Machine learning techniques for modeling ships performance in waves

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Abstract

This paper presents a design of a system for monitoring and recording the influence of a running sea on a vessel in motion. Our approach is based on machine learning techniques that relate measured wave parameters (encounter angle, wave height and wave amplitude) with measured motion characteristics of the vessel. High quality GRIB data for wave measurements are available for some regions (e.g. North Sea and Adriatic) and we use those for generating training sets. We store this correlation in a neural net and use this information in conjunction with the targeted performance indicator (RMS of linear acceleration, RMS of roll or pitch angle, fuel consumption) to create historical directed performance charts for the vessel in consideration. We use this information for rational route planning and optimization. We report on the conclusions of experiments.

Keywords: polar diagram; IMU sensor; machine learning; performance optimization

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1. Introduction

A major challenge for devising route optimization schemes that optimize ship's performance in a running sea is in correlating a performance parameter to be optimized to the encounter angle of a ship with the waves. The encounter angle will be denoted by β and will run from 0 degrees meaning the following sea to 180 degrees meaning the head sea.

For a solution to be widely applicable, it is a prerequisite to design a system that will either use typical on-board sensors or that will require a use of retail sensors that are based on a broadly available and easily obtainable MEMS concept. Furthermore, the solution has to be installable on a vessel already in operation. In this note we present a method for measuring the influence of encountered waves on a vessel and a method for creating a historic directed performance tables for performance indicators under study. In what follows we shall present several performance indicators in more detail.

We reconstruct from IMU (inertial measurement unit) the following measurements: rotation amplitudes and periods, accelerations amplitude and periods, displacements and most importantly the encounter angle. For IMU sensors we have experimented both with high-end as well as retail solutions. The results of our approach based on machine learning, rather than on the solution of the inverse problem for the ship's motion, were tested on a merchant vessel (5000 GT tanker), a harbor tug, a platform supply vessel (4800 t displacement) and two small coastal cruisers (cca. 500 GT). Also, the encountered sea-states covered a broad scope (up to sea state 8 for the platform supply vessel) of cases.

To measure the performance of the hardware and our motion reconstruction software a comparison has been performed to the forecast wave data that are available for the North Sea region. We have found that the system has an accuracy of more than 80% for estimating the significant amplitudes of motion (like significant wave height). In section 2.1 we will report on an experimental and theoretical validation on which this claim is based. The low-end retail IMU had a similar performance indicator at a much lower procurement price. In the second step of the project, we present a system for generating and refreshing vessels directional performance charts. In these tables, we correlate the wave encounter direction and wave parameters (frequency, amplitude) to e.g. fuel consumption, passenger satisfaction, speed over ground, or passenger safety. This directional performance charts are then used in conjunction with our legacy route optimization software to compute the optimal travel route from the perspective of the time of arrival while keeping the performance parameter optimal. We envisage that such optimization results should give master the ability to optimize even at the level of tactical maneuvering of a vessel.

2. Modelling the influence of encountered waves on a vessel

The wind wave system, called the wind sea, is described by the wave parameters from the standard Gaussian model of wind generated waves (Journée, 2001) or (Lloyd, 1998). This is to say that the irregular waves are assumed to behave as a random Gaussian process. The influence of the sea on the vessel is then measured using a retail IMU unit mounted on the vessel. Thus, we obtain a time series of linear and rotational motions of a reference point on the vessel. We perform the spectral analysis of these time series using the same Gaussian assumption and estimate first four statistical moments of these time series from the measurement.

To obtain a theoretical framework for relating the measured moments to the performance parameter to be optimized, we make a modest assumption that this relation is continuous, in the mathematical sense. The general approximation theorem for feed forward neural networks from (Cybenko, 1989) reads:

"Let φ be a fixed smooth, non-constant and uniformly monotone increasing univariate function, then linear combinations of compositions of function φ and a set of affine functionals uniformly approximates any continuous function of n real variables with support in the unit hypercube."

This theorem effectively says that for any continuous real function f on a hypercube $I_m = [0,1]^m$ and the tolerance $\varepsilon, 0 < \varepsilon$ there exists an integer N, constants $v_i, b_i \in \mathbb{R}$ and vectors $w_i \in \mathbb{R}^m$ with $i = 1, \ldots, N$ such that

$$|F(x) - f(x)| < \varepsilon, \; x \in I_m$$

Where

$$F(x) = \sum_{i=1}^{N} \varphi(w_i^{\tau} x + b_i)$$

The problem with applying this theorem is in the inherent computational complexity of the algorithm, since we are determining $N(m + 2)$ parameters by optimizing the approximation property on a measured training set. In particular, it should be noted that we need to make an a priori assumption on the size of integer N.

In practice, this theorem is applied in a general optimization loop, possibly increasing N adaptively, that is efficiently implemented within neural network framework. This is the approach that we will pursue. Note that this approach to modelling has to be considered as heuristic and we will use appropriate heuristic validation techniques to justify the approach, later on.

Under the hypothesis that the wave parameters continuously depend on the momenta of linear and angular motions as measured by the IMU device we construct a neural network using the neuralnet package in R from (Fritsch, Frauke, Suling, & Mueller, 2016). For a given N, the package neuralnet uses stochastic gradient descent to minimize the quadratic cost functional

$$C(v_i, b_i, w_i) = \frac{1}{2m} \sum_{x_j, j=1,..,s} \| F(x_j) - f(x_j) \|^2$$

over all possible constants $v_i, b_i \in \mathbb{R}$ and vectors $w_i \in \mathbb{R}^m$ where $i = 1, \dots, N$. Here $T_s = \{x_j, \; j = 1, .., s\}$ is called the training set. This leads to the quadratic optimization problem in a $2N + mN$ dimensional space. This "curse of dimension" is what makes this a hard optimization problem. Another challenge is in interpreting the results in the context of an application. Typically, this is done by computing the value of the quadratic cost functional on the set $V_d = \{x_j, \; j = 1, .., d\}$ called the test set. The test set V_d has to be disjoint from the training set T_s and the choice of the test set is delicate problem if robust conclusions are to be made.

2.1. Test cases and data acquisition

Our choice of the test cases has been influenced by two practical constraints. The availability of a good quality wave forecasts and the accessibility of training vessels for the purpose of readjusting the experimental setup. We will report on a testing of one merchant and of one work vessel in the North Sea region, where high quality wave data are available both based on the buoy as well as on the simulation data, and on two coastal passenger vessels in the Adriatic region where we have used high quality wave data from the simulation model (Gekom, 2017). When we say simulation data we mean data that are obtained from a mesoscale forecasting model that takes as input the data from the global forecasting system (GFS) that is maintained by the National Weather Service, USA. The GFS delivers the forecast at the accuracy of 50 km, and a mesoscale model, called weather research and forecast model (WRF), computes the local forecast at the scale of up to 100 m. The wave data for the Adriatic are obtained from the WWM II (Wind Wave Model II) from (Dutour Sikiric, Roland, Janekovic, & Kuzmic, 2013).

2.1.1. SailRouter device

The SailRouter device contains a IMU unit (Inertial measurement unit) which measures linear accelerations in all three axes and the rotational velocities. From these measurements the displacement time series are computed by filtering and time integration. As IMU unit we use Multi-Standard CC2650 SensorTag from Texas Instruments that includes low-power MEMS sensors in the small package with Bluetooth Smart connection. It is based on the low-power and high-performance CC2650 wireless MCU, ambient light sensor OPT3001, Infrared Thermopile Temperature Sensor TMP007 and Humidity Sensor with Integrated Temperature Sensor HDC1000.

Multi-Standard SensorTag is connected to an external power supply with 4x1,5V AA batteries see (Fig. 1) instead of its original 3V Coin cell battery in order to ensure longer lifetime. Connection with the cloud server is enabled by Android smartphone with GPS unit and SailRouter application which collects data from SensorTag via

Bluetooth Smart connection and sends the motion and position data to the shore office for a presentation on the SailRouter dashboard.

Fig. 1 SailRouter IMU unit

The data were collected by the SailRouter device see (Fig. 2) over the course of several weeks. The use of retail MEMS devices for safety monitoring in maritime operations has recently been favorably evaluated, see (McCue, 2013).

Fig. 2 Mounting of the SailRouter device

2.1.2. Analysis of the data set

The SailRouter device returns the mean, denoted by $m_0(S_d)$, and the second moment, denoted by $m_2(S_d)$, of a time series S_d of linear displacements (Surge, Sway and Heave) and rotational movements (Pitch, Roll and Yaw). The corresponding time series are denoted by S_d, $d = su, sw, he, p, r, y$.

The momenta are calculated for disjoint 10 minute intervals which are considered as events in the SailRouter system. From this data we compute the significant amplitude and the average period of a time series using the standard approach of the Rayleigh amplitude distribution – that is based on the Gaussian assumption, (Journée, 2001) and is given by the formulae

$$A_{\frac{1}{3}}(S_d) = 2\sqrt{m_0(S_d)}, \quad T(S_d) = \sqrt{\frac{m_0(S_d)}{m_2(S_d)}}$$

Note that here the significant amplitude is given in meters/degrees and the average period is given in seconds. Also, for the purposes of assessing habitability and operability of a vessel we will also compute the standard deviation of the time series

$$\sigma(S_d) = \sqrt{m_0(S_d)}$$

that is also called the root mean square displacement of a series and as such it features as a criterion in motion sickness tables, like ISO 2361/3-1985. Furthermore, the ship operability performance indicators like the

probability of slamming, deck wetness or propeller emergence are computed in dependence to the mean square displacement of e.g. relative vertical motion time series.

The neural network for the recognition of the encounter angle has been, on the other hand, trained directly on the momenta of the acceleration time series of the collection of test events as obtained from the BORA system (Gekom, 2017) and (Dutour Sikiric, Roland, Janekovic, & Kuzmic, 2013).

2.2. Validating the concept for wave recognition

We have validated the data both empirically on a test set, as well as against a semi-analytic model for the vessel on the North Sea. To this end the third author embarked the platform supply vessel on the North Sea and monitored ship motions with several commercially certified IMU sensors as it is shown on Fig. 3.
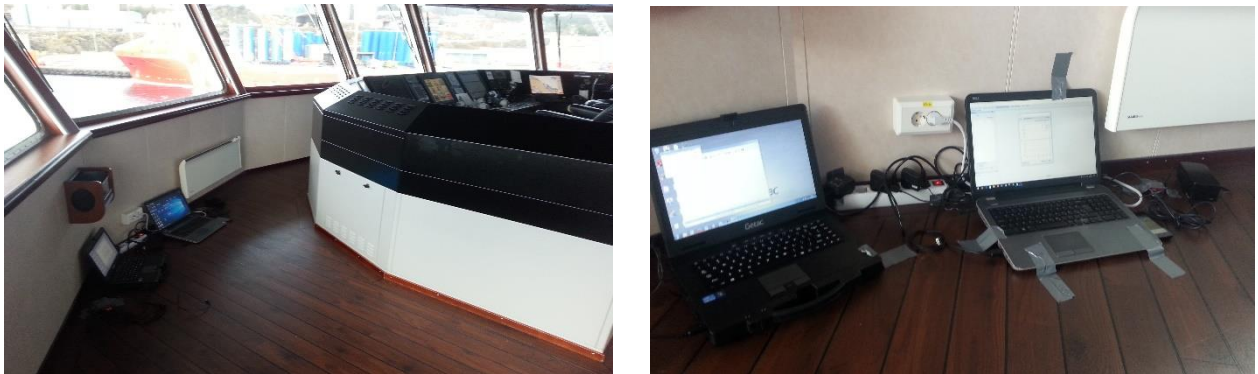

Fig. 3 Position of the sensors on the bridge

Main particulars of the Platform Supply Vessel where monitoring of the motions on the waves was performed:

Table 1. Platform Supply Vessel's particulars

Item	Value
Length between perpendiculars	86,60 m
Breadth	19,70 m
Draught	6,10 m
Block coefficient	0,72
Displacement	4800 t

Semi-analytical expressions for roll, described in (Jensen, Mansour, & Olsen , 2004), were used in validating calculations. Those calculations were used to calculate Response Amplitude Operator of the ship, while JONSWAP wave spectrum was used to represent sea state (Prpić-Oršić & Čorić, 2006). Validating calculations were performed for different heading seas and different significant wave heights. Semi-analytical results (roll of the ship) were compared with two data: (a) Real measured data for roll and (b) data reconstructed from the monitored semi-analytical model. Results of the validation are shown in *Table 2*.

Table 2. Report on the validation experiment on the Platform Supply Vessel

	Hours on date 4.4.2017.					Hours on date 6.4.2017.			
	11:00	13:00	14:00	17:00	20:00	7:00	11:00	17:00	22:00
Beta angle [deg]	45	150	150	150	20	150	180	150	30
H significant (monitored on ship)	3	4	4,5	5	6,5	3	3,5	3,5	2,5
H significant (ML model)	3,15	3,66	3,7	3,28	3,813	2,87	5,09	3,99	2,79
H significant error [%]	*5*	*8*	*18*	*34*	*41*	*4*	*46*	*14*	*11*
Roll significant (ML model)	4,2	4,1	4,9	9,1	6,2	4,71	3,12	3,83	4,23
Roll (semi-analytic model)	4,3	5	5	9,1	6,3	4,9	3,5	4	4,8
Roll Error [%]	*2*	*18*	*2*	*0*	*16*	*4*	*11*	*4*	*12*

Table 2 shows observed sea conditions on two different days and all together nine observations (log entries). Validation against the semi analytical model was performed on these dates. Analysis and the calculations are as described below.

By observing the table, we see that the expected error in estimating the significant wave height is less than 19% and the expected error in estimating the roll angle is less than 6%. The estimated encounter angle in this case was not meeting the accuracy target since the conditions were extreme and the regime corresponded to the cross sea conditions. To validate the encounter angle estimation, we report on the simple twenty fold cross validation performed by comparing the forecast data with the estimate of the encounter angle β based on the forecasted wave direction. We carried out cross validation on the data from three vessels (two passenger ships in the Adriatic and the platform supply vessel in the North Sea) and the results are as follows.

Table 3. Report on the cross validation for estimating the encounter angle β

	Vessel 1	Vessel 2	Vessel 3
Expected error [deg]	37,77	31,29	24

If we segment the encounter angles β in the typical five categories: following sea, quartering sea, beam sea, bow sea and head sea, then the machine learning model will miss the correct encounter angle by at most one category. We propose that this is acceptable for optimal route calculation bearing in mind the spreading of the wave spectrum which was particularly significant for the experiment in the North Sea (Vessel 3).

3. Directional performance charts

An algorithm to optimize vessels routes and fuel consumption based on the isochrone and isopone regions given a current position of the vessel while varying the heading to obtain a minimum time route and minimum fuel consumption route. Alternatively, optimal route can be found using grid search based on an evolutionary algorithm, and thus determining the optimal route in terms of a given cost function, see (Walther, Rizvanolli, Wendebourg, & Jahn, 2016) and (Hinnenthal & Clauss, 2010). The routes are further restricted to satisfy operability and safety constrains expressed through theoretical transfer functions relating time series of ship motions to the motion of the sea surface. The theoretical transfer functions, relating the sea motion to the ship's motion, can be computed by the trip theory as implemented in e.g. SEAWAY system (Journee, 2001). The critical operational conditions are then expressed from these theoretical transfer functions using polar plots.

Unlike standard approaches we do not use theoretical transfer functions. Instead we use the IMU measurements from the SailRouter device to determine the wave parameters and the encounter angle and then we compute the polar plot of a given performance indicator in dependence of the encounter angle. In Fig. 4 we see polar plots relating the RMS of the roll $\sigma(S_r)$ with the encounter angle and the significant wave amplitude. In the right hand plot, we relate the RMS Heave $\sigma(S_{he})$, to the encounter angle and to the significant wave amplitude for a catamaran passenger ship as reconstructed from a month of operations in Adriatic.
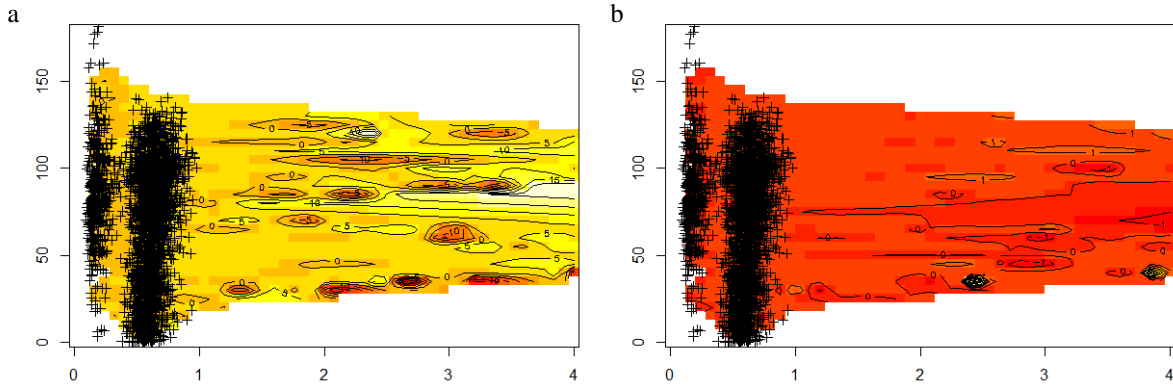
Fig. 4 (a) Performance plot for the catamaran passenger ship relating the encounter angle β and $\sigma(S_r)$, the RMS of the Roll time series; (b) Relating the encounter angle and the RMS of the vertical acceleration $\sigma(S_{he})$ Note: Crosses mark the measured data

On Fig. 5 we see the same plots for a car ferry operating in the same period of the year, also in the Adriatic. The polar plots were obtained by Akima's spline interpolation from the measured data. Similarly, we make directional plots relating reduction in the speed of operations, as recorded by the GPS, against performance on calm sea. With this information, we search for the route with optimal fuel consumption.

As a criterion for rejecting a route we use the classification of vessels motions based on the measured $\sigma(S_{he})$ for the time series of vertical accelerations and reject possible directions where $\sigma(S_{he})$ or $\sigma(S_r)$ are larger than a safety threshold. Unlike standard approaches using simulation software, see (Journee, 2001) (Hinnenthal & Clauss, 2010), we use directional performance tables obtained by machine learning. Examples of such polar tables are presented in Fig. 4 and Fig. 5.
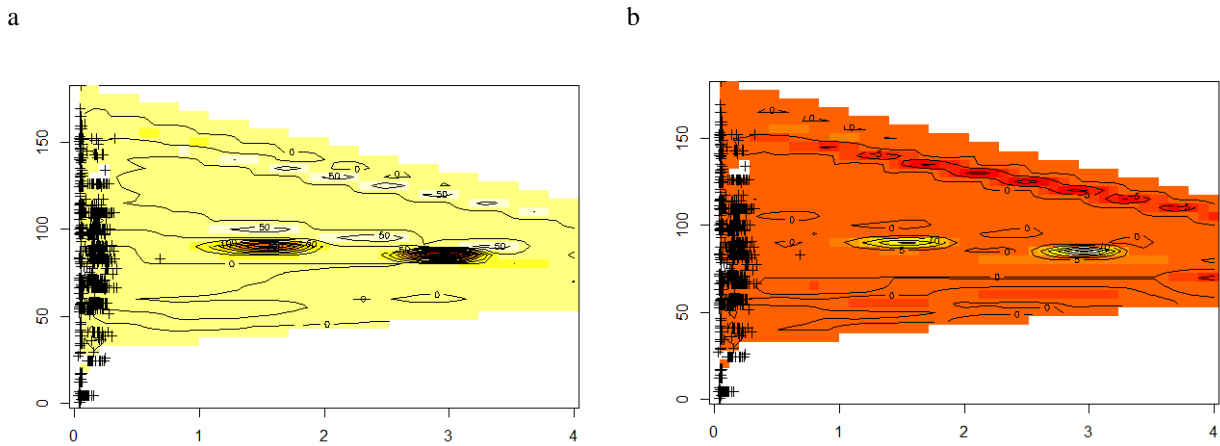

Fig. 5 (a) Performance plot for the car ferry relating the encounter angle and $\sigma(S_r)$, the RMS of the Roll time series; (b) relating the encounter angle β and the RMS of the vertical acceleration $\sigma(S_{he})$ Note: Crosses mark the measured data

4. SailRouter description

SailRouter™ is a desktop and cloud software solution that offers users easy to use and tailor-made decision support systems based on real world weather and ship data to reduce ship CO_2 emission and operational costs. Its key product is a software application that helps ship owners to reduce fuel consumption in the

maritime transport by calculating an optimal route relative to sea state (waves and sea-currents) and real ship hydrodynamics (relationship between ship speed and waves). SailRouter™ desktop software calculates an optimal route where ship will consume as less as possible fuel and arrive to a destination within predefined time frame. Besides onboard using, SailRouter™ enables user online monitoring of the ship performance in the real time and reporting of the past performance.
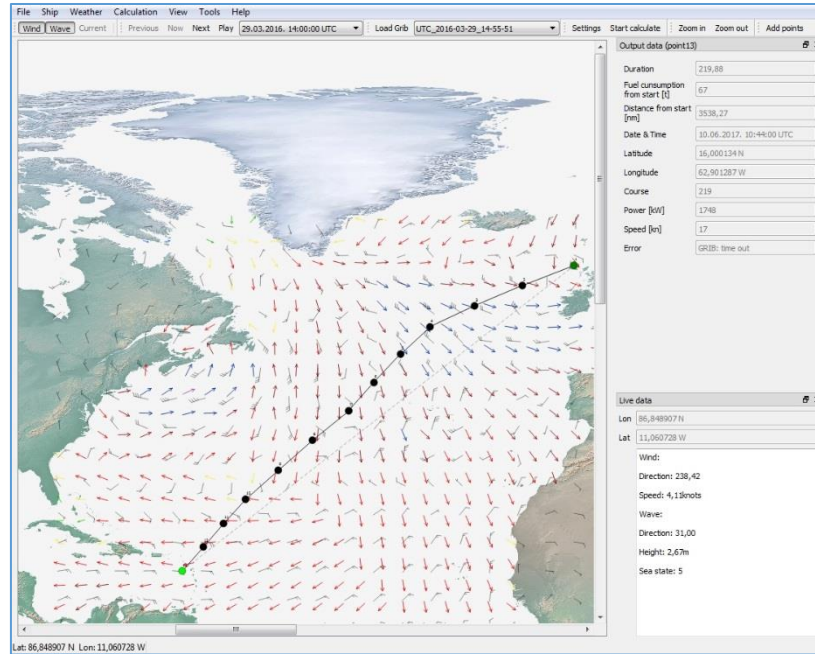

Fig. 6 SailRouter desktop application

5. Integration in the SailRouter™ framework

SailRouter™ is a software solution for optimizing the sailing route based on a polar diagram of the dependence of sailing speed on the wind angle and strength. It was developed as part of the master thesis by the second author, (Mandic, 2008) and (SailRouter B.V., 2016). Based on the polar chart, presented as a directional speed table an optimal route is determined using grid optimization based on an evolutionary algorithm, see Fig. 6. The performance table for a vessel is transmitted to the software using a format for representing polar files that is standard for the use with route optimization software like (True Heading AB, 2011) or (Laurent, 2017).

The optimization loop in the SailRouter™ software has been extended in (SailRouter B.V., 2016) to also handle polar charts describing the ship's performance on waves. Here the GRIB data for waves, which can be obtained from e.g. mesoscale meteorological models from the GFS data are used to optimize the route of a vessel with regard to the encounter angle with the waves β.

The optimal route, either with regard to fuel consumption or time of arrival, is computed under the restriction that it satisfies the safety restrictions. An example of a polar file relating $\sigma(S_r)$ and the wave encounter angle is given in Fig. 7.
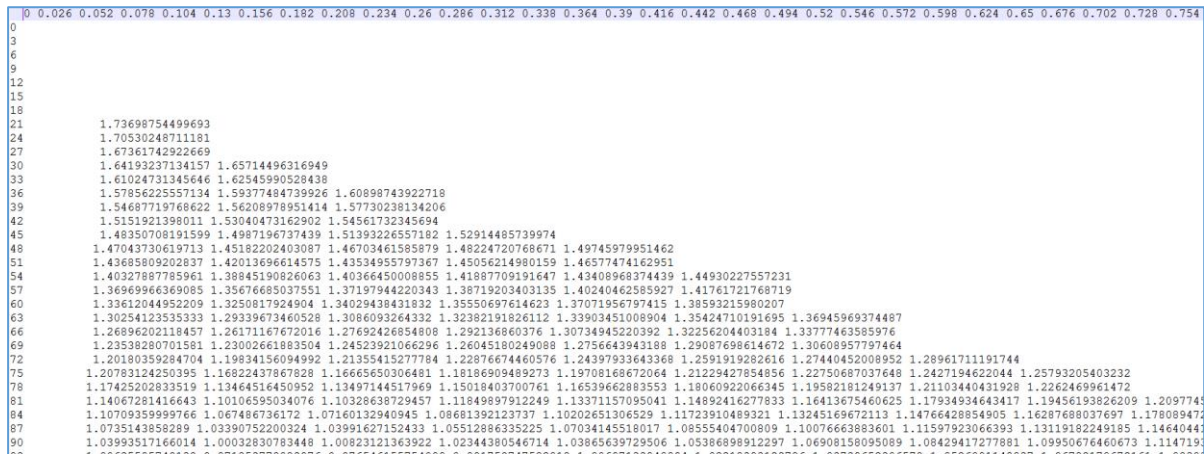

Fig. 7 Polar file representing the directional performance table for test case of the car ferry from Fig. 5

6. Conclusion

Based on the comparison to the ships log, the analytical model of the ship supplied by the data from the weather forecast model, and by the measurement from other sources we propose that the method for recognizing sea wave parameters is sufficiently accurate to yield plausible directional performance charts from the actual measured performance indicators for a vessel in motion. These performance charts can then be used as predictors for implementing the performance constraints necessary for the optimization software to return the optimal route (eg. In terms of the time of arrival) for a given mission dependent safety indicators.

Acknowledgement

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