予測バイアス除去手法がウェザールーティングの精度におよぼす影響に関する研究

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A Study on the Effect of Various Forecast Bias Removal Methods on the Accuracy of Ship's Weather Routeing

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Abstract

Numerical Weather Prediction products used in ship's weather routeing contain significant forecast errors due to imperfect initial conditions and or imperfect knowledge of the mechanic governing the evolution of the atmosphere, a part of these errors occurs systematically (called bias). The optimal routes computed using such forecasts show a deviation from the actual optimal route. Because these biases are so systematic, statistical methods can be successfully used to correct for them.

In this study the temporal and spatial evolution of forecast errors and their systematic biases, for surface wind and ocean wave fields issued by the Japanese Meteorological Agency are studied. The systematic biases are computed for various training period, and the effect of these removal methods on the accuracy of a minimum time route is investigated by carrying out simulations using a container ship sailing over the Northern Pacific Ocean. The different obtained routes are compared to and scored against the most optimal route obtained relying only forecast analysis. Results show that a dynamic running bias method requiring a relatively short period of forecast data archival achieves relatively good results especially during periods of unstable and or bad weather.

Keywords: *Ship's weather routeing, forecast error, systematic error, minimum time routeing.*

1.1 Introduction

Ship's weather routeing is a weather forecast based decision making tool, which using the ship's characteristics and responses to particular winds and waves help the operator to find an optimal route and estimate the possible danger encountered during the voyage. The route obtained meets a preset cost function and/or conditions to achieve different objectives, such as the shortest voyage time, minimum fuel consumption, and minimum ship movement and so on.

The accuracy of the weather routeing solution is closely related to the accuracy of the input data,

among which the most erroneous are the weather data; the reliability of a generated optimal route depends largely on the accuracy, resolution and range of available weather forecasts. In spite of improvements in the atmosphere modeling techniques over the last decades, models still have some errors in their forecast, some of these errors occurs systematically⁽¹⁾⁽²⁾.

The efficiency of the weather routeing technique has been largely proven and demonstrated as shown by the large amount of publication. In this study we will try to answer to some several questions of different importance for the ship's routeing problem:

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- What is the scale of variation of the forecast errors in space and in time?
- Would this degree of accuracy allow a reliable routing?
- What should be the expected error on routing?
- Would any method of systematic bias removal have an impact on the accuracy of the computed optimum route?

In this paper various methods for bias removal are tried and their effect of the ship's weather routing investigated, aiming to determine if it is possible to reduce the size of the necessary data storage to have a good approximation of the routing errors

2. Data used in the study

Two types of data were used to carry out this study.

2.1 Weather forecast data

In this study, the Numerical Weather Prediction (NWP) system products issued by the Japanese Meteorological Agency (JMA) are used. Data is available for education and research purpose from the web page of The Research Institute for Sustainable Humanosphere (RISH) of Kyoto University⁽³⁾.

Running their global spectral and wave forecast models four times a day, the JMA produces surface wind and wave forecasts with a spatial resolution of 0.5°; four times a day for a forecast lead time up to 84 hours with a forecast step of 6 hours and once a day for the forecast lead time between 96 and 192 hours with a forecast step of 12 hours.

The issued data were collected, verified and analyzed for a period of three years, 2008, 2009 and 2010.

2.2 Bathymetry data

When planning a route for a ship, information about sea depth is of vital importance for distinguishing between sea and land; and also for setting allowable and safe passage depth according to the nature of the voyage and/or type of the vessel. For this purpose, the One Minute Grid bathymetry data set for world's oceans is used, the data is issued by The General Bathymetric Chart of the Oceans (GEBCO) which is an international group operating under the joint auspices of the Intergovernmental Oceanographic

Commission (IOC) of UNESCO and the International Hydrographic Organization (IHO)⁽⁴⁾.

2.3 Concerning Ocean Currents

Ocean currents are an important factor in weather routing and incorporating them in the optimization method is quite straight and simple. However, we did not take them into account in this study for the following reason. Any optimized route computed using both the forecasted weather and the currents will have an error which is nearly impossible to decompose and attribute either to the forecast errors or the current. Since the main aim of this study is to investigate the effect of forecast errors and systematic bias removal methods on the accuracy of the optimized route, we thought it would be better to analyze results obtained using only weather forecasts; and that to have only one source of error.

3. Forecast error

All operational Numerical Weather Prediction models try to predict the evolution of the weather state through the time using information about the original state of the atmosphere and a set of equations describing the evolution of the atmosphere over the time. Even with the large development in computer science, mathematical modeling, there are always inherent limits to numerical weather prediction. Forecasts are right a part of the time, giving good predictions and miss a part of the time. The difference between the forecasted state and the actual state represent the total forecast error and is commonly measured by the difference between the forecast and the analysis at the verifying time, assuming the analysis to represent the best approximation of the actual state of the atmosphere.

Let F_T and A represent the forecast at lead time T and the verifying Analysis fields respectively.

Hence the forecast error variable E_T is

$$E_T = F_T - A \quad (1)$$

Computing forecast errors for both the GSM and GWM models is quite a heavy task, so we restricted ourselves to the computation of the errors on forecast that are of interest to the ship's weather routing; forecast errors for the surface wind and ocean wave fields were computed for a three year period, for all the forecast lead times.

Fig.1 shows the evolution of the wave height forecast error over the northern Pacific Ocean for the 15th October 2010 12H00 issued forecast for forecast lead time of 48, 96, 144 and 192 hours. Contour lines are drawn for each 0.5 m, positive contour lines are shown in continuous lines (representing over-forecast), whereas the negative contour lines are shown in discontinuous lines (representing under-forecast). We can see clearly that the forecast errors grow as function of forecast lead time, as well as their downstream travelling.

Fig.1 Evolution of the wave height forecast error over the Northern Pacific.

4. Systematic bias

The total Forecast field error E_T for any starting date, for forecast lead time T can be expressed as the sum of two parts, the systematic error part and the random error part:

$$E_T = E_s + E_R \quad (2)$$

Where:

E_s is the systematic error (also called bias); synonymous with a non-zero mean forecast error over a large number of forecasts, is a stationary component of the total forecast error and is due to mainly imperfections in the modeling system.

If we have N forecasts corresponding to N initial values, over a determined period, then the systematic error field is:

$$E_s = \frac{1}{N} \sum (F_T - A) \quad (3)$$

The necessary period of time for collecting the N forecasts and their verifying analyses is called the "training period".

E_R is the Transient error or Random Error, identified as a deviation from non-zero mean at each forecast, and is considered to be mainly due to errors on the initial conditions; it is such that it fulfills the following function (same denotations as above):

$$\frac{1}{N} \sum E_T^2 = E_s^2 + \frac{1}{N} \sum E_R^2 \quad (4)$$

The systematic errors in models usually have coherent patterns in space. These geographically fixed error patterns shows large variation with the increase of forecast lead time. Previous studies shows that the systematic errors account for more than one third of the total forecast error in the medium range forecast (5).

For the purpose of this study systematic bias for each grid point were computed for the period of 2009 and 2010 using two methods, a static bias methods and a Dynamic running bias method.

4.1 Static bias method

As stated earlier the model bias is calculated from comparison of forecasts and verifying analysis over a long period of time called training period; for the static bias (hereafter SB) method, the training period for any forecast is the one month period from the previous year, (example for a forecast issued in 12 march 2010, the training period is March 2009), hence

for each forecast issued in the same month the bias is the same.

This method has several disadvantages, calculation of the static bias requires that years of forecasts be run with the same model version, large data storage is required and averaging over a long period dampens the shape of the bias, and this by averaging large negative and large positive values. But on the other side this method requires only a small amount of computations and is easy to implement.

4.2 Dynamic running bias method

Model bias is calculated every day for each issued forecast, using a shorter moving (or running) training period. In this study three training periods were used, 8 days, 15 days and 30 days. The available forecast errors for every forecast lead time, during the training period prior to the forecast issue time are used to compute the model bias (hereafter referred to as 8DRB, 15DRB and 30DRB), as a results, each model run and lead time will have a unique bias value.

This method requires model bias to be computed every day, implying large amount of computation and the model bias may be subject to the effect of localized forecast errors. But on the other hand no large amount of forecast data storage is required and

we may be able to capture more efficiently error change pattern.

Fig.2 shows different computed systematic biases for the wave height forecast field, over the northern Pacific Ocean for the same forecast as in Fig. 1; but only for 192 hours forecast lead time. The top left, the top right, bottom left and bottom right panels show the SB, the 8, 15 and 30 DRB respectively. Contour lines are drawn for each 0.5 m, positive contour lines are shown in continuous lines and negative contour lines are shown in discontinuous lines. We can see that the 15DRB shows a closer shape to the error field.

5. Weather routing simulations

5.1 Simulation conditions

To carry out the study the modified isochrone method developed by Hagiwara and Spaans⁽⁶⁾ was chosen. A weather routing simulation program was run for a period of nearly two years, between the 1st of January 2009 and 20th December 2010, with daily departure (departure at 12H00 UTC) to generate minimum time routes (MTR) between Tokyo and San Francisco.

The model ship used is 42,442GRT, 247.85m long container ship, propelled with one diesel engine developing 32,700PS and a service speed of 21.5 knots at 71RPM⁽⁷⁾.

Fig.2 Different systematic biases for wave height over the Northern Pacific for 192 hours.

Unequal distribution of heating of the surface of the earth and the Coriolis force affect the atmospheric circulation and hence the weather patterns move on east-west direction affecting the optimum route. Routes were generated for both eastbound and westbound course for every voyage; the simulated voyages were 719 for each course.

5.2 Conditions for the simulation

Simulations for generating MTRs are done using three types of inputted weather data:

I- The analysis data: assumed to represent the best approximation of the true state of the atmospheric conditions. (Gives the best possible optimized route and will be used to judge the accuracy and reliability of the other obtained route).

II- The forecasted data: the deterministic forecasted wind and wave data issued by the JMA are used to quantify the wind and wave up to 192 hours and from this point the monthly means are used.

III- The forecasted data corrected for systematic bias: The deterministic wind and wave data are corrected for systematic bias using mainly two methods of bias removal.

(a) Static Bias removal, where forecasts are corrected for static bias.

(b) Dynamic Running Bias removal, where forecasts are corrected for dynamic running bias.

6. Weather Routeing Simulations Results

Ten types of Minimum Time Routes were generated.

1. Analysis MTR: only analysis data were used to generate the MTR.
2. Forecast MTR: forecast data available at departure time were used to generate the MTR.
3. SB all MTR: forecasts were adjusted for static bias.
4. 8DRB all MTR: forecasts were adjusted for 8 days dynamic running bias.
5. 15DRB all MTR: forecasts were adjusted for 15 days dynamic running bias.
6. 30DRB all MTR: forecasts were adjusted for 30 days dynamic running bias.

In the same way as for the above mentioned corrections, routes were generated for both static bias and dynamic running bias, by correcting only

the wave height; and were called successively:

7. SB h MTR.
8. 8DRB h MTR.
9. 15DRB h MTR.
10. 30DRB h MTR.

The subject of this study is to investigate how ship weather routeing is affected by different methods of bias removal, so the different generated routes are compared to and scored against the optimal route obtained from the analysis data.

Actual voyage time for a predicted route is defined as the passage time obtained by running a simulation of the ship's passage along the predicted route (using the predicted waypoints) and the analysis data to describe the weather conditions. Due to forecast errors, the actual voyage time of a predicted route is different from its predicted one.

The difference between the actual voyage time for the different generated routes and the analysis generated MTR will give an idea about the accuracy of the forecasted routes and their deviation from the most optimal route.

As in other business, in shipping not only speed is essential but punctuality is also required, a ship has to sail fast and arrive in schedule. The punctuality of a ship is expressed through its delay of arrival (timeliness), which is the difference between the predicted voyage time and the actual voyage time for the different generated routes (negative values express late arrival vice-versa).

6.1 Westbound route results

Fig.3 shows the results for a westbound course voyage departing on the 5th of September 2009 at 12H00 UTC.

Fig.3 Westbound voyage simulation results.

The 15 DRB all and 8 DRB all generated MTRs are spatially closer to the analysis generated MTR than the other generated routes, the 15 DRB all MTR achieves the best results with a difference in actual voyage time of 0.31 hours (over a voyage of more than 9 days) and a earlier arrival than expected with a delay of arrival of 0.50 hours (the predicted voyage time being 229.69 hours), whereas the other generated MTRs take the ship on a more northern course achieving larger actual passage times (the forecast MTR actual passage time is 231.34 hours).

Fig.4 shows the difference between the actual voyage time for the different predicted MTRs and the analysis MTR voyage time over all the period of the study (the patterns being similar, we show the plot only for all to make the figure more readable).

Fig.4 Difference in the actual voyage time for the westbound course.

From this figure we can see that the forecast MTR and the other bias corrected routes achieves generally closer actual voyage time, and tends to deviate from the analysis MTR in the Autumn and the winter seasons with a deviation of over 13 hours in some cases.

To have a better and easy quantification of the closeness of the predicted MTRs to the analysis MTR, we set a parameter called hit number. For each simulation run, the predicted MTR that achieves the closest voyage time to the analysis MTR is attributed one point, increasing its hit number. Table1 shows the mean and the standard deviation of the difference between the actual voyage time for the different predicted MTRs and the analysis MTR voyage time in hours, as well as the hit number for each season (for

every season, the best hit rate is shown in larger font). In this work, the relation between then mean, standard deviation and hit number was not investigated due to its complexity; and that for all the parameters.

Table 1 Main statistics for difference of actual voyage times for the westbound course.

		Winter	Spring	Summe	Autum
Forecast	Mean	1.265	1.051	0.315	1.075
	S.D	1.944	1.854	0.389	1.95
	Hits	22	21	28	23
SB all	Mean	1.51	1.094	0.308	1.216
	S.D	2.407	1.753	0.397	1.938
	Hits	19	22	24	24
SB h	Mean	1.375	1.064	0.302	1.123
	S.D	2.06	1.737	0.362	1.862
	Hits	18	19	(29)	15
8DRB all	Mean	1.607	1.138	0.37	1.429
	S.D	2.403	1.945	0.488	2.342
	Hits	22	22	15	18
8DRB h	Mean	1.55	0.997	0.328	1.288
	S.D	2.403	1.644	0.407	2.028
	Hits	(23)	(28)	20	17
15DRB all	Mean	1.369	1.129	0.341	1.134
	S.D	2.096	1.821	0.441	2.065
	Hits	18	17	22	(27)
15DRB h	Mean	1.427	1.078	0.315	1.209
	S.D	2.189	1.809	0.393	2.063
	Hits	16	25	18	18
30DRB all	Mean	1.357	1.071	0.311	1.242
	S.D	2.062	1.877	0.378	2.35
	Hits	18	18	16	17
30DRB h	Mean	1.278	1.117	0.323	1.057
	S.D	1.86	1.903	0.383	1.945
	Hits	13	12	12	23

We can see the seasonal variation of the accuracy of the predicted MTRs; predicted MTRs are more accurate in the summer season and show larger variation in the autumn and winter seasons. We can see also that the predicted MTRs corrected for bias achieve larger hits numbers; the 8DRB all and 15DRB all predicted MTRs perform quite well during the autumn.

Fig.5 shows the delay of arrival for the different predicted MTRs during all the period of the study (the patterns being similar, we show the plot only for all to make the figure lighter).

We can see that the different predicted MTRs have a tendency to show negative delays of arrival, especially during the end of winter, the beginning of spring and in the autumn seasons; which means that the ship arrives later than scheduled. This is mainly due to forecast errors, and the fact that the JMA wave model tends to under-predict wave height.

Fig.5 Delay of arrival for westbound course.

The same as for the difference of voyage time, we set a hit number; but since we are looking for the routes that generates the minimum value of delay, for each simulation run the predicted MTR that achieves the smallest absolute value of delay of arrival is attributed one point, increasing its hit number. Table 2 shows the mean and standard deviation (in hours) of the delay of arrival, as well as the hit number for every season.

Results for the delay of arrival of the predicted MTRs correlate with the accuracy of the MTRs; with loss of accuracy the delay of arrival becomes larger. MTRs corrected for bias have a higher hit rate than the forecast MTR in all seasons except summer.

6.2 Eastbound route results

On eastbound routes, the ship moves downstream along the storm track so the accuracy of the predicted MTR is higher than that for the westbound voyage.

The eastbound route was processed in the same way as the westbound route, obtaining nearly the same results and seasonal variation, except that the accuracy for the eastbound route is higher, so for shortening the paper we will skip the figures showing the delay of arrival for the different predicted MTRs and their delay of arrivals during the period of study and we

Table 2 Main statistics for the delay of arrival for the different MTRs for the westbound course.

		Winter	Spring	Summe	Autum
Forecast	Mean	-1.523	-1.542	-0.937	-1.531
	S.D	2.945	2.917	0.965	2.886
	Hits	17	18	(68)	20
SB all	Mean	-1.865	-1.717	-1.114	-1.51
	S.D	3.191	3.039	0.994	2.941
	Hits	26	(31)	25	(34)
SB h	Mean	-1.712	-1.534	-1.037	-1.436
	S.D	2.99	2.76	0.95	2.814
	Hits	12	23	27	16
8DRB all	Mean	-1.864	-1.782	-1.286	-1.908
	S.D	3.215	3.003	1.101	3.395
	Hits	(32)	21	10	21
8DRB h	Mean	-1.791	-1.549	-1.141	-1.734
	S.D	3.135	2.694	1.054	3.011
	Hits	24	21	8	22
15DRB all	Mean	-1.462	-1.639	-1.252	-1.567
	S.D	3.059	2.791	1.033	3.049
	Hits	18	17	12	20
15DRB h	Mean	-1.586	-1.568	-1.125	-1.67
	S.D	3.082	2.763	1.021	2.989
	Hits	9	13	11	13
30DRB all	Mean	-1.534	-1.502	-1.214	-1.662
	S.D	3.055	2.835	0.956	3.125
	Hits	17	19	8	22
30DRB h	Mean	-1.48	-1.553	-1.134	-1.545
	S.D	2.859	2.825	0.941	2.873
	Hits	14	21	15	14

present only Table 3 and Table 4, which in the same way as Table 1 and Table 2 show the main statistics but for the eastbound route for each season through the study period. Seasonal variation and good skill performance of the forecast bias removal methods are also noticed.

Fig.6 shows a plot for the westbound and eastbound MTRs generated using only the analysis data for all the period of study, we can see that for the westbound routes, on several occasions the MTR take a northern route through the Aleutian Islands; whereas the eastbound routes show less variation and have a more southern shape. The solid line represents the average latitude of the vertex of all the generated MTRs, whereas the dotted lines show plus and minus the standard deviation of the latitude of the vertexes.

Table 3 Main statistics for difference of actual voyage times for the eastbound course.

		Winter	Spring	Summe	Autum
Forecast	Mean	0.355	0.258	0.106	0.344
	S.D	0.508	0.465	0.094	1.721
	Hits	24	18	23	17
SB all	Mean	0.371	0.243	0.124	0.332
	S.D	0.505	0.415	0.124	1.359
	Hits	(24)	20	(26)	18
SB h	Mean	0.352	0.244	0.122	0.298
	S.D	0.499	0.43	0.111	1.099
	Hits	19	(25)	16	23
8DRB all	Mean	0.382	0.281	0.124	0.388
	S.D	0.507	0.478	0.115	1.888
	Hits	15	17	25	23
8DRB h	Mean	0.362	0.264	0.118	0.358
	S.D	0.514	0.506	0.096	1.821
	Hits	15	19	22	(25)
15DRB all	Mean	0.361	0.243	0.131	0.364
	S.D	0.48	0.412	0.119	1.816
	Hits	23	21	10	16
15DRB h	Mean	0.353	0.235	0.107	0.338
	S.D	0.514	0.409	0.098	1.581
	Hits	17	17	18	22
30DRB all	Mean	0.372	0.255	0.117	0.351
	S.D	0.506	0.44	0.12	1.859
	Hits	15	25	21	22
30DRB h	Mean	0.6345	0.24	0.114	0.32
	S.D	0.484	0.409	0.118	1.559
	Hits	17	22	23	16

Table 4 Main statistics for the delay of arrival for the different MTRs for the eastbound course.

		Winter	Spring	Summe	Autum
Forecast	Mean	-0.365	-0.434	-0.06	-0.42
	S.D	0.878	0.817	0.364	1.763
	Hits	24	29	(34)	23
SB all	Mean	-0.299	-0.371	-0.124	-0.45
	S.D	1.298	1.021	0.367	1.951
	Hits	24	(30)	26	27
SB h	Mean	-0.305	-0.398	-0.153	-0.409
	S.D	0.887	0.807	0.354	1.211
	Hits	18	28	30	16
8DRB all	Mean	-0.235	-0.475	-0.116	-0.494
	S.D	0.959	0.855	0.389	1.954
	Hits	(25)	12	24	18
8DRB h	Mean	-0.221	-0.485	-0.137	-0.486
	S.D	0.957	0.817	0.376	1.814
	Hits	15	21	21	14
15DRB all	Mean	-0.227	-0.449	-0.133	-0.466
	S.D	0.895	0.802	0.39	1.797
	Hits	16	20	17	20
15DRB h	Mean	-0.229	-0.444	-0.143	-0.462
	S.D	0.92	0.797	0.381	1.588
	Hits	17	15	13	21
30DRB all	Mean	-0.228	-0.443	-0.128	-0.46
	S.D	0.886	0.807	0.381	1.85
	Hits	18	16	9	(27)
30DRB h	Mean	-0.216	-0.432	-0.149	-0.455
	S.D	0.882	0.808	0.372	1.591
	Hits	12	13	10	16

7. Conclusions

In this work, several methods for forecast bias removal were tried for parameters of great importance to the ship's weather routing, that are surface wind and ocean wave fields, using JMA issued wind and wave forecasts for a period of three years (2008,2009 and 2010). Two methods of bias removal were studied; the first method uses a static running period as a training period for the computation of the bias and the second one uses a dynamic running period (8,15 and 30 days) as training period.

The effects of the proposed forecast bias removal methods on the ship's weather routing were investigated by carrying out minimum time routing optimization using a container ship plying between Tokyo and San Francisco for a period of nearly two years. The proposed methods for removing bias have

been shown to work, with nearly equal performance, achieving better performances especially during periods of bad and/or unstable weather conditions.

The difference in the different routes obtained using different bias removal methods could be used as an indication on the reliability of the forecasted route accuracy. For the purpose of ship's routing, a storage of weather forecasted data of up to one month can be large enough to perform bias removal using different training periods.

Further studies needs to be carried, using different training periods for different weather patterns and seasons, the bias should be also computed differently for different weather regimes; the information conveyed by the forecast bias can be used advantageously to estimate the delay of arrival on a predicted route.

Fig.6 Eastbound Analysis generated MTRs

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extremely similar but slightly different initial conditions, any complex system will rapidly move to different states, with an exponential amplification of the initial errors and Unpredictability of long-term behavior.

Questions and answers

Kiyokazu Minami, Tokyo University of marine science and technology:

- (1) Why are there forecast errors?

Brahim MEZAOU:

- (1) No weather forecast is foolproof, it always and will always contains errors. The weather is certainly predictable -at least in the short time- but forecasts can still fail because of the following main reasons:
 - Errors in the initial conditions used to initiate the models, the knowledge of the present state is not perfect, the initial conditions are not accurate enough, observation's coverage is limited in space and time, and the observations also contains errors.
 - The models describe only in an approximate way the true atmospheric phenomena; in fact no one knows correctly the laws governing the atmosphere. Another problem is that in any atmospheric model the laws are expressed as nonlinear partial differential equations. Their solutions are not usually possible by precise mathematical methods, but are achieved by approximation using numerical analysis. Thus any forecast is subject to model errors.
 - The atmosphere being as stated by Edward N. Lorenz a chaotic system shows a sensitive dependence on initial conditions, that is, starting from