INTELLIGENCE VOYAGE PLANNING FOR EMISSION LOWERING

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ABSTRACT

Several decision support tools for optimization of fuel oil consumption and consequently energy efficiency, that suggest the optimum route based on weather forecasts and hydrodynamic vessel data have been developed and evaluated some years ago. Weather routing was an EC partially funded R&D innovative projects on routing based on weather forecasting simulation of ship in a seaway. Danaos being participant in the project invested to apply the results implementing a decision support tool for voyage planning to optimize bunkering cost and moreover the emission lowering function. During the evaluation period different type of vessels (containers, tankers etc), and clients (owners, managers or charterers) participated. The useful feedback of hundreds passages was analyzed and system has been adjusted to be feasible., Functional specifications adopted, the concept has proven, the importance of models integration with navigation expertise is signified, the key factors are identified and the optimality against the least cost routing is proven. Paper is also focused on the theoretical hydrodynamic model using neural networks as it has been developed within the scope of EU IP Flagship project

Keywords-Voyage optimization; artificial neuron networks; control theory, Added resistance; Multicriteria analysis

1. INTRODUCTION

Cargo transportation crossing ocean from science point of view is considered as a typical case of energy transformation. From operational point of view is considered as process producing tonmiles consuming among the others tones of bunkers. Bunkering is the most substantial cost factor and at the same time is the main cause of carbon emissions. Hereafter any decrease of fuel consumption even less than 3% is significant. Before any attempt for bunkering saving it should be known the required bunkers in quantity and cost.

A build-in technical performance module gives the answer. Based on the required technical and hydrodynamic data (propeller and Main Engine characteristics and diagrams, sea-trial information, booljean lines etc) utilizes several functions like Calm water resistance cwr=f(V_s), mean added resistance due to wind mar=f(V_w,d) (V_S ,V_w: correspondingly speed vectors of vessel and wind, d:ship draught) applies appropriate interpolation techniques and return the values that are combined to produce the *I* performance index (tones/mile) for a given leg retrieving the weather variables for the defined waypoint (time and spatial coordinates).. In the following figures typical screenshots of the performance monitor of developed vip@sea model is presented. The speeds as vectors (value and direction) and the corresponding *I* performance indexes are provided and the optimum speed is emphasized.

sr@sea:Danaos Performance Monitor — Draught (m) 17

Weather data	Current V(kn)	Current (°)	Wind V (kn)	Wind D	Wave h(m)	Wave D	Wave T	Swell h(m)	Swell D	Swell T
	0.6	170	20.2	SE	1.2	SE	2.8	1.5	E	3.4
observed data	0.2	150	15.1	SE	2	S	3.0	2.5	SE	4.1

Range: V (kn) 14.1 14.3 (°) 220 223

	Real data	V (kn)	(°)	Resistance (tns) Rs	Rw	Rwv	Rsw	Rt	Engine rpm	Pkw	FOC Tn/100nm
Performance for the specific weather conditions per V and direction		14.1	220	84.0	4.0	2.0	3.0	93.0	85	11588	14.54
			221	84.0	3.8	1.8	3.2	92.8	85	11563	14.20
			222	84.0	3.7	1.6	3.4	92.7	85	11550	14.20
			223	84.0	3.6	1.4	3.1	92.1	85	11476	14.00
		14.2	220	86.0	5.0	3.0	2.2	96.2	85	11987	14.40
	RL:14.4(85@12000)		221	86.0	5.0	2.8	2.7	96.5	85	12024	14.20
			222	86.0	5.0	2.7	2.6	96.3	85	11999	14.00
			223	86.0	5.0	2.6	2.5	96.1	85	11974	13.80
		14.3	220	87.0	2.0	2.0	2.4	93.4	85	11638	13.20
			221	87.0	2.0	1.8	2.3	93.1	85	11600	13.00
			222	87.0	2.0	1.4	2.1	92.5	85	11526	12.90
			223	87.0	2.0	1.3	2.5	92.8	85	11563	13.10

Indicative cost saving from worst scenario for 500 nm: 2870 $

Figure 1: Performance monitor

The model may be formulated as follows:

$$w_z = \{wd, sw, ww, cur\},$$

$$foc_z = \phi(Rt_z, EhpV) \qquad (1)$$

Where *wd, sw, vw, cur* define the wind, swell-wave wind-wave and currents parameters correspondingly, *Ehp* is the Engine horse power, RC is calm water resistance, Rt_z, foc_Z is the total resistance, and the fuel oil consumption (tones/hour) correspondingly in point z.

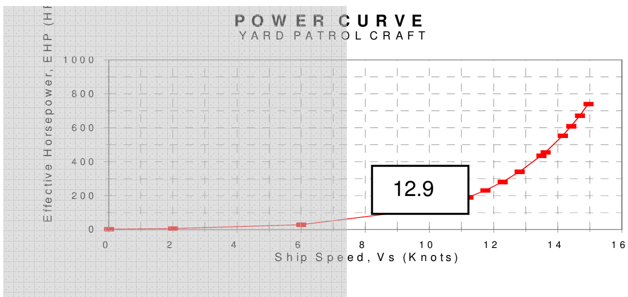

Figure 2: Alternative performance monitor

2. OPTIMIZING THE SOLUTION

2.1 ALL MODELS ARE WRONG BUT SOME ARE USEFUL

A sea voyage is divided into passages. Each passage is defined form its ends. These points are identified by its spatial-time coordinates *(x(φ, λ), t).* For a given passage, there are alternate seaworthy routes providing on time arrival that constitute a Heiseberg orbital. A route r_j (t=>x) *is* a mapping of t (time) to x (position). For points in a given route a performance index should be calculated. The calculated fuel oil consumption per mile l_i to cover the distance *S* from point x_i to x_{I+1} as well as any possible deviation dv_i for those points are used for the total fuel oil consumption *foc* in tones per route. A dynamic (time depended) program based on Dijiktra model finds the route with the minimum total *foc*. The optimization problem can be formulated as follows:

$$\exists r_j \in O\{r_j = \{x_{ij} \mid i = 1 : n\}\} : foc_{\min} = foc(r_j) = \sum_i^{i+1} (l_i x (S + dv_i)) \quad (2)$$

Where *O* is the orbital set of all the alternate routes r_j. Each route is defined by n ordered x_{ij} nodes that are linked with the shortest path. And the problem is to find the route with minimum fuel oil consumption as the summary of the *foc* of each leg that links two consecutive points plus the consumption of any deviation. Consumption per leg is calculated as the product of the performance index (l_j consumption per mile) by the sum of the traveling distance and the overhead of the deviation if any.

2.2 THE OPTIMIZATION ALGORITHM

If a problem has more than one solution needs resolution!

During the last years there are several operational research algorithms for cost optimization for oceangoing passages. The dynamic (time depended) as well as the quanta attributes are considered fundamentals. The most suitable approach is based on the “principle of optimality” which states that:

“an optimal policy has the property that, whatever the initial state and the initial decision, the remaining decisions must from an optimal control strategy with the respect to the state resulting from the first decision”

Because of this principle, the number of iterations can be drastically reduced. The appropriate algorithm has been presented from ECWMF (Hoffschift, 1999). An alternative algorithmic approach by best-fitted function definition as either polynomials or Euler-Maclauren numerically integrated b-splines may be applied taking into consideration the quanta nature of the problem. During the evaluation period it found out that the problem has some important constraints that allow the algorithm improvement. Particularly according the navigation practice:

- ✓ *Vessel speeds belongs in a small range. Typically there are at most only 20 different values.*
- ✓ *Speed vector change either on direction and/or value cannot change more than 4 times per s per time.*

Based on the above the algorithm has been improved expanding the optimality principle and the problem is formalized as follows:

‘’In a two-dimensional surface (time, space) with given resolution each node has a particular value that depends upon on each next and prior node. Find the route with the minimum additive value of its nodes’.

3. REALIZATION PHASE

3.1 HOMEOSTATIC ADAPTATION IN THE REAL DATA IS REQUIRED

Besides by winds, waves and currents the FOC performance index is influenced by trim, pitch, rpm of propeller(s), the condition of hull and propellers etc. So it is usual to have fluctuations between the theoretical calculated index and the on-board real measurement. Vessel may submit the related measurements either in a email or by utilizing the vip@sea model. The measurements are validated and the theoretical module is adjusted to real conditions using neural networks. Hereafter the adjusted module provides most reliable advice. Finally it is important to underline the following axiom.

3.2 AXIOM: ARTIFICIAL INTELLIGENCE CAN NOT SOLVE LOW STRUCTURED LEVEL PROBLEMS

Algorithms to find the best seaway for calm weather conditions between any two waypoints that avoids lands, restricted areas, war zones, draft limitations and navigation rules are not feasible.

The passage pattern must be defined by Captain and can be verified easily and rapidly and will be used as basis for closed alternative seaways. Searoutes research team spent a lot of time and energy to develop an artificial intelligence module providing the short path route between two waypoints but it should be considered indicative and in no case can replace the route pattern lanned by the navigation officer.

4. PROOF OF CONCEPT

For the purpose of the FLAGSHIP project a typical case of weather routing advantage is presented as proof of concept. A bulk carrier with draft 17m Engine power 25000 HP , max 91 RPM sailed from [58° 16' N 8° 20' W] with destination the Canal port at [43° 0' N 65° 18 W].. It was found that the suggested route avoids high resistance especially on head of swell and with wind wave. The next graph compares the fuel oil consumption distribution over the propulsion and added resistances for both cases the actual and the optimum suggested route.

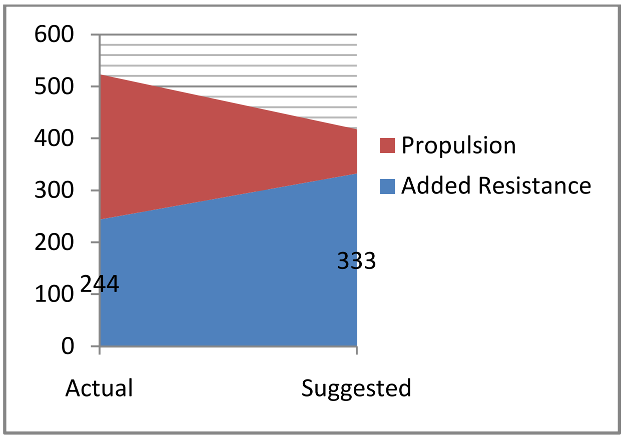

Figure 3: Actual and Suggested FOC distribution

The corresponding recap comparison table between actual and simulated seaway of vip@sea is summarized as follows:

Table 1: Recap comparison table

Variable	Actual	Opt	Saving	%
Distance	2580 Nm	2317 Nm	263 Nm	10.2
Duration	292h 00m	157h52m	134h08m	45.9
Propulsion	244 Mt	333 Mt	**-89 MT**	**-36.5**
Forces	280 Mt	85 Mt	195 MT	69.4
Total FOC	524 Mt	418 Mt	106 MT	**20.3**

Taking into consideration the weather factors and the vessel behavior the optimum route reduces the distance about 10%, more closed to GC, substantially minimizes the en route time about 45% and reduces the total consumption about 20.3 % despite the fact that FOC consumption for propulsion is increased about 36.5 because of higher speed.

With 350$/MT IFO price and 66000 $ TCE (Time Chartering Equivalent) the above figures can easily interpreted in terms of money as follows

Table 2: Savings summary

Cost Element	Saving
Bunkering cost saving	37,100 $
Time cost saving	368,500 $
Total cost saving	**405,600$**

Provided that fuel consumption is directly proportional of carbon emission the consequent positive impact of environmental protection is substantial and be easily measured.

5. CALIBRATION USING FF ARTIFICIAL NETWORKS

The implemented weather routing model seems to be the first integrated approach for voyage planning that incorporates maritime expertise and provides in-time with negligible communication cost the required support for decision making. As it was expected the real consumption data and the calculated from the hydrodynamic model differed more or less with a systematic deviation. To overcome this deviation the model has been enriched with a feed forward back propagation artificial network with four input and one output without hidden layer.

Input variables are S, W, SW, WW: the vessel speed and, the wind, swell and wind wave speed constituents in vessel direction respectively. The output is the C (fuel oil consumption). The applied method or weight assignment is quite simple recursive procedure and is based in the known as "the training the network" process. Initially a random weight function W is applied, the first observation feeds in network values V of output Y are predicted, training data of Y are back propagated and compared with corresponding predicted values and optimum weight function is adjusted to minimize the error prediction:

$$E = \Sigma \, (Yi - Vi)^{2} \qquad (3)$$

The new weight function is used in the next observation and the repetitive training cycles are finished when the prediction error is small.

6. CONCLUSIONS

Intelligent voyage planning integrates sea weather prediction, hydrodynamic theoretical model, sea keeping data to provide support in decision making focused on optimization of fuel consumption protecting the environment lowering emissions. The impressive acceptance from the market assures its advantages. Of course the provided advice guarantees the betterment for the decision in comparison of the related conventional but is not considered the best. Further refinements may be applied improving decision even better.
The innovation the simplicity and the accuracy are also considered three key factors of the produced service.

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