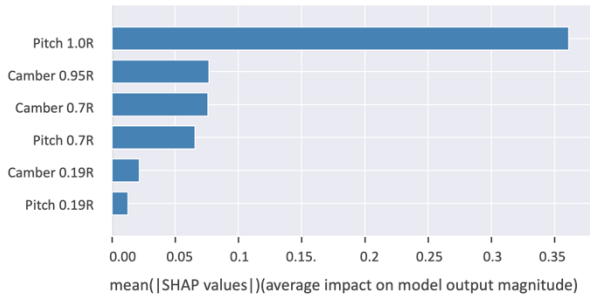
In more detail, in Figure 11a it is shown that middle and lower values of pitch at 1.0R have a more positive impact



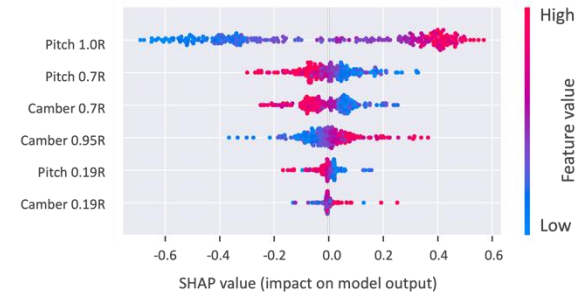
(a) I-SS



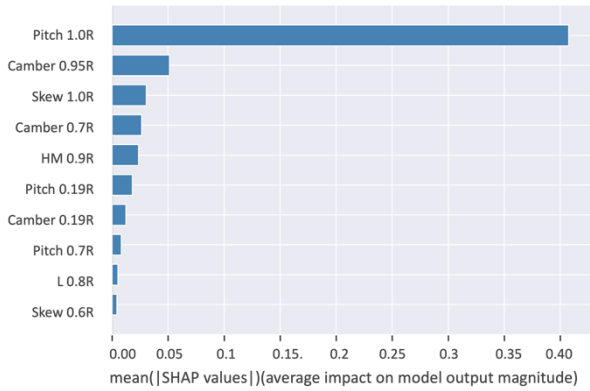
(a) I-SS



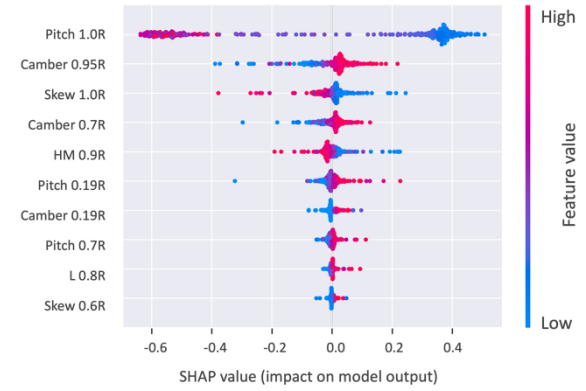
(b) I-PS



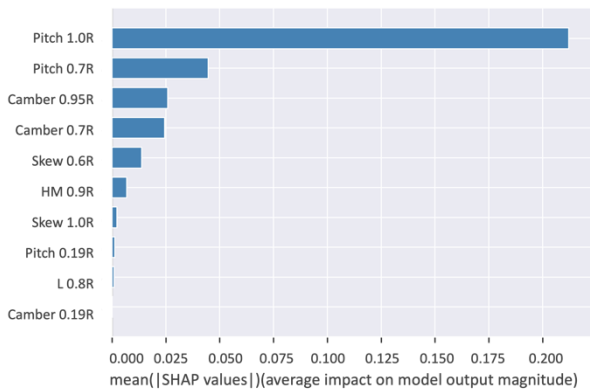
(b) I-PS



(c) II-SS



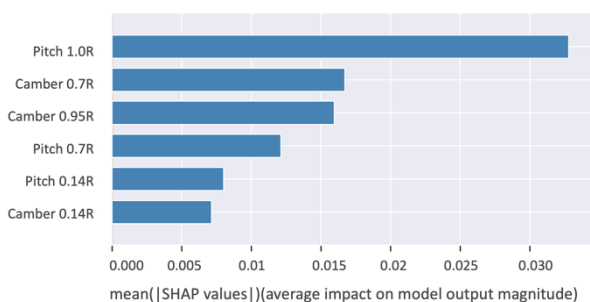
(c) II-SS



(d) II-PS



(d) II-PS



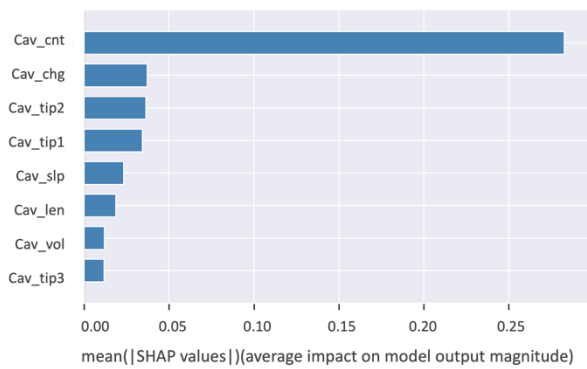
(e) III-SS



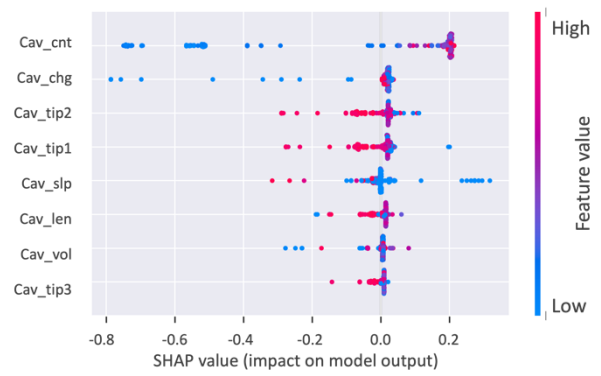
(e) III-SS

Figure 10: Variable importance plot – Design variables

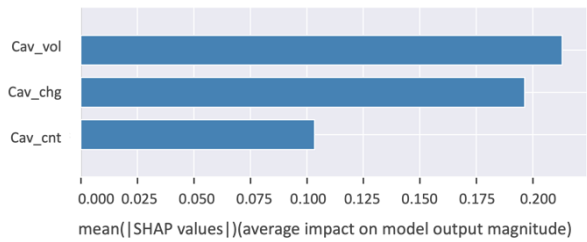
Figure 11: Directionality impact – Design variables



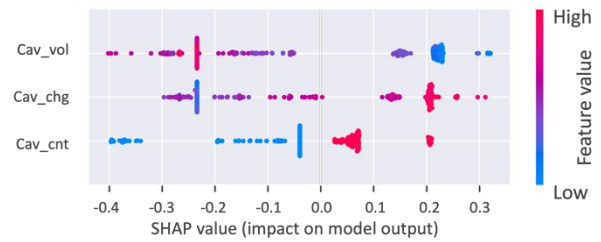
(a) I-SS



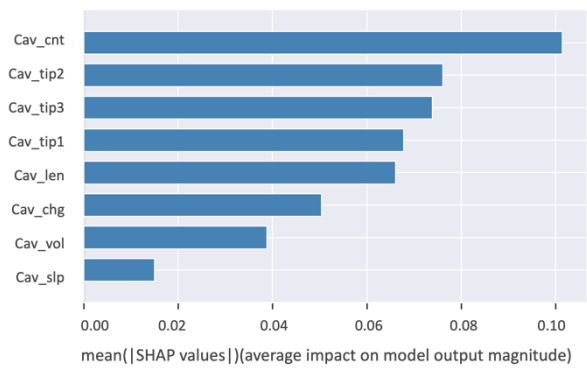
(a) I-SS



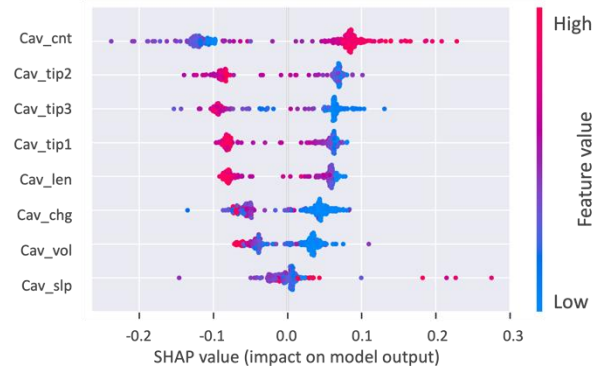
(b) I-PS



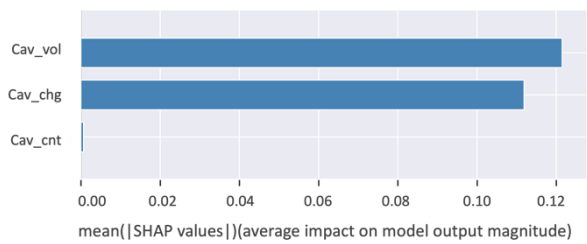
(b) I-PS



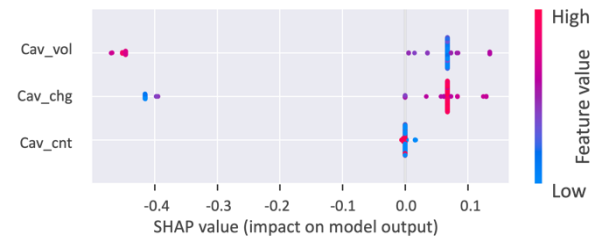
(c) II-SS



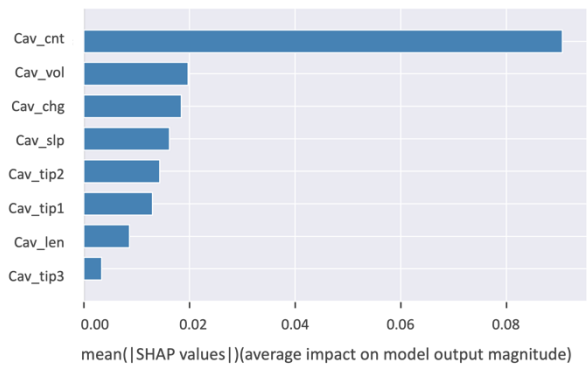
(c) II-SS



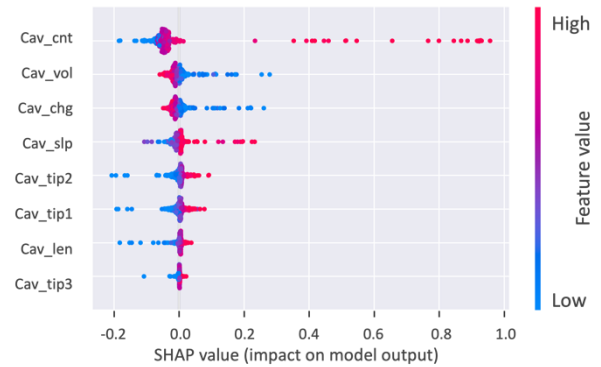
(d) II-PS



(d) II-PS



(e) III-SS



(e) III-SS

Figure 12: Variable importance – Cavitation parameters

Figure 13: Directionality impact – Cavitation parameters

on the model, while lower values of pitch at 0.7R have a negative impact on the model. For the two cases with pressure side cavitation I-PS and II-PS, higher values of pitch at 1.0R have a positive impact on the model and in II-SS it is the opposite. For the propeller case III-SS, it is a bit unclear which values of the features had a positive or negative impact on the model.

For the models that have the cavitation parameters as input in Figure 13 starting from the case I-SS, middle and high values of the cavity centroid harmfactor had a positive impact on the model. For the cases I-PS and II-PS, low values of the maximum cavity volume had a positive impact on the model and high values of the cavity centroid harmfactor had a negative impact. In case II-SS, high values of the cavity centroid harmfactor had a positive impact, while for all the other features, low values had a positive impact on the model. Again in case III-SS the impact of the values of the input features is unclear.

4 CONCLUSIONS

In this paper we presented the results of an ML (machine learning) pipeline that we use as part of an interactive optimisation process, where cavitation was assessed by the blade designers manually. The goal was to accelerate and improve the existing optimisation procedure, by reducing the risk of user fatigue, through selecting an ML model that does part of the cavitation nuisance identification automatically and offers high predictability with a small training set.

The performance of five ML algorithms was investigated with the aid of NCV (nested cross-validation) and different hyperparameters were tested through the grid search method. The output was one model that offered the highest prediction accuracy and combined one ML algorithm with the most suitable values of its hyperparameters. Then this model was used for predictions of new datasets. This process was repeated for three propeller designs, two of which had both suction and pressure side cavitation.

According to the results, the prediction accuracy proved to be high (above 90%) for almost all propeller cases, except the I-SS that was approximately at 87%. In general, highest accuracy was achieved when the cavitation parameters were the input features. The investigation on the training size of the best models showed that for cases II-SS, II-PS and III-SS, training sizes of 20% provided satisfactory accuracy, while for cases I-SS and I-PS, training sizes of 30-50% of the dataset were more satisfactory.

In addition to investigating the predictability of the different models, the output of the models was explained by using and presenting the SHAP values. We used the variable importance plots in order to show which input features contributed to the model the most and the directionality plots, in order to show which values of the input features had positive or negative impact on the prediction of the model.

Using ML as part of our interactive optimisation method proved to be beneficial in order to identify cavitation

nuisance faster, by requiring fewer manual evaluations by the blade designer. An interesting future study would be to use the ML pipeline for a complex propeller design scenario, with contradicting objectives and with both suction and pressure side cavitation.

ACKNOWLEDGEMENTS

Funding for this study was provided by Chalmers University of Technology Foundation for the strategic research project Hydro- and aerodynamics; by the Swedish Transportation Agency via Lighthouse through the SailProp project; and by Kongsberg Maritime Sweden AB through the University Technology Centre in Computational Hydrodynamics hosted at the Department of Mechanics and Maritime Sciences at Chalmers.

REFERENCES

- Chen, T. & Guestrin, C. (2016). 'Xgboost: A scalable tree boosting system', Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining.
- Cortes, C. & Vapnik, V. (1995). 'Support Vector Networks', Machine Learning.
- Deb, K., Pratap, A., Agrawal, S., & Meyarivan, T. (2002). 'A fast and elitist multiobjective genetic algorithm: NSGA-II', IEEE transactions on evolutionary computation.
- Fix, E. & Hodges, J. L. (1989). 'Discriminatory analysis. Nonparametric discrimination: Consistency properties', International Statistical Review.
- Gypa, I., Jansson, M., Wolff, K. & Bensow, R. (2021). 'Propeller optimization by interactive genetic algorithms and machine learning', Ship Technology Research.
- He, L., Chang, S. & Kinnas, S. (2010). 'MPUF-3A Version 3.0'. Report. University of Texas.
- Hopfield, J. J. (1982). 'Neural networks and physical systems with emergent collective computational abilities.', Proceedings of the national academy of sciences.
- Lundberg, S. M. & Lee, S.-I. (2017). 'A unified approach to interpreting model predictions', Advances in neural information processing systems.
- Quinlan, J. R. (1986). 'Induction of decision trees', Machine learning.
- Stone, M. (1974). 'Cross-validatory choice and assessment of statistical predictions', Journal of the royal statistical society: Series B (Methodological).
- Vapnik, V.N. (1995) The Nature of Statistical Learning Theory. Springer-Verlag.
- Vesting, F., Bensow, R., Johansson, R., Gustafsson, R. & Costa, N. A. (2016). 'Procedure for Application-Oriented Optimisation of Marine Propellers', Journal of Marine Science and Engineering.
- Wahde, M. (2008). Biologically inspired optimization methods: an introduction. WIT pres