The Green Ship Routing and Scheduling Problem (GSRSP): A conceptual approach

Christos A. Kontovas

Department of Transport, Technical University of Denmark, Lyngby, Denmark

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ABSTRACT

Recent reviews of the literature on ship routing and scheduling note the increased attention to environmental issues. This is an area of paramount importance for international shipping and will be even more so in the future. This short communication is motivated by the increasing attention to 'green' routing and scheduling and outlines some possible ways to incorporate the air emissions dimension into maritime transportation OR. The main contribution of this note vis-a-vis the state of the art is that it conceptualizes the formulation of the 'Green Ship Routing and Scheduling Problem' (GSRSP) based on existing formulations and highlights all the important parameters of the problem.

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Introduction

There is a large body of literature on maritime vehicle routing and a wide range of models and algorithms has been used to solve these problems. The first major review of Operations Research (OR) work in ship routing and scheduling appeared in 1983 (Ronen, 1983), and it traced papers back to the 1950s. The latest review on the area, see Christiansen et al. (2013), highlights the fact that mainly due to the increasing price of bunker fuel, more attention has been devoted to sailing speeds and environmental impact of ships. They add that the two main trends that have brought the issue of bunker fuel management to the forefront of maritime transport OR in recent years are: (a) the increase in bunker fuel price, and (b) the increasing attention to environmental impacts and especially to ship air emissions. These finding are in line with Wang et al. (2013) that review studies from the past 30 years that use OR methods to tackle containership routing and scheduling problems at the strategic, tactical, and operational planning levels. They note that minimization of the environmental impact is becoming more important in designing shipping networks and they analyze recent papers that deal with the optimization of ship sailing speed as a measure to reduce both operating costs and emissions.

Maritime transport is the backbone of international trade and a key engine driving globalization. As noted in the 2nd International Maritime Organisation (IMO) GHG Study 2009 (see Buhag et al., 2010) international shipping emitted 2.7% of the world’s anthropogenic CO₂ emissions in 2007. Air pollution from ships is currently at the center stage of discussion by the world shipping community and the role of OR in reducing the environmental externalities of maritime transport will get more and more attention. However, the gap in the interface of routing and scheduling, and emissions is apparent based on the scarcity of relevant models in the maritime logistics literature; see the review presented in Christiansen et al. (2013). We also note a parallel body of research in road transportation on the vehicle routing problem with emission considerations. This short communication is motivated by the increasing attention to sustainable routing and scheduling. The aim of this
note is to be a starting point for synthesizing two research areas: (a) the area of ship routing and scheduling and (b) the area of emissions from ships. We shall call this category of problems as ‘Green Ship Routing and Scheduling Problems’ (GSRSP). One part of this paper clarifies some important issues as regards estimating fuel consumption and ship air emissions. In our opinion, the main contribution of this paper vis-à-vis the state of the art is the conceptualization of those fundamental parameters and other considerations that are necessary to formulate the GSRSP. The proposed formulations can be solved by existing techniques and as such the complexity of these models is essentially the same as in any other vehicle routing problem (VRP) formulation. The topic is at the beginning of being studied and the purpose of this paper is to stimulate more research in this emerging area and to enhance the state of the art in this area by investigating possible reformulations of existing models so as to incorporate emissions considerations that explicitly include the emissions dimension.

The rest of this paper is organized as follows. In Section “The relationship between fuel consumption and emissions, and how to estimate them” we present the way to estimate ship air emissions based on the consumption of fuel. In Section “The Green Ship Routing and Scheduling Problem” we outline some possible ways to incorporate the environmental dimension into existing maritime transportation OR formulations and highlight the need of embedding speed optimization. Section “Further research considerations” presents some issues for further research, including multiobjective optimization and Section “Conclusions” concludes this short communication.

The relationship between fuel consumption and emissions, and how to estimate them

The objective in most cases of GSRSP would be either related to the economic performance (including minimizing the cost for bunkers) or to the environmental performance (for example to minimize emissions). In this section we present information on the relationship between ship’s speed and fuel consumption, and fuel consumption and emissions and we clarify some misconceptions presented in the literature. To begin with, air emissions are proportional to the fuel consumption of mainly three systems. The emission sources of vessels include mainly (a) propulsion systems that provide movement for the ship through water, (b) auxiliary power systems that provide for the electrical demands during ship operations, and (c) auxiliary boilers, which produce hot water and steam for use in the engine room and for crew amenities.

In that sense, the emissions produced by each source can be estimated by multiplying bunker consumption with appropriate emissions factors; see Section “Estimating fuel consumption”. In addition, most emission inventories for ship air emissions divide the operation of a vessel into typically three modes of operations: transit, maneuvering, and hotelling. During hotelling a ship is either docked at a berth or anchored, so the ship is not moving (zero speed). During maneuvering, for example, when the ship arrives in a terminal the speed is very low in comparison to the normal transit speed and ships go from half speed to dead slow to stop in order to dock. While in transit, where ships, spend most of their time, the vessels do not travel in a constant speed. This means that the speed over a leg or a trip is not constant but what we call ‘speed’ in GSRSP is actually the average speed. In most papers found in the literature fuel consumption is mainly related to the main engine, which is by far the largest one. Therefore, there is a need to develop more comprehensive models to estimate emissions and speed should be explicit parameter, see Section “Approach 3: A constraint on produced emissions”.

Estimating fuel consumption

In most of the maritime OR-related literature it has been assumed that fuel consumption is related to the vessel’s speed by some kind of cubic relationship. This is generally not true. It is indeed true that the fuel consumption of the main engines (only) depends on the vessels speed, as it is proportional to the total installed power. This is indeed the major part of total fuel consumption but not the only one. The cubic relationship has been used by naval architects for rough estimations and to predict the power requirements of a vessel during the design phase. However, in reality fuel consumption mainly depends on the speed of the vessel and her displacement but also on various other factors such as the weather conditions (waves, winds, currents, etc.), the condition of the hull (there may be added roughness due to fouling or the degradation of the hull coating), the trim of the vessel (the difference between the forward draft and the aft draft), etc. The displacement of a vessel is equal to the weight of the ship without any payload (lightship) plus the total deadweight; the latter includes the payload, ballast water, provisions, fuel, lubricants, water, persons and personal affects, etc. It is obvious that payload (the cargo that the vessel carries) is very important. That is especially true when addressing the fuel consumption of tankers or container vessels. Tankers use to carry cargo from one port to another (laden condition) and then travel to another port empty (ballast leg) in order to load cargo. In liner shipping, for example container vessels, the amount of cargo carried in each leg is not the same. For instance in a westbound leg (Asia-US) a vessel carries less cargo than it does in the eastbound leg. The difference is great and, thus, fuel consumption in these two directions is not the same even in the case the vessel sails at the same speed in both directions. Indeed, in practice the speed in both directions is not the same.

Based on the above, it is obvious that estimating fuel consumption is not an easy task. For more information on fuel consumption functions that can be used in GSRSP the reader is referred to Kontovas and Psarafitis (2010) and Psarafitis and Kontovas (2014). A realistic closed-form approximation of $f$ that takes both speed ($v$) and payload ($w$) into account is $f(v,w) = k(p + p^q)(w + A)^{2/3}$ with $k$, $p$ and $q$ constants such as $k > 0$, $p \geq 0$ and $q \geq 3$, and $A$ is the ‘lightship weight’, that is, the weight of the ship (in tonnes) if empty, plus fuel and other consumables (modified admiralty formula). The rationale for such a formulation is that fuel consumption is proportional to the wetted surface of the ship, which is crudely
This makes sense to obtain solutions within, say, 1%, 2% or 5% from the ‘optimum’, or even at the exact ‘optimum’, if the fuel consumption function is misrepresented by 10%, 20% or 30%. Thus, there is also a clear need to use more accurate models to estimate fuel consumption; see the parallel body on road transport. Finally, we urge our colleagues that work in this area to obtain real data from shipping companies especially fuel consumption in relation to speed and payload. This is also not easy to get. Many shipping companies may be reluctant to report data since this in many cases is business-sensitive information. Once the fuel consumption is estimated the emissions factors discussed in the next section can be used to estimate air emissions.

**Estimating emissions**

There are generally two main methods that can be used to produce fuel consumption and emission estimates that can be used in routing problems. One method uses actual bunker consumption data in combination with fuel-related emission factors. An alternative method is based on modeling and uses activity-based data like sailing time, load factors of the engines, etc. to calculate fuel consumption; see Psaraftis and Kontovas (2009), Buhaug et al. (2010, Chap. 3) and Kontovas and Psaraftis (2010) for more. Note that emissions interact in different ways and the total impact is complex to estimate. For instance, sulfur oxide emissions have a different effect when emitted near populated areas (e.g. ports) due to the related health effects than high-seas. The nature of the contribution of emissions of different gases with different atmospheric lifetimes and different radiative properties to climate change is complex. In addition to warming by CO₂ emissions, ship emissions of sulfur dioxide (SO₂) cause cooling through effects on atmospheric particles and clouds, while nitrogen oxides (NOₓ) increase the levels of the greenhouse gas ozone (O₃) and reduce the GHG methane (CH₄), causing warming and cooling, respectively. This is however out of the scope of this work. A difficult task is to aggregate the effect of (long-lived) greenhouse gases, such as CO₂, with other gases such as SO₂ and NOₓ. This could be useful in the case of multi-objective optimization.

As mentioned above, air emissions are proportional to the fuel consumption of the main and auxiliary engines (including boilers). In that sense, the emissions produced can be estimated by multiplying bunker consumption with appropriate emissions factors as follows.

**Carbon dioxide emissions**

One way to estimate CO₂ emissions is to multiply total bunker consumption (F) by an appropriate emissions factor (F_{CO₂}):

\[
\text{CO}_2 \text{ emissions (tonnes CO}_2\text{)} = F_{CO₂} \left[ \frac{\text{tonnes CO}_2}{\text{tonnes fuel}} \right] \times F [\text{tonnes fuel}]
\]

Before 2009, an emissions factor of 3.17 kg CO₂/kg fuel has been the empirical mean value most commonly used in CO₂ emissions calculations based on fuel consumption. The 2009 IMO GHG study uses slightly lower coefficients, different for heavy fuel oil and for Marine Diesel Oil. The actual values are 3.082 for Marine Diesel and Marine Gas Oils (MDO/MGO) and 3.021 for heavy fuel oil (HFO). In order to ensure harmonization of the emissions factor used by parties under the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol the Carbon to CO₂ conversion factors used by the IMO should correspond to the factors used by the Intergovernmental Panel on Climate Change (IPCC). Therefore, IMO has established new conversion factors in its guidelines (IMO, 2008). The default values are 3.19 for diesel or gas oil and 3.13 for heavy fuel oil. In some recent regulation that is used to measure the energy efficiency of new ships, IMO has used the values of 3.1144 kgCO₂ per tonne of fuel for heavy fuel oil and 3.206 kgCO₂ kg per tonne of gas/diesel oil fuel. These are the figures that we propose to be used in GSRSP.

Thus, there are no single accepted values. One can even choose for reasons of simplicity to use a single factor regardless of fuel type (the one for heavy fuel oil), in which case minimizing emissions and fuel consumption are equivalent problems. In this case, the figure of 3.1144 kgCO₂ per tonne of fuel is suggested to be used.

**Sulfur oxide (SOₓ) emissions**

Sulfur dioxide (SO₂) emissions – that is 98% of SOₓ emissions – depend on the type of fuel used and in particular on the amount of sulfur present in the fuel. One has to multiply total bunker consumption (in tonnes) by the percentage of sulfur present in the fuel (for instance, 3.5%, 1.5%, 0.5%, or other) and subsequently by the exact factor of 0.02 to compute SO₂ emissions.
emissions (in tonnes per day). The factor of 0.02 is exact in the sense that it is derived from the chemical reaction of sulfur with oxygen. For example, 100 tonnes of fuel with 3.5% sulfur content produce 7 tonnes of SO\textsubscript{2} emissions, whereas the same amount of fuel with a sulfur content of 0.1% produces only 0.2 tonnes. Thus, in the case of sulfur oxide, one can reduce emissions by burning less fuel but also by using fuel that less amount of sulfur.

**Nitrogen oxides (NO\textsubscript{x}) emissions**

NO\textsubscript{x} emissions depend on the way that fuel is burned in the engine. One has to multiply total bunker consumption (in tonnes) by an emissions factor, which corresponds to the ratio of NO\textsubscript{x} emissions to fuel consumed. (There is no need to differentiate between MDO/MGO, LSFO and HSFO). The emissions factors are empirical and depend on the engine; these are also different for SSD (slow speed Engines) and MSD (medium speed engines). For engines built prior to 1 January 2000, the ratio of NO\textsubscript{x} emissions to fuel consumed ranges from 0.087 for slow speed engines to 0.057 for medium speed engines (EEA, 2002, Table 8.2). The original Tier I limit on NO\textsubscript{x} emissions applies to engines built on or after 1 January 2000. For Tier 1 engines, the emissions factor is 0.051 for medium speed and 0.078 for slow speed engines (Buhaug et al., 2010).

**The Green Ship Routing and Scheduling Problem**

We note a parallel body of research in road transportation on the vehicle routing problem with emission considerations (also referred to as ‘Pollution Routing Problem’, ‘emissions VRP’, ‘Green VRP’, etc.) and related problems; see Figliozzi (2010), Bektas and Laporte (2011), Erdoğan and Miller-Hooks (2011), Özceylan et al. (2011) and Kopfer and Kopfer (2013). After 2006, Green VRP covering energy consumption (G-VRP), pollution emissions (PRP), as well as recycling and reverse logistics (VRPRL) started to draw researchers’ close attention and became a hot topic. For a complete literature review the reader is referred to Lin et al. (2014) who present a survey of green vehicle routing problem and to Demir et al. (2014), a paper reviewing the area of ‘Green Road Freight Transportation’. According to the latter, in the last decade, the body of knowledge on the reduction of CO\textsubscript{2} emissions from road transportation has grown notably and as of August 2013, they state that there are aware of at least 59 papers on this topic.

However, in the maritime logistics literature, the gap in the interface of routing and scheduling, and emissions is apparent based on the scarcity of relevant models; see Christiansen et al. (2013). Thus, this short communication is motivated by the increasing attention to sustainable routing and scheduling and tries to outline some possible ways to incorporate the environmental dimension into maritime transportation OR. Existing formulations and solution techniques can be used.

There are various ways to embed emissions considerations into maritime OR models, including the following:

1. One way is the construction of an objective function to minimize total emissions, which completely changes the mathematical formulation.
2. Another one is by internalizing the external cost of emissions. This could be the easiest way as the goal in most VRP problems is to minimize the overall operating cost. In this case, we can put a monetary cost on air emissions by assuming a cost per unit of gas emitted (usually in grams).
3. Another way is, to add a constraint that will limit the emissions produced on a per leg, trip, year or fleet basis.

To illustrate these 3 approaches we will use the mathematical formulation presented in Christiansen et al. (2004), which is essentially a generalized assignment problem. Note that various VRP formulations are available in the literature and assuming the set partitioning formulation is no loss of generality as any kind of formulation may be used. The approaches can also be used for any type of problem and existing formulations, especially the ones that include fuel cost in the objective function.

The problem definition that we shall use as an example is the following: In the so-called industrial shipping the cargo owner owns or charters a fleet of vessels. Denote the set of ships to be scheduled as \( V \), indexed by \( v \), and let \( N \) be the set of cargoes, indexed by \( i \). Assume that for each ship \( v \), a set of potential schedules is available, denoted \( R_v \), and a specific schedule is indexed by \( r \). Let \( x_{vr} \) be a binary variable equal to one if ship \( v \) sails schedule \( r \) and zero otherwise. Let \( C_vr \) correspond to the transportation cost for by ship \( v \) when operating in schedule \( r \), and constant \( a_{ivr} \) is equal to 1 if schedule \( r \), serviced by ship \( v \), carries cargo \( i \) and 0 otherwise. The set partitioning formulation of the ship scheduling problem described above can then be given as follows (Christiansen et al., 2004):

\[
\min \sum_{v \in V} \sum_{r \in R_v} C_{vr} x_{vr} \quad (2)
\]

subject to

\[
\sum_{v \in V} \sum_{r \in R_v} a_{ivr} x_{vr} = 1 \quad \forall i \in N \quad (3)
\]

\[
\sum_{r \in R_v} x_{vr} = 1 \quad \forall v \in V \quad (4)
\]
The objective function (2) minimizes the transportation costs. Constraints (3) ensure that all cargoes are serviced. Constraints (4) ensure that each ship in the fleet is used in one of the voyages (this can be relaxed to allow part of the fleet to be idle), and (5) imposes binary requirements on the variables. In addition, other constraints may be included such as time windows. Thus, more generic formulations of routing and scheduling can be used. In the GSRSP it is important that ship speed is included as a decision variable, see next Section. In the case of variable speeds, the objective function becomes non-linear which makes the solution of this problem much harder. For instance, according to Fagerholt and Ronen (2013), non-linearity of the bulk fleet scheduling problem with speed optimization makes it quite impossible to find optimal solutions within any reasonable time frame for realistic size problems.

\[ x_{vr} \in \{0, 1\} \quad \forall v \in V, \forall r \in R_v \] (5)

The main problem with the non-linear fuel consumption function is that it makes the solution of relevant models much more complicated. However, non-linear solvers, dynamic programming, discretizing the sailing speed range and approximation techniques (e.g. transforming the constraints with power functions to second-order cone programming (SOCP) constraints or using piecewise-linear functions) have been used in the literature in speed/fuel consumption optimization problems, see for instance Wang and Meng (2012) for some optimization methods and approaches that can be used to solve the bunker optimization problem. For instance, given a shipping route of a sequence of ports with a time window for the start of service at each port, Fagerholt et al. (2010) present a single ship speed optimiser for each leg and they solve it both with a non-linear programming solver and using an alternative solution methodology, in which the arrival times are discretized and the problem is solved as a shortest path problem on a directed acyclic graph. Wang et al. (2013) investigate the optimal sailing speed of container ships on each leg of each ship route in a liner shipping network. This problem is formulated as a mixed-integer nonlinear programming model. Then, they prove that the nonlinear objective function is convex and they employ an approximation method by using sum of many piecewise-linear functions to approximate the convex function and, thus, transforming the model to a mixed-integer linear programming model.

**Approach 1: Fuel/emissions minimization objective**

The first way to incorporate emissions consideration is by reformulating the GSRSP. Instead of minimizing total transportation cost, or distance, the new objective function would be to minimize emissions. First, we should clarify some optimization objectives related to this problem.
Minimizing distance is NOT equivalent to minimizing time

The two problems (min Distance and min time) are equivalent only when speed is constant. In general, speed is not constant. In addition, the average speed per leg depends on various parameters including for example the freight rate (the reward that the owner receives when delivering a cargo) and on fuel price; see Psaraftis and Kontovas (2013). In addition both problems are also not equivalent to fuel (or emissions) minimization problems. The reason is that fuel consumption (or emissions) rate per distance travelled or per unit time is not constant. However, there are some figures that could be used for rough estimations, see for example Psaraftis and Kontovas (2009) that present CO₂ per tonne-km figures for different vessel type and size. Note that these figures take into account the amount of cargo transported and the distance travelled.

Minimizing fuel cost or emissions is NOT equivalent to minimizing fuel consumption

In many papers it is stated that fuel cost and emissions are proportional to the amount of fuel used. This can be true in some cases, especially when there is only one type of fuel oil used. It is true that for each different type of fuel used, fuel costs and emissions are directly proportional to fuel consumption. However, in general, vessels use different type of oils for their main and auxiliary engines. These fuels have different properties and the emission factors that should be used to estimate emissions are different. In addition their prices are different; the fuel used in auxiliary engines is way more expensive than the one used in main engines. In addition, SO₂ emissions depend not only on the amount of fuel consumed but also very much on the type of fuel, especially the sulfur content of it. NOₓ emissions depend also on the engine type. Thus, the above problems are not in general the same.

Therefore, it is essential to formulate a model that explicitly addresses the minimization of emissions. This is a very important and not so trivial task. If we want to formulate a robust GSRSP the first step will be to use a robust emissions model. This was also the case for green VRPs in road transport. Demir et al. (2011) have compared several emissions models, and mentioned other relevant factors such as load weight and distribution, engine type and size, vehicle design, and road gradient. To that extent, Section “The relationship between Fuel Consumption and Emissions, and how to estimate them” presents all the necessary information to construct the optimization objective. In most cases, the easiest way is to model emissions is to multiply fuel consumption by the appropriate emissions factor. This has to be done for every different fuel type if available, usually different for main engines and auxiliaries but also for normal fuel and fuel used within the so-called emission protection areas where there are specific regulations for the amount of sulfur contained in the fuel. However in most cases one single fuel is assumed. In this case (which is a subset of the case that will be presented next), the objective function takes into account the total emissions \( E \) generated by each vessel \( v \) that services schedule \( r \) as follows:

\[
\min \sum_{v \in V} \sum_{r \in R} E_{rv} X_{rv}
\]

(6)

Approach 2: Internalizing the external cost of emissions

In the realm of transportation, the external costs due to congestion, noise, the health effects due emissions and climate change are widely recognized. In economics, an external costs occurs when producing or consuming a good or service imposes a cost upon a third party. In that sense, vessels emits air emissions and create costs to other people in society, that are not actually benefited as the shipowner or charterer that gets money for the transportation provided. In principle, any ‘damage’ is monetisable although this is a very controversial issue. Although there is no single acceptable figure for that, there exists a number of works on the estimation of the social costs of emissions; see for example Miola et al. (2008) which presents a methodological approach to estimate the external costs of maritime transport. This is also related to the on-going discussions at the International Maritime Organization (IMO) regarding the so-called Market Based Measures (MBM); see Psaraftis (2012) for more. Placing a price on GHG emissions through an MBM (this could be for instance a tax on emissions or fuel consumption or the inclusion of shipping in an emissions trading scheme which would force owners to buy allowances that will essentially give them the right to pollute, or actually offset for the damage cause) is still a hot topic at the IMO, and also the European Commission. An MBM, which may be a reality in the coming years, will essentially put a price tag per unit of emissions. Note that there may be in addition other costs related to the total cost of regulations. See for instance Schinas and Stefanakos (2012) who present a methodological framework for the estimation of the cost impact of some of the environmental measurements, and specifically on the increase of operating expenses of seagoing vessels due to regulations on sulfur limits.

This approach could be the easiest way to incorporate emissions considerations in VRP problems as the goal in most of them is to minimize the overall cost. In this case, the total emissions are monetized by multiplying the amount of emissions \( F \) by the cost per unit of gas emitted, \( p \), for example \( p \) $ per tonne of emissions. This cost is then added to the transportation cost \( C \) which is usually the objective function. Note that this way we can take into account all different types of emissions (CO₂ which is related to climate change, SOₓ and NOₓ which are mainly related with health effects) but also other environmental effects such as noise, congestion, etc. In this approach, the minimization objective includes the transportation cost plus the cost of emissions per schedule sailed as follows:

\[
\min \sum_{v \in V} \sum_{r \in R} (C_{rv} + F_{rv} \cdot p) X_{rv}
\]

(7)
Approach 3: A constraint on produced emissions

Another way, probably the least straightforward, is to add a constraint that will limit the emissions produced. The most common side conditions in VRP include capacity restrictions (such as that the sum of weights on any vehicle route may not exceed the capacity of the vehicle) or total time restrictions (such as that the length of any route may not exceed a prescribed bound). In our case, a constraint on emissions can also be included by imposing a limit on total emissions per year or per vessel or, even, per leg. Besides, operational limits, such as that the vehicle cannot produce more than a prescribed amount of emissions in grams per km travelled, could also be imposed as constrains. The latter is also related to the possible proposal of ship-specific operational fuel efficiency standards from the European Commission or the International Maritime Organization. Suppose that for each leg (or trip or annually) there is a maximum permitted amount of emissions, $E_{\text{LIMIT}}$. The constraint that has to be added is $E_{vr}x_{vr} \leq E_{\text{LIMIT}}$.

The problem could be also relaxed by removing the emission constrain and putting it into the objective function, assigned with a weight (the Lagrangian multiplier), see Eq. (8).

$$L(\lambda) = \min \sum_{v \in V} \sum_{r \in R_v} (C_{vr} + F_{vr} \cdot p)x_{vr} - \lambda(E_{vr}x_{vr} - E_{\text{LIMIT}})$$

(8)

In the case of (convex) linear programmes, the optimal solution of the Lagrangian dual coincides with the optimal solution of the initial problem. Note, that if speed was a decision variable (and it should clearly be one) then emissions would be a nonlinear function and there would be an optimality gap between the two problems, see Section “Speed optimization” above.

Further research considerations

The paper conceptualized the formulation of the “Green Ship Routing and Scheduling Problem” (GSRP) which combines ship air emissions and the vehicle routing problem as it is applied in maritime transportation. This is an area of increasing importance. The main benefit is that this formulation does not add more complexity to the existing problems as the approaches presented are generic and could be used in a variety of existing models especially the ones that already include fuel consumption optimization.

In the GSRP it is important that ship speed is included as a decision variable. As described above there will be some difficulties to solve the nonlinear formulations so further research on this topic is essential. It is also obvious that fuel prices are a very critical determinant of fuel costs, and, as such, of the speed chosen by the vessel. In fact fuel price is the one of two main factors that play a critical role in the determination of ship speed. Containership speeds of up to 33 knots in the late 60s are nowhere to be seen these days, and the main reason is the significant increase of fuel prices. An implicit formulation (for instance a fuel cost function $c(v)$ of speed $v$), means that the fuel price is not explicitly part of the problem’s input. An implicit formulation has the drawback of not allowing someone to directly analyze the functional dependency between fuel price and vessel speed, which can be very important.

It is also important to link the relevant problems with the relevant policy framework since maritime emissions are progressively being integrated into the international and regional policies for reducing its domestic greenhouse gas emissions. Psaraftis and Kontovas (2014) has confirmed that solutions for optimal environmental performance are not necessarily the same as those for optimal economic performance. Also policies that may seem at first glance optimal from an environmental viewpoint may actually be suboptimal. As a private operator would most certainly choose optimal economic performance as a criterion, if policy-makers want to influence the operator in his decision so as to achieve results that are good from a societal point of view, they could play with parameters that would internalize the external costs of CO₂ produced and move the solution closer to what is deemed more appropriate for the environment and for the benefit of society. For instance, imposing a tax on fuel would artificially increase fuel prices, induce slower steaming and further reduce emissions.

Multi-objective optimization

Another important consideration is that several, and often contrasting, objectives can be considered for the vehicle routing problems. Typical objectives include for example the minimization of the total transportation cost, dependent on the total distance travelled (or on the global travel time) and on the costs associated with the vehicles used, the minimization of the number of vehicles required to serve all the customers. Indeed, most real-world problems involve multiple objectives. For instance, in the so-called Green VRP presented in Demir et al. (2013) two important objectives are taken into account, namely minimization of fuel consumption and the total driving time. Jemai et al. (2012) present another bi-objective GVRP where they consider minimizing carbon dioxide emissions and total travelled distance. Thus, in GSRP there is a need for a multi-objective approach. The problems could deal with different considerations such as: distance, time, different kind of emissions, cost, revenue, etc. Proposed approaches to multiobjective optimization problems that could be explored are (a) the Weighted-Sum or Scalarization Method and (b) the ε-Constrained Method.

The first approach combines the multiple objectives into one single-objective scalar function. By using the above the problem is actually reduced to a single optimization problem. For instance a bi-objective problem of emissions and total cost
minimization can be reduced to a single problem if the one weight is the external cost of the emissions (e.g. in monetary value per unit of emissions). In addition, we may also use this method to reduce multiobjective problems to bi-objective ones, especially when investigating the problem of multigas emissions. Emissions of different gases with different atmospheric lifetimes and different radiative properties can only be compared and weighted by using a climate change metric. Carbon dioxide equivalents (CO2-eq) provide a standard of measurement against which the impacts of releasing (or avoiding the release of) different greenhouse gases (e.g. Methane, Nitrous oxide, etc.) can be evaluated. A more difficult task is to aggregate the effect of (long-lived) greenhouses gases, such as CO2, with other gases such as SO2 and NOx. Although this is not an easy task, there are some studies (e.g. Fuglestvedt et al., 2010; Lauer et al., 2007) which can be used to determine the weights needed to aggregate the effects of various gases in the shipping sector.

In the second approach, only one objective function is selected to be minimized; the remaining objectives are constrained to be less than or equal to given target values. Thus, the formulation of the optimization problem takes the following form:

$$\min f_k(x)$$

$$f_i(x) \leq e_i, \forall i \in \{1, \ldots, n\} \setminus \{k\}$$

$$x \in S$$

In order to generate as many Pareto optimal solutions as possible, the right-hand side of constraint is gradually increased by a small amount and the problem is solved again whenever \(e_i\) is increased. This method offers several advantages over the weighted sum method. However, there are also some drawbacks of this method, i.e., the decision maker has to choose appropriate upper bounds for the constraints, i.e., the \(e_i\) values. Moreover, the method is not particularly efficient if there are more than two objective functions and in this case it is better to used an improved method, for instance AUGMECON2. Mavrotas and Florios (2013) present an improvement of their augmented \(\varepsilon\)-constraint method (AUGMECON2) which addresses some weak points of the conventional \(\varepsilon\)-constraint, namely, the guarantee of Pareto optimality of the obtained solution in the payoff table as well as in the generation process and the increased solution time for problems with more than two objective functions.

Conclusions

This paper has clarified some important issues as regards estimating ship air emissions and their relationship with fuel consumption as there is a clear need to use more accurate models to estimate fuel consumption. The proposed fuel consumption formula takes into account speed and payload (extremely important in pickup and delivery problems) is more realistic compared to other formulas used in existing models. There are a number of combined ship speed optimization and routing papers in the literature that assume a so-called ‘mixed’ chartering scenario (see for instance Fagerholt and Ronen, 2013). In scenarios such as this, ship payload will generally vary along the ship’s route. Thus, in order not to misrepresent the fuel consumption and costs along the route a fuel consumption formula also depending on payload should be used. It would not make much sense to obtain solutions within, say, 1%, 2% or 5% from the ‘optimum’, or even at the exact ‘optimum’, if the fuel consumption function is misrepresented by 10%, 20% or 30%. Based on this fuel consumption formula we present a way to estimate CO2, SOx and NOx emissions.

Then, the paper conceptualized the formulation of the ‘Green Ship Routing and Scheduling Problem’ (GSRSP) which combines ship air emissions and the vehicle routing problem as it is applied in maritime transportation. This is an area of increasing importance. This can easily be extended to incorporate other environmental effects, such as noise, congestion, etc. The conceptual formulation of GSRSP is done in such a way that most available models can be reformulated in order to incorporate emission considerations. The main benefit is that this formulation does not add more complexity to the existing problems and most GSRSP models can be solved using existing solution techniques. The main issue that can arise especially regarding solving these problems is the nonlinearity in the case that speed optimization is included in the problem. Speed is an important parameter for the GSRSP and should be included in the proposed models. However, as emissions are nonlinearly related to speed, the inclusion of speed will in many cases lead to nonlinear programming models with nonlinear terms in the objective function and/or constrains. Thus in many cases it will be difficult to solve the optimization problem directly. There are however some papers that deal with this issue especially within the area of bunker optimization. As fuel consumption and emissions are proportional to each other these techniques can be used in the case of GSRSP. In addition, in most cases the objective function is convex and based on this property a lot of approximations can be used, see Section “Speed optimization”.

To our knowledge this is the first approach to present the so-called GSRSP, noting that there is already a parallel body of research in road transportation on the vehicle routing problem with emission considerations, which is referred to as ‘Pollution Routing Problem’, ‘emissions VRP’, ‘Green VRP’, etc. As such, it can hopefully contribute to further research in this area.

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