SSC Project Recommendation for FY 2019

Development of a data-driven, near real-time monitoring and pre-warning system for propulsion shaft alignment using machine learning

1.0 OBJECTIVE.

1.1 This proposed study is to develop methodologies for establishing a data-driven model that can predict displacement of propulsion shaft structure, provide pre-warning of potential occurrence of metal-to-metal contact between shaft and bearing, and advise ship operations to alleviate excessive shaft misalignment. In particular, a combination of Machine Learning, Computational Fluid Dynamics (CFD) simulation and Fluid-Structure-Interaction (FSI) analysis is expected to provide accurate prediction of propulsion shaft structural displacement and stern tube bearing performance as a result of ship operations.

2.0 BACKGROUND.

2.1 Recent engine room design trends have resulted in propulsion shafting arrangements that are increasingly sensitive, with lower tolerances and margins, heightening the risk of stern tube bearing failures. The introduction of IMO's Energy Efficiency Design Index (EEDI) also impacted vessel design, resulting in wider use of more efficient, larger diameter propellers. Their greater weights lead to an increased cantilevered load on the shafting system. As a result, it is very important to have a good understanding of the propulsion shaft behavior during ship operations, and have means to not only monitor, but to predict the shaft structural displacement and stern tube bearing behavior to advise ship operations, and in turn provide feedback to new shaft alignment design.

2.2 As digital twin is transforming the engineering world, and it has been proven by many case studies that it can benefit the marine industry significantly. A digital twin provides a virtual model of a physical ship, producing valuable insights from data to advise ship design, operation and maintenance. Among the many aspects of ship digital twin, two components are relevant to the scope of the proposed work:

- Analytical models for structures and hydrodynamics, including CFD, FEA, FSI, etc.
- Sensor data measured from the real vessel and used for performance monitoring, condition-based maintenance and design feedback

While ship digital twin is a holistic system, the monitoring and analysis have to be done on component level given the complexity of ship systems. The proposed work is focusing on the continuous monitoring of shaft structure and stern tube bearing using a hybrid model combining data from sensor data and simulation data and build a data-driven model to do the actual prediction of shaft displacement and stern tube bearing performance during ship operation.

CFD has proven to be a reliable tool for marine applications. It was traditionally considered too computationally expensive to provide design and operation inputs. However, with the modern computation power, especially with high performance computing and sophisticated software package, it becomes practical to make use of CFD to provide hydrodynamic insights of ship design and operation. FSI model serves as a translator to predict shaft structure displacement due to the external hydrodynamic forces during propeller, rudder and ship operations. Machine learning is widely used in data-intense engineering problems to provide near real-time predictions. Based on multiple studies, it is found that with the correct machine learning algorithm selected and trained, it has a good potential to make accurate predictions of shaft structural displacement and stern tube bearing behavior based on several basic ship operation parameters (RPM, Rudder angle, ship speed, etc.).

The data-driven model for predicting shaft alignment combines sensor-measured data, high-fidelity simulation, and machine learning to create a reliable, near real-time monitoring and predicting shaft alignment during operation. Some major benefits include:

- Sensor data only needs to be acquired during sea trial for initial model building. Therefore, the measurement devices can be rented instead of being permanently installed. Especially for a fleet of ships with same design, a final production model trained and calibrated for one ship will be directly applicable to other sister ships without the need to install extra sensors to monitor shaft alignment.
- After the model deployment, measurement devices can still be brought back, as needed, to provide sensor data to re-calibrate the machine learning model based on the working status of the ship. Alternatively, CFD and FSI models calibrated during the development of the data-driven model based on sea trial data can be updated over the life cycle of a ship to account for the change of vessel conditions and operational conditions and provide additional simulation-generated data sets to further upgrade the data-driven model.
- For ships equipped with a permanent digital shaft alignment monitoring system, the data-driven model can serve as an evaluation baseline. Difference between machine learning model prediction and sensor measurement can provide another set of reference indicators of potential problems inside the shaft and bearing (cracks, wearing, etc.)
- The production model is pre-trained with the possible operating conditions the ship might be exposed to, and therefore it can serve as a route planning tool that provides input on how shaft is going to behave in response to operation selection.

2.3 The proposed work looks to explore the accuracy level and robustness of a calibrated data-driven model to predict shaft displacement and stern tube bearing performance. The scope will start with building initial machine learning model with the existing measurement data for a specific ship during sea trial. The data model will have some basic ship operating parameters like propeller speed, rudder angle, ship speed, draft, etc. As a second step, fast and simplified CFD analysis is used to generate more input data used in the data model, to complement the hydrodynamic calculations for more operating conditions (other than the conditions in sea trial). The machine learning model now has a larger parameter range. As a third step, accurate and computationally heavy CFD calculations and FSI analysis will be done on several ship operating conditions to predict the shaft structural displacement and stern tube bearing behavior. The data-driven model is then validated against the results from CFD + FSI calculations and updated if there are calibrations needed. As an optional step, if the sensor measurement data is also available for multiple conditions other than sea trial condition, the data model will also be validated against the measurements.

3.0 REQUIREMENTS.

3.1 Scope: The proposed study includes three phases for developing a data-driven monitoring and pre-warning model for propulsion shaft displacement and stern tube bearing behavior.

3.1.1 Phase 1 Initial data-driven model building: An initial machine learning model will be developed based on the shaft measurement data available from sea trial. Different machine learning algorithms will be tested and benchmarked. The algorithm with the best overall prediction performance will be chosen for the next phases. The different machine learning algorithms will be tested based on the following criteria:

- Mean squared error on the test set – to evaluate whether the machine learning model fits to the training data well, and at the same time generalize well to avoid overfitting problem
- Small variance in squared error – to evaluate whether the machine learning model have uniform performance across all the operating conditions, instead of having good performance only under certain operating conditions
- The model should be able to preserve the time sequence of operating condition.

3.1.2 Phase 2 CFD data generator: CFD calculation with simplified propeller model will be developed to generate the operating parameters for operating conditions different from the sea trial condition. A detailed operating condition matrix including draft, speed, rudder angle, etc. Based on the defined operation matrix, CFD simulation with simplified propeller model (either body force model or boundary element model) will be used to give prediction for propeller RPM. The simplified propeller models have proven to be reliable for predicting propeller speed with reasonable accuracy level. However, in this process, the simplified propeller model will be tested against measurements to further build confidence in the prediction.

3.1.3 Phase 3 Data-driven model validation and calibration: The operating data (speed, RPM, rudder angle, etc.) generated in phase 2 will be fed into the initial machine learning model built in phase 1, and then use the machine learning model to predict shaft structural displacement and stern tube bearing behavior. Several selected operating condition will be simulated with high-fidelity propeller resolving CFD simulation and FSI analysis to provide high fidelity prediction of shaft displacement and stern tube bearing behavior. The results from data model will be compared with the ones from CFD and FSI analysis. The machine learning model is then updated based on the discrepancy observed to generate the final calibrate machine learning model.

3.2 Tasks: The following tasks are included in the proposed work scope.

Phase 1: Initial data-driven model building

3.2.1 Data Preparation – Pre-process the available data for training the model. This includes finalizing on the features that have the most prediction power, train/test split scheme, data scaling and regularization if required by the particular machine learning algorithm

3.2.2 Model Selection - Investigate the best machine learning algorithm that fits the purpose of this proposed work. The algorithm should be able to fit to the training data well and generalize well enough to keep small error in the test data set. Also, the error should be uniformly distributed across different operating conditions. The algorithm should also be able to capture the time sequence associated with the operating data.

3.2.3 Model Tuning – Tune the hyperparameters of the selected algorithm to further improve prediction accuracy.

Phase 2: CFD data generator

3.2.4 Benchmarking - Benchmark the propeller speed predicted by the simplified propeller model (body-force model or boundary element model) against available measurement data to further improve confidence over prediction

3.2.5 Define Matrix of Operating Conditions - Prepare a matrix of operating conditions (speed, draft) that will be simulated using CFD with simplified propeller model to produce a matrix of corresponding propeller speed

3.2.6 Propulsion Shaft Structural Displacement and Stern Tube Bearing Behavior Prediction – Use the initial machine learning model from phase 1 to predict the shaft structural displacement and stern tube bearing behavior based on the new operating conditions generated by CFD simulations, and collect the predicted values

Phase 3: Data-driven model validation and calibration

3.2.7 Validation – Several selected conditions generated in phase 2 will be repeated with high-fidelity CFD simulation with propeller-resolved method, combined with FSI analysis. This is a validated process that is used for accurate prediction of shaft structural displacement and stern tube bearing behavior. The results will be used to test against the results generated in 3.2.6.

3.2.8 Calibration - If enough discrepancy is observed, the initial machine learning model will be calibrated based on the relation matrix of ship operation in different conditions to produce the final machine learning model.

3.3 Project Timeline.

3.3.1 Data preparation and initial model building: 2 months
3.3.2 Benchmarking of simplified propeller model accuracy: 1 month
3.3.3 Define operation matrix and produce shaft structural displacement and stern tube bearing behavior prediction: 2 months
3.3.4 Validation of predicted results: 4 months
3.3.5 Model calibration: 2 months
3.3.6 Final report: 1 month

4.0 GOVERNMENT FURNISHED INFORMATION.

4.1 Standards for the Preparation and Publication of SSC Technical Reports.

5.0 DELIVERY REQUIREMENTS.

5.1 The Contractor shall provide quarterly progress reports to the Project Technical Committee, the Ship Structure Committee Executive Director, and the Contract Specialist.

5.2 The Contractor shall provide best practices for developing the data-driven monitoring and pre-warning model for propulsion shaft structural displacement and stern tube bearing behavior.

5.3 The Contractor shall provide a print ready master final report and an electronic copy, including the above deliverables, formatted as per the SSC Report Style Manual.

6.0 PERIOD OF PERFORMANCE.

6.1 Project Initiation Date: date of award.

6.2 Project Completion Date: 12 months from the date of award.

7.0 GOVERNMENT ESTIMATE.

These contractor direct costs are based on previous project participation expenses.

7.1 Project Duration: 12 months.

7.2 Total Estimate: $100,000

8.0 REFERENCES.

8.1 ABS Guide for Enhanced Shaft Alignment, Dec. 2018.