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The value of foresight in the drybulk freight market

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Abstract

We analyze the value of foresight in the drybulk freight market when repositioning a vessel through space and time. In order to do that, we apply an optimization model on a network with dynamic regional freight rate differences and stochastic travel times. We evaluate the value of the geographical switching option for three cases: the upper bound based on having perfect foresight, the lower bound based on a "coin flip", and the case of perfect foresight but only for a limited horizon. By combining a neural network with optimization, we can assess the impact of varying foresight horizon on economic performance. In a simple but realistic two-region case, we show empirically that the upper bound for large vessels can be as high as 25% cumulative outperformance, and that a significant portion of this theoretical value can be captured with limited foresight of several weeks. Our research sheds light on the important issue of spatial efficiency in global ocean freight markets and provides a benchmark for the value of investing in predictive analysis.

Keywords: dry bulk market, dynamic programming, neural network, foresight

1 Introduction

As in most business sectors, the ocean freight industry has recently seen a surge of interest in the digitalization of business processes and the adoption of machine learning and "big data" applications to improve economic performance. Such investments often take place in the belief that there are market inefficiencies that can be exploited, without any verification of the actual economic potential.

In this paper we propose a model to evaluate the economic potential of investing in predictive analysis of regional freight rates. Specifically, we consider an optimization problem that all operators of vessels in the bulk shipping freight markets face: How to optimally reallocate a ship or fleet of ships through space and time by sequentially accepting freight contracts (charters) for spot market cargoes between port pairs in a transport network, often called tramp shipping. We note here that tramp shipping differs from the liner shipping networks usually considered in the optimization literature (see [Christiansen et al., 2013] for a comprehensive literature review) in that there are no fixed routes, schedules or contract cargoes. Instead, a large number of ships and full loads (cargoes) are continuously matched by shipbrokers in a perfectly competitive market where the future trading pattern and employment of the vessel is largely unknown.

As our goal is to assess the potential value of investing in predictive analysis, we solve two versions of this problem. First, the case where future rates are completely known (perfect foresight). The optimization task to be solved here can be classified as *dynamic assignment problem with stochastic travel times.* Dynamic assignment problems on networks often arise in logistics applications, for instance [Powell, 1996] in the context of truck logistics or [Topaloglu and Powell, 2006] in business jets repositioning. In both these cases, the authors use a reformulation of the problem into a dynamic programming framework (see [Bellman, 1957]) by exploiting the special structure of the network. Uncertainty comes naturally in dynamic environments, where new information arrives over time, and usually demand is the main source of uncertainty in logistics applications. Handling stochasticity in the optimization problems is a big topic itself, see for instance [Wallace, 1986] for a pioneering work on stochasticity in network problems, or [Lium et al., 2009] for more recent work. In our analysis, we work with stochastic travel times. However, we use the uncertainty as a desirable feature of the model that makes exact planning of the distant future impossible, rather than aiming for the most precise description of the underlying probability distribution.

In the second part of the paper, we assume that we have freight rate predictions for only a short horizon (limited foresight). We introduce an innovative approach that deals with the "end of horizon" issue based on a neural network algorithm. The aim of the algorithm is to predict correct decisions by using only information from the limited foresight horizon. As a learning objective for the neural network, the optimal decisions from the perfect foresight model are used. Although neural networks, or more generally machine learning algorithms, have been around for decades, they have recently attracted a lot of interest thanks to some extraordinary results achieved in fields such as image and sound recognition, classification problems, and games playing, etc.

In practice, the outcome of operators' decisions is a market where the world fleet of vessels is slowly reallocated around the globe in an attempt to match overall supply and demand. However, in the short run, the bulk shipping freight market can be thought of as several regional markets with their own supply and demand dynamics. As described in [Adland et al., 2016], each matching of a cargo and a ship can be thought of as a micromarket, where only those ships commercially available and able to physically meet the loading window can offer transportation. Accordingly, the spot freight rate in one loading region is set by the immediate equilibrium of cargoes offered and vessels available to load within a particular future time window. As vessels can only move slowly between regions, shortages or oversupply of tonnage – and the corresponding high or low regional freight rates – can persist for weeks. This inertia in regional supply – which implies a slow move towards equilibrium - is present even though the market is considered transparent and perfectly competitive, purely because there is as a cost of relocating tonnage. This cost can be implicit in terms of time (which has an alternative cost) or explicit (fuel and other voyage costs) if an owner is moving the ship speculatively at his own expense. The solution to our optimization problem is therefore closely related to the macroeconomic question of whether the ocean freight market is spatially efficient: If there are no economic gains to be had from spatial optimization – even with the benefit of limited foresight – then the market is efficient[1].

The issue of spatial market efficiency has been approached in several parts of the literature. [Berg-Andreassen, 1996], [Berg-Andreassen, 1997], [Glen and Rogers, 1997] and [Veenstra and Franses, 1997] investigate the statistical properties of regional freight rates. The general finding is that regional prices are non-stationary and co-integrated, that is, there exists a stable long-run relationship between them. This is consistent with the observation that regional spot freight rates must revert towards some common (global) stochastic trend because of the ability of ships to continuously move from regions of oversupply towards regions of undersupply. [Koekebakker et al., 2006] question the findings of non-stationarity for spot freight rates and argue that non-linear dynamics and weak power of the linear unit root tests used results in a failure to reject non-stationarity. [Adland et al., 2017a] emphasize that statistical co-integration of regional spot freight rates is a necessary but not a sufficient condition for an efficient freight market, as it does not preclude the possibility that short-term regional differentials are large and persistent enough to enable operators to take advantage through well-informed chartering decisions.

Other studies assess the impact of spatial differences directly. [Adland et al., 2017b] employ a real option framework to calculate the value of the geographical switching option in the drybulk market. They find that the main source of option value is the observed persistent premium in Atlantic freight rates over Pacific freight rates and that proactive switching does not add further value. However, they acknowledge that certain assumptions imposed by their analytical model (such as immediate switching and constraints on switching costs) are not realistic. The issue of spatial freight market efficiency has also

[1]We note here that short-term predictability of the regional spot freight itself does not preclude market efficiency, as spot rates cannot be traded or stored ([Adland and Cullinane, 2006]; [Benth and Koekebakker, 2016]).

been investigated in the economic geography literature. For instance, [Laulajainen, 2007] studies systematic geographical differences in drybulk freight rates and proposes that the difference between regions can be explained through a Revenue Gradient, equivalent to the ratio of demanded and available tonnage weighted by sailing distance to a discharge or loading region. [Laulajainen, 2006] fits route-specific freight rates in a static gravity-type model and finds the sailing distance to be the most important explanatory variable. [Laulajainen, 2010] argues that operational and tactical decisions are governing at a regional level, while dynamic inter-regional allocation of the fleet represents a strategic decision with an inherent risk.

The contributions of this paper are twofold. Firstly, we propose a new model that combines optimization and a neural network approach to assess the value of having limited foresight of regional freight rates. Secondly, we assess empirically the value of optimization in the bulk shipping freight markets when varying the foresight horizon between the extremes of zero ("know nothing") and the full duration of the sample ("perfect foresight").

Our findings are important for vessel operators and academic researchers alike. We show that the theoretical upper bound of the value of optimization is dependent on vessel size, with large vessels showing greater potential than small- and mid-size vessels. We also show that most of the economic benefit depends on correctly predicting short-term trends in regional freight rates, offering some hope to current investors in predictive analysis based on "big data" and machine learning.

The remainder of this paper is structured as follows: Section 2 outlines our methodology, Section 3 presents our numerical results and Section 4 concludes.

2 Methodology

In this section, we formulate a general model of freight trading that we use for our analysis.

Let us assume $\mathcal{T} = \{1, 2, \ldots, T\}$ is a finite time horizon (days) and $\mathcal{I}$ is a set of ports/regions. If not stated otherwise we use indices $i, j \in \mathcal{I}$ and $t \in \mathcal{T}$. The task is to reallocate a single ship through this region-time space. The tripcharter rate (price) for a single trip[2] on a route from origin i to destination j at time t is r_{ijt} for every day of the duration of the trip, which takes from $\tau_{ij}^{\min}$ to $\tau_{ij}^{\max}$ days. We assume that the trade duration is unknown before the commencement of the trip (due to weather, port queues, etc.), but is observed at the moment of arrival, and, thus, the consecutive decision (i.e. choosing a destination for the next trip) can differ for different arrival days. We assume that the fixture for the next trip takes place only upon discharging and completion of the previous trip. We assume a discrete uniform distribution $\mathcal{U}\{\tau_{ij}^{\min}, \tau_{ij}^{\max}\}$ of trip duration

[2] A single trip usually comprises one ballast leg to the origin of a cargo, loading the cargo and then a laden leg to a destination port, where it is discharged.

as in [Adland and Jia, 2017]. In the real world, the uncertain sailing duration is obviously not uniformly distributed. However we do not aim to make a perfect model for a real decision-making process, so rather than capturing the real distribution of trip durations, the cumulative impact of the stochasticity of travel times is used to decrease the capability of exact planning the further we go to the future. This is a required feature of the model and it reflects the nature of planning in this uncertain environment.

We simulate and compare two types of fleet allocation strategies, the *oracle* and *coin* trading strategy, respectively. For the *oracle* one, we assume that all future prices are known. We analyze two cases; first with known prices for the whole horizon $\mathcal{T}$, and second the case of limited foresight for which prices are known only for a given number of future days Δ ($\Delta \ll \mathcal{T}$). The task in both cases is to reposition a vessel to maximize the overall expected earnings. We do not take into account any discounting of money.

The *coin* based strategy does not exploit any knowledge of future prices. Instead we define quantities x^c_{ijt}, which can be interpreted as probabilities[3] of making a decision "go to j" for a vessel positioned in region i at time t, where superscript c refers to the coin strategy. So naturally $\sum_j x^c_{ijt} = 1 \;\; \forall i, t$. The probabilities x^c_{ijt} are set upfront and disregard the future prices. If only two options for the next destination were available and probabilities were 50-50, the operator could flip a coin to determine where to go next, hence the name. Another possible interpretation, with respect to further modelling, is that vessels are divisible assets and x^c_{ijt} represents a fraction of a vessel capacity located in i at time t that is allocated to j. A similar thought process can be applied to stochastic trip durations (different fractions sail different amount of days).

In [Adland and Jia, 2017], a similar approach is used for trade simulation, and the values x^c_{ijt} are set proportionally to real tradeflows. In this special case, the expected profit of such a strategy reflects the average earnings of an agent in the market.

2.1 Perfect foresight

In the perfect foresight case, we assume that the rates r_{ijt} for the *oracle* strategy are known for the whole time horizon and ship capacity is positioned optimally to maximize the expected profit at the end of the time horizon.

The assumption of known prices for the oracle strategy is not realistic and results obtained by this strategy are therefore an optimistic estimate (upper bound) to any realistic achievable earnings. It is worth noting here that some additional features that could increase the profit are not assumed here, for instance speed optimization (with respect to freight market condition, weather etc.) or exercising the option to wait between contracts.

[3] For simpler presentation, x represents both probabilities in the coin flip case and decisions in the oracle case, even though most readers may be accustomed to a probability being denoted by p.

Here it is assumed that the vessel must enter into a new contract immediately after transporting the previous cargo. However, we believe these additional operating options have smaller impact than the knowledge of future prices (when corresponding optimal allocation is applied). On the other hand, achieving the results of the *coin* strategy is relatively easy in real life: all the operator needs to do is to flip a coin (generate a random number) and have a good network of brokers to secure some cargo to carry. Therefore, it establishes the lower bound for the expected results. In real life, we can work only with limited predictions, where we have some partial, imperfect, knowledge. For instance, we may have a probability distribution constructed for future rates, and such a distribution will have higher variance (will be less accurate) the further we look into the future. Accordingly, any smart strategy based on a realistic prediction should achieve results between the bounds established by the oracle and coin strategy.

Generally with this type of model, we need to be aware of the modeling issues with regards to the end of the horizon - naturally we do not expect that the real trade ends that day. This repositioning game often has a fronthaul-backhaul dynamic, which means that we often accept a cargo with lower immediate profit (i.e. a backhaul trip) in exchange for having our vessel (resource) positioned in a better region to increase future profits. With a finite horizon, a backhaul trip should never be chosen at the end, and any such (non-optimal) decision may propagate back through time and affect all the previous decisions in a bad (non-optimal) way. In our case, decisions do not have irreversible consequences and the stochasticity of trip duration makes exact planning in the future impossible. Thus, with a sufficiently large time horizon, the impact of non-optimal decisions that are made towards the end of the horizon vanishes in several steps.

2.1.1 Solution

Since we use most of the variables in both types of strategies, we distinguish them by superscript $X \in \{o, c\}$ denoting oracle or coin strategy, respectively.

To store the optimal decisions for the oracle strategy, we introduce variables x^o_{ijt}, which have the same interpretation as x^c_{ijt} in the coin setting, that is, the probability of repositioning the ship from i to j, given that she is located in region i at time t. However, in the oracle case, the decisions are not set upfront, but are obtained as a solution to the maximization of expected earnings problem. To track the expected allocation of the vessel, we define a parameter R^X_{it} denoting how much of the expected ship capacity is allocated in region i at time t. Further, we define the expected flow of the ship capacity f^X_{ijt} going from i to j at time t. The relation between decisions and the flow is then:

$$f^X_{ijt} = x^X_{ijt} R^X_{it} \tag{1}$$

We assume that only trips that are finished within the time horizon are considered. To simplify the notation in the algorithms, we use π_{ij} for the probability of a particular trip duration:

$$\pi_{ij} = \frac{1}{\tau_{ij}^{\max} - \tau_{ij}^{\min} + 1} \tag{2}$$

The operator earns in expectation

$$e_{ijt} = \sum_{s=\tau_{ij}^{\min}}^{\min\{\tau_{ij}^{\max}, T-t\}} \pi_{ijt}\, r_{ijt}\, s \tag{3}$$

by performing a trip from i to j at time t with a single vessel. The solution for the oracle strategy can be obtained by solving the following optimization program determining the optimal flows f (superscript $X = o$ is omitted):

$$\max_{f} \sum_{ijt} e_{ijt} f_{ijt} \tag{4}$$

$$\text{s.t.} \qquad R_{it} = \sum_{j} f_{ijt} \qquad \forall i, t \tag{5}$$

$$R_{jt} = R_{jt}^{0} + \sum_{s=t-\tau_{ij}^{\max}}^{t-\tau_{ij}^{\min}} \pi_{ij} f_{ijs} \qquad \forall j, t \tag{6}$$

where R_{it}^{0} is used as an initializing vector. Let us assume the vessel is positioned in region i_0 in the first period. Then $R_{it}^{0} = 1$ if $i = i_0$ and $t = 1$; 0 otherwise.

The objective is to maximize expected earnings given by (4). Constraints (5) and (6) ensure proper flow balance at every i-t node. The model is a version of the minimum-cost flow problem when a new artificial node is added. Therefore, its special structure can be exploited and the problem can be solved by dynamic programming, which runs faster than solving the model (4) - (6) by standard linear programming techniques. In dynamic programming, we go backwards through the time horizon and reconstruct the performance in a retrospective manner. Notice that a decision made for a ship positioned in region i at time t does not depend on any of the previous decisions.

We define values V_{it}^{X} to store expected earnings generated from time t till the end of the horizon by a vessel positioned in region i at time t, when the corresponding policy X is applied. Values V_{it}^{o} can be obtained as dual variables to constraints (5) if the classical optimization model (4) - (6) is used. Although we do not need V_{it}^{o} for the evaluation of performance in this case, given the perfect knowledge of prices, the values are used in further analysis (sections 2.1.2 and 2.2). Due to the character of the optimization task, it is sufficient to consider only values 0 or 1 for the variables x_{ijt}^{o}. Binarity of the variables is not our requirement, but it results from the special structure of the optimization problem, i.e. one decision is always more profitable than others. If more than one decision lead to the same maximal expected earnings, we can choose arbitrarily among them. Thus, we do not need to assume fractional decisions x^o_{ijt}.

The procedure for the calculation of values V^o_{it} and determination of optimal decisions at the time is summarized in Algorithm 1 below. As a temporary variable, we introduce W^o_{ijt} denoting expected earnings generated from time t till the end of the horizon by a vessel positioned in the region i at time t and making the consecutive decision "go to j". W^o_{ijt} is used to store the earnings of all the available alternative destinations j for the ship located in i at time t. The optimal decision is obtained by simple comparison of these candidate values (rows 4 - 7 in Algorithm 1).

A similar approach is used for simulation of the coin strategy. In fact, calculation of V^c_{it} is simpler, since it does not include an optimal destination decision. The expected earnings are constructed by summing expected contributions of all alternatives with non-zero probability of choice x^c_{ijt}. This procedure is described in Algorithm 2.

The simulation of trade is the same for both strategies, once the values V^X_{it} are computed. To observe the development of the expected earnings over time, we define variable M^X_t where we store the sum of expected earnings from time period t. We assume that the payment is spread over all days of the trip duration, not concentrated in the first day of the trip as in (3). That is, every day of the trip duration the operator receives the rate r_{ijt}, where t is the first period of the trip. Notice that this interpretation is simply for the sake of results visualization and has no impact on the chosen decision. The simulation of trade is summarized in Algorithm 3.

Algorithm 1 Values for oracle strategy

Set $W^o_{ijt} = 0,\ x^o_{ijt} = 0,\ V^o_{it} = 0\ \ \forall i, j, t$
for $t := T$ to 1 **do**
  for $i \in \mathcal{I}$ **do**
    $j = \arg\max_j W^o_{ijt}$
    $V^o_{it} = W^o_{ijt}$
    if $W^o_{ijt} > 0$ **then**
      $x^o_{ijt} = 1$
  for $j \in \mathcal{I}$ **do**
    for $i \in \mathcal{I}$ **do**
      for $\tau := \tau^{\min}_{ij}$ to $\tau^{\max}_{ij}$ **do**
        $s = t - \tau$
        if $s > 0$ **then**
          $W^o_{ijs} = W^o_{ijs} + \pi_{ij}\big(r_{ijs}\,\tau + V^o_{jt}\big)$

Algorithm 2 Values for coin strategy

Set $W^c_{ijt} = 0,\ x^c_{ijt} = 0,\ V^c_{it} = 0\ \ \forall i, j, t$
for $t := T$ to 1 **do**
  for $i \in \mathcal{I}$ **do**
    for $j \in \mathcal{I}$ **do**
      for $\tau := \tau^{\min}_{ij}$ to $\tau^{\max}_{ij}$ **do**
        $s = t - \tau$
        if $s > 0$ **then**
          $V^c_{is} = V^c_{is} + \pi_{ij}\, x^c_{ijs}\big(r_{ijs}\,\tau + V^c_{jt}\big)$

Algorithm 3 Trade simulation (same for both type of strategies)

Set $M_t = 0, R_{it} = 0 \ \forall i, j, t$
Set the initial position of the ship, for example $R_{i_0 1} = 1$
for $t := 1$ to T **do**
  for $i \in \mathcal{I}$ **do**
    for $j \in \mathcal{I}$ **do**
      for $\tau := \tau_{ij}^{\min}$ to $\tau_{ij}^{\max}$ **do**
        if $t + \tau \leq T$ **then**
          $R_{js} = R_{js} + \pi_{ij} x_{ijt} R_{it}$
          for $s := t$ to $t + \tau$ **do**
            $M_s = M_s + \pi_{ij}\, x_{ijt}\, r_{ijt}\, R_{it}$

2.1.2 Value of geographical switching

By the procedure described in Algorithm 1, we obtain optimal decisions x_{ijt}^{o} indicating the next destination j given that a vessel is positioned in i at time t in the case of known prices. For some positions, the optimal decision is more important (a trader gains higher earnings) than for others. In this section, we introduce the methodology used for the comparison of different decisions.

We denote by Z_{ijt}^{X} the expected earnings generated from time t till the end of the horizon by a vessel positioned in region i at time t that makes the consecutive decision "go to j" and trade according to the corresponding strategy after that. We can calculate the values Z_{ijt}^{X} from V_{it}^{X} by the simple formula:

$$Z_{ijt}^{X} = \sum_{s=\tau_{ij}^{\min}}^{\tau_{ij}^{\max}} \pi_{ij}\big(r_{ijt}\ s + V_{js}^{X}\big). \tag{7}$$

We evaluate Z_{ijt}^{X} for all possible destinations j and compare the results. From these values, we can observe how valuable it was to choose the best decision, compared to the second best, etc. to the worst one. If the difference between some decisions is close to zero, the operator is (almost) indifferent between the decisions at that time and place. Such comparison provides us an insight into the dynamic of the market, highlights its spatial (in)efficiencies and the capability of the market to anticipate future prices, and it reveals some exploitable opportunities in freight mispricing that have occurred in the past. It is also useful to study the discrepancy between Z^{o} and Z^{c}, since it reveals the importance of planning several steps ahead. This is discussed in Section 3.

2.2 Limited foresight for two-region case

Although, the time horizon in Section 2.1 was inherently finite, it was long enough for us to ignore the decisions that are impacted by the approaching end of the horizon. Therefore, it produced the same output as a theoretical infinite horizon would do. In this section, we describe the methodology used for cases where the horizon of known prices is very short - usually allowing us to evaluate just a couple of future steps. In this case, we can not use the same technique to find the optimal decisions due to the different states (both in time and space) in which a vessel may occur at the end of the horizon. In the real-life decision-making process, if market participants received information about prices for a certain number of future days, they would incorporate them into the planning together with an additional assumption of the vessel's value at different positions at the end of the horizon. This would often be processed in an intuitive way based on years of experience. We mimic this natural way of handling the end of horizon issue by introducing a learning algorithm based on a neural network approach.

Let us consider the case with only two regions, where the operator can either undertake an intra-region trip or inter-region trip.

We introduce the function S_{it}^{X} showing the value of switching from region i at time t. The function is defined as follows:

$$S_{it}^{X} = Z_{ijt}^{X} - Z_{iit}^{X} \text{ , where } j \neq i. \tag{8}$$

That is, the function expresses how much more (or less if the value is negative) of the expected earnings an operator makes when he decides to undertake an inter-region trip (i.e. switching region) compared to performing the intra-region trip. In both cases, it is assumed that after such decision, the operator continues with the strategy X till the end of the horizon.

We assume that prices are known for Δ future consecutive days. Let us consider a policy described by the vector x_{ijs} consisting of 0's and 1's, where $s \in \{t, t+1 \ldots, t+\Delta\}$. For such policy, we can assign a value $F_t(x_{ijs})$ of expected earnings made on trips that started between periods t and $t+\Delta$.

It is theoretically possible to construct $2^{\Delta+2}$ different x vectors. However, many of them induce the same behaviour from a given initial position. Morover, due to the duration of the trip, not all states are reachable. We consider only the subset of policies that induce unique strategies.

For every time period t we construct a vector of inputs comprising the expected earnings of the selected subset of strategies on interval $\{t, t+\Delta\}$, and the freight rates at the end of the foresight horizon $r_{ij,t+\Delta}$. We split the region $\mathcal{T}$ into a training horizon $\mathcal{T}_\alpha = \{1, 2, \ldots, T_\alpha\}$ and a testing horizon $\mathcal{T}_\beta = \{T_\alpha + 1, \ldots, T\}$. We compute the function

S^X_{it} on interval $\mathcal{T}_\alpha$ by using the methodology described in Section 2.1. The function S^X_{it} is used as an output of the neural network model for each region i. After the training phase using the horizon $\mathcal{T}_\alpha$, we have a neural network that predicts the switching function from an arbitrary vector of inputs; we denote these predictions $\hat{S}^X_{it}$. We can evaluate the in-sample predictions on interval $\mathcal{T}_\alpha$, denoted ${}^\alpha\hat{S}^X_{it}$, but the real focus is on the out-of-sample predictions ${}^\beta\hat{S}^X_{it}$ evaluated on interval $\mathcal{T}_\beta$ with corresponding inputs. This is a general set-up for simple neural networks. We discuss more detail regarding the network and inputs in Section 3 since there are some case-specific adjustments applied.

Finally, we reconstruct the decisions $\hat{x}^X_{ijt}$ from estimated $\hat{S}^X_{it}$ as follows: if $\hat{S}^X_{it} \geq (<) 0$, then $\hat{x}^X_{ijt} = 1$ for $j \neq i$ $(j = i)$, 0 otherwise. We can then simulate the trade for decisions x^X_{ijt} by using Algorithm 3 and compare them with the oracle and coin strategies. Since no information from $\mathcal{T}_\beta$ was used to train the network, the results obtained on this interval correspond to real achievable earnings if the prices were known only for Δ future days. We perform this analysis for different values of Δ to assess the impact of the length of the foresight horizon.

3 Numerical results

In the methodology part for perfect foresight, we formulated a general model for an arbitrary number of regions. In our numerical analysis, we work with a simplified model of the world with only two regions - Atlantic and Pacific. This creates four possible routes for trade: trans-Atlantic (TA), trans-Pacific (TP), from the Atlantic to the Pacific basin, also called fronthaul (FH) in the shipping literature (see for instance [Adland and Jia, 2017]), and finally the backhaul (BH) trip from the Pacific to the Atlantic. For each of the routes we have rates (prices) for the period July 2005 - April 2017 provided by the Baltic exchange and obtained by [Clarkson Research, 2017] for three segments of dry bulk shipping according to the standardized size of vessels: Supramax (52,000 mt), Panamax (74,000 mt) and Capesize (172,000 mt).

For all sectors we assume the same discrete uniform distribution of trip durations with the following ranges: TA: 30 - 45 days, TP: 30 - 40 days, FH: 60 - 70 days, BH: 60 - 70 days. For the coin strategy, we set probabilities $x^c_{\mathrm{TA}} = 0.634$, $x^c_{\mathrm{FH}} = 1 - x^c_{\mathrm{TA}}$, $x^c_{\mathrm{TP}} = 0.65$, $x^c_{\mathrm{BH}} = 1 - x^c_{\mathrm{TP}}$. These probabilities are set such that the vessel spends an equal number of days on each route (in expectation). Although not shown here, the results would not be significantly different if probabilities were 0.5 for each route according to our numerical tests.

Cumulative earnings for the perfect foresight case in the Capesize market, computed at every time period t as $\sum_{s=1}^{t} M^X_s$, are shown in Figure 1. The steeper growth of cumu-

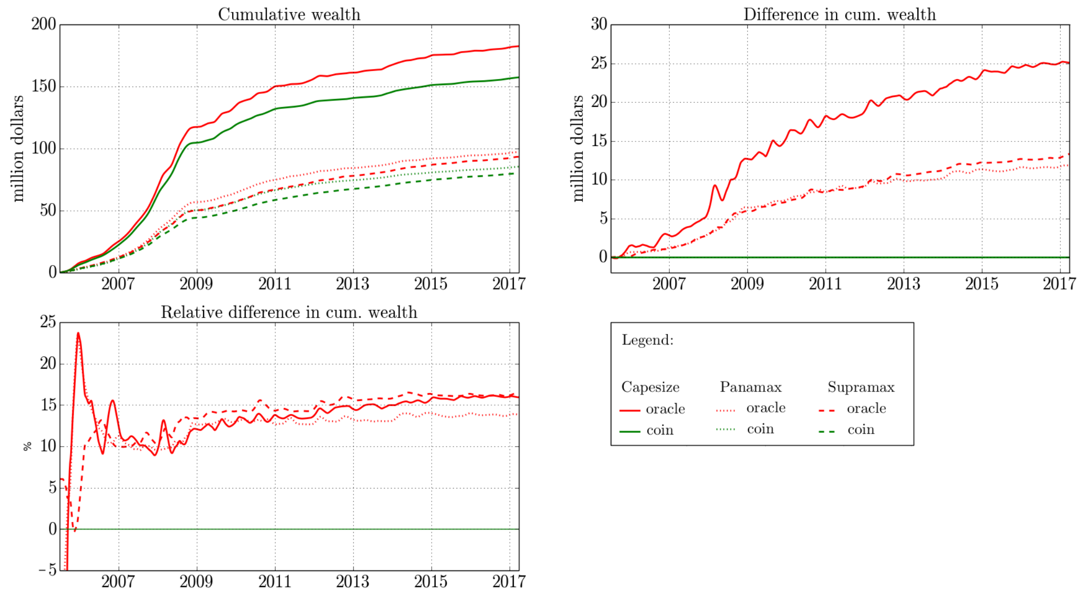

Figure 1: Cumulative earnings for the oracle and coin strategy in Capesize market.

lative earnings till the second half of 2008 is caused by higher rates in this period. After the rates dropped sharply following the financial crisis (for instance, the BCI[4] dropped from over \$200,000/day in June 2008 to less than \$5,000/day in October 2008), the absolute differences decrease as there are lower regional rate differences in a competitive and oversupplied market (Adland et al, 2017b), but the relative differences increase as there remains some inability to correctly anticipate future prices.

Table 1 compares different segments of bulk shipping by vessel size. We see that the relative gains for the Capesize and Supramax segments are around 16%, while the mid-size Panamax sector shows approximately 14% outperformance over the period 2006 - 2016. If we exclude the boom period and compare cumulative earnings obtained from 2009 to 2016, relative differences are higher, namely 19.5% for Supramax sector, 15.5% for Panamax, and ca 24% for the Capesize sector. In Table 1 we can also see that the gains from perfect knowledge differ from year to year. However, it is necessary to emphasize here that the comparison across years is not entirely precise. The values shown in Table 1 for every year are calculated as the sum of M_s^X over that particular year, but the optimization problem (4) - (6) is solved over the whole time horizon (July 2005 - April 2017). This means that the decisions are taken such that the cumulative expected earnings are maximized at the end of the horizon (April 2017). Therefore, we may have situations where the earnings in one year is sacrificed for a better position of the ship in the following year. Since the start/end conditions differ across years, the comparison is imperfect. However, detailed

[4]Baltic Capesize Index

analysis of the performance in individual years is not the aim of this paper.

Year	Supramax			Panamax			Capesize		
	o	c	%	o	c	%	o	c	%
2006	9.09	8.05	12.85	9.08	8.34	8.88	17.15	15.82	8.39
2007	18.29	16.54	10.6	21.48	19.74	8.84	43.14	40.06	7.69
2008	19.57	16.51	18.53	22.90	19.51	17.37	49.27	42.50	15.94
2009	7.07	5.86	20.54	7.43	6.43	15.52	17.02	14.29	19.14
2010	9.62	8.37	14.84	10.47	9.43	11.03	15.55	12.76	21.84
2011	6.18	5.32	16.28	5.86	5.17	13.52	6.26	5.65	10.9
2012	4.95	3.60	37.5	3.73	2.99	24.64	4.94	3.30	49.89
2013	4.21	3.59	17.51	3.59	3.28	9.48	6.19	4.84	28.04
2014	4.71	3.72	26.55	4.13	2.98	38.48	7.57	5.58	35.73
2015	3.10	2.65	16.73	2.40	2.11	13.77	3.44	2.73	26.12
2016	2.36	2.18	8.27	2.00	1.90	4.93	3.18	2.62	21.18
$\sum_{2006-2016}$	89.15	76.39	16.70	93.07	81.88	13.67	173.71	150.15	15.69
$\sum_{2009-2016}$	42.20	35.29	19.58	39.61	34.29	15.51	64.15	51.77	23.91

Table 1: Overview of annual results obtained by oracle (o) and coin (c) strategy (all in millions \$), % is the relative difference.

Value of geographical switching

In our two-region world, we construct the switching function S_{it}^{X} for both strategies and each region i according to (8). The functions are shown in Figure 2 for the Capesize segment. We observe quite low discrepancy between the functions for the coin and oracle strategies. There appears to be a correlation between market level and volatility of the switching function. In the post-crisis period, we see asymmetry in the function for the Atlantic market. Although not shown here, it is observed across all sectors. This suggests that a wrong decision to go to the Pacific basin is potentially more costly than to choose incorrectly to stay in the Atlantic basin. In other words, the vessel should remain in the Atlantic basin once it is located there, unless there is strong evidence in favour of a FH trip. This corresponds to findings in [Adland et al., 2017a] suggesting that a persistent Atlantic premium is the main contributor to outperformance.

To understand the low discrepancy between the switching functions for the oracle and coin strategies and its implications, it is important to realize the following: The switching function is defined as a difference of expected earnings generated by two possible alternative decisions and subsequent trade. We can decompose the value of the switching function into two parts. The first part is the contribution of the very first decision, that

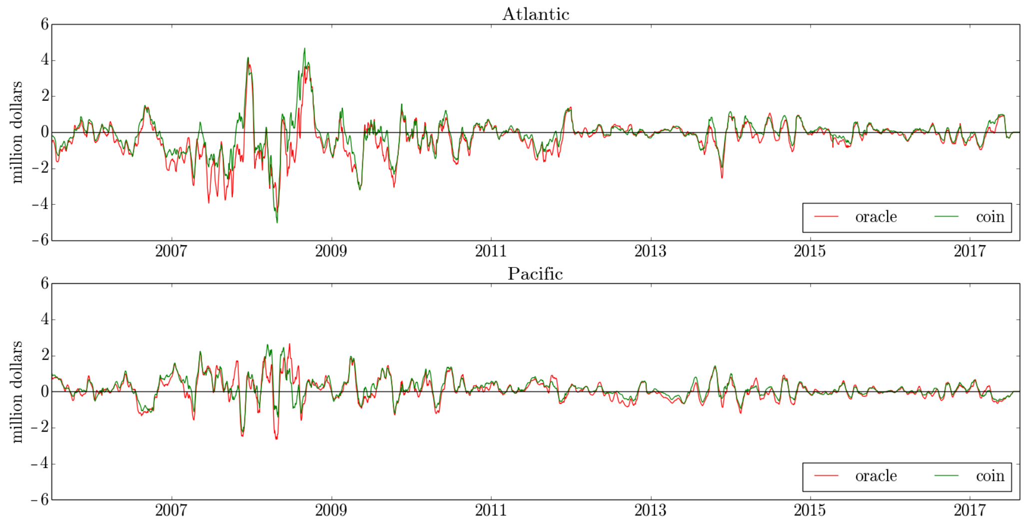

Figure 2: Value of geographical switching function - Capesize sector

is, the difference in earnings defined as:

$$\sum_{s=\tau_{ij}^{\min}}^{\tau_{ij}^{\max}} r_{ijts} - \sum_{z=\tau_{ii}^{\min}}^{\tau_{ii}^{\max}} r_{iitz} \tag{9}$$

The second part comes from the difference in earnings from subsequent trading after the first decision is made. In the coin strategy case, the randomized choice of the next destinations is applied from initial positions $j-s$ and $i-z$, respectively, and its difference contributes to the value of switching function. In the oracle case, the second part is given as the difference between results of optimal positioning from initial positions $j-s$ and $i-z$.

We see that the contribution of the first decision (9) is shared by both strategies. Therefore, the discrepancy between the switching functions of the two strategies is caused by the second part. Since the discrepancy is low, the difference between randomized and optimal sequences, starting from the same initial positions $j-s$ and $i-z$, is very similar. This suggests that the first decision is relatively more important compared to planning into the distant future. Such phenomena are analyzed in the following section.

3.1 Limited foresight horizon

We use $\Delta \in \{20, 50, 80\}$ days long horizons of foresight for evaluating the proposed strategy. These lengths are chosen such that the number of possible trips that can be exactly evaluated is expanding. With 20 days of foresight, we know the earnings from the current trip, and this would be the same if we had no future information, but we may yet gain some benefit from knowing regional price trends in the next 20 days. With 50 days of foresight, we can exactly evaluate earnings from two intra-region (let us denote it A) trips, i.e. two TAs or TPs - depending on the position of the vessel, and only one inter-region (E) trip (FH or BH) due to trip durations. In addition, the operator is in a better position to estimate future prices because of the observation of price changes in the next 50 days. In the case of 80 days foresight, it is possible to at least partly evaluate the following combinations of trips: AAA^5, AAE^5, AE, EA, EE.

The training phase of the model should not depend on any information from the testing period. However, we believe it is realistic to assume that high freight rates as they were observed in the boom period prior to financial crisis in 2008 will not be repeated any time soon. Rather, we expect similar order of magnitude in freight rates and their differences as observed in the post-crisis period. Therefore, we exclude the boom period from the training horizon $\mathcal{T}_\alpha$ and consider only the period 1.1.2009 - 10.11.2013. Since the last decisions are impacted by the end of the horizon, we do not consider last 120 days of the training period for actual training.

We use a neural network with an input layer and one hidden layer of the same size as the input vector. Both layers use rectified linear units as activation function [Nair and Hinton, 2010]. Then, a single neuron output layer with sigmoid activation function follows. As a loss function, the standard mean squared error is applied. The output is assumed to be in the interval $(0, 1)$. Thus, we need to transform the switching function into that interval. We test two different methods. The first is simple *linear* transformation, that is, the minimum of the switching function on the training horizon is projected to 0 and maximum to 1 with linear scaling between them. This approach has a weakness when the maximum and minimum of the switching functions on the training horizon are asymmetric with respect to the zero axis, in other words, one of the values is significantly larger in absolute value than the other. Then, the zero value, which is our main interest since the decision is changing there, would be projected too far from the middle point, which would not be optimal for the output layer. Therefore, we introduce a second *adjusted* linear approach, where we first transform the negative part of the switching function into the $(0, 0.5)$ interval and the positive part into the $(0.5, 1)$ interval. This approach projects 0 correctly to 0.5, which is desired but, on the other hand, it distorts the loss function applied on the evaluation of predictions during the training period.

We also experiment with the input values, which can be divided into trading contributions, i.e. the set of earnings obtained by selected strategies, and freight rates at the end of the foresight horizon. We note that the optimal decisions would be the same if all rates

[5] In the case of TA trip, we can evaluate this sequence only partialy. That is, the duration of first two trips exceeds 80 days in some scenarios.

are increased by a constant value, in other words, it is not the absolute value of freight rates, but the regional differences that are crucial for making a decision.

We consider four different settings of inputs by creating all combinations of absolute values/differences of contributions/freight rates. For each combination we apply both transformations, so in total we test 8 instances with different settings for each sector.

After the training phase, we let the model predict values of the switching function on the testing horizon, which is Oct 2013 - Dec 2016. From the value of switching, we reconstruct decisions for each i, t position and simulate the trade according to Algorithm 3.

We compare these results with the results obtained by the oracle and coin strategies. In Table 2, we report which fractions (in percentage) of the oracle strategy gains (compared to the coin strategy) can be captured by this approach for different input settings. We show only the final numbers reached at the end of 2016. On average, we observe the expected result that a longer foresight horizon brings better performance both in average gains and stability of the results. We see, for example, that the results for 20 days foresight in the Capesize segment differ from -20% up to +38% for different settings. This gives the impression of a great deal of randomness involved in the computation. We cannot conclude on the comparison across different vessel size segments, since we performed this analysis only on one date, which splits the horizon into the training and test samples. Thus, it is possible that such splitting was more favorable to one sector than the other. For instance, it might happen that some pattern from the training horizon repeated in the testing sample, but cannot be generalized.

		LF 20			LF 50			LF 80		
		S	P	C	S	P	C	S	P	C
lin	ar-ac	38.34	47.19	35.3	89.15	75.33	48.7	61.56	96.27	82.42
	ar-dc	54.64	37.87	34.47	81.74	48.98	53.28	87.86	95.29	79.05
	dr-ac	62.34	-9.89	11.42	87.72	69.45	68.7	61.19	86.12	81.99
	dr-dc	62.11	49.94	-20.35	70.01	72.09	74.98	89.06	83.3	77.09
adj	ar-ac	62.96	21.84	38.19	92.06	72.18	65.26	85.04	96.46	74.13
	ar-dc	72.27	12.85	38.36	84.27	75.03	50.85	83.6	90.77	77.75
	dr-ac	59.67	27.23	15.47	68.19	51.15	67.38	86.91	92.8	80.91
	dr-dc	65.24	38.78	-10.99	90.1	41.32	71.05	78.26	78.82	73.15

Table 2: Percentage of the oracle gains over the coin trade for limited foresight horizon. LF X - limited foresight for X future days; S - Supramax, P - Panamax, C - Capesize; lin - linear, adj - adjusted linear transformation of output value; ar - absolute rates, dr - difference of rates, ac - absolute contribution, dc - difference of contributions as input.

In Figure 3 we show the simulation of the trade throughout the whole testing period and all sectors with simple linear transformation of output and differences in contributions (but not in rates) being used as input setting.

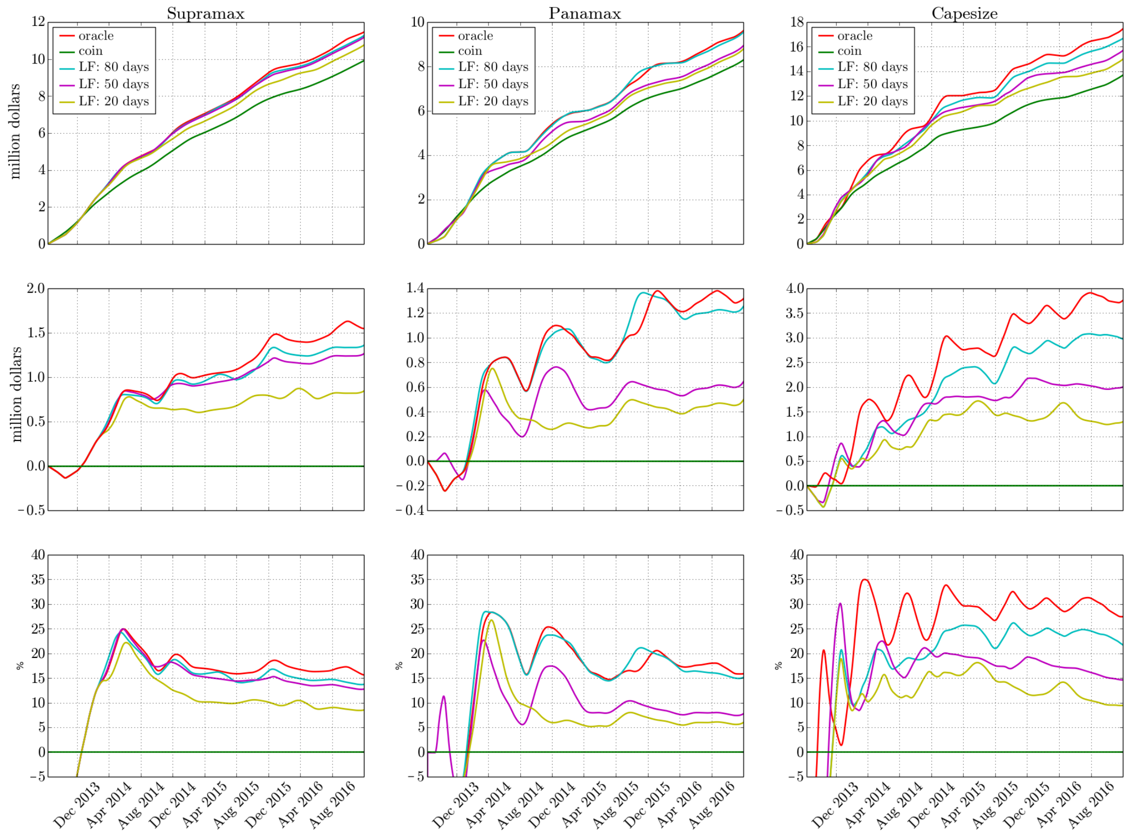

Figure 3: Demonstration of limited foresight gains.

It is fair to note here that there are plenty of other different modifications of the neural network and other methods from the machine learning field that might perform better at this specific task than the presented approach. It is possible, for example, to let the model to learn the decisions directly instead of learning the switching function and reconstructing the decisions afterwards. The disadvantage of such approach would be that it does not take into consideration the different importance (value) of optimal decisions at different points. In other words, a higher number of correctly forecasted optimal decisions does not have to lead to higher earnings. However, the aim of this paper is not to search for the best possible machine learning method for this particular task. The problem itself is still unrealistic in real life due to the requirement on exact predictions of prices. The goal is to demonstrate whether some significant portion of the theoretical gains from perfect knowledge can be captured with only several future steps taken into account. For this objective, the results from the presented approach represents a lower bound.

4 Conclusion

In this paper, we have addressed the problem of spatial efficiency in the drybulk freight market by combining optimization and a machine learning approach. The main objective was to determine the upper bound of earnings obtained by optimal vessel positioning in space and time by assuming perfect knowledge of future regional freight rates. The upper bound is a first indicator of whether it makes sense to continue developing chartering strategies based on imperfect forecasts of future prices.

To achieve this, we have formulated a simple model for optimal vessel repositioning through space and time that takes into account uncertainty in travel times. Although we work with two-region world in the numerical section, the model is formulated in a general way for an arbitrary number of regions. Empirically, we have shown that with perfect knowledge it is possible to achieve approximately 15% higher cumulative earnings between the years 2006 - 2016. This number is distorted by exceptionally high freight rates up to late 2008, after which the financial crisis hit the shipping market and freight rates dropped sharply. However, with the lower market level in the post-crisis period, the relative outperformance is higher, at around 20% for Supramax, 15% for Panamax, and 23% for Capesize sector in the period 2009 - 2016.

We have also extended the concept of perfect knowledge to the case where we assume perfect knowledge only on a limited (and relatively short) time horizon. This required a different methodology to overcome the so-called end of the horizon issue. For that purpose, we have introduced a new approach based on the neural network model that learns to predict the optimal decisions obtained in the perfect foresight section, but in this case, using only information from the foresight horizon. This model naturally produces better results the longer the foresight horizon is. The assumption of perfect foresight on a limited horizon is still unrealistic, but our results demonstrate that it is possible to capture a large portion of the theoretical "perfect foresight" value with only several future moves taken into consideration.

It is also possible to use the optimization model to provide further insight into the market. For instance, we have calculated the value of each decision at every point in space and time. With that, we have observed an asymmetry in the geographical switching function for the Atlantic region. That is, an incorrect decision "go to Pacific" is potentially more costly if applied at the wrong time than an incorrect decision to "stay in the Atlantic".

In our view, the empirical findings reveal a big potential of exploiting spatial inefficiencies by a sophisticated chartering strategy. A natural continuation of this research would be to apply stochastic programming to handle uncertainty in freight rates. For instance, to use a scenario tree for describing the future development of freight rates instead of the assumption of perfect foresight. In contrast to many other applications of stochastic programming, the difficult part of such approach would be to construct the scenarios (and build predictive models to do that), not the subsequent policy search.

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